

Original Article

Using GenAI for Personalization and Customer Journey Intelligence in Wealth Management

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Abstract: Applying GenAI to personalization in wealth management presents unique challenges because investment decisions are financially consequential, emotionally significant, and unfold over long client relationships. This review positions customer journey intelligence as the central organizing construct and synthesizes the evidence into a Governed Customer Journey Intelligence (GCJI) Framework for GenAI-enabled wealth management. The article synthesizes peer-reviewed evidence on robo-advisory adoption, AI-enabled service, customer-experience analytics, financial-services AI, and GenAI in business and consumer contexts. The literature suggests that personalization benefits depend less on model novelty and more on suitability controls, explainability, governance, and human oversight of automated content with fiduciary responsibility. While there are reported benefits of better engagement, scalability and the potential for bias reduction, there is still limited direct evidence of GenAI in the wealth management sector. Persistent gaps concern performance measurement, protection of vulnerable clients, validation of advisors' models, matching trust and reliance of advisors and clients, and personalisation that can be audited. The field is significant since the choices about wealth management are very high stakes and relationship-centric.

Keywords: Customer Journey Intelligence, Generative AI, Personalization, Robo-Advisory, Wealth Management

I. INTRODUCTION

The use of GenAI in personalisation within the wealth management space has its own set of complexities, given that investment decisions have a significant financial impact, emotional resonance, and are settled over a long-term client relationship. In this review, customer journey intelligence means using the ongoing application of inference to gather a client's changing financial environment, behavioural status, life events, engagement history and advice readiness across interactions, to better inform and tailor personalized interventions. It goes beyond the static approach of personalising client segments and single touch points, linking a series of signals from acquisition to onboarding, advice, service, life events and retention. Customer-journey research also considers experience as a chain of chronologically ordered interactions as opposed to a single transaction [1]; marketing analytics research has also shown how fine-grained and granular behavioural, transactional, and interaction data can inform decision-making more contextually relevant [2]. In wealth management, however, this is especially risk sensitive as poorly-managed personalisation can exacerbate risk misalignment, overconfidence, inappropriate product steering and/or intrusive interpretation of client vulnerability.

GenAI extends AI-enabled personalization beyond prediction, classification, recommendation, and workflow automation. Earlier generations of service and marketing AI primarily supported functions such as targeting, scoring, forecasting, recommendation, and process automation. GenAI adds the capacity to produce tailored explanations, summaries, prompts, scenario narratives, client-facing materials, and advisor-support content in natural language. These capabilities are particularly relevant to wealth management because personalization is both informational and relational. AI has been associated with more dynamic targeting, service automation, and decision support [3], while service research distinguishes mechanical, thinking, and feeling intelligence as different forms of automation potential [4]. All three are relevant to wealth management: mechanical intelligence can support routine processing and reporting; thinking intelligence can support portfolio and risk analysis; and tightly governed affective capabilities may support client communication without creating manipulative or misleading simulations of empathy.

The literature on robo-advisories offers the closest empirical support for the wealth-management aspect of the theme. Based on adoption research, acceptance of automated financial advice is found to be related to the perceived usefulness, trust, ease of interaction, personal innovativeness and perceived risk [5]. This is still significant for GenAI, as advising through conversation can be more fluent and accessible without being more suitable or of better quality of the investments. The central scholarly question is not whether GenAI can personalize more content, but whether personalization can enhance journey intelligence—the ability to identify a client's state, an advice need, risk constraints, channel preference and the timing of possible intervention throughout the entire journey within the context of the client's wealth-management relationship.



An initial review of the literature suggests that few peer-reviewed studies published since 2015 have examined GenAI, personalization, customer journey intelligence, and wealth management within a single empirical design. The relevant peer-reviewed evidence is distributed across several adjacent fields: robo-advice, AI customer service in financial services, personalisation analytics, customer experience theory, or GenAI business research. It implies that the practice is ahead of the science, especially regarding the use of large language models in financial advice. This review aims to collate the most relevant peer-reviewed evidence base, determine its meaning for customer journey intelligence and personalization in wealth management through the use of GenAI tools, uncover methodological boundaries, and set out a minimal agenda for future research.

II. LITERATURE REVIEW

The most directly relevant evidence stream in the wealth-management literature is robo-advisory. The research into robo-advice conceptualizes automated financial advice as a combination of digital onboarding, risk profiling, algorithmic portfolio allocation, monitoring and rebalancing [6]. The value of this literature lies in its focus on automation in the context of the existing structure of wealth-management services, instead of abstract service technology like AI. The emergence of robo-advisors and wealth management highlights scalability, cost savings, a systematic and structured approach to portfolio building, and the ability to penetrate new markets, but also confirms that automated solutions are not particularly good at tackling complex preferences, the intricacies of financial planning and behavioural coaching [7]. Risk-profiling research is particularly relevant because personalization depends on accurate assessment of risk capacity, risk tolerance, financial goals, liquidity needs, and investment horizon.

Table 1: Summary of key Findings

Ref	Focus	Key Findings
[6]	Robo-advisory architecture	Automated advice combines digital onboarding, risk profiling, portfolio allocation, monitoring, and rebalancing.
[7]	Wealth-management automation	Robo-advisors can reduce cost and expand access, but complex planning and behavioural coaching remain difficult.
[8]	Risk-preference assessment	Risk questionnaires differ materially, creating suitability concerns for automated personalization.
[9]	Investor outcomes under robo-advice	Automated advice can improve diversification and reduce selected behavioural investment mistakes.
[10]	Substitution between human and automated advice	Robo-advice is not a complete substitute where trust, complexity, and relationship value remain salient.
[11]	AI marketing in financial services	Personalization can support access but may heighten vulnerability, manipulation, and fairness concerns.
[12]	Customer-facing financial-services AI	Chatbots, robo-advice, and personalization dominate the field, with limited longitudinal governance evidence.
[13]	AI-enabled personalized engagement	Personalization value depends on integrated data, decision engines, and delivery discipline.
[14]	AI in customer relationship management	AI extends relationship management but creates oversight and autonomy boundary problems.
[15]	Consumer experience with AI	AI encounters affect agency, identity, privacy, and perceived human connection.
[16]	GenAI in research, practice, and policy	Conversational GenAI creates productivity and service opportunities alongside hallucination and accountability risks.
[17]	GenAI and business-model innovation	GenAI can reshape value creation through knowledge-work automation and new interaction designs.
[18]	GenAI and consumers	Consumer-facing GenAI offers convenience and personalization but raises confidence, transparency, and ethics concerns.

Preliminary findings of robo-advising also suggest that automated advice can help with diversification and mitigate some investment pitfalls, but results depend on the investor and the situation [9]. The human-advice substitution research questions easy-to-tell automation stories because it shows that the substitution of robo-advice for human advice does not simply replace it but changes the context of the client's decision as to whether to accept it, reject it, or combine it with another type of advice [10].

The second cluster deals with the applications of AI in customer facing financial services and personalisation. Customer interaction, vulnerability, transparency and trust are a major component of fintech and are essential to journey

intelligence with AI technology [11]. The customer facing AI application areas in financial services can be classified in five main categories and yet empirical studies often lack detail in terms of risk-governance and the longitudinal outcomes for customers [12]. AI is suggested to increase the relevance of communication and offers by adapting them to the specific context, which necessitates the seamless integration of the three: data, decision logic and delivery [13]. AI can reshape customer acquisition, retention, and development while creating new concerns regarding autonomy, surveillance, and the acceptable boundaries of automated influence [14]. Automated service interactions also raise agency issues, identity and privacy issues, and the latter is exacerbated when the advice is on household wealth and not low-risk consumption, according to consumer AI research [15].

The third cluster is related to GenAI. Some of the advantages of GenAI are scalable natural-language interaction, content creation, and decision support, while risks include: hallucinations, opacity, data leakage, and lack of accountability. The business-model research indicates that GenAI has the potential to influence value creation and capture through new possibilities for knowledge work automation and redesigning client communication [17]. Consumer-focused GenAI research has found that it could offer consumers benefits in convenience, accessibility, and personalization, but also that fluent conversational output might cause an expectation of complete, supported, or correct output that may be incomplete, unsupported, or incorrect [18]. For wealth management, the connotation is twofold: If used properly with the right controls, GenAI can enhance customer journey intelligence by making it more continuous, contextual and accessible; if used incorrectly, or with the wrong controls, weak or inappropriate content can appear authoritative.

As shown in Table 1, the relevant literature base is substantial but incomplete. The most directly relevant wealth-management evidence comes from robo-advisory rather than from GenAI-specific studies. Consequently, many implications for conversational personalization must currently be inferred from adjacent evidence rather than from direct evaluations of GenAI-enabled wealth-management systems. This separation has some implications for causal claims in wealth management using GenAI. It also suggests that there is a great opportunity for the design of research that integrates journey-stage measurement, advice quality assessment, and client outcome tracking.

III. REVIEW METHODOLOGY

A. Review design, search strategy, and selection criteria

The review was conducted using a structured narrative approach. The actual databases used were chosen to give the coverage of the disciplines of marketing, finance, information systems and management and searched from [insert final search date]. The search strings included generative AI, large language models, artificial intelligence, robo-advisory, wealth management, financial advice, personalization, customer journeys, customer experience and human-AI collaboration. The titles and abstracts of records were first screened based on conceptual relevance to the design, suitability, governance, implementation, or evaluation of GenAI personalisation in the wealth management space and then the full text of the records was screened for conceptual relevance to the same focus areas. Duplicate, non-peer-reviewed, purely technical, and non-relevant publications were excluded; neighbouring evidence was retained only where its relevance to wealth management could be clearly established. Studies included were coded for research method, principal contribution, limitations, evidence stream and implications to the GCJI framework. Since screening and coding was done by one reader, inter-rater reliability was not calculated. Finally, twenty-one peer-reviewed articles were selected to form the analytical corpus. The review did not follow a PRISMA protocol since the goal was to develop theory and synthesize the results.

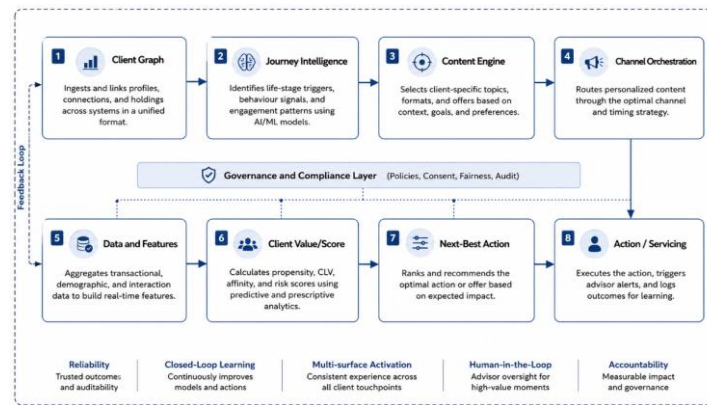
B. Methodological characteristics of the included literature

The literature reviewed is based on four methodological approaches. First, customer journey and customer experience research offer models of the process of customer experience, which view it as a series of temporally ordered touchpoints, not as one-off service interactions [19]. It is a useful strategy for wealth management products because it is an acquisition, onboarding, goal setting, investing, monitoring, coping, life change, and retention process. But journey research may be descriptive without link to decision models, suitability tests and measurable financial outcomes. Whilst the theory of customer experience provides a multi-dimensional approach to cognitive, emotional, behavioural, sensory and social experience [20], attention needs to be paid to the fiduciary constraints and to the harm that could be done to the client in the context of wealth management.

Secondly, robo-advisory research uses empirical adoption models, investor-behaviour analysis and system evaluation. Adoption models have been proposed to understand why clients take on automated advice, but intention measures are less strong than the actual behaviour of their portfolios and long-run client welfare. Investor outcome research is better since investor behaviour can be compared before and after they are implemented, but the outcomes are typically measured on previous robo-advice systems, not GenAI interfaces. The relevance of the risk profiling comparison is highlighted as personalisation with GenAI is not a solution to an inaccurate suitability foundation.

Table 2: Method Comparison

Ref	Method	Strengths	Limitations
[5]	Technology-adoption modelling for robo-advisors	Identifies trust, usefulness, and perceived risk as adoption drivers.	Intention does not prove advice quality or long-term welfare.
[8]	Comparative risk-profile evaluation	Directly examines suitability foundations for automated advice.	Limited insight into conversational GenAI explanations.
[9]	Investor-behaviour outcome analysis	Connects automation to observable portfolio behaviour.	Context-specific evidence may not generalize to GenAI interfaces.
[10]	Survey-based advice substitution analysis	Clarifies client preference for human versus automated advice.	Stated preference may differ from high-volatility behaviour.
[12]	Systematic review of financial-services AI	Maps applications and governance gaps across financial services.	Wealth-management journey metrics remain underdeveloped.
[13]	Conceptual engagement-marketing framework	Links data, decision logic, and personalized interaction.	Financial suitability and fiduciary tests are not central.
[16]	Multidisciplinary GenAI review	Identifies cross-domain opportunities and risks.	Direct wealth-management evidence is limited.
[21]	Human-AI collaboration experiment	Explains delegation and confidence calibration.	Not specific to portfolio advice or client journeys.

**Figure 1: Governed Customer Journey Intelligence (GCJI) Framework for GenAI-Enabled Wealth Management**

Third, research into AI service and personalization uses conceptual modelling, systematic review, and analysis. While these studies shed light on the impact of AI on relationship management, service automation, and engagement, the supporting data can be broad and extend across numerous industries. When designing and building a wealth management application, one needs to take into consideration risk tolerance, product suitability, explainability, protecting vulnerable clients, and regulatory auditability. Fourth, the field of GenAI research is emerging from conceptual, policy and early empirical studies of consumers. These studies provide insight into changes in natural-language interaction capabilities but offer limited evidence concerning portfolio outcomes, advisor–client relationship quality, or model-risk validation.

Human–AI collaboration research provides an additional methodological layer. For productive delegation, the tasks need to be allocated, confidence needs to be calibrated and knowing the limitations of AI [21]. That's important because any GenAI system that drafts a client message, summarizes events in the portfolio, or recommends what to do next based on the content is capable of changing what an advisor thinks. From a methodological perspective, future work should therefore entail assessing the joint system (client, advisor, model, governance layer, and journey-stage trigger).

The Governed Customer Journey Intelligence (GCJI) Framework (Figure 1) is a controlled process, continuously evolving cycle that connects client signals, inference of the client's journey-state, verified contextual information, GenAI powered personalization, advisor supervision, suitability check, client interaction, and outcome feedback. The GCJI framework places journey intelligence as the glue that links disjointed client data with contextually relevant intervention. The production of personalization is thus not the exclusive responsibility of the generative model, but requires client verification information, authorized knowledge sources, human judgement, suitability controls and ongoing outcome monitoring. This is a conceptual framework, rather than an empirical model, which is a synthesis of the literature reviewed [1]–[21].

IV. DISCUSSION

The reviewed studies indicate that: Quality of the advisory service is a more prominent barrier than the sophistication of the interface when it comes to AI-driven personalization in wealth management. Studies on robo-advisory confirm that automation can help to reduce some behavioural errors, standardise rebalancing and enhance cost efficiency [6] [7] [9]. However, risk-profiling research reveals that the personalization base can be precarious if questionnaires and scoring models are based on the same customer data and draw different risk conclusions [8]. This means that using natural-language fluency to personalize explanations and journeys does not mean that the content is suitable, and that suitability still depends on structured data, validated risk models, and domain controls. Adoption findings support this conclusion because people's sense of usefulness and trust affect their adoption acceptance [5] and substitution evidence suggests that human advice is still valuable when complexity or relationship confidence is important [10].

Table 3: Results Comparison

Ref	System / Context	Metric / Basis of Comparison	Outcome
[5]	Robo-advisor adoption	Perceived usefulness, trust, attitude, perceived risk	Acceptance depends on usefulness and trust, with risk concerns reducing adoption.
[8]	Automated risk profiling	Variation in risk-preference classification	Suitability can be weakened when profiling instruments classify similar clients differently.
[9]	Robo-advised investors	Portfolio diversification and behavioural investment mistakes	Automated advice can improve diversification and reduce selected biases.
[10]	Human versus robo-advice	Advice-substitution preference	Automated advice does not fully replace human advice in complex or trust-sensitive contexts.
[11]	AI financial-service marketing	Vulnerable-customer exposure	Personalization can improve access but may increase manipulation and fairness risk.
[12]	Customer-facing financial-services AI	Application domains and governance issues	Trust, explainability, privacy, and accountability recur as adoption constraints.
[13]	AI engagement marketing	Data-decision-delivery integration	Personalization is strongest when analytics and interaction channels are connected.
[14]	AI relationship management	Acquisition, retention, and development logic	AI extends relationship management but creates autonomy and oversight boundaries.
[16]	Conversational GenAI	Capability and risk assessment	Adaptive language output supports service productivity but creates hallucination and accountability risk.
[21]	Human-AI collaboration	Delegation and confidence calibration	Performance depends on correct task allocation and calibrated reliance on AI output.

The evidence distribution in figure 2 shows the main imbalance of the field. The direct GenAI studies on wealth management are not as developed as studies on Robo-advisory and AI personalisation. This imbalance is important because contemporary applications of large language models to journey intelligence are being developed largely through extrapolation from related, but not equivalent, evidence streams. Figure 2 shows the distribution of the 21 peer-reviewed articles included in the final analytical corpus according to their primary evidence stream.

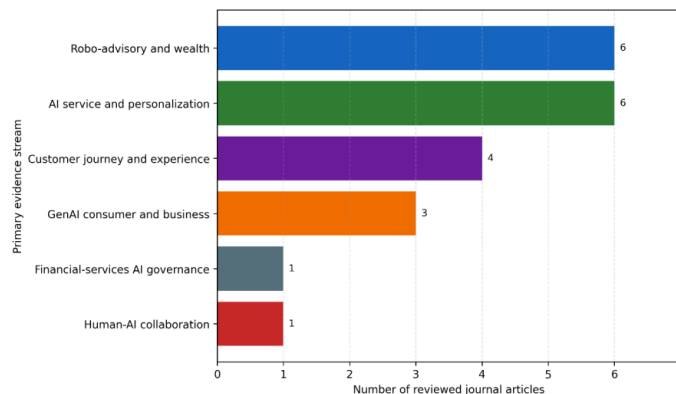


Figure 2: Distribution of Evidence Streams in the Reviewed Source Pool

This imbalance indicates that the literature on applying GenAI to wealth management journey intelligence is still in its early stages, even as claims of success are made, with the literatures of robo-advisory, customer experience, and AI-

services being thicker than the literature on the application of GenAI in wealth management. The distribution represents a manual classification of the 21 peer-reviewed articles included in the analytical corpus [1]–[21].

The second major finding is that the personalization method is altered by GenAI. Traditional robo-advisors customize primarily via inputs and through a set of rules that govern the portfolio. Through analytics, AI engagement systems tailor messages, offers and service timing based on customer data. GenAI-based journey intelligence extends personalization to narratives, questions, explanations, and real-time advisor support. These models are shown in comparison in figure 3 for the core capacities. The figure illustrates why GenAI is not just a more sophisticated robo-advisor: There is also more potential for natural-language and contextual communication, but more governance load. This comparative pattern is consistent with existing GenAI research focusing on both productivity and interaction benefits as well as risks of hallucination and accountability [16, 17, 18].

Figure 3 compares four personalization approaches across six capability dimensions relevant to wealth-management journey intelligence. It shows that the ability of GenAI journey intelligence is strong in contextual and language features, and that embedded governance and human judgment might lead to the most even profile when combined with hybrid advisor copilots. The scores are interpretive rather than empirically measured and were developed from the comparative patterns reported in the reviewed literature on robo-advisory, AI-enabled personalization, GenAI, and human-AI collaboration [5]–[18], [21].

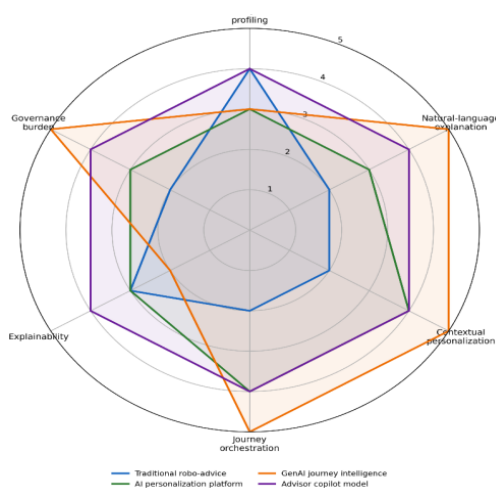


Figure 3: Comparative Capability Profile of Personalization Systems in Wealth Management

A third result has to do with the contradiction of the personalization literature. While personalization is typically described as a means to enhance relevance and engagement [13, 14], in financial services, research has cautioned that personalisation can make people feel more vulnerable when systems project financial events, stress, low confidence and/or lack of financial literacy [11]. In fact, this is not a simple trade-off for wealth management. The same retirement rollover or inheritance, divorce, job loss, or market-anxiety signal also can facilitate providing timely advice or exploiting susceptibility. In addition, the automated systems are also shown as having an influence on perceived agency and identity through consumer research [15]. An empathetic GenAI agent may increase persuasive influence, raising questions about the autonomy of the client and vulnerability.

Fourth, evidence reviewed here indicates that the usefulness of human-AI collaboration increases with the importance of advice, complexity, and the sensitivity to relationships. The study of human-AI collaboration focuses on proper task delegation and proper utilization of AI-generated content [21]. For wealth management, GenAI can help summarize information, write explanations, find changes in the journey state, create scenarios, and facilitate follow-ups. However, human advisors are still required to make complex suitability decisions, interpret conflicting preferences, make life changing decisions, make fiduciary decisions and make client recommendations which are accountable. So, it is unlikely that the preferred architecture will be the same across the board. Rather, the level of autonomy must be tailored to the complexity of the client, financial risk, relationship expectations, vulnerability and expressed channel preference.

This review builds on this evidence and proposes a practice-informed proposition on segment-model fit. For clients with relatively simple financial situations and objectives, a primarily autonomous or AI-robo approach, with suitable controls and escalation paths to humans, may be sufficient. The more assets a family owns, the more exposure they have to products, the more they need to think about tax, the more focused their positions are, the more they own, the more they plan for their estate, and the more they consider family governance, the more they should consider semi-autonomous and advisor-led

models. The advisory model is not to be based on the level of wealth alone; client relationship expectations, financial literacy, vulnerability, preference for personal interaction and the complexity of the client's overall balance sheet should also be taken into account.

Table 4: Illustrative Practice Examples from Wealth-Management Institutions

Illustrative segment	Preferred advisory model	Principal human requirement	Illustrative public industry alignment
Below USD 1 million in investable assets	Primarily autonomous or AI-robo advice for standardized goals, diversified portfolios, routine rebalancing, and general education, with access to human escalation	Suitability exceptions, vulnerability identification, complaints, significant life events, and non-standard planning needs	Morgan Stanley offers automated Core Portfolios and a Virtual Advisor pathway; Merrill offers Guided Investing with and without an advisor; Wells Fargo offers Intuitive Investor with professional guidance when needed; UBS uses a digital-led, advisor-supported Wealth Advice Center model rather than a completely autonomous model [22], [23], [25], [26].
USD 1–10 million in investable assets	Semi-autonomous or advisor-led hybrid model combining journey intelligence, digital tools, GenAI explanations, and a dedicated advisor	Integrated financial planning, tax-aware coordination, concentrated-position management, lending, business-owner needs, and relationship continuity	UBS publicly distinguishes high-net-worth clients and advisor-led services; Morgan Stanley offers dedicated Financial Advisors and comprehensive planning; Merrill Lynch Wealth Management uses dedicated advisors, with Bank of America Private Bank overlapping the upper portion of this band; Wells Fargo Advisors provides personalized planning through dedicated advisors [22], [24]–[26].
Above USD 10 million in investable assets	Human-centric advice supported by GenAI advisor copilots, specialized analytics, and governed journey-intelligence systems	Final judgment, fiduciary accountability, estate and trust coordination, cross-border issues, philanthropy, family governance, liquidity events, and multigenerational relationship management	UBS Private Wealth Management identifies USD 10 million or more as a typical ultra-high-net-worth threshold; Morgan Stanley Private Wealth Management provides highly tailored UHNW and family-office services; Merrill provides Private Wealth and Premium Access offerings for clients with significant or complex assets; Wells Fargo Private Wealth offers an exclusive, personalized model for qualifying clients [22], [24]–[26].

The asset bands shown in Table 4 are thus approximate analysis categories and not absolute regulatory and institutional boundaries. The UBS Wealth Advice Center is an advisor-led approach that is both personalized and technology-driven, according to UBS. According to their official segmentation, affluent clients are those with an investable asset value of up to USD 2 million, high-net-worth clients are those with USD 2–10 million in investable assets, and ultra-high-net-worth clients are those with USD 10 million or more in investable assets [22]. Morgan Stanley currently provides fully automated Core Portfolios that have a minimum investment of USD 500, Virtual Advisor support, dedicated Financial Advisors and a separate Private Wealth Management model for complex UHNW clients. Merrill is named a more streamlined outgrowth of Merrill publicly on its list of more personalized options, as is dedicated Merrill advisors and Bank of America Private Bank. In addition to automated investing, dedicated Financial Advisors and an exclusive Private Wealth offering [22] – [26], Wells Fargo also sets up different sections for its clients.

Note: The institutional examples are based on publicly available descriptions of current service offerings and are included as illustrative practice evidence rather than as peer-reviewed findings. Individual eligibility requirements, minimums, service configurations, and advisor discretion may differ. The three analytical bands should therefore not be interpreted as precise institutional eligibility thresholds. Each GenAI function has been mapped to the relative relevance within the wealth-management journey in Figure 4. The conceptual scores were obtained from the literature they evaluated and suggest potential locations for the benefits of narrative explanation, advisor copilot, event detection, next-best-action support, and suitability guardrails. [1]–[21].

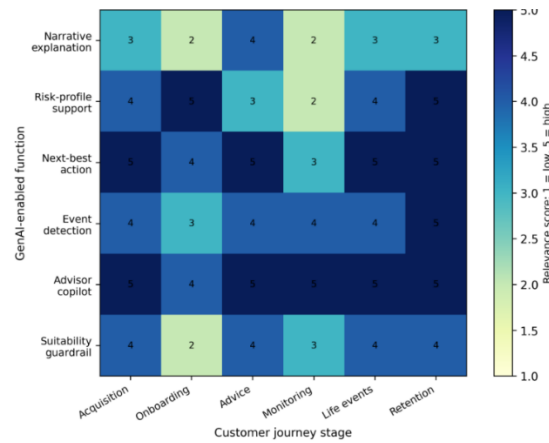


Figure 4: Function-Stage Relevance Matrix for GenAI in Wealth-Management Journeys

Figure 4 shows that GenAI functions have different levels of relevance across the customer journey; however, functional relevance does not determine who remains accountable for the resulting action. Table 5 therefore distinguishes the role that GenAI may perform, the role that should remain with human professionals, and the principal governance requirements at each journey stage. The allocation is conceptual and should be adapted to the institution's jurisdiction, product set, client population, and operating model.

Table 5: Human Role and Governance Requirements Across the Wealth-Management Journey

Journey stage	GenAI role	Human role	Principal governance requirements
Acquisition	Lead prioritization, segmentation support, personalized educational content, and initial query handling	Relationship development, validation of client needs, and prevention of inappropriate targeting	Marketing approval, consent, disclosure, fairness testing, privacy controls, and prevention of manipulative targeting
Onboarding	Document extraction and summarization, missing-information prompts, workflow support, and initial profile consolidation	Identity verification, KYC/AML review, interpretation of client circumstances, and suitability validation	KYC/AML requirements, data accuracy, privacy, cybersecurity, record retention, and source verification
Advice	Scenario generation, explanation drafting, portfolio-context summarization, and next-best-action support	Final recommendation, fiduciary judgment, suitability determination, conflict management, and client consent	Suitability review, fiduciary controls, product governance, model validation, explainability, approval records, and communication retention
Monitoring	Portfolio explanations, drift detection, anomaly identification, event alerts, and preparation of review materials	Strategic adjustment, interpretation of changing circumstances, exception handling, and escalation	Audit trail, continuous model monitoring, data freshness, performance testing, escalation rules, and accountable approval
Life events	Detection of potential life-event signals, contextual summarization, and identification of possible advice needs	Empathetic interpretation, confirmation with the client, reassessment of goals, and coordination with relevant specialists	Explicit consent, privacy, sensitive-data controls, vulnerable-client protection, non-discrimination, and restrictions on intrusive inference
Retention	Personalized outreach, service-recovery prompts, educational messages, and engagement recommendations	Trust management, relationship repair, complaint handling, and judgment concerning the appropriateness of contact	Communication oversight, conduct-risk controls, complaint monitoring, opt-out management, vulnerability safeguards, and documentation

Note: Human accountability should not be inferred to decrease merely because GenAI performs a larger share of information processing or communication preparation. The regulated institution and its authorized professionals remain responsible for the suitability, accuracy, and consequences of client-facing advice.

There are also some limitations in measurement as shown in literature. Adoption, attitude, trust or conceptual readiness are many of the studies that are used to measure instead of the direct financial welfare. The outcomes that are relevant for wealth management include the alignment of risk, diversification, savings attitude, awareness of fees, understanding of clients, their response when they have a drawdown, incidence of complaints, quality of client retention, and productivity of advisors. An increase in engagement, with a decrease in understanding, would be a bad trade with a less engaging system that improves understanding and financial discipline. This distinction is central to customer journey intelligence as it should be judged based on the quality of decision support over time, not on interactions.

Lastly, there is a lack of evidence of model behaviour under stress in the field. Client circumstances and preferences may change rapidly, such as in the event of a market decline, taxation shock, inheritance or sudden need for liquidity. Without verified client data, approved knowledge bases, portfolio constraints, and escalation rules, GenAI systems may generate inconsistent, plausible-sounding, but unsupported advice. Based on the research reviewed in this paper, one can make a cautious conclusion as follows: there is a strong potential for GenAI to augment personalization in wealth management, but at this time the scholarly evidence is stronger for governed augmentation than for autonomous advice.

V. FUTURE DIRECTIONS

Future studies should move away from one-off studies to journey-stage studies, and to ongoing field tests. One of the priorities is to see if the GenAI explanations enhance the client's understanding of risk, fees, diversification, tax implications and trade-offs over traditional robo-advisor explanations. This type of research involves examining understanding, decision quality, and then behaviour and should not be based on satisfaction or intention. Further, it would be worthwhile to expand the research on risk-profiling to the conversational context as information clients provide may differ between the questionnaire and the conversational context. Research is important to determine if these GenAI interviews increase the inconsistency in the suitability assessment process or whether they are part of the assessment process.

The second priority is personalization with a focus on governance. Financial-services AI studies frequently come face-to-face with issues of trust, privacy, transparency and vulnerability [11, 12]. These concepts need to be quantified for future research, including inappropriate recommendation rate, unsupported claims frequency, and escalation accuracy, as well as minimization of client data and differential performance by age, wealth, literacy and vulnerability groups. When evaluating GenAI solutions in the wealth management sector, hallucination of product features, misleading market comments and too-strong nudges in behaviour should be included.

The third direction has to do with advisor copilots. It is demonstrated that the allocation of tasks and calibration of trust is key to the study of human-AI collaboration [21]. It is crucial to evaluate the performance of direct-to-client GenAI, advisor-facing GenAI, and hybrid workflows with respect to the accuracy of the advice provided, time savings, compliance requirements, and the quality of the relationship. This should go some way towards resolving the debate over the value of GenAI to the client in a self-service manner or enhancing the advisor's capacity.

Interdisciplinary research is the fourth direction. The finance team can provide portfolio and welfare metrics, the information systems team can review workflow integration and delegation, a model of journey personalisation can be offered by the marketing team and fiduciary responsibility and protection of vulnerable clients can be achieved by law and ethics. There are opportunities and risks in GenAI that have been identified in a more general fashion before [16, 17, 18] but more domain-specific designs are needed in the wealth management space. Future research should evaluate grounded, auditable, and stage-specific GenAI systems.

VI. CONCLUSION

In wealth management, the reviewed evidence indicates that GenAI can enhance journey-state recognition, portfolio explanation, service continuity, advisor support, and structured escalation. These findings support governed augmentation, as represented in the GCJI framework, rather than the universal substitution of human financial advice. The appropriate level of autonomy remains contingent on client complexity, financial risk, vulnerability, and the need for accountable fiduciary judgment.

The review demonstrates the state of the fragmented scholarship. Research in Robo-advisory presents the most compelling evidence for wealth-management, customer journey research provides a customer process perspective, AI service research provides insight into customer personalisation and threat related to trust, and GenAI research provides a glimpse into new conversational capabilities and threats. The key research gap in the literature is the lack of studies evaluating the effect of GenAI personalization on the understanding, appropriateness, financial action and client relationship from a longitudinal perspective within specific subject areas.

The most plausible future operating model is human-AI collaboration, with the appropriate degree of autonomy determined by client complexity, financial risk, vulnerability, and relationship preference. More autonomous models may be suitable for standardized and comparatively lower-complexity needs, whereas higher-risk and more complex client relationships are likely to require human-centric advice supported by GenAI advisor copilots. Two characteristics make human oversight particularly important. First, GenAI is probabilistic and context-sensitive rather than deterministic; materially similar inputs may therefore produce different wording, emphasis, interpretations, or proposed actions across repeated runs. Second, unsupported or hallucinated statements might continue even after retrieval, validation, and policy controls are put in place. Consequential outputs, therefore, must be evaluated, suitability assessed, and approved by a human being who takes responsibility for the actions [16], [21]. Future progress should be evaluated not by conversational fluency alone, but by accuracy, consistency, auditability, suitability, client welfare, and the quality of human-AI collaboration over time.

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