Supplementary material C. Corpus construction

The sole purpose of Supplementary material C is to document the Tier A qualitative corpus that complements the Tier B 8+44 study reported in Gimmelberg et al. (2025), and to show how each of the 24 core studies maps onto the six PCA macro-codes (C1–C6) and the related question blocks in Supplementary material B. Table S6 summarises the empirical evidence base that underpins the Perceived Cognitive Assistance (PCA) coding framework. For each study, we report the setting, design and sample, the key experiential themes, and the way these themes map onto the PCA codes C1–C6.

The PCA codes capture six recurring functions of AI tools in financial decision-making: C1 structural and path support (roadmaps, risk profiling, diversification discipline), C2 cognitive load and information compression (handling more information without overload), C3 bias mitigation and error checking, C4 support under time pressure and market complexity, C5 trust, transparency and explainability, and C6 autonomy, control and the risk of over-reliance. The final column indicates which Supplementary material B question blocks (for example PCA scale items, perceived usefulness, trust, attitudes) are directly grounded in each study's findings.

The studies listed in Table S6 are the subset of the broader search corpus that make a direct, non-redundant contribution to at least one PCA code and to the wording of Supplementary material B items. Policy guidelines, news or practitioner summaries, and adoption surveys that did not add new experiential themes beyond these six codes were consulted for background but are not listed as separate rows in Table S6.

C1. Corpus construction and paper selection

The studies summarised in Table S6 were drawn from a broader qualitative preparatory study carried out prior to PCA scale development. The aim of this preparatory work was to ground the PCA codes C1–C6 in investors' lived experience of digital advice and AI tools, using published qualitative material rather than conducting new interviews. Qualitative scale-development guidance recommends such an initial qualitative stage to define domains, surface participants' own language, and avoid ad hoc item generation (Hinkin, 1995; DeVellis, 2016). We therefore treated published interview excerpts, focus-group quotations, and user-study narratives on robo-advisors, social trading, and LLM-enhanced advisory tools as legitimate data for Tier A thematic analysis.

C1.1 Search strategy and screening

We used iterative web-based searches supported by AI-assisted search tools, combined with backward and forward citation tracking from key studies. In November 2025, we searched for terms describing (i) the technology (for example robo-advisor, digital investment advice, social trading, AI financial assistant, large language model, generative AI), (ii) study design (for example qualitative, interview, focus group, user study, case study), and (iii) the retail investing context (for example personal finance, retail investors, investment advice). For LLM-specific studies, the search was restricted to 2022 onwards to reflect the post-2022 emergence of conversational LLM advisors. Candidate references were exported, deduplicated, screened against the inclusion criteria below, and supplemented through citation tracking. The Tier A and Tier B labels are used only to distinguish technology generations: Tier A covers robo-advisor, digital-advice and social-trading narratives; Tier B covers conversational LLM advisors and LLM-augmented trading interactions.

Inclusion criteria focused on relevance to PCA and the availability of rich experiential material. The core of the corpus consists of studies that (i) examined investment or portfolio decisions involving robo-advisors, AI-enhanced investment platforms, social- or copy-trading systems, or conversational LLM assistants; (ii) reported a qualitative or mixed-methods component (for example, semi-structured interviews, focus groups, ethnography, think-aloud protocols, open-ended user-study feedback or interview-based case studies) with at least some verbatim quotations or closely paraphrased participant narratives; and (iii) featured retail investors, social-trading users, advisors describing clients' experiences, or experimental participants placed in explicit advice-taking roles analogous to retail investors making portfolio decisions. Alongside these qualitative and mixed-method sources, we deliberately retained a small number of widely cited experimental and survey studies on algorithm aversion, robo-advisor adoption and virtual finance assistants where user responses to automation, trust, over- and under-reliance, and perceived control were central, even though the designs were not primarily qualitative. For these sources we treated authors' summary descriptions of participant reactions, vignettes and any reported verbatim remarks as experiential material. Within all retained studies we focused on segments where participants explicitly discussed cognitive effort, discipline and emotion, perceived understanding, trust or over-reliance, and perceived control when using the tool.

We excluded purely technical or algorithmic work without user perceptions, large-scale adoption surveys that reported only construct scores with no interpretable experience narratives, and high-level conceptual or regulatory pieces that did not report investor or user experiences. Policy documents, scoping reviews and TAM-style surveys that did not add new experiential themes beyond the PCA codes C1–C6 were consulted for conceptual background but, unless they met the experiential criteria above, were not counted as separate rows in Table S6.

C1.2 Tiered corpus and final selection for Table S6

Conceptually, the corpus was structured into two tiers. Tier A consists of robo-advisor and digital-advice studies with investor narratives, including qualitative work on behavioural biases, interview-based studies of automated portfolio tools, and social-trading interviews in which users describe how copying or following signals simplifies complexity. Tier B adds LLM-specific material, including user studies of conversational LLM advisors and mixed-methods work on perceived usefulness, trust and risk when using generative AI for financial decisions. Within Tier B, a small set of experimental and survey-based sources (for example, algorithm-aversion experiments, virtual finance-assistant surveys and large investor surveys on hybrid advice) are treated primarily as conceptual anchors for trust, reliance and over- and under-delegation. Supplementary material C reports only those 24 core studies that make a direct, non-redundant contribution to at least one PCA code (C1–C6) and to the wording of Supplementary material B items. Studies that replicated already-covered patterns of usefulness, ease of use and trust were not listed separately in Table S6.

Together with Section C2 (Theoretical saturation of the Tier A qualitative corpus), this corpus-construction and selection description documents how the qualitative evidence base for PCA was assembled and where we judged saturation to have been reached at the level of experiential codes rather than raw interview counts. This follows methodological guidance on code and meaning saturation in qualitative research (Guest, Bunce & Johnson, 2006; Hennink, Kaiser & Marconi, 2017).

For transparency, we recorded additional sources during screening (for example, policy guidance, media summaries, duplicate versions of included studies, and adoption-only surveys). These informed the background framing but were excluded from Table S6 because they did not add new experiential themes beyond C1–C6.

Table S6. Evidence table for the 24 core studies grounding PCA codes C1–C6 and Supplementary material B items.

C.ID	Full reference (short form)	Platform / setting	Method	Key user-experience themes (PCA-relevant)	PCA codes	Linked survey block(s) in Supplementary material B
C1	Zhu et al. (2023) – "Not transparent and incomprehensible"	Bank robo / AI investment advisor for retail clients	Qualitative lab user study; 24 retail bank clients; Sweden	Opaque decision logic, users cannot see how advice is generated; desire for stepwise explanations and visible path from idea to order; distrust and need to double-check AI before acting	C1, C2, C5, C6	PCA transparency items (PCA1, PCA5); Trust / explainability block
C2	Bhatia et al. (2021) – robo focus groups (India)	General robo-advisor services used by active retail investors	Focus groups with active investors; India	Robo seen as cost-effective and convenient; possible bias mitigation but concerns about data security and lack of empathy; robos treated as supplements, not substitutes	C2, C3, C5, C6	Trust block; PU/PEOU (TAM); overconfidence and emotion blocks
C3	Bhatia et al. (2020) – robo and behavioural biases	Robo-advisor and digital advisory tools from product-developer perspective	Qualitative expert interviews (FinTech / BFSI); India	Structured risk profiling and automation can reduce client biases; current questionnaires too crude; low awareness and trust constrain adoption	C1, C2, C3, C5	PCA "discipline / error-checking" items; PU block; bias/error items
C4	Bhatia et al. (2022) – robo as moderator of biases	Wealth-management robo-advisor	Mixed-methods; investors and robo	Robo as digital innovation moderating behavioural	C1, C3, C5	PCA C1–C3; TPB attitude to complex tactics

		as digital innovation	users; India	biases; supports better decision making for passive/long-term portfolios; complements human advice		("good practice")
C5	Komatireddy et al. (2024) – UX trust design	Robo-advisor prototype interface (fintech UX study)	Design + lab testing with robo prototype	Step-by-step flows, rationales, and personalisation increase clarity and perceived control; good UX lowers cognitive effort and boosts trust	C1, C2, C5, C6	PCA1–PCA3, PCA6; Trust block; PEOU in TAM section
C6	Senteio & Hughes (2024) – trust and satisfaction with robo vs human	Robo versus human financial advice	Mixed-methods; survey (≈86) + interviews (10); USA	Trust in robos generally positive but fragile; brand and competence matter; human preferred for complex / high-stakes cases; many unaware of robo services	C4, C5, C6	Trust block; Attitude/Norms around using AI vs human; supports PCA7 ("complex markets")
C7	Cheng et al. (2019) – robo-advisor trust model	Retail robo-advisor services	27 interviews + survey (n=230); China	Trust driven by reputation, information and service quality, regulation, and AI attitudes; human / regulator oversight increases acceptance	C1, C2, C5, C6	Trust antecedents; PCA5 (error-checking & quality); human-oversight principle
C8	Verma et al. (2025) – AI attitudes and resistance	Robo-advisors / cognitive systems	Quantitative survey (n=409); India	Inertia, overconfidence, distrust in AI, and privacy concerns reduce uptake; AI-positive	C2, C3, C5, C6	Bias / overconfidence blocks; TAM / TPB adoption path; "healthy

				attitudes soften these barriers; "value" barrier less important		skepticism" wording
C9	Nourallah et al. (2023) – young retail investors	Financial robo-advisors for youth	UTAUT survey; ≈430 young investors; Malaysia and Sweden	Initial trust shaped by performance expectancy, hedonic motivation, trust propensity; perceived risk less salient; UX and accessible information are vital	C2, C5, C6	PU/PEOU; Trust; youth segment in LLM-use block
C10	Tan et al. (2023) – robo adoption (millennials)	Robo-advisory services	Survey (≈86); Malaysia	Higher literacy, ease of use, and trust increase intention to adopt; low trust or perceived difficulty reduce adoption	C2, C5, C6	PU/PEOU; Trust; supports literacy and LLM-education items
C11	Northey et al. (2022) – "Man vs machine" AI in banking	AI systems in banking, including robo-style tasks	Experiments; Australia	Robo/AI acceptable for low-stakes tasks; as stakes rise, trust falls and demand for human involvement increases; doubts about AI under high risk	C1, C4, C5, C6	Trust under high stakes; supports PCA7 and "hybrid and escalation" wording
C12	Skiera et al. (2022) – robo adoption in a bank	Bank-provided robo-advisor for retail clients	Field difference-in-differences; German bank; adopters vs non-users	Robo draws in new investors and improves diversification and discipline; experienced investors use it marginally; no evidence of harm	C1, C3, C4, C6	PCA empowerment pathway; supports portfolio discipline and diversification themes

C13	D'Acunto et al. (2019) – "Promises and Pitfalls of Robo-Advising"	Broker-provided robo-advice tool	Field data (~5,500 accounts); India	Robo improves diversification and reduces disposition/trend-chasing for under-diversified users; limited benefit for well-diversified; sometimes more trading without performance gain	C1, C3, C4, C6	Bias metrics; supports PCA empowerment vs distortion framing
C14	Belanche et al. (2023) – benefit vs risk model	Consumer robo-advisor adoption	Survey; Spain	Adoption driven by perceived benefits (low fees, optimisation) versus perceived risks; trust in robo and output quality crucial; emotional comfort varies	C2, C3, C4, C5	PU/PEOU; Trust; supports "value vs risk" paragraph
C15	Vanguard Research (2022) – "Value of human and robo advice"	Human, robo, and hybrid advice for investors	Large survey (1,500+ investors); US	Human advice perceived as more valuable and comforting; robo valued for low-cost portfolio tasks; many robo clients willing to switch to human; hybrid model preferred	C1, C4, C5, C6	Trust and emotional-support blocks; supports "hybrid" framing and PCA C5–C6 discussion
C16	Vanguard Survey (2025) – "Peace of mind & time"	Advised vs DIY investors (human and robo)	Survey of 12,443 Vanguard clients; US	Advice (human or robo) reduces stress/confusion and saves time; digital-only lowers "shame	C2, C4, C5, C6	PCA C2/C4; "hidden value of advice" paragraph; emotional-wellbeing intro

				barrier" for asking questions		
C17	Cui (2022); Back et al. (2023) – anthropomorphism	Anthropomorphic vs non-anthropomorphic robo-advisor UIs	HCI experiments; USA/EU	Anthropomorphic robos can increase risk aversion and reduce reliance among independent traders; more "robotic" UIs feel like neutral tools	C2, C5, C6	Interface-framing notes; "one size does not fit all UX" remark
C18	Gimmelberg et al. (2025) – LLMs and retail investing	Conversational LLM assistants (conversational LLM) used by experienced retail traders	8 semi-structured interviews + 44 curated YouTube videos	LLMs improve access to expert-like explanations and help structure research; users remain cautious in complex / fast markets; LLM used as assistant rather than replacement	C1, C2, C4, C5, C6	Direct foundation for PCA construct; supports multiple PCA items and LLM-use block
C19	Hidajat et al. (2024) – social trading biases	Social/copy-trading investment platforms	11 interviews + survey (n=342 copiers)	Herding, optimism, confirmation and stereotype biases drive copying; trust in "leaders" amplifies over-reliance; followers often surrender autonomy and do not check trades	C3, C5, C6	Over-reliance / automation-bias block; warnings around social proof and LLM
C20	Brenner & Meyll (2020) – robo vs human as substitute	Robo-advice vs human advice for investment decisions	Lab experiment; investors; Germany	Participants follow robo advice for simple decisions almost as readily as human advice; for high-stakes or complex choices they prefer human experts	C4, C5, C6	Trust under high stakes; supports PCA7 and "hybrid and escalation" wording

C21	Dietvorst et al. (2015) – algorithm aversion	Generic prediction algorithms (non-finance)	Experiments; MTurk participants	People abandon algorithms after a single visible error even when algorithms outperform humans; very low tolerance for machine mistakes	C3, C5, C6	Justifies PCA5 and Trust calibration; informs over- vs under-reliance discussion
C22	Prahl & Van Swol (2017) – adjustable algorithms	Generic adjustable algorithmic advisors	Forecasting experiments; volunteers	Allowing users to tweak algorithmic output increases acceptance and reliance; small degrees of control reduce algorithm aversion and improve perceived fit	C5, C6	Design note that LLM/robo should allow user adjustments; PCA C6 items
C23	Castillo et al. (2021) – dark side of AI service	AI chatbots / robo across services, including fintech	In-depth qualitative interviews; multi-sector including fintech	Uncorrected AI errors, lack of empathy, and blocked escalation to humans create frustration and "value co-destruction"; lack of transparency and control central	C3, C5, C6	Trust / failure-case evidence; motivates guardrails and "human override" wording
C24	Nashold (2020) – virtual finance assistants	AI-based virtual finance assistants for consumers	TAM-based survey; consumers	Trust in AI assistants depends on perceived usefulness, ease of use, and risk; trust mediates adoption; overlaps with robo-advisor TAM evidence	C2, C5, C6	Background TAM evidence for Trust + PU/PEOU; underpins LLM-use TAM paragraph

Note: PCA = Perceived Cognitive Assistance; TAM = Technology Acceptance Model; PU = perceived usefulness; PEOU = perceived ease of use; TPB = Theory of Planned Behavior; UTAUT = Unified

Theory of Acceptance and Use of Technology; UX = user experience; HCI = human-computer interaction; DiD = difference-in-differences; MTurk = Amazon Mechanical Turk.

C2. Theoretical saturation of the Tier A qualitative corpus

After approximately 18–20 Tier A studies, additional Tier A sources stopped adding new PCA codes and mainly elaborated existing C1–C6 patterns. A full justification of code-level saturation for the combined 8+44+24 qualitative base is provided in Supplementary material B, Section 1.1.

C3. Snapshot table of PCA code coverage

To make the distribution of PCA experiences more visible, Table S7 summarises, for each macro-code C1–C6, one or two illustrative Tier A sources from the robo-advice or social-trading corpus, one or two Tier B sources from LLM and adjacent algorithm-trust or AI-service work, and a one-sentence description of the typical investor experience that these sources jointly represent (Zhu et al., 2023; Bhatia et al., 2020; Hidajat et al., 2024; Gimmelberg et al., 2025; Dietvorst et al., 2015; Prahl and Van Swol, 2017; Castillo et al., 2021).

Table S7. Snapshot of PCA code coverage across Tier A and Tier B sources

PCA code	Illustrative Tier-A sources (robo / social / apps)	Illustrative Tier-B sources (LLM / algorithm-trust / AI service)	Typical investor experience (one sentence)
C1 – Structural and path support	Robo-advisory work on risk-profiling and automated portfolio construction, for example Bhatia et al. (2020, C3), where investors describe predefined portfolio paths and default allocations that can be followed with minimal design effort	LLM-augmented investing study in which traders use conversational models as scaffolds that turn complex multi-step strategies into explicit sequences of actions, for example Gimmelberg et al. (2025, C18).	The tool offers a predefined route from initial idea to concrete portfolio or trade sequence, so the investor feels able to follow the path instead of designing the strategy from scratch.
C2 – Cognitive load reduction / information compression	Robo and digital-advice interfaces that translate questionnaires and market data into simple dashboards and labelled options, such as the AI-based advisory system in Zhu et al. (2023, C1) and the bias-focused robo-advisory work in Bhatia et al. (2020, C3), Chandani et al. (2021)	LLM-based investing study where retail traders systematically use the model to summarise earnings reports, compress news and prioritise key points from long documents, thereby reducing perceived overload	The system digests complex market and product information into a small number of options, summaries or highlights, so that choices feel manageable rather than overwhelming.
C3 – Bias mitigation, discipline and error-checking	Robo-advisory work in which automated rebalancing, diversification rules and suitability checks are explicitly framed as ways to counteract under-diversification and behavioural biases, for example Bhatia et al. (2020,	Algorithm-aversion experiments that treat statistical models as potentially more consistent and less biased, but show how trust collapses after visible errors, for example Dietvorst et	The investor experiences the tool as a disciplinarian that checks calculations, enforces limits and warns about mistakes, but may also become frustrated or abandon the system after

	C3), alongside social-trading research that documents platform-imposed guardrails on copying and leverage	al. (2015) and Prahl and Van Swol (2017)	seeing an error or an overly rigid constraint.
C4 – Navigation of volatility, scenarios and stress	Applied robo and advisory-comparison studies in which clients are exposed to stress tests, scenario messages and automated de-risking rules during turbulent markets, and report valuing automated handling of routine volatility but remaining cautious about high-stakes crises	LLM-augmented investing work in which conversational models are used to spin out multiple what-if macro and volatility scenarios and to translate complex risk narratives into more digestible stories	During volatile or stressful conditions, the tool helps the investor imagine and evaluate different paths for the portfolio, which can either calm them and support staying the course or prompt defensive repositioning.
C5 – Explanations, transparency and perceived opacity	Qualitative robo UX work where users repeatedly describe advice as not transparent and incomprehensible, highlighting missing rationales and hidden decision rules, for example Zhu et al. (2023, C1), complemented by robo-advisory and social-trading studies where investors cannot see how recommendations or leader trades are generated	Dark-side AI-service research in which customers experience chatbots and other AI interfaces as opaque black boxes that block escalation and generate confusion or anger when errors cannot be explained, for example Castillo et al. (2021)	The investor receives recommendations and automated actions but does not fully understand how they were produced, oscillating between scepticism and over-trust because the system's reasoning remains partly hidden.
C6 – Responsibility drift, complacency and blame-shifting	Social-trading research documenting how followers attribute losses to platform defaults or copied leaders and successes to the system rather than to their own skill, together with robo-advisory work where investors externalise responsibility for both risk and performance	Algorithm-aversion experiments highlighting discomfort about being solely responsible for following machine advice	The investor starts to feel that the system knows better, relaxes their own monitoring and, when outcomes materialise, tends to credit or blame the algorithm, copied trader or platform rather than treating the decision as fully theirs.

Note: Tier A refers to robo-advisor, digital-advice and social-trading studies; Tier B refers to conversational LLM advisors and adjacent algorithm-trust or AI-service work.

C4. Final list of 24 core studies

The PCA evidence table in Supplementary material C is defined as a 24-study core corpus that underpins codes C1–C6 and the wording of Supplementary material B items.

For ease of reference, the 24 core studies are labelled C1–C24 in Table S6, as follows:

1. Zhu et al. (2023) – "Not transparent and incomprehensible" (bank robo / AI advisor lab study; Sweden).
2. Chandani et al. (2021) – focus groups with active investors on general robo-advisors (India).
3. Bhatia et al. (2020) – expert interviews on robo-advisors and behavioural biases (FinTech/BFSI developers; India).

4. Bhatia et al. (2022) – robo-advisors as behavioural-bias moderators in wealth-management innovation (mixed-methods; India).
5. Komatireddy et al. (2024) – UX trust design for robo-advisor interfaces (design + lab).
6. Senteio & Hughes (2024) – robo versus human advice (mixed-methods, US).
7. Cheng et al. (2019) – robo-advisor trust model (interviews + survey; China).
8. Verma et al. (2025) – AI attitudes and resistance to robo-advisors/cognitive systems (survey; India).
9. Nourallah et al. (2023) – young retail investors' initial trust in financial robo-advisors (Malaysia & Sweden).
10. Tan et al. (2023) – robo-advisory adoption among millennials (survey; Malaysia).
11. Northey et al. (2022) – "Man vs machine" AI in banking (experiments; Australia).
12. Skiera (2021)– robo-advisor adoption and trading behaviour in a German bank (field DiD).
13. D'Acunto et al. (2019) – "Promises and Pitfalls of Robo-Advising" (broker robo tool; account-level field data; India).
14. Belanche et al. (2025) – benefit versus risk model of consumer robo-advisor adoption (Spain).
15. Vanguard Research (2022) – "Value of human and robo advice" (US investor survey).
16. Vanguard Survey (2025) – "Peace of mind & time" (12,443 Vanguard clients; US).
17. Cui (2022) and Back et al. (2023) – anthropomorphism in robo-advisor UIs (HCI experiments; USA/EU).
18. Gimmelberg et al. (2025) – LLMs and retail investing (conversational LLM assistants; 8 interviews + 44 YouTube videos).
19. Hidajat et al. (2024) – social/copy trading biases (11 interviews + survey of copiers).
20. Brenner & Meyll (2020) – robo versus human advice as substitute in investment choices (lab experiment; Germany).
21. Dietvorst et al. (2015) – algorithm aversion (generic decision algorithms; experiments, MTurk).
22. Prahl & Van Swol (2017) – adjustable algorithms and user control (forecasting experiments).
23. Castillo et al. (2020) – "dark side of AI service" (AI chatbots/robo across services, including fintech; in-depth interviews).
24. Nashold (2020) – virtual finance assistants (AI financial assistants; TAM-based survey).