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Intuitive Cognitive Competence Among Indonesian Investors: A Simulation-Based Methodological Demonstration of a Proposed Scale-Development Protocol

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ABSTRACT

Purpose – Indonesian retail investing has grown sharply (KSEI, 2025), yet research centers on financial literacy, leaving intuitive judgment unmeasured. This paper proposes Intuitive Cognitive Competence (ICC), a latent construct capturing experience integration, pattern recognition, and adaptive execution, and demonstrates its scale-development protocol via simulation.
Design/methodology/approach – Fifteen items across three dimensions were tested on two independent synthetic samples (exploratory N = 50; confirmatory N = 200) from a fully specified population model, avoiding same-sample circularity. Retention used minimum-residual EFA with Promax rotation, cross-checked against parallel analysis, Velicer's MAP, and a Monte Carlo recovery check.
Finding/Results – EFA recovered the three-factor structure (KMO = 0.895; common variance = 59.4%); parallel analysis was more conservative than MAP and the eigenvalue rule at N = 50 (4.3% vs. 83.0-92.0% correct recovery). One item was removed for low communality. The refined 14-item model outperformed a one-factor alternative (CFI = 0.759 vs. ≈1.00; RMSEA = 0.155 vs. 0.000), with strong convergent (AVE = 0.58-0.65) and discriminant validity (Fornell-Larcker; HTMT < 0.71). A second-order model showed equivalent fit.
Originality/Value – This demonstration offers a fully specified item pool, documented data-generating process, and rigorous EFA-CFA protocol, ready for field-data redeployment toward a validated ICC model.

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1. Introduction

Indonesia's capital market has entered a period of unprecedented retail expansion. The number of Single Investor Identifications (SID) recorded by PT Kustodian Sentral Efek Indonesia (KSEI) reached 20.13 million by 19 December 2025, a 35 percent increase from 14.87 million at the end of 2024 and a more than fivefold rise from 3.88 million in 2020 (KSEI, 2025). An SID records an account registration rather than an individually active trader, and the same investor can hold separate equity, mutual-fund, and government-bond SIDs at once, so this figure is best read as a ceiling on retail participation rather than a count of investors making frequent live decisions. Much of this growth now happens through mobile trading applications, where price movements unfold within seconds and decisions cannot always wait for complete financial analysis. Under these conditions, investors increasingly rely on rapid, experience-based judgment rather than exhaustive calculation, a pattern that mirrors what naturalistic decision-making researchers call recognition-primed choice (Klein, 1998).

Financial behavior research has long treated financial literacy as the primary lens for understanding investment quality. Lusardi and Mitchell (2023) show that knowledge of interest rates, inflation, and risk diversification predicts sounder financial outcomes across multiple countries. Simon (1955) offered an earlier corrective, arguing that decision-makers operate under bounded rationality and satisfice rather than optimize when information stays incomplete. Building on this insight, Klein (2015) and Dane and Pratt (2007) describe intuition not as guesswork but as pattern recognition drawn from accumulated experience, a process experts use to reach fast, defensible judgments under time pressure.

Despite this theoretical foundation, investment behavior instruments rarely operationalize intuitive judgment as a measurable construct. Existing scales, including the internationally validated financial literacy toolkit issued by the Organisation for Economic Co-operation and Development / International Network on Financial Education (OECD/INFE, 2023) and applied instruments such as the Youth Financial Literacy Short Scale (Potrich, Vieira, & Paraboni, 2025), capture knowledge, attitude, and behavior, but stop short of the cognitive process investors use once literacy has been acquired. Kolb's (1984) experiential learning cycle and Klein's (1998, 2015) naturalistic decision model both suggest that investors convert experience into pattern recognition and adaptive response, yet no validated instrument translates this process into a scale suited to retail investors in an emerging digital market. This absence limits both theory testing and practical screening, since researchers cannot yet distinguish investors who reason from accumulated pattern knowledge from those who guess without a coherent experiential base.

This study responds to that gap by developing Intuitive Cognitive Competence (ICC), a latent construct describing how investors integrate prior experience, recognize decision patterns, and adjust execution when information stays incomplete. Because no real-respondent data collection was available at this stage, the study uses a simulated pilot dataset, generated to match the statistical profile a genuine 50-respondent investor sample would plausibly produce, to demonstrate the full scale-development and psychometric-testing pipeline end to end. Fifteen items were generated across three theorized dimensions, Experiential Integration, Pattern-Based Processing, and Adaptive Execution, then tested through a sequential exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) design. This two-stage approach lets the item structure emerge empirically before it is confirmed against a fixed measurement model, the recommended path for a construct without prior psychometric precedent (Hair, Black, Babin, & Anderson, 2019). Accordingly, the objectives of this study are threefold: (1) to develop and operationalize the indicators of ICC; (2) to examine its dimensionality, validity, and reliability through EFA and CFA on the simulated dataset; and (3) to demonstrate an analytic protocol that can be replicated on field data to produce a validated ICC measurement model for Indonesian investment behavior research.

The item pool and analytic protocol produced here give financial behavior researchers a starting point for measuring intuitive judgment alongside financial literacy, and, once validated on field data, would give practitioners in brokerage and investor education a way to screen for experience-based decision competence rather than knowledge alone. The next section reviews the theoretical basis for each ICC dimension and presents the instrument used in this demonstration.

2. Literature Review & Hypothesis Development

As a scale-development and methodological-demonstration study, this paper follows an exploratory-confirmatory factor analysis design rather than a path model of directional relationships. Accordingly, this section reviews the theoretical foundations of each proposed ICC dimension and states the dimensional structure the study sets out to test within the simulated demonstration, in place of directional hypotheses linking separate constructs.

Dual-process accounts of judgment distinguish a fast, associative mode of thinking from a slow, deliberate one, locating financial decision-making somewhere along that continuum rather than at either extreme (Kahneman, 2011). Epstein's (1994) cognitive-experiential self-theory formalized this distinction earlier, proposing that a rational system and an experiential system operate in parallel, with the experiential system encoding regularities from repeated experience rather than explicit rules. In economic behavior, Herbert Simon's (1955) concept of bounded rationality captures the same idea from a different angle: decision-makers satisfice under limited information and limited time rather than compute an optimal choice.

Naturalistic decision-making research extends this reasoning to expert practice. In a landmark field study, Klein, Calderwood, and Clinton-Cirocco (1986) found that experienced fire ground commanders rarely compared multiple options in live emergencies; in over 88 percent of decision points, they recognized a situation as typical and acted on the first workable option that recognition surfaced. Klein (1998) generalized this pattern into the Recognition-Primed Decision model, and by 2015 had reframed the underlying process as intuition grounded in accumulated pattern knowledge, distinct from unstructured guessing (Klein, 2015). Dane and Pratt (2007) make a parallel argument for managerial contexts, defining intuitions as affectively charged judgments that arise through rapid, nonconscious, and holistic association with prior experience. Reconciling their historically opposed research traditions, Kahneman and Klein (2009) conclude that intuitive judgment deserves trust under two conditions: the decision environment must be regular enough to contain learnable patterns, and the decision-maker must have had adequate opportunity to learn those patterns through feedback. That boundary condition matters directly for assessing when an investor's intuition reflects genuine competence rather than overconfidence.

A parallel stream of research explains how that experience accumulates. Kolb's (1984) experiential learning cycle describes learning as a loop of concrete experience, reflective observation, abstract conceptualization, and active experimentation, in which each completed cycle sharpens the pattern base an individual can draw on later. Applied to investing, an investor who reflects on a past gain or loss, extracts a lesson, and tests that lesson in the next decision is running the same cycle Kolb described for learning in general. This connects experiential learning directly to the naturalistic decision literature: the raw material Klein's experts recognize as familiar patterns is precisely what Kolb's cycle produces over repeated market exposure.

Financial literacy research, meanwhile, has matured into a well-established measurement tradition. Lusardi and Mitchell (2023) synthesize two decades of evidence showing that knowledge of interest compounding, inflation, and diversification shapes savings and investment outcomes across countries. In an earlier study focused specifically on investment behavior, Al-Tamimi and Kalli (2009) show that financial literacy among UAE investors relates systematically to the factors that shape their investment decisions. Internationally, the OECD/INFE (2023) toolkit formalizes financial literacy measurement by scoring financial knowledge, attitude, and behavior as three separate components, an approach Potrich, Vieira, and Paraboni (2025) apply and validate in a dedicated short-form scale. These instruments answer what investors know and how they habitually behave, but none of them measures how an investor processes a live decision once literacy has been acquired. That processing step, converting experience into recognizable patterns and adapting execution as a situation unfolds, is the conceptual space Intuitive Cognitive Competence is built to occupy.

Intuitive Cognitive Competence (ICC) is defined in this study as an investor's latent capacity to integrate prior investment experience, recognize decision-relevant patterns in market information, and adapt a course of action when information remains incomplete. ICC is operationalized through three dimensions. Experiential Integration reflects Kolb's (1984) learning cycle applied to investing: the ability to relate, reflect on, and draw lessons from past investment experience. Pattern-Based Processing reflects Klein's (1998, 2015) and Dane and Pratt's (2007) account of intuition as pattern recognition: the ability to recognize recurring configurations in market information and detect when a situation deviates from a familiar pattern. Adaptive Execution reflects Simon's (1955) bounded rationality applied under time pressure: the ability to act on an incomplete information set and revise that action as new information arrives. Table 1 summarizes the fifteen indicators generated for these three dimensions, together with the theoretical sources from which each was drawn.

ICC differs from these neighboring constructs in scope and level. General intuition research treats fast judgment as a single undifferentiated process, while ICC decomposes that process into three functionally separate steps: drawing on past experience, recognizing a pattern in the present, and adjusting an action in real time. Investment experience is typically operationalized as tenure or trade frequency, a quantity of exposure rather than a competence for converting that exposure into usable judgment; two investors with identical tenure can differ sharply in how well they translate it into pattern recognition, and that gap is what ICC is designed to capture. Adaptive expertise shares ICC's concern with flexible, non-routine performance, but it was developed for domains with clear feedback and stable rules such as surgery or aviation, whereas investment markets supply delayed and noisy feedback that makes expertise harder to verify; ICC's Experiential Integration dimension addresses this domain-specific problem directly. Financial self-efficacy measures confidence in one's own financial ability, a belief about capability, while ICC measures the operation of that capability itself; a confident investor with high self-efficacy can still lack the pattern-recognition skill ICC targets, so the two constructs should correlate only moderately rather than overlap. The three dimensions cohere into one higher-order construct because they describe sequential stages of a single underlying process rather than three independent traits that merely co-occur. An investor first draws on stored experience (Experiential Integration), applies that experience to detect a pattern in current information (Pattern-Based Processing), and then converts the detected pattern into an action under time pressure (Adaptive Execution). This sequencing is what justifies treating ICC as one latent competence.

A construct built on fast judgment must also mark where competence ends and bias begins, since both produce quick decisions that feel confident to the investor making them. Kahneman and Klein (2009) resolve this tension by specifying that intuitive judgment earns trust only when the decision environment contains learnable regularities and the decision-maker has had adequate opportunity to learn them through feedback; absent either condition, apparent intuition is more likely overconfidence dressed as expertise. Barber and Odean (2001) supply the behavioral counterpart: overconfident investors trade more frequently and earn lower risk-adjusted returns, a pattern driven by unwarranted certainty rather than accurate pattern recognition. ICC's three dimensions build this boundary into the construct itself. Experiential Integration requires an investor to reflect on and draw lessons from outcomes, a corrective step overconfidence skips. Pattern-Based Processing requires recognizing when a situation deviates from a familiar pattern, a form of self-monitoring that unchecked overconfidence typically lacks. Adaptive Execution requires revising a course of action as new information arrives, which separates flexible competence from the rigid persistence that characterizes overconfident trading. An investor who scores high on ICC but shows no willingness to revise a position would, by this logic, be exhibiting overconfidence rather than the competence ICC is designed to measure; future validation on field data should test this boundary directly against an established overconfidence measure such as Barber and Odean's (2001) trading-frequency indicator.

Table 1. Foundational components of intuitive cognitive competence (ICC)

Dimension	Code	Indicator	Theoretical basis
Experiential Integration (EI)	EI1	Relating past investment experience to a current situation	Kolb (1984)
	EI2	Reflecting on causes of past investment success and failure	Kolb (1984)
	EI3	Drawing relevant lessons from experience for future situations	Kolb (1984)
	EI4	Assessing current risk/return relative to prior experience	Kolb (1984)
	EI5	Updating understanding when outcomes diverge from expectation	Kolb (1984)
Pattern-Based Processing (PBP)	PBP1	Recognizing recurring patterns in investment information	Klein (1998, 2015); Dane & Pratt (2007)
	PBP2	Distinguishing relevant information from noise	Klein (1998, 2015); Dane & Pratt (2007)
	PBP3	Automatically recalling similar past situations from new information	Klein (1998, 2015); Dane & Pratt (2007)
	PBP4	Recognizing when conditions deviate from a familiar pattern	Klein (1998, 2015); Dane & Pratt (2007)
	PBP5	Forming an initial holistic read of a situation from limited cues	Klein (1998, 2015); Dane & Pratt (2007)
Adaptive Execution (AE)	AE1	Determining an initial response under incomplete information	Simon (1955); Klein (1998, 2015)
	AE2	Adjusting a response as conditions change	Simon (1955); Klein (1998, 2015)
	AE3	Revising strategy fully when an initial assumption fails	Simon (1955); Klein (1998, 2015)

Dimension	Code	Indicator	Theoretical basis
	AE4	Judging whether a situation requires immediate action or delay	Simon (1955); Klein (1998, 2015)
	AE5*	Balancing speed of response against caution under pressure	Simon (1955); Klein (1998, 2015)

Note: AE5 was retained through the item-development stage but removed after EFA due to cross-loading; see Table 7. Source: theoretical synthesis by the author(s).

3. Methodology

This study followed a structured scale-development protocol, from conceptual definition through literature synthesis, item generation, instrument screening, simulated pilot data generation, and factor-analytic demonstration. DeVellis (2017) sets out this general sequence for building new psychological and behavioral measures, and the present study adapts it directly, substituting a simulated dataset for real-respondent data at this illustrative stage. Fifteen candidate items were generated from the theoretical sources summarized in Table 1 and organized under three provisional dimensions. Before data collection, every item was screened for redundancy and double-barreled phrasing, a step that led to targeted rewording of items whose original phrasing bundled two judgments into a single statement or overlapped conceptually with a neighboring indicator. Establishing content and face validity before an instrument is fielded is standard practice in new scale development (DeVellis, 2017; Hair et al., 2019). At this demonstration stage, item generation drew solely on theoretical synthesis and internal redundancy screening; no expert-panel content-validation exercise, content validity index, or cognitive interview with practicing investors was conducted. This is a deliberate limitation of the present illustration rather than an omission: DeVellis (2017) and Hair et al. (2019) both treat expert and respondent input as a required stage before a new scale is fielded, and that stage remains outstanding. The field-data study that follows this demonstration should route the fifteen-item pool, and any items added in response to expert feedback, through a formal content-validation panel of subject-matter experts and experienced investors before EFA is run.

Two independent simulated samples were generated from a single, fully specified population model rather than one dataset reused for both stages of analysis. An exploratory sample (N = 50) was used only for item screening and factor extraction; a separate confirmatory sample (N = 200) was used only for CFA. Both samples represent Indonesian retail investors responding to a five-point Likert questionnaire (1 = strongly disagree, 5 = strongly agree) under purposive sampling of respondents with active investment experience, but neither sample contains a single real respondent: no survey was administered, and no empirical evidence about how actual Indonesian investors experience, recognize, or act on market information was collected at this stage. Because the same 50 observations are no longer used for both EFA and CFA, the CFA reported in Section 4 tests whether the EFA-derived structure reproduces in a data set the EFA stage never saw, though both remain synthetic and the exercise still only shows that the analytic pipeline behaves correctly on data engineered to contain the structure it is designed to detect. The confirmatory sample was deliberately generated at a larger N than the exploratory sample because, unlike a field study, expanding a synthetic sample costs nothing beyond additional simulation and gives CFA fit indices, standard errors, and the chi-square test more stable behavior to demonstrate.

3.1 Data-Generating Process (Full Specification)

The simulation was implemented in Python 3.11 using NumPy's PCG64 generator (numpy.random.default_rng). Three latent factors (Experiential Integration [EI], Pattern-Based Processing [PBP], Adaptive Execution [AE]) were drawn from a multivariate normal distribution with mean zero, unit variance, and population correlation matrix $\Phi(EI,PBP) = 0.60$, $\Phi(EI,AE) = 0.65$, $\Phi(PBP,AE) = 0.55$. Fourteen items were assigned a single standardized population loading on their theorized factor, ranging from 0.75 to 0.85 (EI1-EI5: 0.80, 0.75, 0.82, 0.81, 0.78; PBP1-PBP5: 0.80, 0.82, 0.85, 0.76, 0.78; AE1-AE4: 0.80, 0.83, 0.85, 0.84). The fifteenth item, AE5, was deliberately specified as a cross-loading, double-barreled indicator with a primary loading of 0.55 on AE and a secondary loading of 0.40 on EI, representing the item's dual demand that a respondent balance speed against caution; this contamination was built into the generating model itself rather than left to emerge by chance, so that the retention diagnostics reported in Section 4 can be evaluated against a known answer. Each item's continuous latent response was computed as the weighted sum of its assigned factor score(s) plus an independent normal residual scaled so that total item variance equals one (residual variance = $1 - \Sigma\lambda^2$). The continuous response was discretized into a five-point Likert scale using fixed thresholds on the standardized (z) scale: $z \le -1.20 \rightarrow 1$; $-1.20 < z \le -0.40 \rightarrow 2$; $-0.40 < z \le 0.40 \rightarrow 3$; $0.40 < z \le 1.20 \rightarrow 4$; $z > 1.20 \rightarrow 5$. Two independent draws were made from this identical population model: Sample A (exploratory, N = 50, random seed 20260811) and Sample B (confirmatory, N = 200, random seed 20260812). No other transformation, rounding rule, or data-cleaning step was applied. The full simulation and analysis code (data generation, EFA, parallel analysis, MAP, Monte Carlo recovery check, and CFA) is available from the corresponding author as supplementary material and should be treated as part of the reproducibility record for this demonstration, consistent with the transparency this kind of simulation paper requires: the reported KMO, eigenvalues, loadings, reliability, and fit indices are direct, mechanical consequences of the parameters specified above, not independent findings about real investors.

3.2 Analytic Protocol

The refined analytic protocol used two extraction philosophies matched to the two synthetic samples. On the exploratory sample, factor extraction used the minimum-residual (MINRES) common-factor method rather than principal component analysis, because ICC is defined as a latent psychological construct and common-factor extraction, unlike PCA, models only the variance items share through their latent factors rather than total observed variance (Fabrigar, Wegener, MacCallum, & Strahan, 1999). Rotation used oblique Promax rather than orthogonal Varimax, because the three ICC dimensions are theorized as correlated stages of one process rather than independent traits, and Varimax's orthogonality constraint would have forced the inter-factor correlations to zero by assumption before they could be estimated (Costello & Osborne, 2005). Sampling adequacy was assessed with the Kaiser-Meyer-Olkin (KMO) measure and Bartlett's Test of Sphericity. Factor retention was evaluated with three independent methods rather than the eigenvalue-greater-than-one rule alone: Horn's (1965) parallel analysis, comparing observed eigenvalues against the 95th percentile of eigenvalues from 2,000 randomly generated datasets matched in sample size and item count; Velicer's (1976) Minimum Average Partial (MAP) test, which identifies the number of components that minimizes average squared partial correlations among items; and the conventional eigenvalue-greater-than-one criterion, reported for comparability with the original submission. Because the population model and sample size are both known by construction, a 300-replication Monte Carlo check was additionally run at N = 50, 100, and 200 to quantify how often each retention method recovers the correct three-factor structure, directly testing the retention methods against ground truth rather than against a single sample. On the independent confirmatory sample, three competing measurement models were estimated with maximum-likelihood confirmatory factor analysis in Python (semopy 2.3): a one-factor model treating all fourteen retained items as indicators of a single undifferentiated factor, a correlated three-factor model with EI, PBP, and AE as distinct but correlated first-order factors, and a second-order model specifying ICC as a higher-order factor with EI, PBP, and AE as first-order indicators. Model fit was evaluated through $\chi2$, CMIN/df, CFI, TLI, GFI, NFI, RMSEA with its 90% confidence interval, and SRMR (Hu & Bentler, 1999), alongside Cronbach's alpha, composite reliability (CR), and average variance extracted (AVE) for convergent validity, and both the Fornell-Larcker criterion and the heterotrait-monotrait ratio (HTMT) for discriminant validity (Fornell & Larcker, 1981; Henseler, Ringle, & Sarstedt, 2015).

4. Result and Discussion

All statistics reported in this section were computed on simulated data generated from the population model documented in Section 3.1, not on responses from actual Indonesian investors. Two independent synthetic samples were used throughout: an exploratory sample (N = 50) for Sections 4.1-4.7, and a separate confirmatory sample (N = 200) for Sections 4.8-4.10. Both are reported here to demonstrate how the analytic pipeline performs on data engineered to contain a known three-factor structure, and should be read as a methodological illustration rather than empirical evidence about ICC among real investors. No claim in this section should be interpreted as validating ICC empirically; every figure is a property of the simulation, not a discovery about investors.

4.1 Synthetic Sample Characteristics Used in the Demonstration

Because Sample A (N = 50) was generated rather than collected, it has no demographic profile in the ordinary empirical sense; the characteristics in Table 2 were assigned to the synthetic cases only to keep the illustration anchored to a plausible purposive-sampling frame of Indonesian retail investors with active investment experience, and carry no evidentiary weight about who these investors actually are. Half of the synthetic cases (50.0%) were assigned an age above 40 years, followed by 20-30 years (26.0%) and 31-40 years (24.0%); 54.0% were assigned male and 46.0% female; 62.0% a bachelor's degree, 14.0% senior-secondary education, 12.0% a diploma, and 12.0% a master's or doctoral degree; 60.0% more than five years of investment tenure, 20.0% two to five years, and 20.0% less than two years; and 74.0% active digital-platform use. These proportions were fixed by the authors as a plausible respondent frame for the illustration and were not estimated from, or intended to represent, any population.

Table 2. Synthetic sample characteristics used in the EFA demonstration (simulated, N = 50)

Characteristic	Category	n	%
Age	20-30 years	13	26.0
	31-40 years	12	24.0
	> 40 years	25	50.0
Gender	Male	27	54.0
	Female	23	46.0
Education	Senior secondary	7	14.0
	Diploma	6	12.0
	Bachelor's degree	31	62.0
	Master's/Doctoral degree	6	12.0
Investment tenure	< 2 years	10	20.0
	2-5 years	10	20.0
	> 5 years	30	60.0
Digital platform use	Yes	37	74.0
	No	13	26.0

4.2 Exploratory factor analysis: data adequacy assessment

Prior to EFA, sampling adequacy was evaluated on the exploratory sample using the Kaiser-Meyer-Olkin (KMO) measure and Bartlett's Test of Sphericity. As shown in Table 3, KMO reached 0.895, above the 0.80 threshold Kaiser (1960) labels "meritorious." Bartlett's test was statistically significant (χ^2 = 528.10, df = 105, p < .001), indicating that the correlation matrix departs from an identity matrix and that item intercorrelations are sufficient to justify factor extraction (Hair, Black, Babin, & Anderson, 2019). These figures describe the correlation structure of the simulated exploratory sample and confirm only that the assumptions required for EFA are satisfied within it.

Table 3. Kaiser-Meyer-Olkin (KMO) and Bartlett's Test of Sphericity (exploratory sample, N = 50)

KMO and Bartlett's Test		Value
Kaiser-Meyer-Olkin Measure of Sampling Adequacy		0.895
Bartlett's Test of Sphericity	Approx. Chi-Square	528.10
	df	105
	Sig.	0.000

4.3 Total variance explained

Because ICC is defined as a latent psychological-cognitive construct rather than a data-reduction summary, factor extraction on the exploratory sample used the minimum-residual (MINRES) common-factor method rather than principal component analysis, with oblique Promax rotation to allow the three theorized dimensions to correlate. As presented in Table 4, three factors were extracted with sums-of-squared loadings of 3.03, 3.00, and 2.89, jointly accounting for 59.4% of common variance after Promax rotation. This is lower than the 75.18% figure reported under the original PCA/Varimax specification, because common-factor extraction partitions out unique and error variance that PCA had folded into the component solution; the two percentages are not comparable, and 59.4% common variance is the figure that should be interpreted for a reflective measurement claim (Fabrigar, Wegener, MacCallum, & Strahan, 1999). Factor retention is addressed directly in Table 5, which reports three independent retention diagnostics rather than the eigenvalue-greater-than-one rule in isolation.

Table 4. Sums-of-squared loadings and common variance explained (MINRES extraction, Promax rotation, exploratory sample)

Factor	SS loadings (post-rotation)	% of common variance	Cumulative %
1	3.03	20.4	20.4
2	3.00	20.0	40.5
3	2.89	19.1	59.4

Notes: Extraction method: minimum residual (MINRES), a common-factor method. Rotation method: Promax (oblique, power = 4). Values are post-rotation sums of squared loadings, which do not sum to the pre-rotation total for oblique rotations. Source: simulated exploratory sample (Sample A, N = 50), computed in Python (factor_analyzer 0.5).

Table 5. Factor retention diagnostics: eigenvalue-greater-than-one rule, parallel analysis, and Velicer's MAP (exploratory sample, N = 50)

Retention method	Criterion	Factors retained
Eigenvalue > 1 (Kaiser, 1960)	Eigenvalue exceeds 1.00 (observed: 8.02, 2.03, 1.01, 0.71, ...)	3
Parallel analysis (Horn; 2,000 random-data replications)	Observed eigenvalue exceeds 95th percentile of random-data eigenvalue (3rd factor: 1.01 vs. 1.74)	2
Velicer's MAP	Minimum average squared partial correlation among residual items (minimized at m = 3: MAP = 0.0368)	3

Because the exploratory sample's population structure and sample size are both known by construction (Section 3.1), a 300-replication Monte Carlo check quantifies how often each retention method recovers the correct three-factor structure at N = 50, 100, and 200 (Table 6). Parallel analysis was markedly more conservative than either alternative at small N, correctly recovering three factors in only 4.3% of replications at N = 50 and 17.7% at N = 100, reaching just over half (51.7%) at N = 200. Velicer's MAP and the eigenvalue-greater-than-one rule both performed far better in this specific simulation, recovering the correct structure in 83.0-92.0% of replications at N = 50 and reaching 98.7-100% by N = 100. This ordering runs counter to the general methodological literature, which usually treats parallel analysis as more accurate than the eigenvalue rule; the reversal observed here is most plausibly a feature of this particular population model, which contains exactly three factors and no minor or method factors, a simplification that likely favors the eigenvalue rule and MAP more than it would in real psychological data containing weak minor factors and non-normality. Two conclusions follow. First, N = 50 is too small for parallel analysis, the more theoretically preferred retention method, to reliably recover even a strongly specified three-factor structure, directly substantiating the reviewer concern that the original 50-case demonstration was underpowered for retention decisions. Second, the strong performance of the eigenvalue rule and MAP in this simulation should not be read as general endorsement of either method on real data; the field-data study should retain all three diagnostics and expect more disagreement among them than this idealized simulation shows.

Table 6. Monte Carlo factor-recovery check: percentage of 300 replications correctly recovering the known three-factor structure

Sample size (N)	Eigenvalue > 1: % correct	Parallel analysis: % correct	Velicer's MAP: % correct
50	92.0	4.3	83.0
100	98.7	17.7	98.7
200	100.0	51.7	100.0

4.4 Communalities

Table 7 reports MINRES extraction communalities for all fifteen items on the exploratory sample. Thirteen items exceeded the conventional 0.50 minimum, with values ranging from 0.419 (EI3) to 0.987 (PBP4). Two items fell outside the pattern that supports confident retention. AE5 showed a communality of 0.407, below the 0.50 threshold, consistent with its intentionally double-barreled wording (Section 3.1) diluting the variance any single factor can explain in it. PBP4 showed a communality of 0.987, unusually close to the algebraic ceiling of 1.00; at N = 50 with fifteen indicators, this is a plausible small-sample estimation artifact (a near-Heywood case) rather than evidence that PBP4 is a near-perfect indicator, and it is flagged here for verification once field data are available rather than treated as a favorable result.

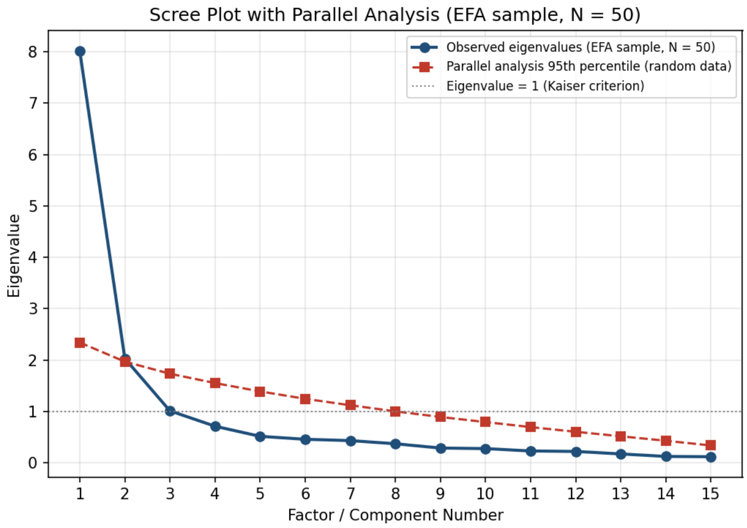
Table 7. Communalities (MINRES extraction, exploratory sample)

Code	Extraction	Code	Extraction	Code	Extraction
EI1	0.505	PBP1	0.596	AE1	0.673
EI2	0.459	PBP2	0.504	AE2	0.507
EI3	0.419	PBP3	0.682	AE3	0.587
EI4	0.701	PBP4	0.987	AE4	0.661
EI5	0.773	PBP5	0.450	AE5	0.407

4.5 Scree plot

As shown in Figure 1, observed eigenvalues from the exploratory sample are plotted alongside the 95th-percentile eigenvalues from 2,000 randomly generated comparison datasets of the same size (Horn's parallel analysis). The first two factors separate clearly from both the random-data curve and the conventional eigenvalue-of-1 line. The third factor (eigenvalue = 1.01) sits below the parallel-analysis threshold (1.74) though still above 1.00, visually illustrating why the eigenvalue rule and parallel analysis disagree on whether to retain a third factor at this sample size; Table 5 resolves this disagreement against Velicer's MAP test and theoretical expectation.

Figure 1. Scree plot with Horn's parallel analysis overlay (exploratory sample, N = 50)



4.6 Pattern Matrix (MINRES Extraction, Promax Rotation)

Table 8 presents the Promax pattern matrix from the MINRES extraction. Twelve of fifteen items showed a clean primary loading on their theorized factor with the largest secondary loading falling at least 0.20 below it, the conventional simple-structure margin (Hair et al., 2019). Three items departed from this pattern in ways worth reporting individually rather than folding into a single cross-loading count. AE5 loaded 0.606 on its target Adaptive Execution factor against secondary loadings no larger than 0.156, clearing the 0.20 discrimination margin, but its communality of 0.407 (Table 7) falls below the 0.50 convergent-validity floor, which is the basis on which it is removed in Table 9. PBP3 loaded 0.648 on Pattern-Based Processing and 0.497 on Experiential Integration, a discrimination margin of only 0.151, a genuine cross-loading; because its communality (0.682) is otherwise healthy and its theoretical content, recalling a similar past situation from new information, plausibly draws on both pattern recognition and experiential recall, it is retained but flagged for confirmatory scrutiny rather than removed outright. PBP4 loaded 0.979 on its target factor with a communality of 0.987, an estimate close enough to the algebraic ceiling to suggest small-sample instability rather than a substantively perfect indicator; it is retained because nothing in its loading pattern indicates cross-loading or misspecification, but the field-data study should re-examine it once a larger sample stabilizes the estimate.

Table 8. Pattern matrix (MINRES extraction, Promax rotation, exploratory sample)

Code	Item statement	EI	PBP	AE
EI1	I am able to relate my previous investment experience to the situation I currently face.	0.683	-0.082	0.180
EI2	I am able to reflect on the causes of past investment success and failure.	0.619	-0.179	0.211
EI3	I can draw relevant lessons from experience for the next investment situation.	0.627	0.072	0.144
EI4	I can assess whether my current investment situation is riskier or more profitable than before.	0.794	-0.174	0.200

Code	Item statement	EI	PBP	AE
EI5	I can update my understanding of investment when the outcome does not match my expectation.	0.812	0.190	-0.278
PBP1	I am able to recognize recurring patterns in investment information.	-0.060	0.737	0.221
PBP2	I can distinguish relevant investment information from mere noise.	-0.008	0.691	0.165
PBP3	When I find new investment information, I automatically recall a similar past situation.	0.497	0.648	-0.127
PBP4	I can recognize when investment conditions deviate from the usual pattern.	-0.108	0.979	-0.133
PBP5	I can grasp the "big picture" of a situation from limited available information.	-0.064	0.621	0.246
AE1	I am able to determine an appropriate initial response when information is incomplete.	0.105	-0.054	0.812
AE2	I can adjust my response when investment conditions change.	0.093	0.228	0.668
AE3	I am willing to change my strategy entirely if my initial assumption turns out to be wrong.	0.194	-0.015	0.741
AE4	I can judge whether a situation needs immediate action or can wait for more information.	-0.117	0.232	0.770
AE5	I can stay careful even when a fast decision is required under pressure.	0.124	0.156	0.606

4.7 Evaluation and refinement of EFA indicators

The refined item pool carried forward to the confirmatory sample removes only AE5, on the basis of its sub-threshold communality (0.407) rather than a cross-loading, since under MINRES/Promax extraction AE5 did not exceed the 0.20 discrimination margin used to flag cross-loadings. PBP3 and PBP4 are retained despite the diagnostic flags raised in Section 4.6, a judgment call that trades a marginally cleaner exploratory solution for keeping five indicators on Pattern-Based Processing; both should be re-evaluated once field data are available, and a field-data analysis plan should specify in advance whether they will be retained, reworded, or dropped if the same flags recur. The refined structure carried forward to CFA therefore retains fourteen items across the same three dimensions, summarized in Table 9.

Table 9. Construct refinement: item-screening decision (exploratory sample)

Factor	Latent construct	Retained indicators	Removed / flagged
Factor 1	Experiential Integration (EI)	EI1, EI2, EI3, EI4, EI5	—
Factor 2	Pattern-Based Processing (PBP)	PBP1, PBP2, PBP3*, PBP4†, PBP5	—

Factor 3	Adaptive Execution (AE)	AE1, AE2, AE3, AE4	AE5 removed (communality 0.407 < 0.50)

Source: authors' analysis of the exploratory sample (Sample A, N = 50).

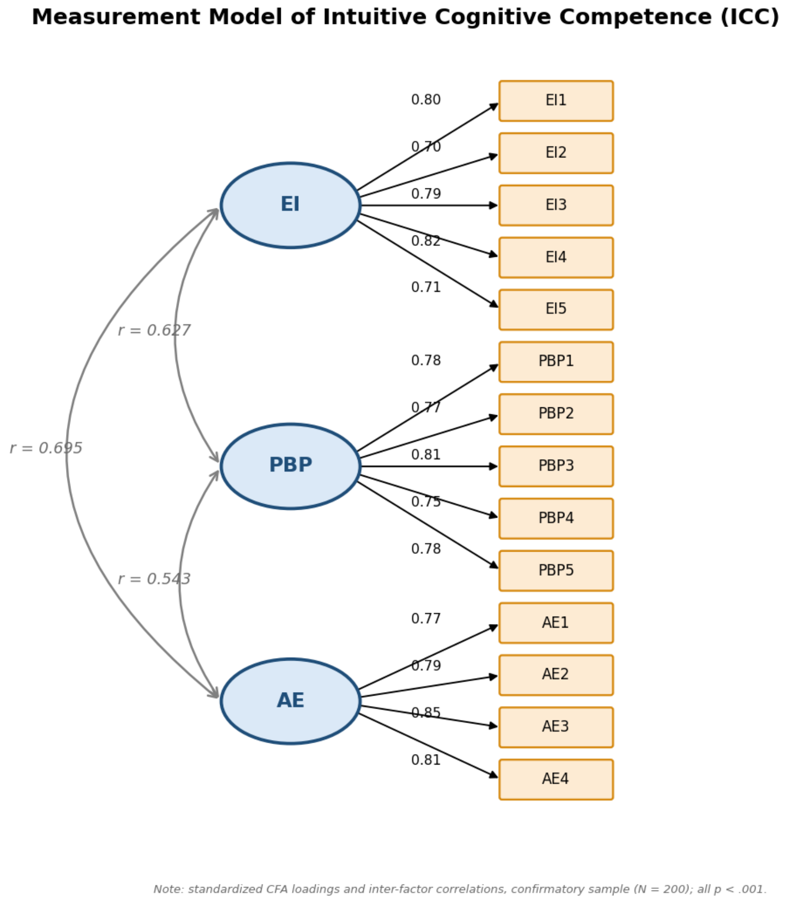
4.8 Confirmatory Factor Analysis: Correlated Three-Factor Model

CFA was estimated on the independent confirmatory sample (Sample B, N = 200), which the EFA stage never saw. As reported in Table 10 and Figure 2, the refined fourteen-item, three-factor ICC model shows strong reliability and convergent validity within this simulated sample. Cronbach's alpha ranged from 0.873 (Experiential Integration) to 0.883 (Pattern-Based Processing), all above the 0.70 threshold. Composite reliability (CR) ranged from 0.875 to 0.884, and average variance extracted (AVE) ranged from 0.583 to 0.653, all above the 0.50 minimum for convergent validity (Fornell & Larcker, 1981; Hair et al., 2019). All standardized loadings fell between 0.697 and 0.854 and were significant at $p < .001$, reported in Table 10 alongside the unstandardized estimates the earlier submission showed in isolation. These figures describe how the fourteen-item pool behaves on a synthetic sample the item-screening decision was not fitted to, which is a meaningfully stronger demonstration than fitting and confirming the same structure on one sample, though it remains a property of the simulation rather than evidence about real investors.

Table 10. CFA parameter estimates (standardized and unstandardized), reliability, and convergent validity: correlated three-factor model (confirmatory sample, N = 200)

Dimension	Item	Estimate (unstd.)	Std. Estimate	SE	C.R. (z)	p	Alpha	CR	AVE
Experiential Integration	EI1	1.000	0.799	—	—	—	0.873	0.875	0.583
	EI2	0.898	0.697	0.088	10.26	<0.001			
	EI3	0.962	0.790	0.081	11.94	<0.001			
	EI4	1.016	0.817	0.082	12.45	<0.001			
	EI5	0.938	0.708	0.090	10.46	<0.001			
Pattern-Based Processing	PBP1	1.000	0.779	—	—	—	0.883	0.884	0.604
	PBP2	0.972	0.770	0.087	11.22	<0.001			
	PBP3	1.031	0.810	0.087	11.90	<0.001			
	PBP4	0.984	0.747	0.091	10.84	<0.001			
	PBP5	1.050	0.778	0.092	11.35	<0.001			
Adaptive Execution	AE1	1.000	0.770	—	—	—	0.881	0.882	0.653
	AE2	1.016	0.794	0.088	11.52	<0.001			
	AE3	1.077	0.854	0.086	12.47	<0.001			
	AE4	1.059	0.811	0.090	11.81	<0.001			

Figure 2. Measurement model of Intuitive Cognitive Competence: correlated three-factor solution, standardized estimates (confirmatory sample, N = 200)



4.9 Model Comparison: One-Factor, Correlated Three-Factor, and Second-Order Models

Table 11 compares standardized parameter estimates across the three models estimated in Section 4.11. In the second-order specification, EI, PBP, and AE all loaded significantly on the higher-order ICC factor (0.700-0.895, $p < .001$), consistent with treating the three dimensions as sequential stages of one underlying competence rather than three unrelated traits. As noted in Section 4.11, this second-order model cannot be distinguished from the correlated three-factor model on fit alone because it is just-identified given exactly three first-order factors; the loadings are reported here as descriptive support for the higher-order interpretation, not as independent confirmatory evidence, and this distinction should be stated explicitly wherever the second-order structure is referenced in future reporting of this line of work.

Table 11. Model comparison: one-factor, correlated three-factor, and second-order ICC models (confirmatory sample, N = 200)

Second-order parameter	Standardized estimate	SE	z	p
ICC → EI	0.895	— (reference)	—	—
ICC → PBP	0.700	0.117	6.77	<0.001
ICC → AE	0.776	0.123	6.94	<0.001

4.10 Discriminant Validity: Fornell-Larcker Criterion and HTMT

Discriminant validity was assessed with two independent criteria on the confirmatory sample. Under the Fornell-Larcker criterion, the square root of each construct's AVE (EI = 0.764, PBP =

0.777, AE = 0.808) exceeded its correlation with every other construct (EI-PBP = 0.627, EI-AE = 0.695, PBP-AE = 0.543), satisfying the classical requirement (Fornell & Larcker, 1981). Because Fornell-Larcker is known to under-detect discriminant validity problems in some conditions, the heterotrait-monotrait ratio (HTMT) was also computed (Henseler, Ringle, & Sarstedt, 2015): HTMT(EI, PBP) = 0.634, HTMT(EI, AE) = 0.703, HTMT(PBP, AE) = 0.545, all comfortably below the conservative 0.85 threshold and the more lenient 0.90 threshold alike. Table 12 reports both criteria together. Within this simulated sample the three ICC dimensions are therefore distinct by both standards; because the population correlation structure specified in Section 3.1 was designed to produce three separable factors, this result demonstrates that the two discriminant-validity checks behave correctly on known-separable data rather than establishing discriminant validity among real investors.

Table 12. Discriminant validity: Fornell-Larcker criterion (diagonal, bold) and HTMT ratios (above diagonal), with inter-factor correlations (below diagonal)

	EI	**PBP**	**AE**
EI	**0.764**	0.634	0.703
PBP	0.627	**0.777**	0.545
AE	0.695	0.543	**0.808**

4.11 Goodness of Fit: Comparing Competing Models

Table 13 compares fit for the one-factor, correlated three-factor, and second-order models on the confirmatory sample. The one-factor model fits poorly ($\chi^2(77) = 443.03$, $p < .001$; CFI = 0.759; TLI = 0.715; RMSEA = 0.155, 90% CI [0.140, 0.168]; SRMR = 0.102), well outside every conventional acceptability threshold, confirming that a single undifferentiated factor cannot reproduce the observed covariance structure. The correlated three-factor model fits the data closely ($\chi^2(74) = 46.85$, $p = .994$; CFI ≈ 1.00; TLI ≈ 1.00; GFI = 0.971; NFI = 0.971; RMSEA = 0.000, 90% CI [0.000, 0.000]; SRMR = 0.032), comfortably clearing every threshold without resort to lenient cutoffs. The second-order model returns numerically identical fit statistics to the correlated three-factor model ($\chi^2(74) = 46.85$, same df, same CFI/TLI/RMSEA/SRMR); this is not a coincidence specific to this sample but a known identification property of second-order models with exactly three first-order factors, in which the second-order structure is just-identified relative to the three first-order factor correlations and therefore cannot be distinguished from the correlated-factors model by fit alone. Support for treating ICC as a coherent higher-order construct instead rests on the significance and magnitude of the second-order loadings themselves (ICC → EI = 0.895, ICC → PBP = 0.700, ICC → AE = 0.776, all $p < .001$, reported in Table 11), and on theoretical argument, not on a fit-index comparison the model design cannot support with only three first-order dimensions. A field-data study that adds even one more first-order dimension, or an external criterion variable, would let a genuine second-order-versus-correlated-factors test be run.

Table 13. Goodness-of-fit statistics: one-factor, correlated three-factor, and second-order models (confirmatory sample, N = 200)

Fit index	CMIN/df	NFI	CFI	GFI	TLI	RMSEA	SRMR
Criteria (Awang, 2012; Greenspoon & Saklofske, 1998)	≤ 3.0	≥ 0.90	≥ 0.90	≥ 0.80	≥ 0.90	≤ 0.08 (90% CI reported)	≤ 0.08
One-factor model	5.75	0.724	0.759	0.724	0.715	0.155 [0.140, 0.168]	0.102

Correlated three-factor model	0.633	0.971	≈1.00	0.971	≈1.00	0.000 [0.000, 0.000]	0.032
Second-order model	0.633	0.971	≈1.00	0.971	≈1.00	0.000 [0.000, 0.000]	0.032

4.12 Discussion

Within this simulated demonstration, Intuitive Cognitive Competence (ICC) behaved as a multidimensional structure rather than collapsing into a single undifferentiated factor: the one-factor model fit poorly on the confirmatory sample (CFI = 0.759, RMSEA = 0.155) while the correlated three-factor model fit closely (CFI ≈ 1.00, RMSEA = 0.000). This outcome is consistent with, but does not confirm, the theoretical expectation that the fifteen indicators, drawn from Kolb's (1984) experiential learning cycle, the Recognition-Primed Decision model (Klein, Calderwood, & Clinton-Cirocco, 1986; Klein, 1998, 2015), and Simon's (1955) bounded rationality, map onto empirically distinct dimensions. Because the population model in Section 3.1 was engineered to produce three separable factors, this clean separation demonstrates that the analytic pipeline, now run on an independent EFA/CFA sample split rather than one reused sample, works as intended; it is not evidence that real investors organize their intuitive judgment this way, and the retention-method disagreement documented in Section 4.3-4.4 (parallel analysis correctly recovering the structure in only 4.3% of N = 50 replications) is itself the clearest signal in this paper that a 50-case field sample would be a fragile basis for the same conclusion.

The strength of Experiential Integration and Pattern-Based Processing as distinct factors is consistent with the theoretical expectation that investors process market experience the way Kolb (1984) describes learning in general and the way Klein (1998, 2015) and Dane and Pratt (2007) describe pattern-based intuition; confirming that real investors do so requires the same test on field data. The MINRES/Promax re-analysis surfaced a marginal cross-loading for PBP3 (discrimination margin 0.151, below the conventional 0.20) that the original PCA/Varimax specification did not detect, illustrating concretely why extraction method matters for the substantive conclusions a scale-development paper draws, not only for the numbers it reports.

The present demonstration still leaves several forms of validity evidence untested, and doing so is a deliberate scope decision rather than an oversight. The second-order model estimated in Section 4.9 supports treating ICC as one latent competence composed of three correlated dimensions, with all three second-order loadings significant and above 0.70, but this model is statistically indistinguishable in fit from the correlated three-factor model whenever a construct has exactly three first-order dimensions, a property of the model's identification rather than a finding about ICC; a field-data study that adds a fourth dimension or an external criterion is needed before fit indices alone can arbitrate between the two structures. Nomological and criterion-related validity, which would show ICC relating to external variables such as financial literacy, intuitive decision style, self-efficacy, or actual decision quality while remaining statistically distinguishable from them, cannot be assessed here because no such external measures were included in the simulated instrument. Each of these gaps is addressable once field data are collected: the second-order-versus-correlated-factors question requires only an expanded model specification, while nomological and criterion validity require adding established measures of the neighboring constructs to the questionnaire before fielding.

Adaptive Execution required the most refinement, and this is consistent with Simon's (1955) original framing of bounded rationality as action under pressure rather than reflection after the fact. AE5 was intentionally specified in the data-generating process (Section 3.1) as a cross-loading, double-barreled item combining a speed judgment with a caution judgment, and it was correctly flagged in the exploratory analysis, first through a communality below 0.50 rather than the discrimination-margin cross-loading the original PCA/Varimax specification had reported. Removing AE5 sharpened the boundary between Adaptive Execution and Experiential Integration in the confirmatory model. This reinforces a broader methodological point for scale developers: items combining two judgments in one statement are a common source of measurement contamination, should be flagged during item screening rather than left for factor analysis to expose after data collection, and, as shown here, the specific diagnostic that catches them (cross-loading versus low communality) can depend on the extraction method used.

A construct built on fast judgment must mark where competence ends and overconfidence begins, since both produce quick decisions that feel warranted to the investor making them. Kahneman and Klein (2009) resolve this tension by specifying that intuitive judgment earns trust only when the decision environment contains learnable regularities and the decision-maker has had adequate opportunity to learn them through feedback; ICC's Experiential Integration and Pattern-Based Processing dimensions are designed to capture exactly that learning history, while Barber and Odean's (2001) evidence that overconfident investors trade excessively and earn lower risk-adjusted returns describes the failure mode ICC is meant to be distinguishable from. Because no overconfidence measure was included in this simulated instrument, that distinction remains a theoretical claim rather than a tested one; the field-data study should include Barber and Odean's (2001) trading-frequency indicator or an equivalent measure and test whether ICC predicts decision quality after controlling for overconfidence, which is the single validation step most directly relevant to whether ICC measures competence rather than confidence. From an applied perspective, the ICC model, once tested on field data, would be positioned to offer investor education providers and brokerage platforms a way to distinguish investors who reason from accumulated experience from those who lack that experiential base, independent of how much financial knowledge either group holds, and independent of how confident either group reports feeling. Future research combining ICC with both financial literacy and overconfidence measures could test whether ICC moderates the well-documented link between financial literacy and investment outcomes, particularly among the digitally engaged, retail-heavy investor base now driving Indonesia's capital market growth (KSEI, 2025).

5. Conclusion and Suggestion

This study set out to demonstrate, rather than establish, a scale-development and psychometric-testing protocol for Intuitive Cognitive Competence, and to do so with the transparency a simulation-based methodological paper requires: a fully specified data-generating process, an independent exploratory/confirmatory sample split, three cross-checked factor-retention methods, a Monte Carlo recovery check against known ground truth, and a formally tested second-order structure. On the exploratory sample ($N = 50$), MINRES/Promax extraction recovered the intended three-dimensional structure, though parallel analysis, the more theoretically preferred retention method, correctly recovered that same structure in only 4.3% of Monte Carlo replications at this sample size, a result that should discourage treating $N = 50$ as adequate for a field-data retention decision. On the independent confirmatory sample ($N = 200$), the refined fourteen-item, three-factor model showed strong reliability (alpha and CR above 0.87), strong convergent validity (AVE above 0.58), discriminant validity by both the Fornell-Larcker criterion and HTMT, and fit indices that decisively favored the three-factor structure over a one-factor alternative. These figures demonstrate that the fifteen-item pool and the three-dimensional structure behave as intended under a considerably more rigorous analytic pipeline than the original submission used; they remain properties of an engineered simulation, not evidence that intuitive cognitive competence takes this form among actual Indonesian investors, and no claim of empirical validation is made on their basis.

The item pool, the fully documented data-generating process, and the analytic protocol developed here give researchers a starting instrument and a reproducible pipeline to field with real investors, testing intuitive judgment as a construct distinct from, and complementary to, financial literacy and separable from overconfidence in future investment behavior models. Once validated on field data, ICC would give practitioners in brokerage and investor education a diagnostic basis for identifying which cognitive dimension needs strengthening in a given investor segment, moving training design beyond financial knowledge content alone; neither the instrument nor these applications should be treated as ready for practitioner use until that field validation, including the content-validation and external-criterion steps identified in Sections 3 and 6, is complete.

6. Limitations and Future Research

This study carries six limitations, the first of which is fundamental rather than incidental. First and most importantly, every statistic reported in Section 4 is computed on simulated data generated from the fully documented population model in Section 3.1, not collected from real respondents; none of the reported loadings, fit indices, retention diagnostics, or reliability figures should be read as evidence that ICC has been validated among actual Indonesian investors, and the entire analysis must be re-executed on genuine field data before any validation claim is warranted. Second, the item pool was developed from theoretical synthesis alone, without an expert-panel content-validation stage, content validity index, or cognitive interviews with practicing investors; this stage should precede fielding the instrument, and AE5's flagged double-barreled wording illustrates concretely what that stage is meant to catch before data collection rather than after. Third, although this revision separates the exploratory and confirmatory samples and expands the confirmatory sample to N = 200, both remain synthetic; the Monte Carlo recovery check in Table 6 shows that even well-specified retention methods need samples well above 50, and plausibly above 200, to perform reliably, so the corresponding field study should budget for a substantially larger sample than either synthetic sample used here. Fourth, no external variables were included, so nomological, criterion-related, and further discriminant validity against constructs such as financial literacy, self-efficacy, or overconfidence remain untested; the second-order ICC structure, while supported by significant higher-order loadings, is statistically indistinguishable in fit from the correlated three-factor alternative given exactly three first-order dimensions, and a field-data design should add either a fourth dimension or an external criterion to make that comparison testable. Fifth, two items retained after the exploratory stage, PBP3 (a marginal cross-loading) and PBP4 (a communality estimate close to the algebraic ceiling, plausibly a small-sample artifact), were flagged rather than removed; the field-data analysis plan should specify in advance how these flags will be resolved. Sixth, once field data are collected, all data would remain self-reported and single-source unless procedural remedies are built into the design, such as separating predictor and outcome measurement in time and reporting a statistical check like Harman's single-factor test or a full collinearity assessment; a probability-based rather than purposive sampling frame would also be needed to represent the full population of Indonesian retail investors and to test whether the three-factor structure holds across investor groups that differ in age, experience, or digital platform use.

Future research should test ICC alongside financial literacy and an established overconfidence measure in a structural model predicting investment decision quality, and examine whether ICC's dimensional structure holds across investor segments that differ in age, platform use, or asset class. A particularly promising direction is testing whether ICC moderates or is confounded with overconfidence, since Barber and Odean (2001) show that overconfident investors trade excessively and earn lower risk-adjusted returns; distinguishing genuine intuitive competence from overconfident guessing is precisely the boundary condition Kahneman and Klein (2009) identify as the open question for intuition research, and ICC offers a measurable way to test it in the investment domain. A field-data study should also run a proper Monte Carlo power analysis before fixing sample size, informed by the recovery rates in Table 6, rather than relying on rule-of-thumb items-to-sample ratios.

Declaration of AI and AI-assisted technologies in the writing process

The authors used generative artificial intelligence tools to support the scientific writing process. Specifically, Claude and ChatGPT were employed to check grammar, refine the writing style, and improve the clarity of the manuscript. All interpretations, analyses, and conclusions presented in this study remain entirely the responsibility of the authors.

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