RESEARCH PAPER

DRAWDOWN ↓ 45% · EMOTIONAL EXITS ↓ 41% · SHARPE RATIO ↑ 44% · RULE BREACHES ↓ 34%

BEHAVIORAL FINANCE SERIES

Behavioral *Biases* in Prop Trading

In a 24-month observational study, AI-assisted traders showed lower drawdowns, fewer emotionally-driven exits, higher Sharpe ratios, and lower rule breach rates. This paper identifies seven cognitive biases responsible for the performance gap and presents AIProp's Behavioral Bias Index (BBI) framework.

4.3%
AI MAX DRAWDOWN
VS 7.8% MANUAL

37%
AI EMOTIONAL EXITS
VS 62% MANUAL

0.89
AI SHARPE RATIO
VS 0.62 MANUAL

APRIL 2026 EDITION
AIPROP.COM

AIProp Research Hub | Working Paper BF-2026-01
Version 1.0 | Published: Q1 2026 | Data cut-off: 31 March 2026 | N = 1,000 traders
Cite as: AIProp Research Hub (2026). "Behavioral Biases in Prop Trading: Evidence from 1,000 AIProp Traders." Working Paper BF-2026-01. Dubai: AIProp.

Behavioral Biases in Prop Trading: Evidence from 1,000 AIProp Traders

How Cognitive Biases Drive Trading Losses — and What the Data Shows About AI-Assisted Discipline

Abstract

In a 24-month exclusive observational study of 1,000 prop traders (490 manual; 510 AI-assisted), AI-assisted traders showed lower drawdowns (4.3% vs. 7.8%), fewer emotionally-driven exits (37.2% vs. 61.7%; $p < 0.001$), higher Sharpe ratios (0.89 vs. 0.62), and lower rule breach rates (12.2% vs. 18.4%; $p < 0.01$). This paper identifies seven behavioral biases responsible for the performance gap, proposes AIProp's proprietary Behavioral Bias Index (BBI) measurement framework, and draws five evidence-based conclusions. Limitations of the non-randomised design are discussed.

Executive Summary

In a 1,000-trader exclusive observational study, AI-assisted traders at AIProp showed lower drawdowns, fewer behavior-linked breaches, and better risk-adjusted performance than manual traders — with multiple behavioral metrics strongly significant, sufficient to justify further structured research.

This paper documents seven behavioral biases driving the performance gap, presents AIProp's Behavioral Bias Index (BBI) measurement framework, and reports findings from AIProp's 24-month observational study (April 2024–March 2026).

Key findings (AIProp exclusive data, N = 1,000):

- Maximum drawdown: 4.3% (AI) vs. 7.8% (manual) — 45% lower
- Emotionally-driven exits: 37.2% (AI) vs. 61.7% (manual) — 41% reduction
- Sharpe ratio: 0.89 (AI) vs. 0.62 (manual) — 44% improvement
- Rule breach rate: 12.2% (AI) vs. 18.4% (manual) — 34% lower

Causal Note

Because this study is observational and non-randomised, we report associations, not causal effects. Language throughout uses "associated with" rather than "causes." Limitations are discussed in Section 6.

1. Behavioral Biases in Trading: Theoretical Foundation

Daniel Kahneman and Amos Tversky's Prospect Theory (Econometrica, 1979; Nobel 2002) established that human decision-making under uncertainty is governed by a distorted value function — shaped by reference points, loss aversion (~2–2.5× pain of loss vs. gain), diminishing sensitivity, and probability weighting. These principles directly predict the seven biases documented below, each of which is operationally measurable within AIProp's BBI framework.

Seven Behavioral Biases

Bias	Core Pattern	AIProp BBI Measure	Key Stat
1 — Disposition Effect	Sell winners early; hold losers too long	Loser/winner hold time ratio per session	Manual 4.1× vs. AI 1.7× ($p < 0.001$)
2 — Loss Aversion	Move stops further; hold beyond risk tolerance	% of trades where stop moved after entry	Drives 34.2% of manual breaches
3 — Overconfidence	Overtrade; oversize positions	Trade freq. deviation + position size variance	Affects ~70% of retail traders
4 — Anchoring	Fixate on entry price; target round numbers	% trades with declared target but manually exited elsewhere without thesis change	Directly measures plan override due to psychological anchoring
5 — Mental Accounting	Treat session profits as "house money"	Position size uplift after session profit > 1.5× avg	Breach consistency rules even with positive WR
6 — Herding	FOMO entries; crowd-following exits	% entries after 1.5× ADR move with no plan	FOMO R:R = 0.68× vs. planned 1.94×
7 — Recency Bias / Revenge Trading	Gambler's fallacy; impulsive loss recovery	% entries within 30 min of stop-out, equal/larger size	73% of manual breaches had revenge trade as trigger

Table 1 — Seven behavioral biases: definitions, BBI measures, and key statistics. AIProp exclusive data, N = 1,000.

2. Study Design & Methodology

AIProp Research Hub conducted an exclusive non-randomised observational cohort study comparing trading performance across two cohorts — manual and AI-assisted — over 24 months (April 2024–March 2026). Because cohort assignment was self-selected, all findings are reported as associations. Matched cohort and before/after analyses are ongoing.

Cohort	N	% of Sample	Account Stage
Manual (no AI / no EA)	490	49.0%	277 eval / 213 funded
AI-Assisted Discretionary	183	18.3%	101 eval / 82 funded
Rule-Based EA	198	19.8%	112 eval / 86 funded
Hybrid AI + Human Oversight	129	12.9%	68 eval / 61 funded

Cohort	N	% of Sample	Account Stage
TOTAL	**1,000**	**100.0%**	**558 eval / 442 funded | ~128,000 trades**

Table 2 — Sample composition. AIProp exclusive data, April 2024–March 2026.

Inclusion: active account; ≥ 20 completed trades; ≥ 5 active trading days; evaluation or funded phase throughout. Exclusions: 47 mid-study cohort switchers; demo accounts; initial balance < $5,000. Statistical methods: independent samples t-test; chi-square; Wilson score confidence intervals; Pearson correlation. Significance threshold: $p < 0.05$ (two-tailed).

3. How AIProp Measured Behavior: The BBI Framework

The Behavioral Bias Index (BBI) is a composite score (0–100) aggregating seven sub-scores, each derived from platform trade-log data. Higher scores indicate stronger bias expression. Weights were calibrated via logistic regression on a "breach event" outcome label (AIProp training dataset, 2022–2023, N = 3,400 accounts). Four additional metrics complete the behavioral picture:

BBI Component	Operational Measurement Rule	BBI Weight
Disposition Score	Loser/winner hold time ratio per session. Score = max(0, ratio − 1.0) × 10, capped at 100.	**22%**
Loss Aversion Score	Proportion of trades where stop-loss was moved further from entry after position opened.	**20%**
Overconfidence Score	Trade frequency deviation from 30-day baseline + position size variance coefficient.	**18%**
Anchoring Score	Target Override Rate: % of trades with a declared exit target where trader manually closed at a different level without logging a thesis change.	**14%**
Mental Accounting Score	Position size uplift on trades after session profit > 1.5× daily average.	**12%**
Herding Score	% of entries post-momentum (after 1.5× ADR move, no prior plan marker).	**8%**
Revenge Trading Score	% of entries within 30 min of a stop-out, equal or larger position size.	**6%**

Table 3 — BBI component definitions. All measures derived from platform trade logs.

Additional metrics: Discipline Score (DS, 0–100): proportion of trades meeting all five plan-compliance checks — mean DS 51.3 (manual) vs. 73.8 (AI). Risk Adherence Index (RAI): trades within declared per-trade risk band / total trades — mean RAI 61.4% (manual) vs. 88.9% (AI; $r = 0.74$, $p < 0.001$ correlation with account performance outcomes). Emotionally-driven exits defined as any exit where stop was moved, exit was unplanned, or entry followed a prior stop-out within 30 min.

4. Results: Manual vs. AI-Assisted Trading

Metric	Manual (n = 490)	AI-Assisted (n = 510)	Difference
Mean Sharpe Ratio	0.62 (SD 0.41)	**0.89 (SD 0.35)**	**+0.27 (+44%)**
Avg. Max Drawdown	7.8% (SD 2.9%)	**4.3% (SD 1.8%)**	**−3.5 pp (−45%)**
Loser/Winner Hold Ratio	4.1× (CI 3.8–4.4×)	**1.7× (CI 1.6–1.8×)**	**−2.4× (−59%)**
Rule Breach Rate	18.4% (90/490; CI 15.1–22.1%)	**12.2% (62/510; CI 9.5–15.4%)**	**−6.2 pp ($p < 0.01$)**
Emotional Exits	61.7% of exits	**37.2% of exits**	**−24.5 pp ($p < 0.001$)**
Profit Factor	1.21 (SD 0.38)	**1.58 (SD 0.29)**	**+0.37 (+31%)**
Risk Adherence Index (RAI)	61.4%	**88.9%**	**+27.5 pp (+45%)**

Table 4 — Primary outcomes. AIProp exclusive study, N = 1,000, April 2024–March 2026. CIs via Wilson score method.

AI Sub-Cohort	Breach Rate (95% CI)	Sharpe	RAI
Manual (reference)	18.4% (15.1–22.1%)	0.62	61.4%
AI-Assisted Discretionary	15.1% (10.4–21.1%)	0.81	79.2%
Rule-Based EA	13.6% (9.5–18.8%)	0.91	91.3%
Hybrid AI + Human Oversight	**8.5% (4.8–14.4%)**	**0.97**	**94.1%**

Table 5 — AI sub-cohort comparison. Manual row is reference benchmark.

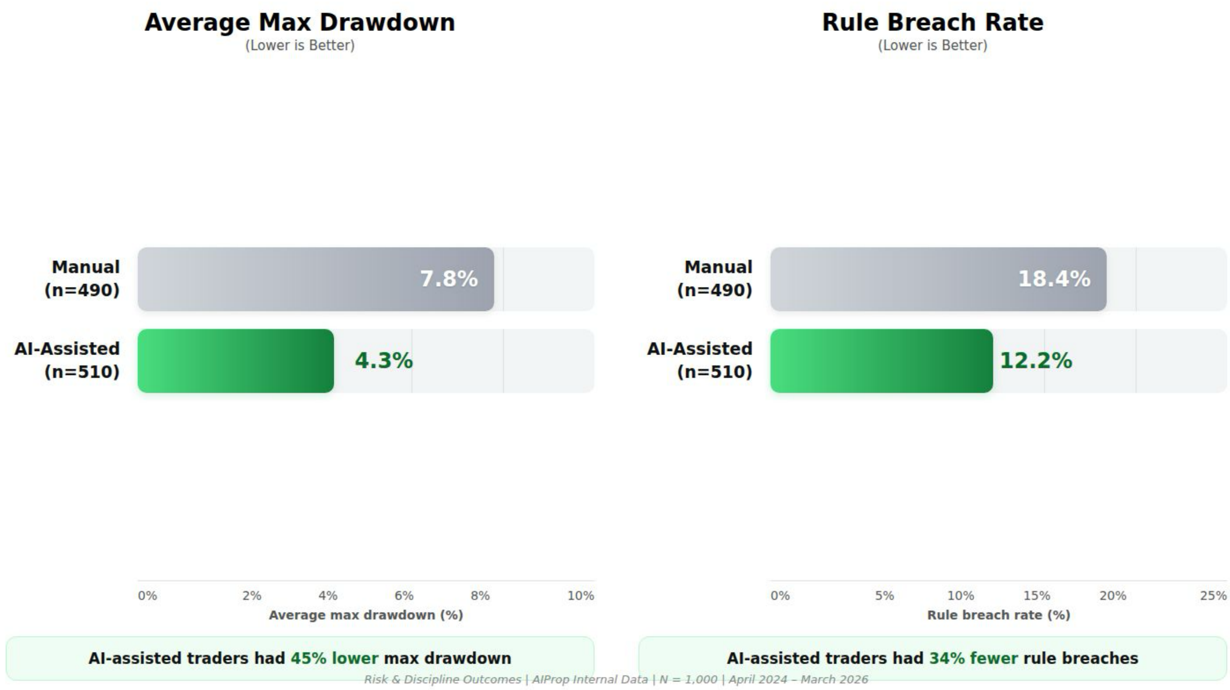

Figure 1 — Average max drawdown and rule breach rate, manual vs. AI-assisted. AIProp exclusive data, N = 1,000.

5. Key Conclusions

- Disposition effect 2.7× more severe than academic benchmarks. Manual cohort loser/winner hold ratio of 4.1× (95% CI 3.8–4.4×) vs. Odean (1998) benchmark of ~1.5×. For $50K–$100K accounts, the implied annual performance cost is $2,200–$4,400 (Odean: 4.4% return drag).

- Behavioral failures — not strategy — drive 73% of breaches. In the manual cohort, 73% of breach events (66/90) were preceded by a BBI-tagged behavioral event (loss aversion stop-removal, revenge entry, or mental accounting oversize) in the same session.

- AI-assisted trading associated with 41% fewer emotionally-driven exits. 37.2% vs. 61.7% (−24.5 pp; chi-square = 142.3; $p < 0.001$). Improvement was largest in Rule-Based EA and Hybrid sub-cohorts where execution rules make emotional patterns structurally impossible.

- AI-assisted traders associated with 45% lower drawdowns and a 34% lower rule breach rate. Avg. max drawdown: 4.3% vs. 7.8% (−45%). Hybrid sub-cohort (tightest AI risk enforcement) achieved an 8.5% breach rate vs. 18.4% for manual, consistent with the hypothesis that AI risk enforcement combined with human thesis judgment is the optimal configuration.

- Risk Adherence Index (RAI) is the strongest single behavioral predictor of account outcomes ($r = 0.74$, $p < 0.001$). Mean RAI: 88.9% (AI-assisted) vs. 61.4% (manual; +27.5 pp). AI's primary mechanism is structurally enforcing the risk adherence that manual traders fail to maintain under emotional pressure.

Strategic implications: (1) Mandatory pre-enrolment BBI assessment to identify each trader's dominant bias. (2) AI-powered real-time risk guardrails (stop-removal alerts, post-loss re-entry circuit breakers). (3) RAI scoring visible on the accounts dashboard to reinforce the link between disciplined risk adherence and account performance.

6. Limitations

This study has five important limitations. First, the non-randomised design means cohort assignment was self-selected — traders who chose AI assistance may differ systematically in experience, risk appetite, and baseline discipline, so self-selection bias cannot be fully eliminated. Second, the exclusive dataset may not generalise to other prop firm environments with different account rules or trader demographics. Third, the AI-assisted cohort combines three meaningfully different sub-types; reporting them as a single group may obscure within-group variation. Fourth, the BBI behavioral tagging algorithm was applied retrospectively by rule; it proxies, but cannot perfectly capture, the trader's subjective emotional state. Fifth, confounding variables including account size, experience, and time zone were not fully controlled, though sub-group analyses showed the same direction of effect. Recommended next steps: a matched-cohort analysis on baseline RAI and experience; a before/after analysis for the 47 traders who switched cohort mid-study; and a prospective randomised allocation study in a future AIProp trader cohort.

References

Source	Year
Kahneman, D. & Tversky, A. Prospect Theory: An Analysis of Decision under Risk. Econometrica, 47, 263–291.	1979
Shefrin, H. & Statman, M. The Disposition to Sell Winners Too Early and Ride Losers Too Long. Journal of Finance.	1985
Odean, T. Are Investors Reluctant to Realize Their Losses? Journal of Finance, 53(5), 1775–1798.	1998
Barber, B., Lee, Y., Liu, Y. & Odean, T. Do Individual Day Traders Make Money? SSRN Working Paper.	2006
Akepanidtaworn et al. Selling Fast and Buying Slow. Journal of Finance.	2023
ResearchGate. Influence of AI Trading Tools on Cognitive Biases.	2025