



Member's-Only Content: Please Read Before Proceeding.

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How Behavioral Science Can Improve the Return on AI Investments

Westover (2025)

Context

Only 26% of companies report tangible ROI and organisations waste an average of \$8.5M annually on stalled pilots. Yet enterprise AI spending is projected to exceed \$300 billion annually by 2026. The problem stems from a "technosolutionist mindset" that treats adoption as an engineering exercise, while ignoring the behavioural complexities (like loss aversion, algorithm aversion, overconfidence) that determine if AI systems create value.

Put simply: AI ROI = Technology × Human Behaviour. Most firms hyperfocus over the first. This article introduces the "Behavioral Human-Centered AI framework" across 3 stages of AI usage.

Key Insights

▶ For case studies across these phases discussing behavioural examples see next page

Design: Build for cognitive shortcuts, not idealised rationality

- People reject what they can't evaluate. Practical design strategies incl. showing confidence levels alongside recommendations, introducing selective friction at key decision points, and revealing system complexity gradually rather than all at once
- Co-designing with end-users ensures tools reflect actual workflows and surface blind spots, while building psychological ownership which sustains engagement → P&G

Adoption: Address loss aversion, trust and perceived control

- Proactive disclosure of AI limitations (incl. known error patterns and human review safeguards) builds realistic expectations and lasting trust → Capital One
- Framing AI as augmentation reduces threat responses (e.g. through concrete task reallocation, skill evolution pathways, human-in-the-loop emphasis) → Deloitte
- Starting with high-visibility, prioritised pain points and clear success metrics; expanding only after demonstrated results creates internal champions for scaling

Management: Prevent ethical fading and performance drift

- After initial adoption, users tend to over-rely on AI without oversight. Multi-stakeholder feedback channels, rapid refinement cycles and regular performance audits mitigate this → JPMorgan
- Structural safeguards (diverse ethics review boards, impact assessment protocols, whistleblower protection) keep ethical dimensions visible under time pressure → Microsoft



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In every case, the technical capability was not the differentiator: the behavioural strategy was.

Case	Behavioural Issues	What They Did	Result
P&G (Consumer insights)	Cultural resistance, lack of buy-in	Involved end-users throughout development with iterative prototype testing on actual tasks	89% adoption in 6 months (vs. 40% historical average)
Capital One (Fraud detection)	Algorithm aversion, reduced trust from unclear AI decisions	Pro actively disclosed algorithm logic, known limitations, and human review safeguards	High adoption and customer acceptance of false-positive friction
Deloitte (Audit automation)	Loss aversion, fear of displacement	Redeployed auditor time from tedious sampling to advisory work; explicitly communicated reallocation	85% adoption in year one; improved quality and engagement
JPMorgan Chase (Contract analysis)	Automation complacency, performance drift	Dedicated lawyer feedback channels, weekly cross-functional reviews, quarterly performance audits	Sustained accuracy and engagement as contract language evolved; replaced 360,000 hours of manual labour
Microsoft (Ethics governance)	Ethical fading (ethical dimensions became less salient under pressure)	Multi-disciplinary committee with authority to block or modify deployments	Prevented multiple deployments with unacceptable fairness/privacy risks

Implications

- At which phase (design, adoption, management) is your AI initiative most exposed to the behavioural challenges discussed?
- How involved are end-users in the design of your AI tools? Are you building for their actual workflows or making assumptions about how they should work?
- Where are you transparent about your AI's limitations, and where are you overselling?
- What mechanisms detect both performance drift in your AI and ethical fading under pressure?