Exploring AI Performance In Dynamic Decision-Making: Case Study on Fishery Management

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Extended Abstract

Sustainable natural resource management, particularly in fisheries, remains to be a pressing global challenge, where mismanagement often leads to ecosystem degradation and economic losses. Classic examples such as the collapse of the Canadian cod fishery in the 1990s underscore the impact of delayed feedback and cognitive biases in human decision-making (DFO, 2009). Moxnes (1998), through his experimental-based model, identified that fishery mismanagement stems not only from competition for shared resources but also from human misperceptions of resource dynamic and ecosystems feedback. It often leads to overinvestment in harvesting capacity despite declining fish stock. Human misperception is not unique to fisheries but is observed across various domains of natural resource management.

This study explores whether an AI system, specifically GPT-4o can either replicate human decision-making in a dynamic fishery management context or overcome such human cognitive limitations, particularly when operating under the same decision framework. Using a replicated version of Moxnes' (1998) system dynamics model, AI was tested as an autonomous agent making sequential decisions on fleet expansion and lay-up strategies.

Prior research highlights three key cognitive human biases affecting natural resource decisions: overconfidence, present bias, and feedback misperception. These biases contribute to overexploitation and policy failure. Behavioral decision-making research (Sterman, 1993; Jensen et al., 2012) has consistently shown that individuals struggle with delayed feedback and nonlinear system behavior, leading to suboptimal policy decisions. While AI is increasingly applied in resource management, including fisheries, forestry, and

energy systems, to optimize regulatory enforcement, its capacity to act as a behavioral proxy or decision support tool remains underexplored. This study advances prior research by employing AI as a decision-making agent in resource management simulations. By systematically comparing AI and human-driven decision trajectories, this study contributes to ongoing efforts to understand the applicability of AI in behavioral simulations.

Using InsightMaker, a dynamic simulation web software, we replicate Moxnes' fishery experiment model and replace human decision-making with GPT-4o as our AI tool. Key parameters such as biomass growth rate and spawning were calibrated. GPT-4o received annual updates on financial and ecological indicators and made decisions on boat ordering and lay-up. The AI's responses were fully automated and evaluated both quantitatively and qualitatively through reasoning logs. Performance was compared to the original human-based experiment. Comparative metrics include fish population, biomass, equity, and fortune trajectories under AI vs. human decision-makers.

The results revel a contrast between human participants-decision behavior and AI (GPT-4o). While human decision-makers focused on maximizing short-term economic gains, often leading to aggressive fleet expansion, overfishing, and rapid biomass depletion, the AI exhibited a more cautious and adaptive strategy. AI exhibited the ability to recognize opportunities for fleet expansion under favorable conditions and refrain from further expansion when biomass depletion was detected. It demonstrated an ability to balance and synthesize financial and ecological indicators, account for delayed system effects for long-term sustainability. Additionally, the AI avoided key cognitive biases observed in the original experiment, such as feedback misperception, present bias, and risk-seeking behavior. Its decisions reflected a consistent prioritization of long-term sustainability over short-term exploitation, synthesizing multiple sources of information, accurately identifying dynamic interdependencies between variables, and making rational, evidence-based decisions. Qualitative analysis further confirmed that GPT-4o accurately identified interdependencies between variables and adjusted strategies accordingly.

While human decisions led to sharp biomass decline and short-term equity spikes, AI maintained ecological stability and ultimately achieved a higher final fortune (22.5K vs. 20K NOK), suggesting its potential as both a behavioral proxy and a decision-support tool in dynamic resource systems. This highlights the AI's potential to model adaptive behavior in dynamic environments, though, future studies should more rigorously test whether such performance stems from endogenous system understanding or from prior exposure to optimal policy heuristics embedded in the training data.

Despite the valuable insights gained from the simulations of comparing AI and human-based decision-making in a dynamic fishery management context, several limitations of this study must be acknowledged. First, the study cannot conclusively determine whether GPT-4o's decisions emerged from endogenous understanding of system behavior or from pre-trained exposure to similar optimization problems. Without conducting a reparameterization test, it remains unclear whether the AI adapted dynamically to novel system states or simply recalled effective policy patterns. Second, the use of a single AI model (GPT-4o) with a single experimental run further limits the robustness of the conclusions. Moreover, the decision space was narrowly focused on fleet ordering and lay-up, excluding broader governance choices such as quota setting, investment strategies, or compliance enforcement. Finally, the absence of comparisons with contemporary human participants restricts the behavioral relevance of the baseline used. To advance this line of inquiry, future research should incorporate parameter variation, model comparisons, and expanded decision variables. Evaluating multiple AI systems, including those not trained on internet-scale data, can also help disentangle learned reasoning from pre-trained recall. Collectively, these directions are essential for clarifying AI's role in modeling and supporting decision-making in sustainability-focused and dynamically complex systems.

Appendix: Simulation Result

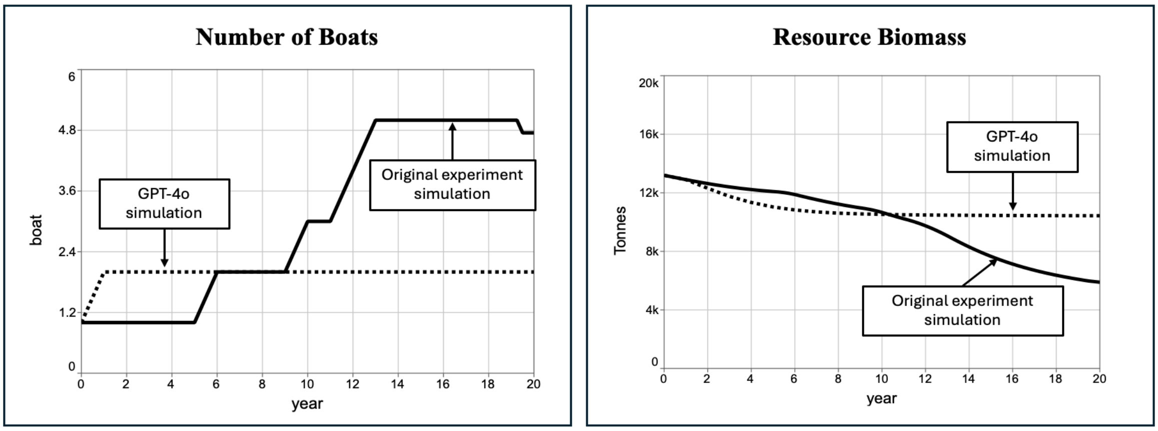

Figure 1: Comparing (a) Number of Boats and (b) Resource Biomass between original experiment and GPT-4o simulations

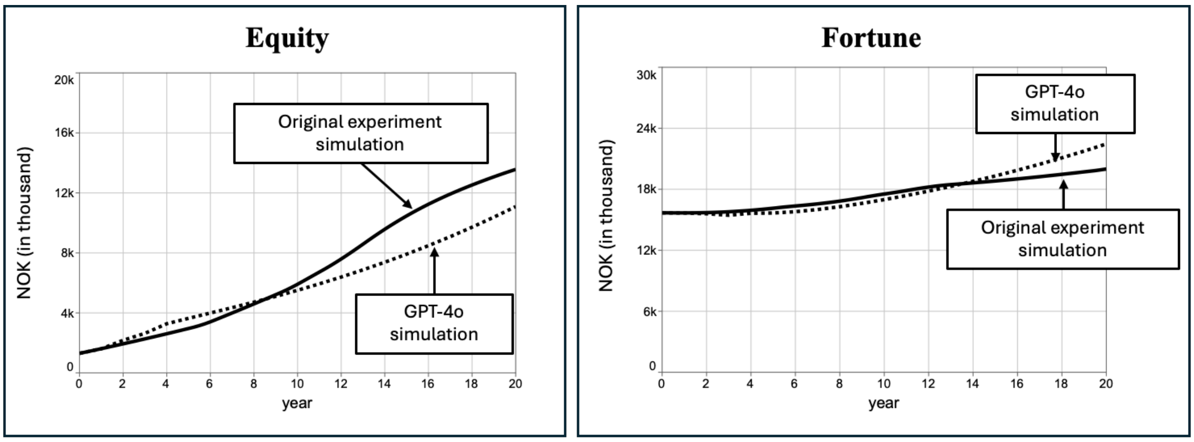

Figure 2: Comparing (a) Equity and (b) Fortune between original experiment and GPT-4o simulations

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