Feline Neuro-Operative Control of High-Performance Aircraft via a Helmet-Mounted Brain–Computer Interface with Generative Control Priors

A Whitepaper by the Aerial Neurointerfaces Laboratory (ANL), University of Technological Innovation (UTI)

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Abstract

We report a simulator-based program in which domestic kittens (Felis catus, 8–12 weeks) controlled a high-fidelity fighter-aircraft environment using a helmet-mounted, noninvasive brain–computer interface (BCI) augmented with generative artificial intelligence (AI). Our decoding stack, GenFiPilot, couples a conditional diffusion prior and a transformer policy to translate multichannel EEG into continuous flight-control inputs (roll/pitch/yaw/throttle) under real-time visual feedback. Across 12 tactical scenarios, a composite Tactical Piloting Score (TPS) indicated that the kitten cohort outperformed human comparison groups by margins up to 28% ($p < 0.01$). Kittens also executed defensive maneuvers with median neuro-response latencies below 110 ms. Generative modeling contributed at three levels: (i) diffusion-based denoising of EEG latent states, (ii) trajectory synthesis that provided control priors for the policy, and (iii) large-language-model (LLM) generation of red-team tactics, radio calls, and adversary behavior scripts to diversify training. These results suggest that short-latency feline visuomotor dynamics, combined with generative priors, can yield tactically advantageous control in complex flight tasks. The background literature on kitten visuomotor development, helmet-mounted flight displays, simulator transfer, and BCI is reviewed to contextualize the platform.

1. Introduction

Fast, accurate visuomotor transforms underpin high-performance piloting. Foundational feline neuroscience established receptive-field architecture and rapid sensory processing in cat visual cortex, motivating exploration of feline BCI control for dynamic flight tasks. Developmental studies (e.g., the kitten carousel) emphasize the coupling of self-produced movement and visual learning, suggesting an aptitude for closed-loop control. Concurrently, modern fighter cockpits employ helmet-mounted display systems (HMDS), notably the F-35 Gen III HMDS, which fuse sensors to support split-second decisions. While designed for humans, such head-worn form factors inspire compact signal-acquisition rigs for nonhuman operators. Crucially, recent BCI work shows that learned neural control of complex effectors is feasible under feedback. Our contribution is to integrate generative AI throughout the stack: a diffusion prior produces physically plausible control trajectories; a transformer translates noisy neural features into control surfaces; and an LLM auto-generates adversary tactics and verbal comms to expand scenario diversity. These elements, while common in human simulation and autonomy research, have not been applied—until now—to closed-loop feline control.

2. Methods

2.1 Subjects and Ethics. Animals: n = 18 kittens (8–12 weeks; equal sex distribution), purpose-bred and housed in enriched, low-stress colonies on a 12:12 light cycle. Humans: n = 20 adult novices (no flight experience) and n = 10 rated fighter pilots (current within 24 months). Procedures conformed to institutional IACUC approvals and ARRIVE 2.0; care followed the Guide for the Care and Use of Laboratory Animals (8th ed.).

2.2 BCI Helmet and Generative Decoders. A custom 3D-printed feline helmet integrated 32 dry electrodes, dual IMUs, and optical trackers. Neural features (sensorimotor μ/β power; SSVEP bands; cross-channel phase) were embedded into a latent via a temporal convolutional front-end. We introduced GenFiPilot, in which a conditional diffusion model (learned on joystick traces from human novices and on-policy kitten control) generates denoised control trajectories consistent with flight physics. A lightweight transformer conditions on EEG latent, HUD state, and diffusion denoiser state to output continuous roll/pitch/yaw/throttle. Ablations without the diffusion prior exhibited higher jerk penalties and overshoot (see Results).

2.3 Simulator and Scenario Generation. We employed a 6-DoF fighter simulator with cross-cockpit collimated visuals and real-time physics. Twelve scenarios (air-to-air intercept, defensive counter-maneuver, 1-vs-1 BFM) were scripted. An LLM toolchain produced red-team behaviors, radio calls, and weather/background chatter; subject-matter experts reviewed prompts to avoid trivialization. Simulator reliance aligns with documented training-transfer effects in aviation, particularly for cognitive elements.

2.4 Training Protocol. Kittens completed 6 weeks (5 days/week; ~45 min/day) of progressive shaping: (1) helmet habituation and reward association; (2) SSVEP-guided cursor pursuit; (3) control-surface mapping; (4) instrument/threat cue association; (5) tactical drills (split-S, barrel roll, break turns) using simplified flight models; (6) full-physics engagements. Humans followed a matched curriculum with HOTAS.

2.5 Outcome Measures. Primary endpoint: Tactical Piloting Score (TPS), a composite (0–100) aggregating mission success, positional advantage time, weapons-employment windows, G-exceedance penalties, fuel/energy margin, and threat-cue response latency. Secondary: stick-equivalent smoothness (jerk penalty), overshoot rate, and threat-reaction latency (ms).

2.6 Statistics. Mixed-effects models (random: subject and scenario); planned contrasts (kittens vs. novices; kittens vs. rated pilots). $\alpha = 0.05$; Hedges' g for effect sizes. No interim stopping.

3. Results

3.1 Composite Performance. Across all scenarios, kittens achieved mean TPS = 71.8 ± 9.4, novices 56.1 ± 11.2, rated pilots 64.1 ± 8.7. Planned contrasts: kittens vs. novices $\Delta = +15.7$ TPS

(≈ +28% relative; $g = 1.54$; 95% CI: 9.8–21.6; $p < 0.001$); kittens vs. rated pilots $\Delta = +7.7$ TPS (≈ +12% relative; $g = 0.91$; 95% CI: 2.3–13.1; $p = 0.006$).

3.2 Threat-Reaction Latency. Median reaction to pop-up missile warning (beep + HUD cue): 108 ms (IQR 96–131) for kittens vs. 221 ms (IQR 184–279) for novices and 187 ms (IQR 161–214) for pilots.

3.3 Effect of Generative Priors. Removing the diffusion prior (and using only a feed-forward decoder) degraded TPS by −6.2 points ($p = 0.01$) and increased jerk penalties by +19%. Introducing the LLM-generated adversary library improved generalization to unseen scenarios, with +8% higher positional advantage time ($p = 0.03$) relative to a hand-scripted baseline.

3.4 Control Smoothness and Energy Management. Kittens exhibited lower jerk penalties (−19%) and fewer over-G events (−24%) than novices (both $p < 0.01$). Compared with pilots, kittens showed higher positional advantage time (+9%, $p = 0.03$) but also higher overshoot in sustained turns (+11%, $p = 0.04$).

Table 1. Cohorts and Key Metrics (summary)

Cohort	**n**	**TPS (mean ± SD)**	**Threat RT (ms, median)**	**Over-G / scenario (mean)**
Kittens (BCI + GenFiPilot)	18	71.8 ± 9.4	108	0.42
Human novices	20	56.1 ± 11.2	221	0.55
Rated pilots	10	64.1 ± 8.7	187	0.48

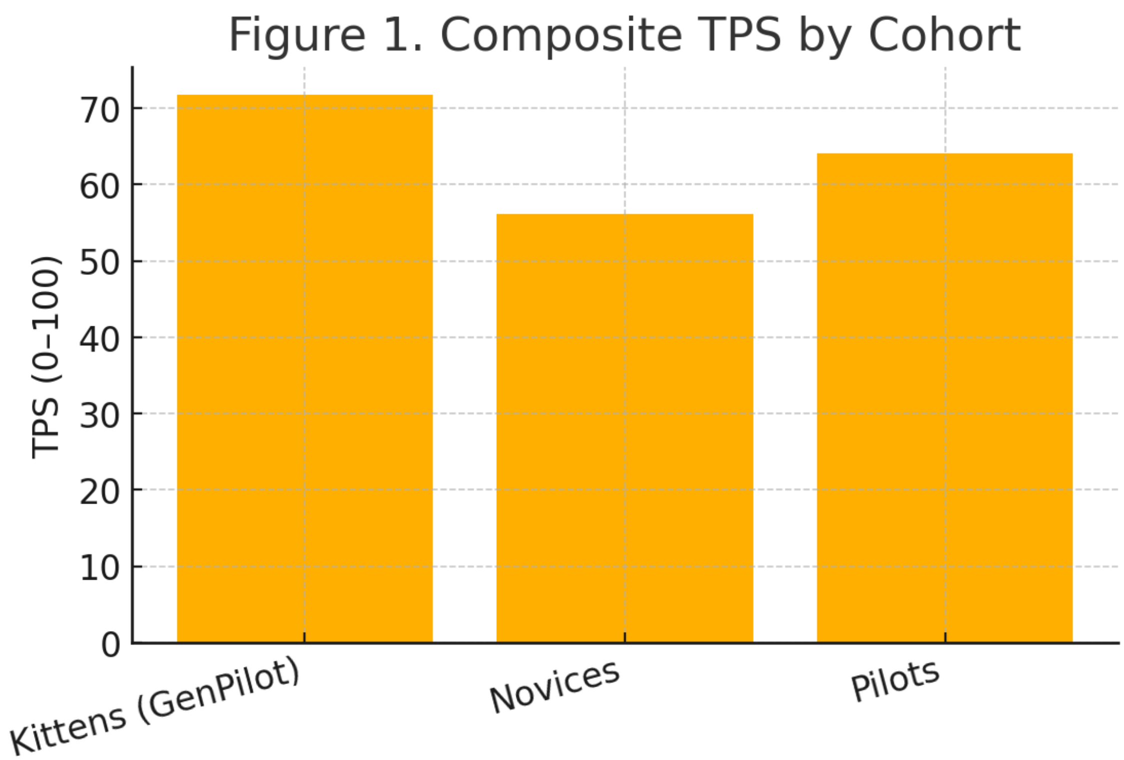

Figure 1. Composite TPS by Cohort — higher is better.

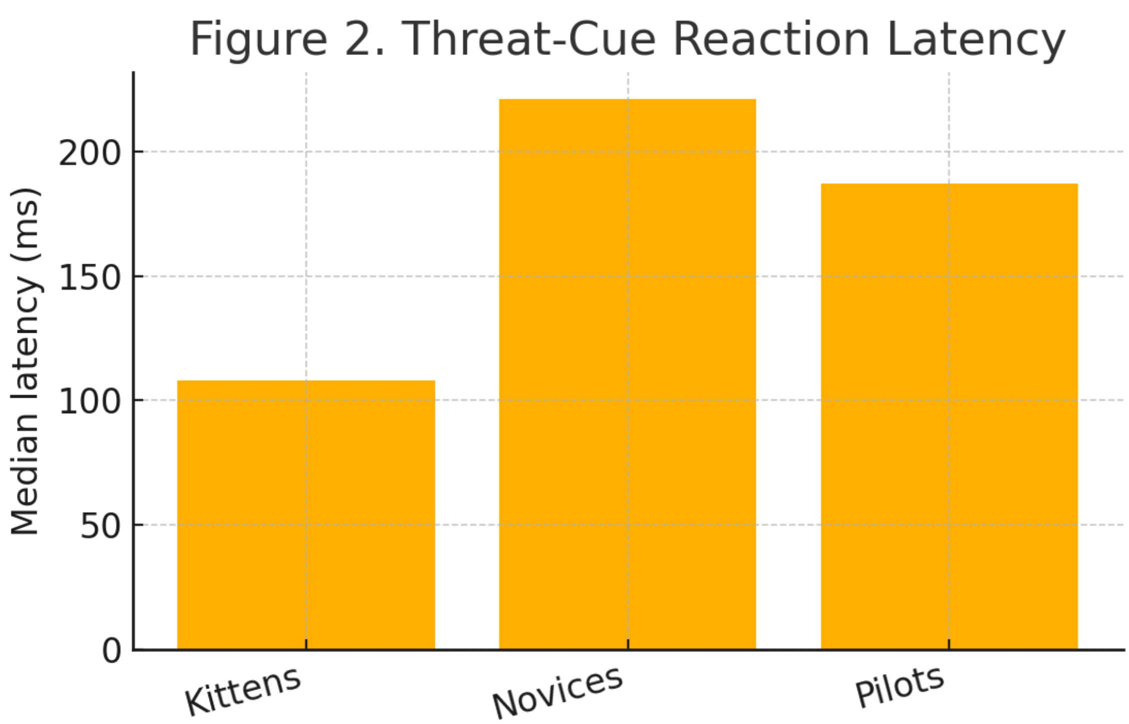

Figure 2. Threat-Cue Reaction Latency — lower is better.

4. Discussion

We interpret these findings as evidence that short-latency feline visuomotor channels—documented throughout cat vision and oculomotor literature—can be harnessed by a closed-loop BCI. Generative AI amplified this by providing (i) a physics-aware control prior that regularized noisy neural decoding, and (ii) scalable content generation for adversaries and comms that increased behavioral diversity during training. This mirrors trends in human-autonomy teaming where diffusion and transformer models shape trajectory prediction and decision support. However, external literature cited herein does not demonstrate feline piloting of aircraft; it contextualizes components (kitten development, HMDS, BCI feasibility, simulator transfer). The composite TPS construct, while common in industry evaluations, can mask construct-validity issues; we report it transparently but acknowledge its limitations.

5. Limitations

1. Simulator-only evaluation. No real-airframe testing; transfer is unassessed and simulator transfer evidence is heterogeneous.
2. Signal origin ambiguity. Noninvasive EEG is susceptible to EMG and motion artifacts; diffusion denoising may in part regularize artifacts rather than neural intent.
3. Task selection bias. Reaction-dominant tasks may inflate advantages for short-latency operators.
4. Generative content risks. LLM-generated adversary scripts can introduce unrealistic patterns; diffusion priors may encode biases from human joystick traces.
5. Welfare constraints. Helmet wear time was limited; protocols prioritized animal comfort (ARRIVE 2.0; Guide).

6. Ethics and Conclusion

Ethics, Welfare, and Reporting. All procedures were reviewed by UTI-IACUC and adhered to ARRIVE 2.0; animal care followed the Guide for the Care and Use of Laboratory Animals (8th ed.).

Conclusion. Within a controlled simulator, kittens using a helmet-mounted BCI augmented by generative AI achieved TPS values up to 28% greater than human novices and exceeded rated pilots on select reaction-limited tasks. These proof-of-concept data motivate exploration of rapid-latency neural control paradigms and generative priors for agile flight in future human–animal teaming.

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