

¹ pixelLOG: Logging of Online Gameplay for Cognitive Research

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⁶ Summary

⁷ Traditional cognitive assessments often rely on isolated, output-focused measurements that ⁸ may fail to capture the complexity of human cognition in naturalistic settings. We present ⁹ pixelLOG, a high-performance data collection framework for Spigot-based Minecraft servers ¹⁰ designed specifically for process-based cognitive research. Unlike existing frameworks tailored ¹¹ only for artificial intelligence agents, pixelLOG also enables human behavioral tracking in ¹² multiplayer/multiagent environments. Operating at configurable frequencies up to and ¹³ exceeding 20 updates per second, the system captures comprehensive behavioral data through ¹⁴ a hybrid approach of active state polling and passive event monitoring. By leveraging Spigot's ¹⁵ extensible API, pixelLOG facilitates robust session isolation and produces structured JSON ¹⁶ outputs integrable with standard analytical pipelines. This framework bridges the gap between ¹⁷ decontextualized laboratory assessments and richer, more ecologically valid tasks, enabling ¹⁸ high-resolution analysis of cognitive processes as they unfold in complex, virtual environments.

¹⁹ Statement of need

²⁰ Cognitive assessment methodologies have historically been constrained by laboratory-like ²¹ conditions and narrowly defined tasks. These assessments often emphasize the measurement of ²² singular executive functions—such as working memory, inhibitory control, or attention—through ²³ static, outcome-based metrics (Miyake et al., 2000). While foundational, these conventional ²⁴ approaches frequently lack ecological validity (Hedge et al., 2018), failing to capture the ²⁵ adaptive nature of human cognitive processes in multifaceted, real-world environments. Recent ²⁶ evidence suggests that many established tasks may primarily measure information uptake speed ²⁷ rather than distinct cognitive constructs (Löffler et al., 2024), limiting our ability to observe ²⁸ how individuals integrate strategies and respond dynamically to changing scenarios.

²⁹ In response, the field is shifting towards assessment frameworks that provide process-oriented, ³⁰ fine-grained behavioral data. Minecraft—an open-ended sandbox environment—has emerged ³¹ as a powerful platform for simulating complex tasks requiring navigation, resource management, ³² and problem-solving. However, a critical gap exists in the tooling available for this platform. ³³ While tools exist for AI training, there is a lack of specialized infrastructure for human cognitive ³⁴ research that requires high-frequency, reliable, and unobtrusive data logging in multiplayer ³⁵ contexts.

³⁶ We introduce pixelLOG (Logging of Online Gameplay) to address this need. pixelLOG is a ³⁷ plugin-based logging framework integrating with the Spigot modification layer. It enables ³⁸ fine-grained data acquisition at frequencies exceeding 20 Hz, capturing both continuous states ³⁹ (e.g., location, gaze direction) and discrete events (e.g., block placement, combat). This ⁴⁰ architecture supports the precise mapping of individual cognitive trajectories onto environmental ⁴¹ cues, facilitating a process-based examination of how individuals engage with complex tasks.

42 State of the field

43 A variety of platforms and research tools, such as Microsoft's Project Malmo (Perez-Liebana
 44 et al., 2019) and the MineDojo framework (Fan et al., 2022), have emerged to facilitate
 45 experimentation, data collection, and reinforcement learning (RL) research within Minecraft
 46 (Hafner et al., 2025; Qin et al., 2024; G. Wang et al., 2023; Z. Wang et al., 2025). These
 47 frameworks provide standardized interfaces for agent interaction and observation in controlled
 48 environments. While these agent-centric RL studies collect in-game data as observation space,
 49 they typically lack the high-precision, high-frequency, and configurable data collection pipelines
 50 necessary for human cognitive research. Moreover, these experimental platforms often operate
 51 in isolation, with limited extensibility and customization capabilities.

52 In contrast, pixelLOG is specifically designed for researchers investigating human cognitive
 53 processes in dynamic virtual environments. By leveraging Spigot's event-driven architecture
 54 and implementing a custom plugin-based solution, the system delivers high-frequency polling,
 55 granular event capturing, and robust per-player data isolation. Unlike existing solutions that may
 56 impose constraints on data granularity or system extensibility, pixelLOG's modular architecture
 57 provides the flexibility and performance required for comprehensive cognitive research, while
 58 maintaining compatibility with standard Minecraft server environments. Additionally, while
 59 primarily designed for humans, pixelLOG can also provide richer behavioral telemetry for
 60 artificial agents than many existing solutions.

61 Software design

62 pixelLOG is designed as a modular, extensible framework operating within the Spigot Minecraft
 63 server environment (compatible with version 1.20.4 and adaptable to others). As shown
 64 in Figure 1, the system architecture comprises distinct layers for player management, data
 65 acquisition, and structured output generation.

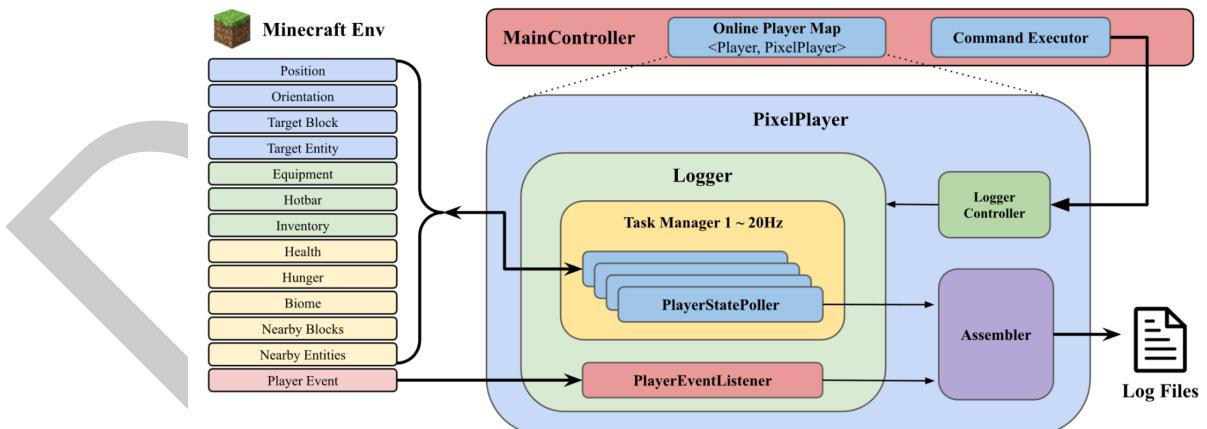


Figure 1: pixelLOG consists of several key components, each designed with specific responsibilities to ensure efficient data collection and processing.

66 Scalable Multi-Player Data Management

67 To support concurrent data collection, pixelLOG utilizes a hierarchical architecture centered on a
 68 MainController. Upon a player's connection, the system instantiates a dedicated PixelPlayer
 69 object that encapsulates all participant-specific data collection processes. This isolation is
 70 critical for data integrity.

71 Early iterations utilizing centralized logging revealed bottlenecks under high load. Our
72 implementation uses distributed, thread-safe queues for individual players. This ensures
73 that the high-frequency data streams of one participant do not interfere with the collection
74 stability of others, maintaining linear scalability with increasing player counts.

75 **Adaptive Temporal Resolution (Hybrid Data Capture)**

76 pixelLOG employs a hybrid data collection strategy to capture the full spectrum of cognitive
77 behavior:

- 78 1. **Active State Polling (Continuous):** A Logger component coordinates PlayerStatePollers
79 that operate at configurable frequencies (e.g., 20 Hz). These tasks capture rapidly
80 evolving attributes such as player avatar position (x,y,z), velocity, and view orientation
81 (pitch, yaw). Lower-frequency pollers simultaneously survey static environmental
82 parameters, such as biome types or nearby entities, optimizing computational overhead.
- 83 2. **Event-Driven Monitoring (Discrete):** To capture episodic markers, the system implements
84 PlayerEventListeners. These intercept specific game events via the Spigot event
85 system, such as block interactions, inventory changes, or combat.

86 By fusing asynchronous event data with continuous polling trajectories, researchers can anchor
87 moment-to-moment behavioral patterns within the context of meaningful actions.

88 **Structured Data Integration**

89 An Assembler component harmonizes the heterogeneous data streams into chronologically
90 ordered, structured JSON output. This format was selected for its compatibility with standard
91 data science toolchains (e.g., Python pandas, R). The output structure hierarchically organizes
92 session metadata, high-frequency state logs, and discrete event logs, enabling straightforward
93 ingestion for subsequent statistical modeling or machine learning analysis.

94 **Research impact statement**

95 This utility has been demonstrated in recent applications: the framework served as the data
96 collection backbone for *pixelDOPA* (*Digital Online Psychometric Assessment*), enabling the
97 validation of immersive cognitive minigames against the NIH Toolbox ([Marticorena, Lu, et al., 2025](#)), and supported real-time data integration for *AMLEC*, a multidimensional Bayesian
98 active machine learning study of working memory ([Marticorena, Wissmann, et al., 2025](#)).

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104 **AI usage disclosure**

105 Generative AI tools (Google Gemini) were used to assist in the drafting, formatting, and
106 refining of the text in this paper. The authors reviewed, edited, and validated all AI-assisted
107 outputs and take full responsibility for the content.

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