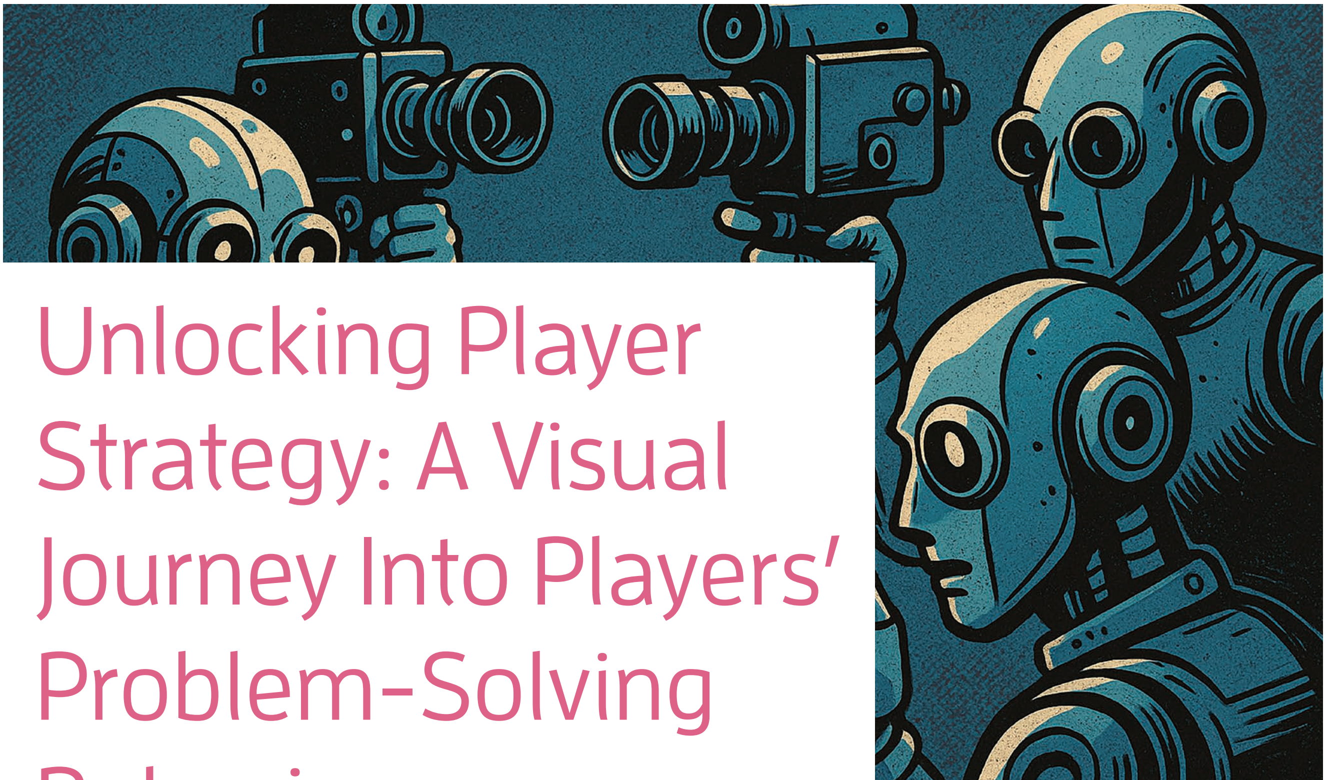

GRAPHICS GENERATED USING CHATGPT 5.0

Unlocking Player Strategy: A Visual Journey Into Players' Problem-Solving Behaviors

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INSPECT, an interactive visualization system, transforms messy gameplay logs into clear visual roadmaps that reveal not just what players do, but how they do it—helping developers spot where players get stuck and coaches identify winning strategies.

What if you could peek into the minds of players and see their strategies unfold in real time? That's the promise of the emerging fields of game analytics and game user research, fields dedicated to understanding not just *what* players do (which is the focus of game analytics methods), but *why* they do it.[1,2,5] For developers, these insights are gold, revealing which tactics are rewarding and which leave players frustrated. For players, it's a chance to learn from the best and discover new paths to victory.[13] But here's the challenge: *How do we transform mountains of raw player data into clear, actionable insights?*

Game analytics has long been the secret weapon of successful game studios. It provides a critical lens for understanding and improving game design, particularly in how players solve problems and strategize.[2] These strategic insights serve a dual purpose: They help players learn from experts and see how victories are achieved, while also revealing to designers which tactics are rewarding and which leave players stalled or frustrated.[10] By analyzing these patterns, developers can identify critical moments when players deviate from intended paths, leading to better game balance, richer choices, and ultimately a more engaging player experience.[12,14]

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THE VISUALIZATION CHALLENGE: BEYOND CHARTS AND HEATMAPS

Visualization has become an indispensable tool in game analytics, prized for its ability to describe complex player behavior[3] intuitively. A single, well-crafted visual can reveal insights far more efficiently than dense tables of numbers.[3,8] However, the field has predominantly relied on statistical graphics such as charts and heatmaps—useful tools but often missing aspects of process and pacing.[11]

Process-oriented visualizations represent a distinct approach.[5,6] These visualizations focus on sequences of actions and decisions over time rather than static snapshots of player behavior. Think of them as maps that show not just where players ended up, but the entire journey they took to get there. Node-edge graphs are a perfect example: They connect events as nodes and use directed edges to show transitions from one event to the next, creating a visual roadmap of player decision-making.

But here's the problem: These process-oriented visualizations often become a mess of overlapping nodes and tangled edges, overwhelming analysts and making it difficult to extract meaningful patterns in player strategy.[3,4] It's like trying to read a subway map where all the lines are jumbled together—theoretically informative, but practically useless.

ENTER INSPECT: MAKING SENSE OF THE CHAOS

To address this challenge, we developed INSPECT, an interactive visualization system that helps analysts navigate and interpret complex player processes. By integrating a suite of interactive features, INSPECT enables analysts to engage directly with the visualization, significantly reducing the need for laborious data cleaning and preprocessing. This approach shifts the focus from the tedious work of wrangling logs to the core objective: exploration and the discovery of meaningful patterns.

OUR TEST CASE: A CIVILIZATION-INSPIRED GAME

To demonstrate INSPECT's capabilities, we designed a conceptual game model inspired by an adventure game. This model defines a hypothetical scenario in which players complete a series of quests, each with a set duration, to achieve one of two victory conditions. The structure of this quest system, shown in Figure 1, serves as the basis for generating the data used in our analysis.

The game model begins with a mandatory *Reveal Map* quest, after which players can pursue four options: two side quests (*Explore Ocean*, *Explore Mountains*) and two main quests that define the paths to victory (*Build Library* or *Found Theater*).

The scientific path (Victory A) begins with the *Build Library* step. Then it offers a strategic choice: Players can either complete *Build University* to unlock an eight-round *Launch Spaceship* quest, or complete *Build Observatory* for a shorter three-round *Launch Spaceship*. The cultural path (Victory B) begins with the *Found Theater* step and requires completing both *Build Museum and Sponsor Festival* in any order to achieve victory.

To generate a dataset for analysis, we simulated 20 player paths through this model using a Wizard-of-Oz approach, designating seven as "experts" and 13 as "normal players." The simulation

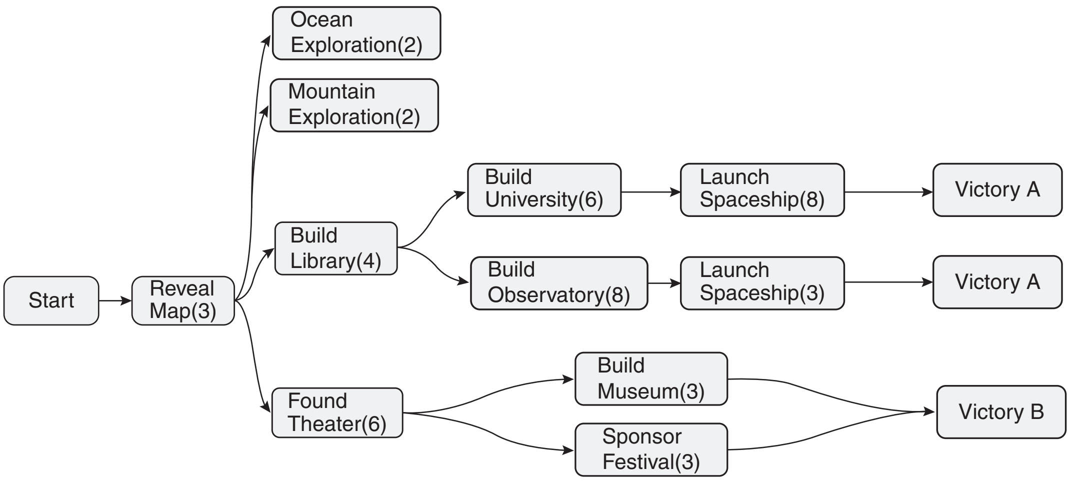


FIGURE 1. Structure of the mock quest-based game. Each node represents a quest, and the number in parentheses indicates the number of rounds required to complete it.

produced compelling results: eight players achieved Victory A, seven achieved Victory B, and five failed to reach a victory condition. Each player's record includes their completed quest sequence, their assigned expertise level, the total rounds played, and the outcome.

THE INSPECT SYSTEM: SEEING STRATEGY IN ACTION

The player journey map: Your window into player minds

The visualization deployed in the INSPECT system is the player journey map.[7] This node-edge graph connects events as nodes and uses directed edges to show transitions from one event to the next. Nodes are color-coded, with color saturation representing player numbers, that is, more saturated nodes indicate more players visited that node. The same principle applies to the edges' width with respect to the number of players taking it, that is, wider edges represent transitions taken by more players.

From this visualization (see Figure 2), we can immediately spot interesting patterns. For example, the three-round *Launch Spaceship* is visited by fewer players compared to the eight-round *Launch Spaceship*, as indicated by the lighter background color. This suggests that most players are taking the longer, perhaps more familiar route to scientific victory, that is, Victory A rather than Victory B.

Fundamental interaction: Detail on demand

Users can interact directly with the player journey map to explore details about each event through detail-on-demand interaction. By clicking a node or edge, they can see how many players visited it and the total number of visits. Moreover, users can filter nodes and edges based on the percentage of players who experienced them.

For example, selecting only events visited by more than 50% (see Figure 3) of players highlights several quests: *Build Library*, *Found Theater*, *Reveal Map*, and *Explore Ocean*. The first three are required steps on the path to victory, but *Explore Ocean* stands out as a frequently chosen side quest. This suggests that the event has particular appeal to players and merits further analysis. Even at this fundamental level, INSPECT helps analysts identify unusual points of interest in the player journey.

SEGMENTATION: COMPARING PLAYER TYPES

Metadata segmentation: Experts versus normal players

INSPECT's segmentation feature enables users to categorize players into subgroups for comparison of their behavioral patterns. The system supports two distinct methods: metadata segmentation, which groups players by attributes (such as expertise level or demographics), and behavioral segmentation, which groups players by outcomes or a selected sequence of in-game actions (such as choosing a specific side quest or repeating particular events).

To highlight differences between groups, INSPECT generates a comparative graph where color-coding indicates which subgroup visited a node or edge more frequently, and color saturation reflects the magnitude of that difference.[9] When comparing expert players (orange) with normal players (blue) (see Figure 4), the resulting difference graph reveals fascinating insights as follows:

- Experts focus on Victory B more often than normal players.
- Within Victory A, experts are more likely to choose the more

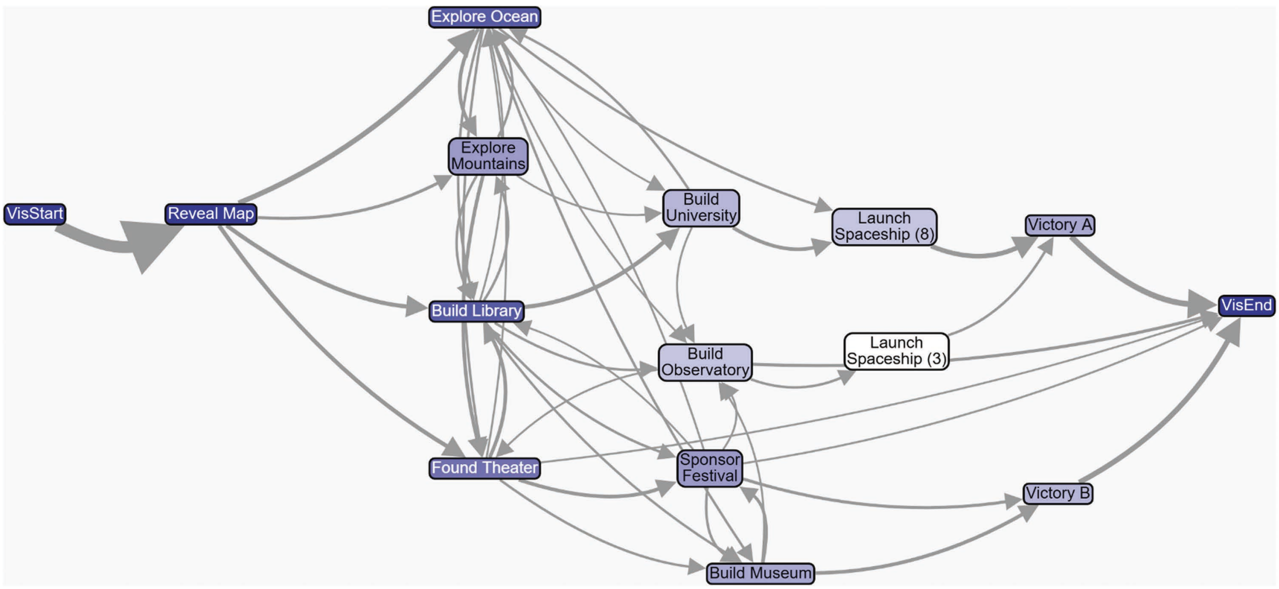


FIGURE 2. Original player journey of 20 players. Nodes with deeper colors and edges with greater width indicate events and transitions visited by more players.

- efficient *Build Observatory* and three-round *Launch Spaceship* path, while the non-expert players tend to follow the longer *Build University* plus eight-round *Launch Spaceship* route.
- Experts engage less in side quests such as *Explore Ocean* and *Explore Mountains*.

Behavioral segmentation: Winners versus losers

Beyond grouping players by attributes, INSPECT also supports behavioral segmentation. Users can define logical combinations of behaviors using the conjunctions "AND" (signifying that players exhibit all selected behaviors), "OR" (signifying that players exhibit any selected behaviors), and "NONE" (signifying that players exhibit none of the selected behaviors).

When contrasting players who failed in the game (orange) with those who achieved either type of victory (blue; see Figure 5), the visualization reveals that successful players invested less in side quests and advanced farther along the main quest trajectories. Defeated players, in contrast, often stopped after the very first step toward victory, such as completing *Build Library or Found Theater*, without progressing deeper into the sequence.

Combo analysis: Identifying popular strategies

The combo analysis feature enables users to identify frequently visited subsequences of events, thereby revealing popular behavioral patterns. This analysis examines sequences of lengths 2 and 3, calculating both their frequencies and their conditional probabilities.

In Figure 6(a), each node represents a combo, while the red line marks the average probability across all combos. Probability is calculated conditionally: The likelihood of a sequence A, B, C equals the frequency of A, B, C divided by the frequency of A, B. The accompanying table lists the most frequent combos, their lengths, frequencies, and probabilities.

From Figure 6(a) and (b), we discovered that most players complete *Explore Ocean* immediately after *Reveal Map*, underscoring the quest's popularity compared to *Explore Mountains*. We also found that five players complete *Build University* after *Build Library*, suggesting that this is the most common path to victory among our sample.

Backward tracing: Understanding critical moments

The backward tracing feature helps users understand how players reach a critical event. Analysts can select an event, such as a victory condition, and INSPECT calculates the nodes that are most frequently visited before it. Users

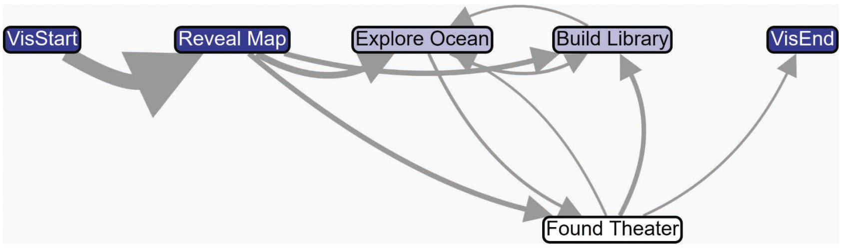


FIGURE 3. Player journey map showing events visited by at least 10 players (that is, more than 50% of players).

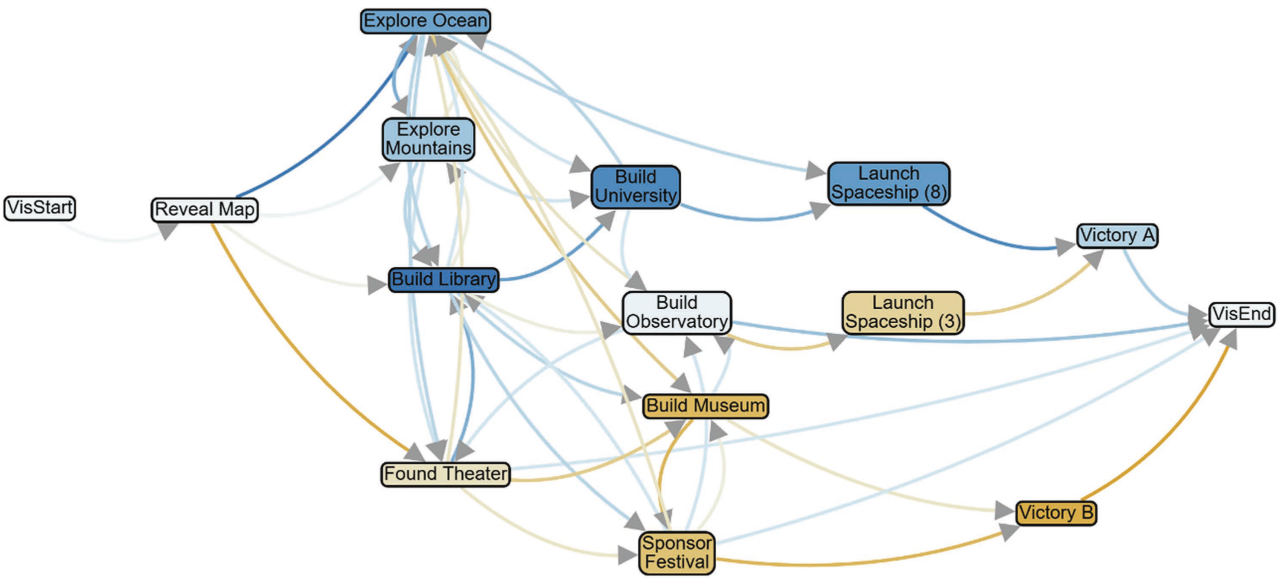


FIGURE 4. Difference graph comparing expert players (group 1, orange) and normal players (group 2, blue). Node color indicates which group visited an event more frequently, and saturation reflects the magnitude of the difference.

can adjust the parameter to determine how many preceding nodes to include in the analysis. In the following, we select Victory A as the target event and visualize the three most visited nodes before players achieve it. Figure 7 presents the probability distribution of all events leading up to the victory node. The *Reveal Map* event is excluded because it is a mandatory beginning step for all players. The top three preceding nodes are *Building Library*, *Explore Ocean*, and *Building University*.

Distance distribution: How far from victory?

The distance distribution graph (Figure 8) shows the distance between the selected event and its preceding popular events. While this view doesn't capture process details, it offers an immediate sense of which quests tend to occur just before the outcome. From the box plot (Figure 9), we can see that the average distance from *Build Library* to Victory A is smaller than the average distance from *Explore Ocean* to Victory A, indicating that many players were distracted by side quests even after completing Build Library.

Sequence cluster graphs: Mapping the journey

As the number of preceding nodes is set to 3, three sequence cluster graphs are visualized (one is shown in Figure 10), each describing all sequences from the corresponding popular preceding node to the selected event. Each node in a cluster graph

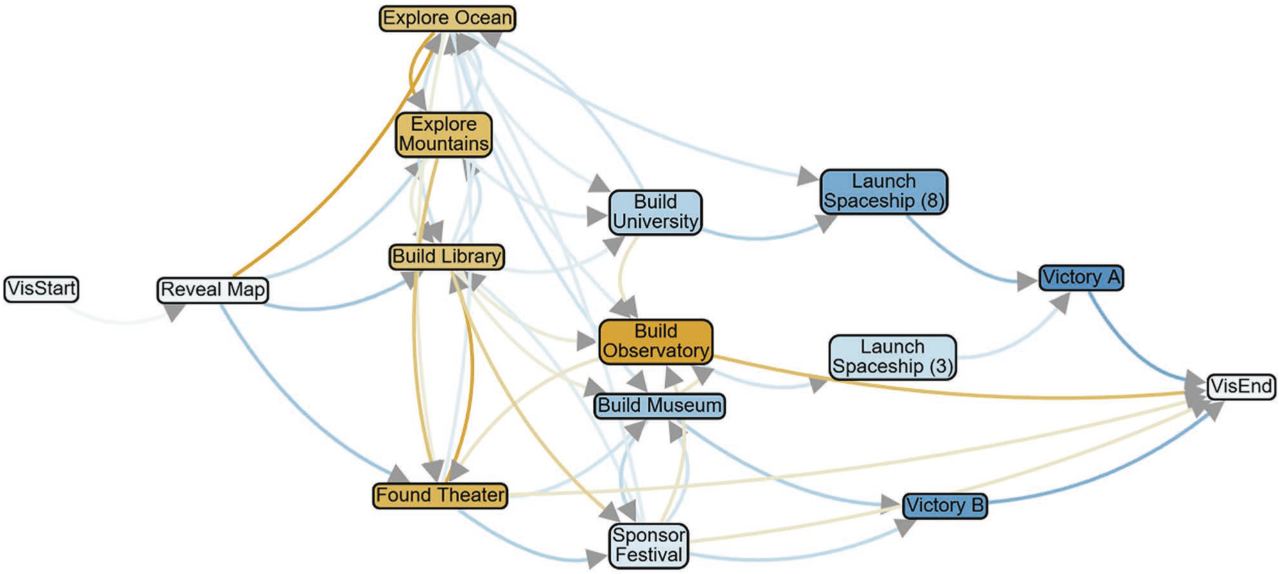
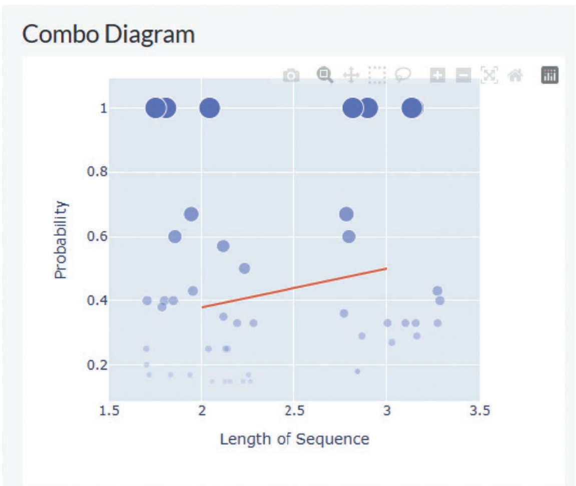


FIGURE 5. Difference graph comparing failed players (orange, group 1) and succeeded players (blue, group 2).

(a)



(b)

Combo Table

Sequence	Length	Frequency	Probability
('Reveal Map', 'Explore Ocean')	2	7	35.0%
('Launch Spaceship (8)', 'Victory A')	2	6	100.0%
('Reveal Map', 'Found Theater')	2	5	25.0%
('Reveal Map', 'Build Library')	2	5	25.0%
('Build Library', 'Build University')	2	5	38.0%
('Build University', 'Launch Spaceship (8)', 'Victory A')	3	4	67.0%
('Explore Ocean', 'Explore Mountains')	2	4	33.0%
('Found Theater', 'Sponsor Festival')	2	4	40.0%
('Found Theater', 'Build Library')	2	4	40.0%
('Explore Mountains', 'Found Theater')	2	4	50.0%

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FIGURE 6. (a) The diagram displays the probability of each combination, along with the average probability for all combinations of a given length. (b) The table lists the combos with their lengths, frequencies, and the conditional probabilities.

represents a unique sequence, and larger nodes correspond to paths followed by more players.

For example, the sequences leading from *Build Library* to Victory A reveal that the most common sequence, *Build Library* → *Build University* → *Launch Spaceship* (8) → Victory A (as shown in Figure 11), was followed by three players, revealing a dominant path among the eight who ultimately achieved this victory without any distraction.

Explainability graphs: Granular path analysis

The explainability graph provides more granular control, allowing analysts to examine details along the path from a preceding event to the selected node. Three options are available: visualizing popular nodes along the route, visualizing the top M most common consecutive N-step subsequences, or visualizing frequently visited but unconnected sequences.

For instance, Figure 12 is an explainability graph examining the path from *Build Library* to Victory A. We can highlight the three most popular nodes along this journey, showing that, in addition to progressing toward victory, many players also detoured into *Explore Ocean*.

Evaluating INSPECT

To evaluate INSPECT, the system was applied to three case studies spanning diverse game genres and analytic goals: *Sky: Children of the Light*, *Guild Wars 2*, and *Wake: Tales from the Aqualab*. In *Sky*, the system supported cross-platform analysis by comparing player behavior across iOS, Nintendo Switch, PlayStation, and PC, helping identify a previously unreported technical issue. Moreover, potential hackers were identified through behavioral segmentation by selecting a combination of events. In a boss battle in *Guild Wars 2*, INSPECT's combo analysis feature revealed optimized skill usage sequences associated with higher damage output. In *Wake*, an open-ended educational game, the system allowed analysts to trace player behavior leading up to key quest completions, highlighting differences in problem-solving approaches. Collectively, these case studies illustrate how INSPECT enables domain-specific

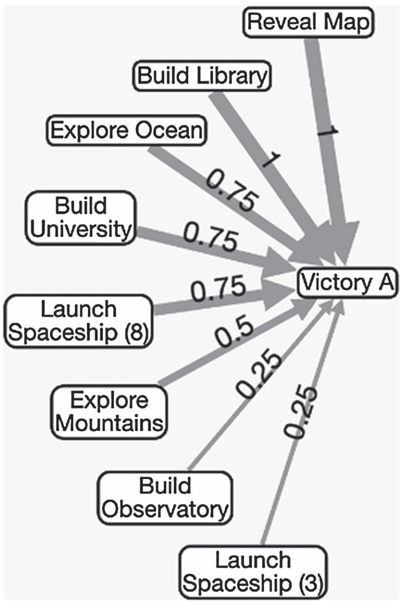

FIGURE 7. The graph shows overall probability from each preceding node to the selected node Victory A.

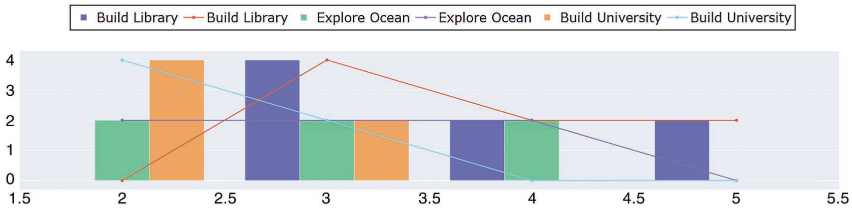

FIGURE 8. The distance distribution bar chart reveals the distance between three popular preceding events (*Build Library*, *Explore Ocean*, and *Build University*) and the selected event Victory A.

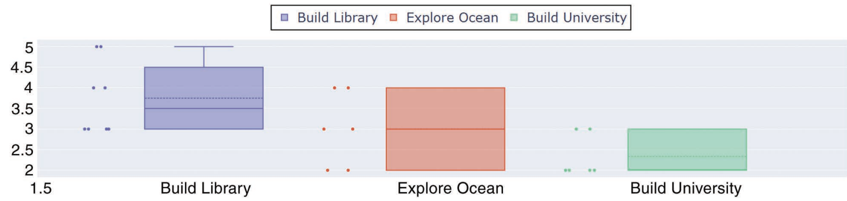

FIGURE 9. The distance distribution box plot reveals the distance between three popular preceding events (*Build Library*, *Explore Ocean*, and *Build University*) and the selected event Victory A.

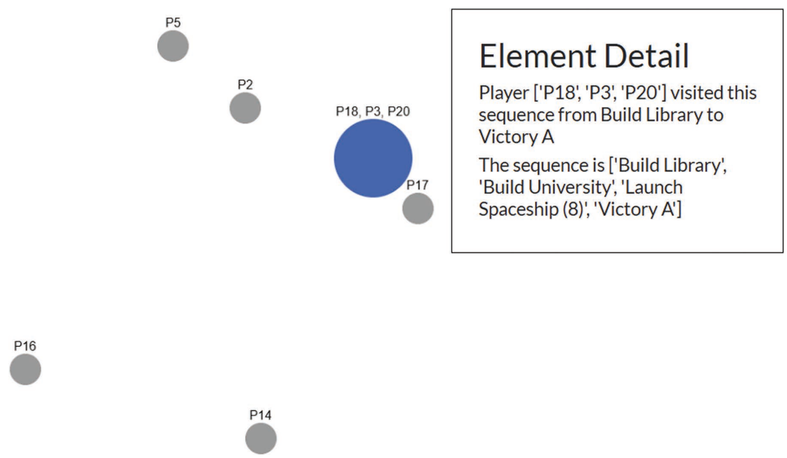

FIGURE 10. One of the sequence cluster graphs that shows the subsequence player took from *Build Library* to Victory A.

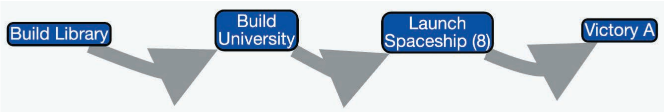

FIGURE 11. The most popular sequence from Build Library to Victory A.

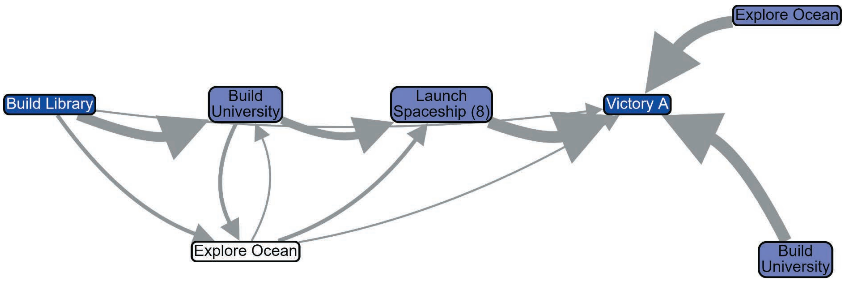

FIGURE 12. The explainability graph that visualizes the three most frequently visited nodes from *Build Library* to Victory A.

insights while offering a generalizable visual structure for analyzing complex gameplay processes.

In addition to case studies, INSPECT was deployed in a real-world esports context to support expert analysis of hero ban/pick strategies in *Dota 2*, one of the most strategically complex team-based competitive games. A user study involving 12 participants, ranging from high-ranking players to coaches, showed that INSPECT's interactive process visualizations helped participants uncover drafting patterns, analyze hero combinations, and evaluate the probability distributions associated with different ban/pick decisions. Participants especially valued features such as metadata and behavioral segmentation, combo analysis, and backward tracing, which enabled them to ask exploratory questions and derive actionable drafting insights. Compared to traditional data sources like Dotabuff or Liquipedia, participants found INSPECT more intuitive, expressive, and useful for interpreting complex draft dynamics. These findings suggest that process-oriented visualization can meaningfully support decision-making and strategic understanding in competitive esports contexts.

The future of game analytics

INSPECT provides analysts and players with an interactive visualization of players' journeys, with opportunities to filter, segment and compare, and trace backward from outcomes. This gives analysts and players ways to examine how victories are achieved as well as where players stall or take unexpected detours. Our case study demonstrates how interactive features on process visualization—segmentation, combo analysis, and backward tracing—make complex data more interpretable and actionable.

Beyond this demonstration, we envision applications ranging from esports coaching to educational analytics, where understanding problem-solving processes is just as critical as outcomes. In esports, coaches could use these visualizations to identify winning strategies and help players avoid common pitfalls. In educational games, teachers could see where students get stuck and adjust their instruction accordingly.

The power of process-oriented visualization lies in making these journeys visible, helping both players and designers imagine new ways to shape richer, more engaging experiences. When we can see the story of how players navigate through our games, we can create better paths for them to follow—and, in turn, better games for everyone to enjoy.

Ultimately, INSPECT facilitates a deeper understanding of player behavior from a process-oriented perspective, shifting the focus from tedious data wrangling to the discovery of meaningful patterns. Making these player journeys visible helps both players and designers imagine new ways to shape richer, more engaging experiences. ■

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