

# Examining Game World Topology Personalization

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## ABSTRACT

We present an exploratory analysis of the effects of game world topologies on self-reported player experience in Computer Role Playing Games (CRPGs). We find that (a) players are more engaged in game worlds that better match their self-reported preferences; and (b) player preferences for game topology can be predicted based on their in-game behavior. We further describe how in-game behavioral features that correlate to preferences can be used to control procedural content generation algorithms.

## Author Keywords

Games; Player Modeling; Procedural Content Generation

## ACM Classification Keywords

H.5.m. Information interfaces and presentation (e.g., HCI):  
Miscellaneous.

## INTRODUCTION

Personalizing game content can increase the enjoyment and reduce the frustration of players to the effect of improving player experience [1]. Furthermore, understanding how in-game behavior relates to player preferences can enable adaptive games automatically tailored to a player's preferences based on behavioral cues. It therefore seems possible to adaptively personalize game content from in-game behavioral cues to increase enjoyment with a game.

In this paper, we examine whether personalizing game world topologies increases user engagement with a Computer Role-Playing Game (CRPG), and whether in-game behavior can predict a player's topological preferences so that a system can adaptively personalize the game world topology based on that behavior.

CRPGs require players to take on the role of a story character and embark on a number of quests. The spatial nature of game content in CRPGs make them ideal for investigating the relationship between in-game behavior and preferences for the topological factors of the game world such as size, shape, and linearity. Indeed, studies

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Figure 1. Screen capture of our CRPG game being played.

have found that exploring non-linear worlds are important to CRPG players [7]. Given this perceived importance of game space, we address the following research questions: (1) How does game world topology affect user experience? and (2) Can we predict player preferences for different world topologies based on their in-game behavior?

We ran an exploratory, within-subjects study where participants played several versions of the same CRPG, differing only in the size, shape and linearity of the world topology. We collected in-game behavioral traces for each player, along with their ultimate topological preference. Using a ridge logistic regression, we were able predict the topological preferences for 13 of our 16 participants, and found that players seemed to be more engaged when they played in worlds aligned with their topological preferences. We further speculate how world topology features can serve as variables that can be procedurally adjusted according to in-game behaviors to personalize game play experiences.

## THE GAME

We created a simple CRPG game for the purposes of this study. The game included a turn-based battle system, the ability for player characters to accumulate “experience points” to become stronger, items for players to gather, an annotated world map to help players navigate through the virtual space, and rare spawns for players to hunt and slay. Slaying these rare spawns provides players with special treasure, a mechanic that mimics the style of many CRPGs that reward players for engaging in challenging tasks. Treasure chests located in side areas reward players for exploration. Items rewarded for combat provided players with incentives to engage in combat. See Figure 1 for a screenshot of the game.

We also implemented several basic measures to avoid player confusion. To ensure that players always had an idea

Recorded Behavior Category	Description
Distance From Path (2)	The average and standard deviation of the avatar's closest distance from the path.
Unique Areas (4)	The number of unique areas the player's visited in a world. Further sub-divided into the number of unique plot areas, main path areas and sidepath areas visited.
Area Visits (4)	The average number of visits/revisits across all plot, main path and sidepath area.
Battles (4)	The number of battles initiated, won, lost and fled.
Time (3)	The amount of time spent in the game, spent exploring and average amount of time to finish plot events.
Rare Spawns (2)	Number of Rare Spawns found and killed.
Items (2)	Number of items used and number of unique items acquired.

**Table 1. Behavioral features and feature categories recorded for every playthrough. Parenthesized numbers indicate the number of features recorded in a particular category. Twenty-one behavioral features were collected in total.**

of what to do next in the story, we provided a map of the game world (see Figure 2). This map annotated the player's current location, the main regions for plot events, the primary path between plot events, and side paths not essential to story progress. The next plot point players had to visit was clearly indicated with an arrow. Additionally, our interface offered instructions on how to progress to the next story event and players were given an in-game tutorial that provided basic instruction on movement in the world and the meaning of various interface elements.

During each playthrough we recorded 21 behavioral features (see Table 1). Examples include all of a player's movements, total time in game, and enemies slain.

#### METHODOLOGY

We recruited 16 participants to play our CRPG, fourteen of who were male. All participants were computer savvy and all 16 reported playing games regularly. Thirteen participants were college students, one was a post-doc, and the remaining two were management professionals.

Participants played through three worlds. The first world was a baseline world of moderate size and linearity. The second and third worlds were presented in randomized order across subjects. They represented relative extremes in the size and linearity of the world according to our parameter space: one was large with many branching side paths ("big"), and one was compact ("small"). The story and playable game mechanics were constant across all three

worlds. To ensure baseline story quality, we implemented a simplified version of a sidequest in the widely acclaimed Playstation game *Final Fantasy 7*.

Upon completing the third and final world, participants were prompted to enter a total order ranking of the three worlds they had played. Participants knew in advance that they would be asked to rank the worlds they played.

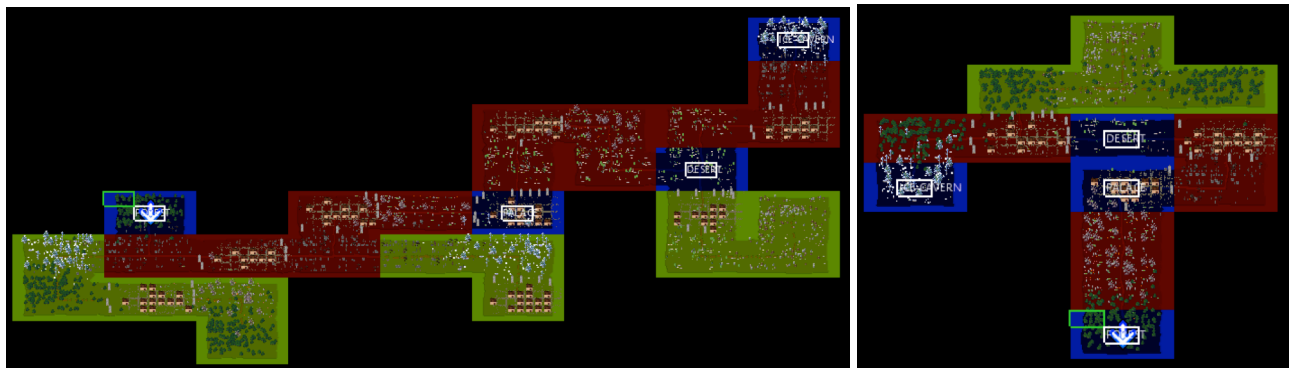
#### RESULTS

The random ordering of the big and small worlds created two groups of players: "*Big First*" and "*Small First*". Eight participants were randomly assigned to each group. Whenever the ordering of worlds impacted a particular analysis, we compared participants within their own groups. Participants took 45 minutes on average to complete the study (s.d. 14.8 minutes), with a range of 27 to 83 minutes.

#### Player World Preferences

Among the sixteen participants, seven ranked the big world first (most liked), seven others ranked the small world first and the remaining two ranked the baseline world first. The two participants who ranked the baseline world first also ranked the small world over the big world. Additionally, among the fourteen participants who chose the small or big world as their favorite, ten rated the baseline world second and the opposite topological extreme as their least favorite.

We did not find that the ordering of worlds significantly affected participants' reported preferences for world



**Figure 2. Maps of the "big" world (left) and "small" world (right) used in the experiment. Areas highlighted in blue contain plot points, areas highlighted in red are direct paths between plot points, and areas highlighted in green are sidepaths. An arrow graphic depicts the player's next destination, and the green square shows the current location.**

Feature	Preference for Big world	Preference for Small world
Opened Treasure Boxes	0.93	1.08
Rare Spawns Found	0.47	2.14
Avg Visit Per Area	2.88	0.35
Unique Items Acquired	3.40	0.29

**Table 2. Odds ratios for the ridge-logistic regression model.**

topology. Among the eight players in the *Big First* group (players who played the big world first), four players ranked big over small and the remaining four players ranked small over big, whereas among the eight players in Small First group, five preferred small over big and the remaining three preferred big over small. According to a Fisher’s Exact Test, these differences were not found to be significant ( $p=1$ , odds ratio=0.61).

These results suggest that players have clear preferences for CRPG world topologies—those participants who preferred either the big or small worlds generally rated the opposite extreme as their least favorite. Some preferred large, sprawling worlds, while others preferred small, compact worlds. In the following analyses, we group the two participants who ranked the baseline world first with those that ranked the small world first to allow comparison between the two major preference categories. We chose this grouping because both players who ranked the baseline world first ranked the small world over the big world. Using this categorization, 7 players preferred the big world and 9 preferred the small world.

#### Behavior-based Preference Prediction

To test whether in-game behavior relates to world topology preference, we modeled participants’ binary world preference (big or small) on a subset of their behavioral features collected in the baseline world (which was always presented first). We started with the 21 behavioral data features and found the most predictive feature subset using the Wrapper feature subset selection algorithm in the WEKA machine learning toolkit [2,3]. To mitigate the effects of overfitting, we limited the number of features Wrapper considered at one time to four, so that we had many more observations than variables (16 vs. 4).

Using the reduced data set of four features found by Wrapper, we built a ridge logistic regression predictive model. We chose to use a logistic regression for classification to obtain coefficient estimates that can intuitively explain the relationship between the selected behavioral variables and topological preference. We chose a ridge-based approach shrink coefficient estimates and mitigate the effects of overfitting given our small dataset. Without the coefficient shrinkage provided by a ridge-based approach, regression models can provide extreme parameter estimates for small datasets [2]. The final variables selected, along with their odds ratio is shown in Table 2. For the “Unique Items Acquired” feature, an odds ratio of 3.40 for

big world preference means that for every additional unique item a player acquired, our model predicted that the player is 3.4x as likely to prefer the big world.

Using leave-one-out cross validation, our ridge logistic regression model accurately predicted the preferences of 13 out of the 16 participants (81.25% predictive accuracy).

The three misclassifications were all players who preferred the large world, but were predicted to prefer the small. Examining the odds ratio suggests where our model erred. We note that a higher propensity to open treasure boxes and find rare spawns was indicative of a preference for the *small* world, which seems odd. This artifact may be a result of our model confounding topological preferences for propensity for exhaustive exploration—i.e., the obligation to *explore* the whole world, but not necessarily *wanting* to explore. Thus, the three users who were misclassified enjoyed exploring large, open worlds but were confused with users who felt obligated to explore the world. These edge-cases highlight the need for future mixed-methods research to tease apart behavior that indicates enjoyment from behavior that indicates un-enjoyed obligation.

In summary, these results indicate that player behavioral traces can accurately predict CRPG topological preferences.

#### World Topology and Player Engagement

Finally, to answer the question “Is there value in personalizing game world topologies?”, we explored the effects of topological preferences on in-game engagement. We divided players into two groups: (i) those who preferred the big world and (ii) those who preferred the small. Then, controlling for ordering effects, we compared players’ relative activity levels in both worlds.

We operationalized engagement as higher overall activity within the world (e.g., more battles initiated, more time spent exploring, more treasure gathered, more sidepaths explored). To control for the effects, on behavior, of world presentation order and world topological differences, we compared players within their own order group (Big First or Small First) and separately within the big and small worlds. Then, we sub-divided players within each of the four populations into two further subgroups based on their preference for the big or small world: **big world first, big world preferred** (BB,  $n=4$ ), **big world first, small world preferred** (BS,  $n=4$ ), **small world first, big world preferred** (SB,  $n=3$ ), **small world first, small world preferred** (SS,  $n=5$ ). Our analysis is based on a qualitative comparison of engagement features, as the number of users in any given bucket is too small for standard statistical comparisons.

We compared the means of engagement features in both the big and small worlds, and observed how the means of the big and small preference groups varied across both worlds. If personalized game world topology positively influences engagement, we would expect that the BB and SB groups—who prefer the big world—should be more engaged than BS and SS in the big world, and vice versa for the small

	Big World				Small World			
	Big First		Small First		Big First		Small First	
	<b>Big Pref</b>	Small Pref	<b>Big Pref</b>	Small Pref	Big Pref	<b>Small Pref</b>	Big Pref	<b>Small Pref</b>
Mean Unique Sidepaths	<b>60</b>	25	<b>50</b>	38	10	<b>29</b>	8	<b>15</b>
Mean Opened Treasures	<b>30</b>	14	<b>22</b>	20	3	<b>4</b>	1	<b>7</b>
Mean Battles Initiated	<b>29</b>	21	<b>35</b>	24	6	<b>11</b>	12	<b>14</b>
Mean Time Spent Exploring	<b>8</b>	3	<b>7</b>	4	1	<b>2</b>	1	<b>3</b>

**Table 3. Comparison of engagement feature means in the big and small worlds, with means computed within ordering and preference groups. Bolded columns represent groups where topology aligns with preference, where we should see higher values.**

world. Table 3 illustrates the general trends seen across the full feature set using a subset of features for brevity (Table 3). We found that preference for big worlds corresponds to greater activity in big worlds, and preference for small worlds corresponds to greater activity in small worlds.

In summary, we believe that there is value to personalizing CRPG topologies—our players seemed to be more engaged when playing in worlds that aligned with their topological preferences. However, as our small sample size ruled out strict statistical comparison, we note that these results do not provide conclusive proof that players are more engaged in game worlds aligned with their topological preferences.

#### MAPPING TO GAME CONTENT

There remains the problem of “closing the loop”—or mapping player behaviors back to configurable elements of game world topology.

We believe that procedural content generation [4,5,6] techniques can close the loop by feeding in-game behaviors to automated content generation algorithms. For example, Hartsook et al. [4] describe a system that generates game levels to optimize a topology given target values for (a) the maximum space between significant story events, (b) the minimum space between story events, and (c) the frequency of side-branches. These variables can easily map to our behavioral features—for example changing the number of sidepaths depending on how much time a player spends exploring or reducing the length of the main path if the player seems to transition through story events quickly.

#### DISCUSSION & CONCLUSION

Overall, we found some support for the following three assertions: (1) players have clear and distinct preferences for world topologies; (2) player behavior in a baseline, neutral world can predict preferences for world topology; and (3) players exhibit greater engagement in worlds aligning with their topological preferences.

It seems, therefore, that topological personalization is both valuable and feasible, and that game designers should consider employing adaptive topological personalization to maximize user engagement with their CRPG. Indeed, we outlined one way that such personalization could be

achieved by directly mapping player behavior traces to procedural-content generation algorithm parameters.

Still, there remains a wealth of direction for future work. The present study is lacking in its small sample size, but has provided us with a theoretical grounding to implement a real-time procedural topology generator to “close the loop”—or, map player behaviors to real-time changes in the game world. In future studies, we plan to evaluate this real-time topology generator in a controlled experiment. We also plan to explore varying combinations of parametrically adaptable aspects of the game (e.g., story) to provide a richer understanding of the relative contributions of different game content to player experience.

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