How General Game Expertise Shapes Player Experience and Problem-Solving Across Different Onboarding Approaches in a Puzzle Video Game

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ABSTRACT

Time spent playing video games varies widely across individuals, meaning research participants bring different baseline knowledge and strategies that shape their interactions with game materials and potentially influence study outcomes. Building on prior work documenting differential effects between novice and expert gamers, we examine how game expertise—measured by self-reported hours per week and years of play—relates to player experiences and problem-solving behaviors across three onboarding conditions in the commercial puzzle game *Baba is You*. Analyzing multiple data sources from over 120 players, we found that general game expertise relates to higher enjoyment, more completed levels, and increased exploratory tinkering behavior, with some effects varying by onboarding condition. These results underscore the importance of accounting for gaming expertise in both game research and design.

KEYWORDS

Game expertise, enjoyment, puzzle game, tutorials, problem-solving

INTRODUCTION

From the mobile sessions of a game like Candy Crush to the sprawling fantasy worlds of games like Elden Ring, more than three billion people worldwide play video games (Gill, 2025). Within this massive player base, however, players engage with games in highly heterogeneous ways. Some play only a few minutes each week, whereas others invest hundreds of hours mastering the intricate mechanics and systems of a game. This variability appears across multiple dimensions. Geographically, for example, gamers in China average 12.4 hours of weekly play, compared with 7.71 hours in

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America and 5.88 hours in South Korea (Turner, 2022). Age differences also matter: younger players tend to log more hours than older adults (U.S. Adults Weekly Gaming Hours by Age 2025, n.d.). Even within these demographic groups, the spread is substantial—among players aged 18 and older, for instance, weekly play ranges from 1 to 5 hours for roughly 30 percent of players to over 20 hours for about 10 percent. This heterogeneity suggests not only that games are widely enjoyable, but also that players begin any new title with vastly different gaming histories and general game skill repertoires. The influence of these histories and skill repertoires is reflected in expertise research across disciplines consistently linking accumulated practice to qualitative shifts in knowledge organization, strategy, and performance (Chi et al., 1981; Ericsson et al., 1993). Within game studies specifically, analogous distinctions between novice and expert players have been documented across metrics such as time-based skill acquisition and performance ratings (Röhlcke et al., 2018), the evolution of strategic problem-solving approaches (Cai et al., 2024), cognitive performance measures like visuospatial attention (Ding et al., 2018), and neural activity patterns (Hafeez et al., 2021)–yet less research examines how accumulated time spent gaming and specific design choices interact to shape player experience and problem-solving.

In the current study, we investigate these relationships within the commercially available puzzle game *Baba Is You* (Teikari, 2019), which presents players with challenging puzzles. To examine how different onboarding approaches influence players, we implemented three alternative designs for the initial levels: a *Tutorialized* version providing explicit text-based guidance, a *Safe Problem-Solving* version leading players to solutions through visually intuitive design, and an *Increased Impasse* version engineered to prompt more moments of being stuck. We collected player-experience metrics through surveys administered at two points—after onboarding and after the final session—and analyzed behavioral data, including gameplay logs tracing players' in-game interactions. While our original intention was to explore learning and problem-solving differences among the onboarding designs, measures of game expertise revealed further nuance in the data. By integrating player expertise across multiple measures, we explore this nuance in this paper to detail a picture of how gaming history shapes players' experience and engagement with a new game. Ultimately, we demonstrate that game expertise functions as a meaningful individual-difference variable that should be considered and controlled for in game studies and show how specific onboarding features amplify or mitigate expertise effects, offering insight into how design choices interact with prior experience to shape outcomes of interest. Throughout this paper, we use game expertise to refer to the accumulated skills and knowledge players bring from their gaming history, and player experience to refer to the subjective, in-the-moment responses—enjoyment, engagement, curiosity, and perceived difficulty—that players report during play. Although "experience" can function as a near-synonym for "expertise" in everyday language, these two terms carry distinct meanings in this work, as elaborated on more below.

LITERATURE REVIEW

The Impact of Game Expertise on How Games are Played and Experienced

Understanding game expertise and how to measure it is a persistent methodological challenge in game research. Researchers have operationalized game expertise through self-reported hours of weekly gameplay (e.g., Anderson, 2020), often

establishing thresholds such as five or more hours per week for "experts" and less than one hour for "novices" (Elliott et al., 2020; Gascon et al., 2015). However, some studies use competitive achievement or official matchmaking ratings (Ding et al., 2018; Valls-Serrano et al., 2022), while others calculate performance-based thresholds from in-game scores (Hafeez et al., 2021; Guglielmo et al., 2022). The field increasingly recognizes that game expertise encompasses not just total hours but also genre-specific experience and the intentionality of practice (Latham et al., 2013; Röhlcke et al., 2018). The various ways to measure game expertise hint at its complexity, and this complexity is compounded by systematic biases: self-reported hours correlate only moderately with expert-rated performance (r=0.65), and players consistently underreport their playtime, particularly older, more educated players with less positive attitudes towards games (Elliott et al., 2020; Kahn et al., 2014). Despite these methodological complexities, research consistently demonstrates that, however measured, game expertise shapes how players engage with games across multiple dimensions.

At the neurological level, accumulated gaming hours create distinct neurological and behavioral signatures. Expert players are distinguishable from novices with up to 98% accuracy based on EEG activity patterns, with experts showing enhanced mental concentration and visuospatial attention (Anwar et al., 2017; Hafeez et al., 2021), higher blink rates suggesting reduced cognitive load (Guglielmo et al., 2022), and larger gray matter volume in regions supporting visual working memory (Tanaka et al., 2013). These neurological differences catalyzed through practice translate directly to performance: time on task emerges as the strongest predictor of competitive rating (β=.73), far outweighing cognitive abilities (Röhlcke et al., 2018), and expert players in citizen science games achieve higher-ranked solutions using more strategic approaches that converge toward efficient patterns over time (Cai et al., 2024).

Beyond performance metrics, expertise fundamentally reshapes cognitive strategies. Expert players demonstrate significantly more analogical thinking (48.5% of processes) while novices rely predominantly on trial-and-error (42.4%), with experts showing more consistent performance patterns (Hong & Liu, 2003). This manifests as "game sense"—intuitive understanding of survival, anticipation, communication, and positioning (Fanfarelli, 2022; Reeves et al., 2009)—and enhanced self-regulation through planning, monitoring, and adaptive strategy deployment (Yilmaz Soylu & Bruning, 2016). However, expertise comes with trade-offs: gaming experts may focus on familiar features while overlooking unfamiliar educational content, despite having higher working memory capacity (Lee & Heeter, 2017), and adopt different visual strategies–like more frequent and shorter fixations and reduced visits to the same location–that don't always translate to performance advantages in novel, complex tasks due to overlooking information (Delmas et al., 2022).

The subjective experience of games evolves significantly with accumulated play. Survey research shows that novices perceive higher flow states in easier levels that match their developing skills, while experts experience peak flow in more challenging content (Gascon et al., 2015; Larche & Dixon, 2020). This expertise also moderates how design elements affect performance. For instance, diegetic interfaces in VR enhanced novice performance but did not affect experts (Marre et al., 2021). Over time, players internalize community norms (Bergstrom et al., 2012) and cultivate nuanced relationships with performance metrics, with experts sometimes strategically limiting metric use during competition to preserve their sense of agency (Rapp & Boldi, 2026).

These findings underscore that game expertise influences player behavior and experience across multiple dimensions. Building on prior self-report measures of game experience (Boot, 2015; Latham et al., 2013; Towne et al., 2014), we use self-reported average weekly hours combined with approximate years of play to approximate broad game expertise and examine how accumulated gaming time interacts with puzzle game play. We prefer the term game expertise over game experience because expertise foregrounds the skill acquisition that accrues through years of practice (Latham et al., 2013; Röhlcke et al., 2018), rather than the act of playing itself — game expertise is thus a stable background characteristic that players bring to a game. Although "experience" can colloquially function as a near-synonym for "expertise," we reserve the word experience for a distinct construct we turn to next: player experience, which refers not to what players bring, but to what emerges while playing.

The Player Experience in Video Games

Player experience (PX) has emerged as a central concept in game research, extending beyond traditional usability metrics to encompass the emotional, cognitive, and affective dimensions that make games uniquely engaging (Wiemeyer et al., 2016). Where game expertise is a stable individual-difference variable reflecting accumulated skill and knowledge, player experience is dynamic and in-the-moment–it is what a player feels, thinks, and does during a session. We adopt the definition of Ermi & Mäyrä (2005), who describe it as "an ensemble made up of the player's sensations, thoughts, feelings, actions, and meaning making in a gameplay setting" (p. 2). Unlike productivity software and general user experience, where efficiency is paramount, games are designed explicitly to evoke these subjective states–challenge, tension, curiosity, and enjoyment–that keep players engaged over time (Sánchez et al., 2012). This shift from user experience to player experience reflects recognition that gaming involves complex psychological states that must be understood holistically rather than through isolated metrics.

Toward this end, researchers have identified multiple dimensions that collectively constitute player experience. Ermi and Mäyrä (2005) propose that immersion operates across three modalities: sensory (audiovisual engagement), challenge-based (cognitive and skill demands), and imaginative (narrative involvement). Calleja (2007) offers a complementary framework through his Digital Game Experience Model, which identifies six frames of involvement–tactical, performative, affective, shared, narrative, and spatial–operating across micro-level moment-by-moment play and macro-level sustained engagement. Crucially, Calleja argues that these frames require varying degrees of conscious attentional investment, with internalization of any frame freeing up attention for others–a dynamic particularly relevant when considering how expert players, who have internalized controls and game conventions, can allocate attention more fluidly across these dimensions. Similarly, Wiemeyer et al. (2016) emphasize that adequate conceptualization requires differentiating dimensions like flow, immersion, challenge, competence, and emotions–psychological constructs that reflect gaming's multidimensional nature.

The challenge in studying player experience lies partly in its measurement. Multiple validated questionnaires exist—including the Immersive Experience Questionnaire (IEQ), Game Engagement Questionnaire (GEQ), and Player Experience of Need Satisfaction (PENS)—yet research reveals considerable convergence among these instruments, suggesting they capture overlapping constructs despite distinct

theoretical origins (Denisova et al., 2016). This redundancy creates challenges for comparing results across studies and selecting appropriate measures. Nevertheless, these tools collectively capture important experiential qualities: engagement reflects sustained attention and involvement, enjoyment represents affective satisfaction, curiosity indicates motivation to explore and discover, and perceived difficulty captures the subjective sense of challenge (Wiemeyer et al., 2016; Sánchez et al., 2012). Measuring these dimensions at multiple timepoints–as in the current work–allows researchers to track how experiences evolve—whether initial impressions persist, how novelty effects fade, and whether early design choices continue shaping later engagement. Overall, these dynamic shifts in perception and engagement underscore that player experience evolves continuously—shaping not only what players feel but how they approach the problems games present.

Problem-Solving in Video Games

Video games are increasingly recognized as environments that inherently engage and develop problem-solving skills (Gee, 2005; Schell, 2015). At a broad level, problem-solving in games involves players encountering clearly defined obstacles — what Aarseth (1999) calls "aporias" — and working toward solutions or "epiphanies" that allow progression (see also Jørgensen, 2003). Operationally, this manifests through observable behaviors such as hypothesis testing, strategic planning, adaptively revising approaches based on feedback, and ultimately overcoming designed challenges (Anderson et al., 2009; Shute et al., 2016). Given this broad conceptualization, researchers have investigated both whether gameplay cultivates these problem-solving capacities and how the problem-solving process unfolds.

Empirical evidence presents a complex relationship between games and problem-solving skills. Several studies demonstrate positive associations between strategic game play and problem-solving abilities, particularly when games require deliberate planning rather than rapid reflexes (Lie et al., 2022). These benefits appear strongest in challenging genres—puzzle games requiring spatial reasoning show measurable improvements in those specific skills (Shute et al., 2015), while simulation games promote computational problem-solving through engagement with complex systems (Liu et al., 2011). However, other research reveals modest or null effects (Dindar, 2018; Emihovich et al., 2022), suggesting that transfer depends critically on game design features, engagement duration, and the specific cognitive processes being measured.

These mixed outcomes may also reflect important individual differences in how players approach problems. Experienced players demonstrate fundamentally different problem-solving patterns than novices—employing more analogical thinking and strategic approaches rather than trial-and-error, exhibiting greater metacognitive awareness, and showing more consistent solution paths (Hong & Liu, 2003; Blumberg et al., 2008). Moreover, general problem-solving styles from everyday life manifest in gaming contexts with real-world preferences correlating to in-game approaches (Hamlen, 2018), suggesting that problem-solving in games reflects broader reasoning patterns that players bring with them into games or perhaps that games develop certain kinds of reasoning and players bring this reasoning outside of games.

These individual differences interact critically with both affective states and game design. Players experiencing flow states (Gascon et al., 2015; Larche & Dixon, 2020) —characterized by optimal challenge and deep engagement—employ more

sophisticated strategies, including experimentation, learning by example, and analytical reasoning, whereas those experiencing anxiety or boredom tend toward superficial approaches (Liu et al., 2011). The scaffolding embedded in games mediates these experiences: well-designed support can reduce frustration and guide players toward solutions, yet excessive or poorly timed assistance may increase dependence and reduce independent problem-solving practice (Sun et al., 2011). This tension becomes particularly salient during onboarding, when players simultaneously learn mechanics and develop initial problem-solving approaches—a critical juncture where both prior gaming experience and instructional design may significantly shape subsequent engagement.

Onboarding in Video Games

The initial onboarding phase—those critical first moments when players learn fundamental mechanics and the essence of a game—shapes player experience and problem-solving behaviors, regardless of the player's gaming experience level. As game complexity has increased over time, designers have developed increasingly sophisticated assistance systems to help players navigate these early learning challenges (Therrien, 2011). While early arcade games relied on minimal guidance through printed instructions, contemporary games employ diverse onboarding strategies ranging from explicit tutorials to implicit, discovery-based approaches (Cao & Liu, 2022).

The effectiveness of these onboarding approaches depends critically on game complexity and genre. Research demonstrates that tutorials significantly improve engagement in complex games—increasing playtime by up to 29% and player progress by 75% in intricate puzzle games—while having a negligible impact on simpler titles where players learn effectively through experimentation alone (Andersen et al., 2012). This complexity-dependent relationship extends to tutorial design features: context-sensitive tutorials that provide just-in-time guidance improve engagement in complex games but show no effect in simpler ones, while restricting player freedom during tutorials consistently limits learning (Andersen et al., 2012). These findings suggest that onboarding design must be calibrated to the specific demands of the game's mechanics and systems.

Complexity is not the only factor to consider in tutorials. The mode of instruction—explicit versus implicit, directive versus exploratory—introduces additional trade-offs that shape both immediate and longer-term learning. Direct instruction through tutorialized onboarding allows players to achieve mechanical understanding more quickly and with fewer mistakes compared to learn-by-doing approaches, without sacrificing engagement or enjoyment (Author(s), 2023). However, while explicit tutorials reduce perceived difficulty and errors during initial learning, they may not better prepare players for tackling complex challenges without guidance later in gameplay (Author(s), 2023). The design of effective tutorials also depends on the complexity of the mechanics—designed experiences where players discover mechanics through guided gameplay work best for simple mechanics, while explicit instructions prove most suitable for highly complex, interwoven systems (Teahan, 2024).

Increasingly, research on onboarding emphasizes a balance between instruction and player agency. Players value personalized guidance during onboarding but emphasize maintaining control over when and how assistance is provided, suggesting that future

systems should prioritize player autonomy while encouraging active learning (Choong et al., 2025). This balance becomes particularly critical in puzzle games, where the challenge lies in predicting whether unassisted exploration will lead to productive learning opportunities or unproductive frustration (Vet & Van Rozen, 2024)—a tension that reflects broader research on productive failure, which shows that initial struggle can enhance deeper learning when appropriately supported (Kapur, 2008). For narrative-rich games specifically, onboarding must integrate learning with storytelling, embedding instructions within meaningful gameplay rather than presenting them as separate, immersion-breaking lessons (Zhang & Huai, 2021). While this rich literature on onboarding in games suggests that supporting players to discover a puzzle solution autonomously, there is less focus on systematically testing different approaches on the nuances of approach and player expertise.

RESEARCH QUESTIONS

At the intersection of game expertise, player experience, and problem-solving behaviors across different onboarding designs, we consider the following research questions:

1. How does game expertise influence player success in different onboarding approaches in *Baba is You*?
2. How does game expertise influence problem-solving behaviors in different onboarding approaches in *Baba is You*?
3. How does game expertise influence player experience—curiosity, enjoyment, engagement, and perceived difficulty—over time and across different onboarding approaches in the game *Baba Is You*?

METHOD

Context: The Puzzle Game Baba is You

This study used *Baba Is You* (Teikari, 2019), a puzzle game where players manipulate text-based rules as physical objects. Rules like "BABA-IS-YOU" and "FLAG-IS-WIN" appear as pushable tiles that simultaneously function as game mechanics and puzzle elements. Players solve levels by reconfiguring the level's rules—changing the win condition from "FLAG-IS-WIN" to "ROCK-IS-WIN" when flags are unreachable or breaking "WALL-IS-STOP" to make wall tiles passable. Figure 1 shows the starting point of the first level, in which players need to access the top area and create a win condition.

Figure 1: The level Where Do I Go? demonstrates Baba Is You's text-manipulation mechanics. Players must push text tiles to break apart WALL-IS-STOP, removing the barrier property and allowing passage through walls to reach the flag after forming the rule FLAG-IS-WIN.

We chose *Baba is You* for several reasons. Its integrated level editor facilitated controlled experimental modifications without sacrificing gameplay authenticity. Building on our established research program with this game (Anderson et al., 2022; Anderson et al., 2024; Anderson et al., 2026; Carpenter et al., 2024; Carpenter et al., 2026), we used previously documented player patterns and misconceptions to inform targeted onboarding variations. Further, the research version recorded detailed gameplay data—every movement, rule change, restart, and undo action. Finally, because the game inherently presents its mechanics as readable text-based rules rather than hidden systems, players' mechanical understanding becomes directly observable in how they manipulate the rules. These features enabled systematic comparisons of how different onboarding approaches influenced mechanical comprehension and problem-solving strategies across the game's levels.

The Alternative Onboarding Designs

We developed three onboarding variants based on the original game. *Tutorialized*, provided clear guidance using text hints, directional arrows, and reinforcement messages after each level. Signs clearly explain mechanics directly. *Safe Problem-Solving*, restructured levels to avoid common failure points. Removed dead-ends, blocked incorrect paths, and organized visual elements to guide players toward solutions without explicit instructions. *Increased Impasse* intentionally included productive failure by directing players to stuck points. This approach requires them to understand why intuitive solutions fall short before they discover the correct mechanics.

Figure 2: Alternative onboarding designs for the same level in Baba Is You. Top left: The Increased Impasse version. Top right: The Safe Problem-Solving version. Bottom: The Tutorialized version.

Participants

We recruited 122 students from a large Midwestern university for our IRB-approved study. All students provided informed consent and were at least 18 years old, comfortable responding to open-ended questions in English, and had no prior experience playing *Baba Is You*. Due to technical issues resulting in data loss, we analyzed data from 110 participants: 28 in the Increased Impasse group, 26 in the Original group, 26 in the Safe Problem-Solving group, and 30 in the Tutorialized group. Participants were primarily undergraduate students with an average age of 21.5 years. Self-reported gender distribution included 47 women, 54 men, 8 nonbinary, and 1 preferring not to report.

Participants varied widely in gaming background. Game expertise was assessed via two self-reported items: "On average, how many hours per week do you play video games?" and "For approximately how many years have you been playing video games?" These scores were combined into a composite expertise measure. Weekly play hours ranged from 0 to 40 hours (M = 8.84, Mdn = 6.0, SD = 8.65; Q1 = 3 hrs/week, Q3 = 10 hrs/week). The composite expertise score was substantially right-skewed (skewness = 1.72), reflecting a sample that spanned from non-gamers to highly experienced players. The four onboarding conditions did not differ significantly in game expertise at baseline (Kruskal-Wallis, p = .414), supporting that random assignment produced comparable groups.

Participants completed the study via Zoom and were randomly assigned to one of the four conditions. Each session lasted approximately 60 minutes of gameplay plus time

for questionnaires and setup. All participants provided informed consent before participation. As compensation, they received a digital copy of Baba Is You (valued at $15 on Steam) and a $56.25 gift card voucher.

Types of Collected Data

This study employed multiple data collection methods to capture both behavioral and subjective dimensions of player experience, combining instrumentation data with self-report measures as recommended for player-experience research (Nacke & Drachen, 2011). The data sources were gameplay recordings, think-aloud transcripts, system-generated interaction logs, and self-report measures. (1) We measured gaming expertise through two self-reported items: 'On average, how many hours per week do you play video games?' and 'For approximately how many years have you been playing video games?' These scores were combined by multiplying weekly hours by years of play and by 52, producing a composite estimate of approximate lifetime gaming hours (e.g., a player reporting 10 hours per week over 5 years would receive a score of 2,600). We acknowledge known limitations of self-reported playtime, including systematic underreporting (Kahn et al., 2014) and the broader concern that hours alone do not fully capture expertise (Latham et al., 2013); we treat this measure accordingly as a rough approximation rather than a definitive expertise classification. (2) Gameplay log data—level starts, quits, restarts, undo frequency, rule manipulations, time per puzzle, and completion rates—was uploaded to cloud storage and analyzed using Python scripts. We selected these specific event types because they directly index the rule-manipulation and backtracking behaviors that constitute problem-solving in *Baba Is You* and are the focus of RQ2. (3) Surveys administered after Sessions 1 and 3 measured player experience across four dimensions: perceived difficulty, enjoyment, engagement, and curiosity. Perceived difficulty was measured with items such as "I found these levels difficult overall" and "I got stuck at some point while playing." Enjoyment was measured with items such as "I enjoyed playing," "I felt happy while playing," and "I found playing tiresome" (reverse-scored). Engagement items — such as "I lost track of time," "Playing seemed automatic," and "I wanted to play longer" — were adapted from Brockmyer et al.'s (2009) Game Engagement Questionnaire, with wording shifted to past tense to target the specific play session rather than general gameplay tendencies. Curiosity was measured with items reflecting openness to exploration and problem-solving, such as "I generally enjoy exploring new places" and "I generally like to try and solve problems." Items were presented in randomized order. Scales demonstrated adequate internal consistency (α = 0.70–0.93 for Session 1; 0.76–0.93 for Session 3).

Procedure and Data Collection

The study consisted of three sessions within two weeks. When scheduling constraints arose, these intervals could extend to seven and ten days, respectively. Each session allotted 60 minutes of gameplay, with total duration typically lasting 60-75 minutes, including setup and surveys. Session 1 began with researcher-supported software setup. Participants then completed their randomly assigned tutorial version until finishing seven levels or reaching the 60-minute limit. The researcher verbally described the mechanics of any levels that participants had not reached, helping move towards all participants having knowledge of the core game mechanics before proceeding, even if they had not directly interacted with them. We acknowledge that verbal description does not substitute for direct interaction with the mechanics, but viewed this as the preferred alternative compared to students not being exposed to

them in the first session. Participants then completed survey instruments assessing gaming background and experience. Sessions 2 only included gameplay, and concluding session 3, participants completed the player experience survey again, along with demographic questions.

Analysis Approach

Levels Completed and Problem-Solving Behavior

To examine relationships between game expertise, levels completed, and problem-solving behaviors, we fitted ordinary least squares regression models aggregating data across the second and third gameplay sessions. Models included centered game expertise rank and onboarding approach as predictors. Game expertise was rank-transformed by converting raw scores to percentile ranks (0–1 scale), calculated as the rank of each score divided by the total number of non-missing values, then mean-centered. This transformation addresses the substantial right-skew in raw scores (skewness = 1.68; range: 0–31,304) and provides robustness to outliers and the presence of zero values (Conover & Iman, 1981). Skewness was near zero after the transformation.

We examined five problem-solving behaviors: unique rule removes, unique rule adds, undo chains (i.e., one or more undo events sequentially), restarts, and level ends. Only behaviors from session 2 and 3 were summed and included in the analyses because these levels were the same across onboarding condition and playtime was consistently an hour. Sensitivity analyses using Cook's distance (threshold = 4/n) identified five influential cases (4.3% of observations). Refitting models without these cases supported that key effects remained significant with minimal coefficient changes: the game expertise effect on levels completed strengthened slightly (β changed from 9.68 to 10.26, a 6.0% increase), demonstrating the robustness of findings.

Player Experience

We fitted linear mixed models examining how game expertise, time (first vs. third session), and onboarding approach influenced four constructs: engagement, difficulty, curiosity, and enjoyment. (i.e., one model for each construct). Models included all main effects, two-way, and three-way interactions, with random intercepts for participants, using REML estimation (Bates et al., 2015; Verbeke, 2000). Game expertise was rank-transformed using the same approach as the behavioral analyses to maintain consistency across all study measures.

To account for potential heteroskedasticity and non-normality in residuals, we planned to compute robust standard errors for all models. We applied false discovery rate (FDR) correction (Benjamini & Hochberg, 1995) separately for each construct (α = .05), treating the 16 effects within each construct as a family of related hypotheses. Effect sizes were calculated as Cohen's d using pooled standard deviations.

RESULTS

RQ 1: Game Expertise and Levels Completed

Linear regression models revealed a significant main effect of game experience, $\beta = 9.68$, SE = 1.79, $t(110) = 5.41$, $p < .001$, 95% CI [6.13, 13.24]. As game expertise was rank-transformed to percentiles (ranging from 0 to 1), this coefficient indicates that moving from the lowest to the highest percentile of experience would be associated with approximately 10 additional levels completed. Further, players at the 75th percentile of game expertise completed approximately 4.8 more levels than those at the 25th percentile ($9.68 \times 0.50 = 4.84$). No significant difference between onboarding approaches emerged (all ps > .27). Together, game expertise and onboarding approach accounted for 24% of the variance in puzzles completed, $R^2 = .236$, $F(4, 110) = 8.49$, $p < .001$.

As illustrated in Figure 3, the positive relationship between game expertise rank and levels completed was evident across the full range of the experience distribution. The scatterplot reveals a clear monotonic trend, indicating that relative game expertise predicts the number of levels completed.

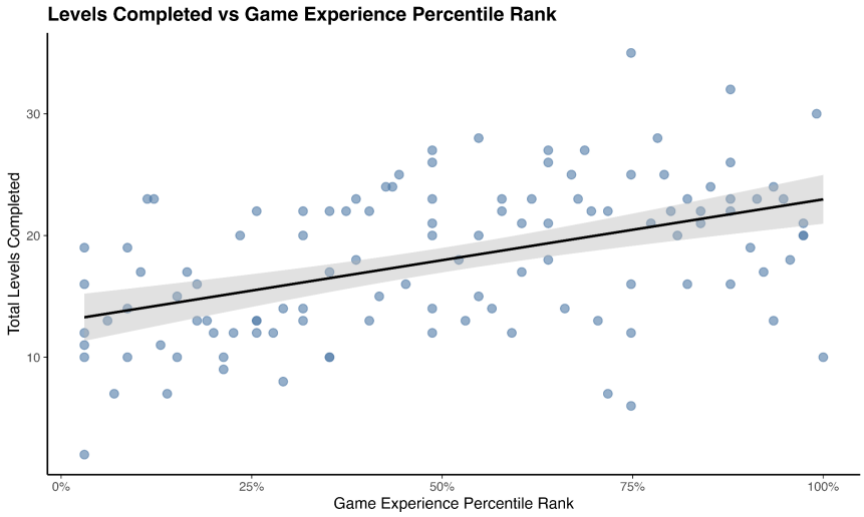

Figure 3: Participants with more game expertise (percentile rank, where 0% = least experienced and 100% = most experienced) completed more puzzle levels across two sessions ($\beta = 9.68$, $p < .001$, $R^2 = .24$, N = 115). The shaded region represents the 95% confidence interval around the regression line.

We identified 5 influential cases using Cook's distance ($D > 4/n = 0.035$) and refitted the model after excluding these observations. The expertise effect strengthened slightly, $\beta = 10.26$, SE = 1.63, $t(105) = 6.31$, $p < .001$, with the coefficient increasing by 6% while remaining significant. This model accounted for 29% of variance ($R^2 = .293$), compared to 24% in the full sample, demonstrating that the positive relationship between game expertise and number of levels completed is robust to influential cases.

RQ 2: Game Expertise and Problem-Solving Behaviors

Linear regression models were fitted for each behavior with centered game expertise rank and onboarding approach as predictors (see Figure 4).

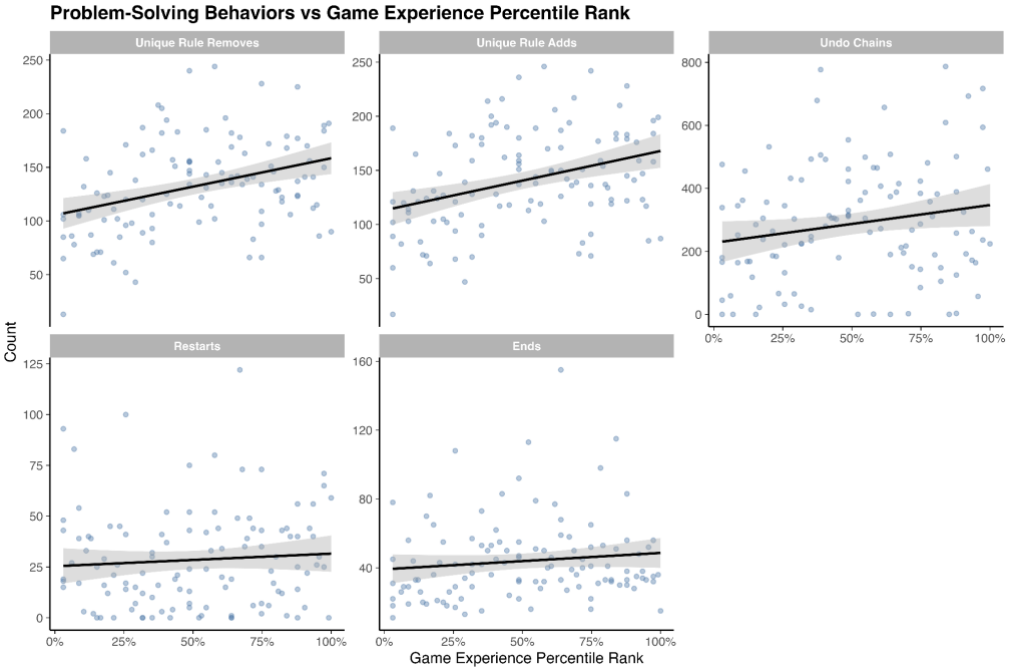

Figure 4: Game Expertise percentile rank (0% = least experienced, 100% = most experienced) was positively associated with rule manipulation (unique removes: β = 50.53, p < .001; unique adds: β = 52.69, p < .001) and undo chains (β = 122.70, p = .039), but not with restarts or ends (both ps > .31). Points represent individual participants (N = 115); lines show linear regression fits with 95% confidence intervals.

Game expertise was significantly associated with rule manipulation behaviors. More game expertise was linked to more frequent unique rule removals (β = 50.53, SE = 12.93, p < .001, R^2 = .18) and unique rule additions (β = 52.69, SE = 13.54, p < .001, R^2 = .18). These two behaviors were highly correlated (r = .90), suggesting they represent a unified rule experimentation approach to puzzle-solving. Game expertise was also positively associated with undo chain frequency (β = 122.70, SE = 58.63, p = .039, R^2 = .08), though this effect was weaker than for rule manipulation behaviors. Undo chains showed moderate-to-strong correlations with both unique rule removals (r = .73) and additions (r = .60), indicating that experienced players more frequently used both rule experimentation and backtracking strategies. In contrast, game expertise was not significantly related to restart frequency (β = 6.15, SE = 8.03, p = .446, R^2 = .01) or game end events (β = 7.70, SE = 7.59, p = .313, R^2 = .07).

Although onboarding conditions did not differ in overall performance, Group S showed significantly reduced engagement in several problem-solving behaviors relative to Group T. Specifically, Group S participants exhibited fewer unique rule removals (β = -23.93, SE = 10.24, p = .021) and unique rule additions (β = -26.94, SE =

10.74, p = .014). No significant differences emerged between Groups I or O and group T for any behavior (all ps > .13). As shown in Figure 4, the positive associations between game expertise and rule manipulation (both removals and additions) and undo chains are evident across the full distribution of game experience, while restarts and ends show relatively flat relationships.

RQ 3: Game Expertise and Player Experience

Three models (engagement, difficulty, curiosity) exhibited singular fits, indicating negligible between-subject variance. We simplified these to fixed effects models by removing random intercepts and computed heteroskedasticity-consistent (HC3) standard errors (MacKinnon & White, 1985; Long & Ervin, 2000). For enjoyment, which retained its random effects structure, we computed CR2 cluster-robust standard errors (Pustejovsky & Tipton, 2018). Nine effects survived FDR correction ($\alpha = .05$). No significant effects emerged for engagement or curiosity. As such, we focus on difficulty and enjoyment.

Perceived Difficulty

Players' ratings of overall game difficulty increased substantially from the first session (M = 19.98, SD = 4.71) to the third session (M = 24.85, SD = 4.48), $\beta = 5.85$, 95% CI [4.06, 7.65], d = 1.32, $p < .001$ (see Figure 5). This effect indicates the game became more challenging after onboarding for all groups.

Group I rated difficulty as substantially greater than Group T at the first session (M = 23.74 vs. M = 18.52), $\beta = 5.12$, 95% CI [3.25, 7.00], d = 1.15, $p < .001$. Group O also rated difficulty higher than Group T, $\beta = 2.54$, 95% CI [0.58, 4.49], d = 0.57, p = .038.

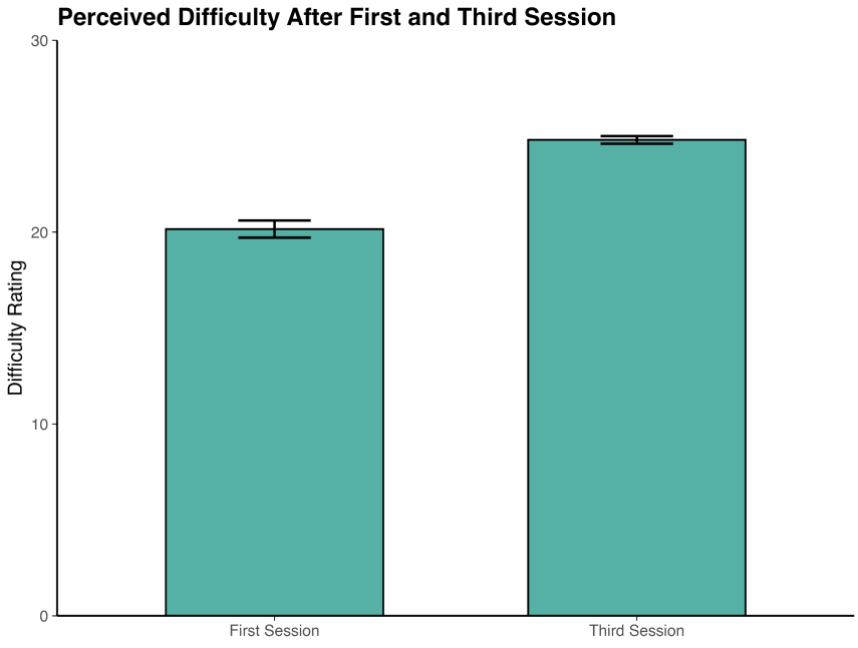

Figure 5: Perceived difficulty increased substantially from pre- to post-test (d = 1.32). Error bars represent ±1 SE.

A Time × Group I interaction qualified these main effects, β = -4.79, 95% CI [-7.03, -2.55], d = -1.08, p < .001 (see Figure 6). While Group T showed a 5.85-point increase in difficulty ratings, Group I showed only a 1.06-point increase. Groups O and S showed increases of 3.87 and 7.71 points, respectively.

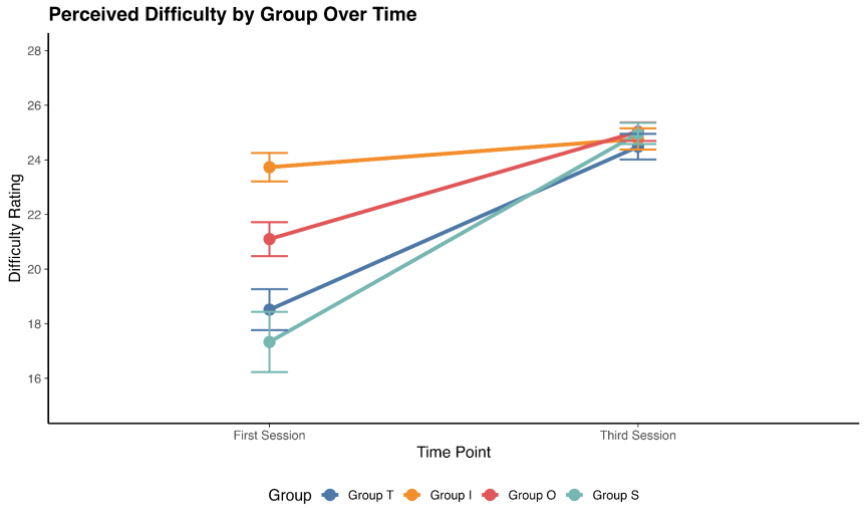

Figure 6: Perceived difficulty by group over time. Error bars represent ±1 SE. Group I showed minimal increase from pre to post (Time × Group I: β = -4.79, d = -1.08, p = .001).

Enjoyment

Overall enjoyment decreased from pre-test (M = 35.24, SD = 4.17) to post-test (M = 32.29, SD = 4.60), β = -3.32, 95% CI [-5.27, -1.38], d = -0.75, p = .013. Group I also showed lower overall enjoyment than Group T, β = -2.61, 95% CI [-4.55, -0.67], d = -0.59, p = .029.

Critically, Figure 7 shows a significant three-way interaction (Game Expertise × Time × Group) emerged for Groups I and O, indicating that the relationship between game expertise and enjoyment change depended on the onboarding approach. For Group I, β = 12.01, 95% CI [4.71, 19.31], d = 2.70, p = .013; for Group O, β = 14.33, 95% CI [5.83, 22.84], d = 3.23, p = .013.

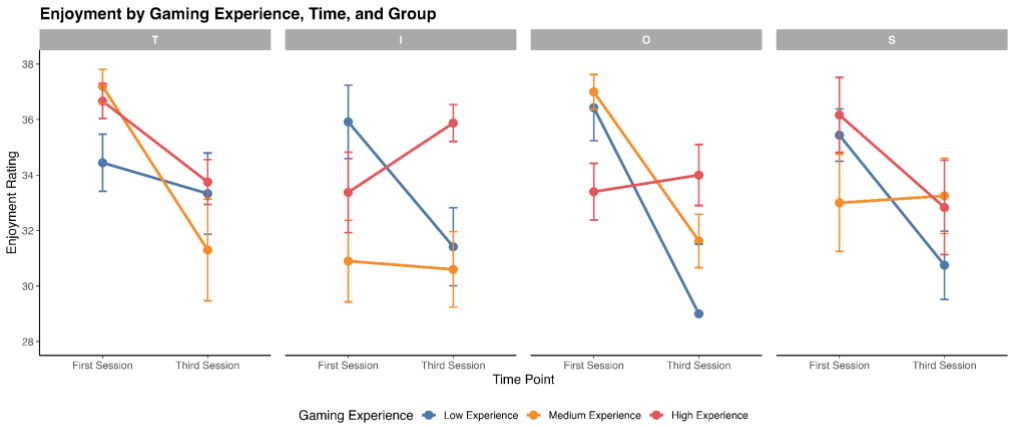

Figure 7: Enjoyment by game expertise, time, and onboarding approach. Error bars represent ±1 SE. Significant three-way interactions emerged for Groups I (β = 12.01, d = 2.70, p = .013) and O (β = 14.33, d = 3.23, p = .013).

To interpret these interactions, we examined simple slopes of game expertise at each session for each onboarding approach using estimated marginal means at low (−0.3), average (0.0), and high (+0.3) experience levels (Lenth, 2021).

In Group T, game expertise was unrelated to enjoyment at the end of session 1 (b = 3.10, p = .232) and the end of session 3 (b = 1.95, p = .451), and these slopes did not differ significantly (p = .741).

In contrast, Groups I and O showed dramatic shifts in the experience-enjoyment relationship. In Group I, the relationship reversed from the first session (b = -3.89, p = .123) to the third session (b = 6.98, p = .006), with slopes differing by 10.87 points (p = .002). Group O showed an even stronger reversal, from a significant negative slope at the first session (b = -5.19, p = .045) to a significant positive slope at the third session (b = 7.99, p = .002), differing by 13.19 points (p < .001).

To contextualize these interactions, we examined estimated marginal means at the 25th, 50th, and 75th percentiles of game expertise. In Group I, low-experience participants' enjoyment dropped from 34.66 to 30.37 (4.29 points), while high-experience participants' enjoyment increased from 32.33 to 34.56 (2.23 points). In Group O, the pattern was more pronounced: low-experience participants dropped from 36.90 to 29.38 (7.52 points), while high-experience participants remained stable, increasing from 33.78 to 34.18 (0.40 points). In Group T, both groups showed similar modest decreases.

Given that 24% of enjoyment observations exceeded Cook's distance thresholds, we refitted models without these observations (n = 184 vs. 242). The three-way interactions for Groups I and O remained stable (coefficient changes of -3.7% and +10.1%, respectively), supporting these findings are robust to influential cases. However, the Group S three-way interaction showed larger sensitivity (40.9% decrease), suggesting caution in interpreting this effect.

Game Expertise Main Effects

Game expertise did not predict any outcome construct as a main effect across models (all ps > .05 after FDR correction), contrasting with the behavioral analysis, where game expertise strongly predicted objective performance (R^2 = .24, p < .001). The lack of main effects for subjective ratings, coupled with the significant three-way interactions, suggests that expertise effects on player experience are highly context-dependent and moderated by both session and onboarding approach.

DISCUSSION

Game research often asks participants about the types of games they typically play but less frequently considers the broader level of expertise they have across games—a variable that can significantly shape how players experience and navigate a game. The study from which these data were drawn aimed to compare different onboarding

approaches in a puzzle game, yet our analyses revealed that game expertise exerted a strong influence on key variables, regardless of onboarding method. These findings resonate with a long tradition of expertise research across domains—from Chi et al.'s (1981) foundational work on knowledge organization to Ericsson et al.'s (1993) emphasis on deliberate practice—that consistently links accumulated experience to qualitative shifts in strategy, performance, and perception. Within game studies specifically, our results build on and extend prior work documenting novice–expert differences (e.g., Elliott et al., 2020; Gascon et al., 2015), situating them within the context of puzzle game onboarding and player experience.

Game Expertise and Progression

Across four different onboarding approaches, players with greater game expertise completed significantly more levels, regardless of how they were introduced to the game's mechanics. This underscores that expertise functioned as a dominant individual-difference variable, not the design of the tutorial. This may speak to what Reeves et al. (2009) describe as the deep internalization of game conventions among expert players—an intuitive familiarity with how game spaces are structured, what designers expect of players, and how to approach novel mechanics.

Game Expertise and Problem-Solving Behaviors

The relationship between game expertise and problem-solving behavior was particularly pronounced. Higher-expertise players showed significantly more unique rule removals, unique rule additions, and undo chain usage—behaviors that collectively index an exploratory, iterative approach to puzzle-solving. This aligns with Cai et al.'s (2024) observation that expert citizen science players converge toward strategic solution patterns over time. Our results also extend this literature by showing that expert-like exploratory behaviors are not just a product of expertise itself but can also be shaped by onboarding design: the Safe Problem-Solving condition produced significantly lower rates of rule manipulation compared to the Tutorialized condition, across all levels of expertise. This suggests that the relationship between expertise and exploratory behavior is partly constructed by design—and that onboarding choices can either preserve or suppress an iterative, tinkering orientation toward play.

Game Expertise, Difficulty, and Enjoyment

The relationships between game expertise, perceived difficulty, and enjoyment were more nuanced, and it is here that the interaction between expertise and onboarding design is most consequential for both research and practice. Perceived difficulty increased for all groups from the onboarding phase to the unmodified levels, which is expected given that the original game levels were deliberately designed to be more challenging. What is important, however, is the differential magnitude of that increase across conditions. Groups whose onboarding levels were rated as easier—particularly Safe Problem-Solving—experienced larger difficulty spikes when transitioning to the unmodified game, consistent with Andersen et al.'s (2012) finding that tutorials shape subsequent engagement in complex games by calibrating players' initial difficulty expectations.

The three-way interaction between game expertise, session, and onboarding condition on enjoyment is perhaps the study's most theoretically significant finding.

In the Tutorialized condition, enjoyment declined modestly and similarly across all expertise levels. But in the Increased Impasse and Original conditions, the expertise-enjoyment relationship reversed over time: high-expertise players increased in enjoyment while low-expertise players declined. Calleja's (2007) Digital Game Experience Model offers some theoretical traction here in that expert players in *Baba is You*, may have internalized control conventions and general game schemas and can direct attention more flexibly across the game's tactical and spatial frames. Lower-expertise players, still allocating cognitive resources to basic navigation and mechanic comprehension, may have fewer attentional resources available for productive engagement with the puzzle system—making the difficulty spike or other changes from the onboarding session to the later sessions less enjoyable.

This finding also connects to Marre et al.'s (2021) demonstration that design features differentially affect novice and expert players—in their case, diegetic VR interfaces benefited novices but had no effect on experts. Our results suggest an analogous dynamic: onboarding designs that impose structure and reduce ambiguity (Safe Problem-Solving, Tutorialized) may serve novices better during initial play but constrain the expert players' preferred mode of exploration. The Increased Impasse design, by contrast, appears to create conditions in which expert players can leverage their accumulated game knowledge advantageously—their higher enjoyment over time may reflect a satisfying alignment between the challenge structure and their existing skills and expectations.

The Broader Role of Gaming History

The broader pattern of results points to something that the introduction to Patrick's Parabox—a puzzle game—makes explicit in the game world itself: a room of optional tips advises players to use undo frequently, work backwards from the solution, and treat dead ends as informative rather than discouraging. According to the developer, this optional content is intended to help newer players to puzzle games adopt approaches that lead to success in puzzle games, which veteran players would have learned through many hours of solving puzzles (Anderson et al., 2026). The expertise effects we document are, in a sense, the measurable behavioral signature of exactly this gap: higher-expertise players in our study already arrived with those strategic dispositions, using undo chains and rule manipulation extensively and naturally, while lower-expertise players did not—regardless of how they were onboarded. This connects directly to the player experience literature's emphasis on the dynamic, evolving nature of in-game subjective states. As Wiemeyer et al. (2016) and Ermi and Mäyrä (2005) note, player experience is multidimensional and shifts over time—it is not simply a function of game difficulty but of the dynamic interaction between player capacities, game demands, and the scaffolding provided by design. Our longitudinal design, measuring player experience at two timepoints, allowed us to capture precisely these shifts: initial onboarding experiences calibrated expectations and approach orientations that then interacted with expertise to shape subsequent engagement with and experience of more challenging content.

Limitations

While this research highlights an important factor in game studies, several limitations should be considered when interpreting the findings and planning future research. Participants reported their general gaming experience rather than their specific experience with puzzle games, so the relationship between puzzle game expertise

specifically and navigation of games like *Baba Is You* may differ from what we observed. This is a meaningful distinction given the literature's recognition that genre-specific experience and the intentionality of practice contribute importantly to expertise beyond raw hours (Latham et al., 2013; Röhlcke et al., 2018). Additionally, the study was not designed primarily to examine differences between players with varying levels of gameplay experience—its central focus was the effect of different onboarding approaches—meaning that reframing future research around expertise as a central variable could yield additional insights. We also relied on self-reported expertise measures, which are subject to the well-documented biases described by Elliott et al. (2020) and Kahn et al. (2014): players tend to underreport playtime, particularly older and more educated players, and self-reported hours correlate only moderately with expert-rated performance. We treat our composite measure accordingly as a rough approximation rather than a definitive classification. Future research that supplements self-report with objective play-history data or genre-specific assessments will help sharpen the picture.

Conclusion

This paper documents a strong influence on variables of interest when investigating how different onboarding approaches prepare players to navigate a puzzle game: general expertise in playing games. Building on a substantial body of prior work linking accumulated play to differences in neurological signatures (Hafeez et al., 2021; Tanaka et al., 2013), cognitive strategy (Hong & Liu, 2003; Cai et al., 2024), self-regulation (Yilmaz Soylu & Bruning, 2016), and flow experience (Gascon et al., 2015; Larche & Dixon, 2020), we show that these expertise-linked differences manifest in the context of a commercially available puzzle game and that they interact with onboarding design in ways that have practical consequences. Players with higher game expertise progressed further, engaged more extensively in exploratory problem-solving, and—in conditions that preserved or amplified challenge—maintained or increased enjoyment over time. Lower-expertise players, by contrast, benefited from more structured guidance but remained more susceptible to enjoyment declines when encountering the game's unmodified difficulty curve.

These findings carry important implications for both game research and game design. For researchers, game expertise represents a critical individual-difference variable that should be measured and controlled in studies of player experience, as expertise level can substantially moderate relationships between design features and player outcomes—a point underscored by the null effects of onboarding condition on levels completed versus the strong expertise main effect. For designers, our results suggest that one-size-fits-all onboarding approaches may inadequately serve players across the expertise spectrum: what engages and supports novice players may feel constraining to experts, while designs that allow experts to flourish may leave novices frustrated. This is consistent with the growing literature on adaptive and player-autonomous onboarding (Choong et al., 2025), which argues that future systems should prioritize player agency while providing scaffolding calibrated to individual needs. Adaptive onboarding systems that adjust the level of guidance and challenge based on player behavior or self-reported expertise might better accommodate the heterogeneity that our data make visible.

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