Support Autonomy: Exploring Player Perspectives on AI-Supported Onboarding in Video Games

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Abstract

Video game onboarding faces the challenge of teaching game mechanics in a fun and engaging way. Artificial intelligence (AI) solutions have become a quick fix to help users understand technology. However, little is known about how AI supports player onboarding in video games. To address this knowledge gap, this research explores player perspectives on AI-supported onboarding. We conducted a qualitative user study ($n = 20$) to investigate player expectations, attitudes, and concerns about AI-supported learning experiences. Players learn primarily through the lived experience of a game and value personalized guidance during onboarding. Participants emphasized the importance of maintaining control over how AI is used during onboarding and the freedom to choose their support level. Our results suggest that players want future AI-supported onboarding systems to prioritize their agency, encourage active learning, and maintain transparency throughout the learning process. We contribute to game design research by proposing balanced, player-centric AI-supported onboarding experiences in video games.

CCS Concepts

• **Human-centered computing → HCI design and evaluation methods**.

Keywords

artificial intelligence, onboarding, player experience, video games

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1 Introduction

Video games pose a unique challenge to game designers: players must learn how to interact with games before they can play them. This initial learning period, also known as the *onboarding* process [4], is a crucial part of new players' experiences. Traditionally tedious, uninspired, and frustrating onboarding methods are the main reasons why players quit during their first experience with a game [1, 13]. This stems from these methods not accommodating diverse learning styles or individual user needs. Interactive media like video games are also more likely to cause information overload (i.e., excessive *cognitive load*) in learners than non-interactive media [40]. This can then affect how players perceive a game's difficulty [21].

Artificial intelligence (AI) has been used in video games to improve players' experiences for decades [10, 59]. Many games use AI to manage computer-controlled characters [61], construct procedurally-generated worlds [58], or create complex models of players' in-game behaviours [60]. In terms of video game onboarding, research suggests that AI could be used to improve players' onboarding experiences in the form of personalized guidance [62], automated gameplay demonstrations [3], or dynamic opponents that match the player's skill level [37, 49]. These AI-supported onboarding systems offer the potential to create more dynamic, responsive, and personalized learning experiences for all users. However, previous research on AI-supported onboarding systems is limited, with a focus mainly on quantitative research and technical findings [26, 27, 63]. This lack of rich qualitative user data on the interplay between AI and onboarding has left a significant knowledge gap regarding players' expectations toward AI-supported onboarding methods and their impact on player experience. Consequently, it remains unclear *how* game designers should implement AI in onboarding and *how much* they should rely on AI during the onboarding process.

To address this research gap, we conducted a qualitative study that focused on two primary topics: the impact of an AI-supported onboarding system on player experience, and players' expectations and concerns regarding the use of AI in video game onboarding. Using these topics as a guide, we conducted semi-structured interviews with 20 participants and analyzed their responses using thematic analysis [7, 14, 50]. Given that AI is not yet regularly used in video game onboarding, we also contextualized each interview with two gameplay sessions of an original turn-based strategy game designed for our study called "Joker." Participants played Joker twice: once with the *Self-Guided* condition (no AI suggestions), and once with the *AI-Assisted* condition (the AI provides a suggestion to the player each turn). The results of our study found that players strongly prefer onboarding that maintains player agency over *how* and *when* they receive AI-supported guidance, and where AI-supported guidance does not remove their incentive to actively learn. All participants expressed a desire for engagement and interaction during the onboarding process, with an emphasis on lived experience as a learning method. In turn, we found that players believe AI-supported onboarding can create dynamic learning experiences that are more engaging than traditional onboarding methods and provide more effective guidance that is personalized to players as individuals.

This paper ultimately makes the following contributions:

(1) A novel implementation of an AI-supported onboarding system as part of an original turn-based strategy game.
(2) Analysis of players' expectations, attitudes, and concerns regarding AI and video game onboarding.
(3) Design considerations for future implementations of AI in video game onboarding.

2 Related Work

Two main areas of literature shaped this research: video game onboarding methods and the current use of AI in video games. This section reviews the existing literature in both fields and identifies the research gap where they intersect.

2.1 Onboarding Goals

Every game proposes a new challenge to its designers: how will they teach new players how to play? *Onboarding*, a term traditionally used in workplaces to define the process of helping new employees succeed in a job [4], also covers the methods game designers use to help new players succeed in a game [45, 51]. Petersen et al. [45] additionally define the onboarding process as starting from the first time a player interacts with a game and lasting until the player has completed a defined learning phase intended to teach core game mechanics. Given that onboarding shapes a player's first experience with a game, it is critical that this initial interaction engages and retains new players [13]. If the initial game experience is too boring or difficult, players may give up on the game and quit [41]. This problem of player retention is especially relevant for live-service games that need active playerbases to support gameplay systems such as matchmaking, as well as for free-to-play games that rely on players purchasing in-game content [16, 36, 43].

Onboarding must also ensure the learning experience does not overwhelm new players. Drawing connections to the concept of working memory, Huang and Johnson [30] define cognitive load as "the amount of mental effort learners invest during the learning process." Cognitive load theory proposes that a higher level of interactivity contributes to increased intrinsic cognitive load when the amount of interaction required exceeds the capacity of a learner's working memory [40]. As video games are an inherently interactive medium, it is essential to factor in how a game's onboarding method affects a player's cognitive load. Mayer and Moreno [38] propose various methods for reducing cognitive load in multimedia learning, such as by offloading some visual instructions to audio to balance the load between information processing channels. In particular, the load-reducing methods of *weeding* and *signalling* act similarly to the onboarding methods of *training wheels* and *scaffolding* respectively: weeding removes some information to reduce load, while signalling adds additional information to guide learners through the provided information [38]. The related onboarding methods are well-discussed in existing research and are described in more detail below.

Another area of research, *game approachability*, is defined as "the ease in which gamers are able to approach and avail themselves of games" [18]. This concept is highly related to game onboarding because a substantial element of game approachability is to help players find enjoyment in games as quickly as possible [18, 39]. However, while approachability principles can help designers identify flaws in their game's design [39], they do not provide designers with concrete or actionable solutions. As onboarding in particular is specific to each game, previous research instead focuses on providing game designers with design principles that can improve the initial player experience [25, 29, 46]. The ideal onboarding experience should be brief, yet still contain enough information for players to succeed [29, 41]. Shannon et al. [48] emphasize the importance of introducing players to game mechanics quickly to prioritize learning through exploration. Additionally, providing a memorable onboarding experience can help games retain players past their first play session [13].

2.2 Onboarding Methods

Games implement a wide variety of onboarding methods. While each method is usually tailored to a specific game or genre, the broader teaching techniques can be categorized into a subset of groups defined in existing literature.

2.2.1 Tutorials.

Tutorials are a common onboarding method in games. White [56] further delineates tutorials as *didactic*—defined as upfront and intentionally intrusive—instructions or exploratory prompts that encourage player experimentation. Other literature also describes this difference as *explicit* versus *implicit* tutorials [11]. These "opposing" tutorial methods demonstrate the challenge of creating a balanced onboarding experience. Too little instruction means players are unable to figure out how to succeed on their own [19], while too much instruction can restrict agency and lead to player boredom or frustration [41, 48]. Furthermore, the effectiveness of a tutorial varies based on game complexity and an individual player's gaming expertise. Non-expert players and complex games generally benefit more from tutorials than expert players or simple games [1, 44, 55].

2.2.2 Additive Support. The concept of scaffolding has its roots in cognitive psychology. Just as with a physical scaffold, cognitive scaffolding provides support at the beginning of the learning experience and is removed when a learner no longer needs the additional support [17]. In video games, this can be implemented by providing additional information on top of standard game information to prevent new players from getting stuck [19]. Prior work by Faber et al. [20] also investigated adaptive scaffolding—where scaffolding instructions adapt to the user—but the identified relationship between adaptive scaffolding and performance could not be generalized to areas outside of game-based learning.

2.2.3 Subtractive Support. In contrast to scaffolding, the training wheels onboarding method simplifies gameplay so players can focus on learning basic gameplay first [29]. Then, as players gain more experience, they are gradually introduced to more complex gameplay mechanics until they can access the entire game. Allowing players to break high-complexity tasks down into simpler ones can also help prevent cognitive overload. However, this can negatively impact the learning process when players need to use the "pieces" of a task in combination [53]. Another common subtractive support method is the concept of sandboxes: safe spaces for players to learn without risk while still feeling a sense of accomplishment [25]. With less risk, players are then more willing to experiment and make mistakes while learning because the punishment for doing so is either non-existent or extremely mitigated compared to "real" gameplay [19, 25].

2.2.4 Real-Time Support. The personal advisor onboarding method gives players advice based on their actions during gameplay [46]. This method is a reactive response rather than a proactive suggestion. The advice appears after the player chooses an action because it provides more detail on that action's consequences. It is similar to the performance coaching method [29], where the game acts as a teacher and uses suggestions to encourage optimal gameplay. Additionally, the just-in-time method—where information is provided to players exactly at the time they need it—can also be considered as a type of advisor or coaching strategy [17, 19, 46, 55]. Information with lower complexity is better suited for the just-in-time method because it is less likely to increase learners' cognitive load during in-game tasks [53].

Unlike additive or subtractive support methods, real-time support does not modify the mechanics of a game. Additionally, it avoids the restrictive teaching methods of didactic tutorials while still allowing for player exploration. The just-in-time method in particular is one of the most common onboarding methods found in games [46]. Because of these benefits, as well as the prominence of just-in-time onboarding in existing games, we decided to implement a real-time onboarding method in the game we developed for this study.

2.3 Video Games and AI

Existing literature on AI for games extends back to traditional board games such as checkers, chess, and Go [59]. One of the most well-known implementations of AI in games is the *Deep Blue* chess program that defeated the world champion Garry Kasparov [10]. This concept of AI as a player is one of the three main areas of research on AI in games identified by Yannakakis and Togelius [59]: AI for playing games [61], AI for generating content [58], and AI for modelling players [60]. However, game onboarding does not fall neatly into one of these categorizations. Instead, principles from all three categories are relevant to the use of AI in video game onboarding. For example, non-player characters are well-suited for the personal advisor onboarding method because they can diegetically present advice within the context of the game's world [46]. Aytemiz et al. [3] demonstrate the potential to use game-playing AI as assistive technology in ways that are applicable to video game onboarding, such as by having an AI system "play" a challenging section in a platformer to visually demonstrate the optimal path.

AI as an opponent rather than an ally also has uses in game onboarding. Chen et al. [12] found that players experienced less cognitive load when playing against AI opponents. Additionally, the authors emphasized the importance of matching players' cognitive load thresholds to maintain an enjoyable experience. Furthermore, Tan et al. [49] and Lavoie-Hudon et al. [37] proposed adaptive AI opponents that can match a player's skill level in real time. Dynamic opponents in tutorials should adjust the selection and timing of the skills they test to create more engaging learning experiences [47].

Additionally, designers may look to incorporate procedural content generation [52] into onboarding to improve adaptability and personalization. However, AI-generated onboarding is a non-trivial problem. Games more complex than simple arcade games are difficult for AI systems to properly understand, much less to explain in human-understandable ways [26]. While AI agents have been shown to be capable of generating game levels that teach a specific mechanic, Green et al. [27] found that the AI's levels were often impossible for humans to play.

Another concept closely linked to AI-supported onboarding is player modelling—the use of AI systems to create a model of a player's unique experience during gameplay [57]. Such models can be used to tailor games to individual players, which is useful in onboarding to account for different skill levels [15, 47]. For example, rather than using static tutorials, Benotti and Bertoa [5] relied on natural language generation AI to display context-aware text-based hints in a first-person shooter game. In a similar vein, Zhou et al. [62] implemented a player model similar to the advisor onboarding method that provided players with tips based on their measured performance.

Another method of using player modelling systems in onboarding is *challenge tailoring*: the game adapts to a player's behaviour by changing upcoming gameplay elements to better fit their modelled skill trajectory [37, 47, 63]. Player models can also be used to predict when players might get stuck, become frustrated, or quit playing [22, 60], all of which are relevant aspects of player experience during the onboarding process.

2.4 AI-Supported Learning

The combination of AI and onboarding is also connected to existing research on AI-supported learning. Gajos and Mamykina [24] found that while recommendations from an AI-supported system helped users make better decisions, the recommendations did not inherently help them learn. The effectiveness of AI-supported learning strongly depends on individuals and their learning techniques—learners who mechanically follow guidance from an AI without thinking do not benefit as much from the learning experience as active learners [54]. Learners instead see the most value in using AI to generate tailored learning content and to provide them with personalized guidance during the learning process [35]. While AI-supported learning is still a growing field, Kabudi et al. [33] found that interest in AI-supported adaptive learning systems has drastically increased since the pandemic. At the same time, many publications [32, 34, 42] also echo challenges regarding transparency, reliability, and privacy when using AI-supported techniques for learning purposes. This further supports the need to understand how to best incorporate AI-supported systems into learning processes without compromising learning or user experience.

2.5 The Research Gap

Our examination of existing literature on onboarding and AI in video games found that current research either prioritizes technical aspects of AI-supported onboarding systems over player experience [26, 27, 63] or does not propose broadly applicable conclusions on how AI-supported onboarding impacts player experience [5, 12, 49]. Although we may have the technical capabilities, we still do not know how players perceive AI-supported onboarding or what expectations they have for an ideal video game onboarding experience. Accordingly, our research addresses this critical gap to help game designers use AI technologies effectively in their onboarding implementations.

3 Research Focus

The primary goal of our study is to better understand players' expectations toward AI-supported onboarding systems and their effect on player experience. Key findings in onboarding literature indicate the importance of managing a learner's cognitive load [38, 40] while also making sure that the onboarding process is neither too boring nor too difficult [19, 41, 48]. To provide players with improved onboarding experiences through AI-supported guidance, it is crucial to first understand their expectations. Accordingly, our first research question is:

- **RQ1:** What do players expect from an ideal onboarding experience in video games?

Additionally, Section 2 demonstrated that while both onboarding and AI individually have depth and breadth of prior research, the space regarding the overlap of these two areas is not yet well-defined. Existing research on AI usage in game onboarding mainly focuses on creating more dynamic learning experiences [15, 37, 47, 49]. By contrast, our research examines player expectations to understand *how* AI-supported onboarding methods should best be used within these learning experiences. This subsequently informs our second research question:

- **RQ2:** What do players expect from AI-supported onboarding systems in video games?

Finally, we wanted to assess the impact of an AI-supported onboarding system on player experience. To achieve this, study participants played a game with such a system and shared how it affected their onboarding experience. Because just-in-time onboarding is well-established as an effective onboarding method [46, 55], we created a game with AI-supported onboarding that offers the player action suggestions during gameplay. This practical implementation of AI as a suggestion system led to our third and final research question:

- **RQ3:** How does the presence of an AI-supported suggestion system affect a player's onboarding experience?

Our research aims to bridge the gap between theoretical understanding and practical application of AI in video game onboarding. The goal of our approach is to support the design of AI-supported systems that improve player experience.

4 User Study

We conducted a qualitative user study to answer our research questions. Our study received ethics approval by the Research Ethics Board (REB) at the University of Waterloo (#45535).

4.1 Game Design: *Joker*

First, we needed a suitable game in which participants could experience AI-supported onboarding. Similar to previous onboarding research in games [44], our study required a game that participants had never played before so that their onboarding experience was not affected by existing knowledge. With this in mind, we created a new game for this study: *Joker*, a two-player turn-based strategy game designed to contrast familiarity and unfamiliarity. It uses the familiar game elements of playing cards and a chessboard to create an unfamiliar game. This focuses the onboarding process on learning gameplay mechanics rather than on learning how to interact with unfamiliar game elements. As well, because this study targeted individual players' onboarding and game experiences, participants played against a non-player opponent that simulated a multiplayer setup. This non-player opponent evaluates the units on the board and the cards in its hand, then uses a decision-tree-like function to decide whether to create a new unit, move a unit on the board, or attack the player. Since we were aiming to create an organic game experience, not an optimal opponent, we also included some randomness in the opponent's decisions.

The main gameplay of Joker occurs on a regular chessboard. At the start of each game, both players place a unique unit on their side of the board: the joker. The joker acts similarly to a chess king—players must kill the opponent's joker to win the game. To achieve this objective, players can decide each round whether to create a new unit, move an existing unit, or attack an enemy unit. While the latter two of these concepts are familiar to traditional chess and other turn-based strategy games, the unique gameplay mechanic of Joker is the creation of new units. Each player has a hand of playing cards, and they can combine a pair of cards to create a new unit on their side of the chessboard. By design, Joker's card combination system is intentionally complex to overwhelm new players and introduce high cognitive load. It also capitalizes on familiarity in a negative way. For example, higher cards are not

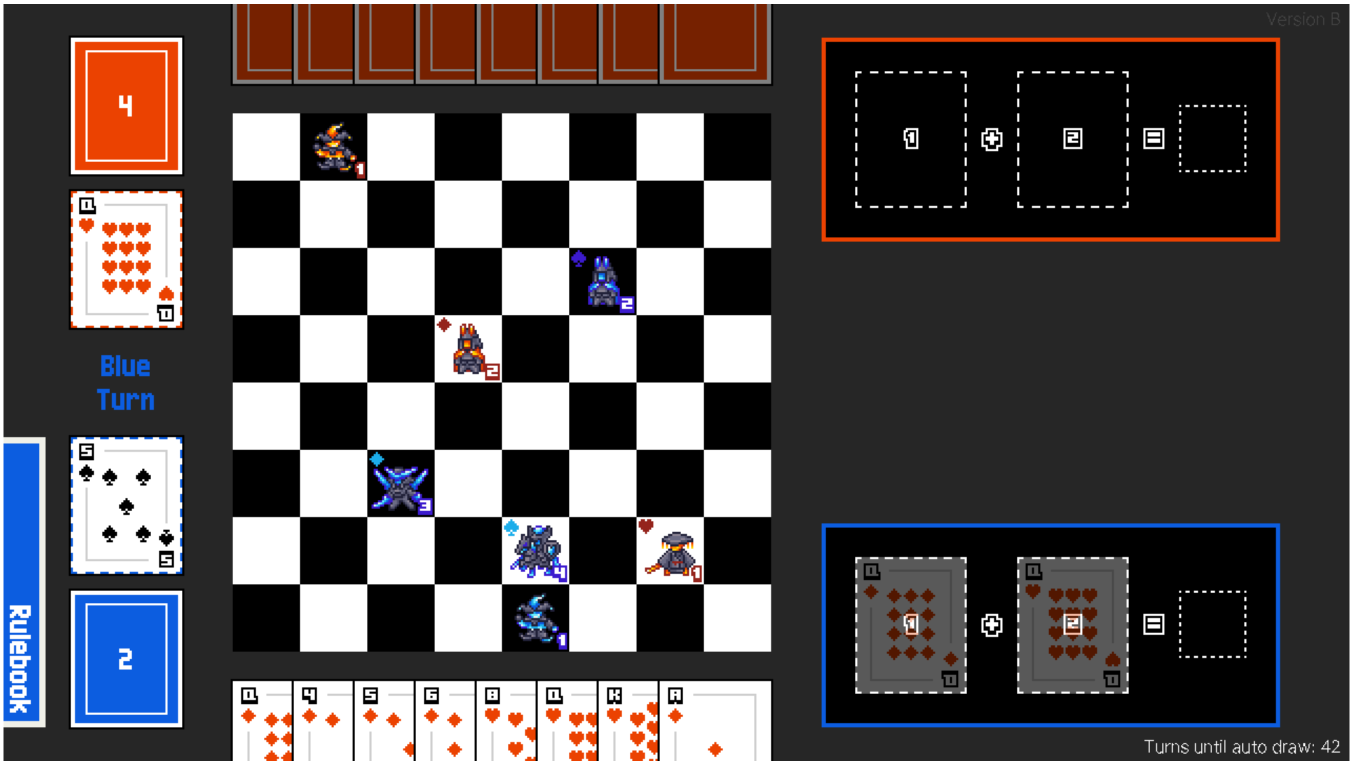

Figure 1: Screenshot of gameplay from Joker's *AI-Assisted* condition. The two suggested cards are presented through animated "pulsing" overlays on top of where the player combines cards (bottom right).

strictly better, so it could be more optimal to combine two low-value cards, and the joker unit cannot attack, which means chess strategies that rely on the king being able to defend itself do not transfer over. As one of the goals of this study was to explore how AI-supported onboarding affects players' learning experiences, we needed a gameplay mechanic that required onboarding to learn. A low-complexity mechanic risked being too easy for participants to understand upfront, which defeats the purpose of examining the onboarding experience.

Joker's onboarding consists of a rulebook[1] and an AI-supported suggestion system. The rulebook acts similarly to the rulebook of a physical board game, and the player can access it during gameplay. The AI-supported suggestion system follows the just-in-time onboarding method to provide players with real-time support during the game. Each turn it suggests the player two cards from their hand to combine into a unit. However, it is not mandatory that the player follows the suggestion. To make its suggestions, the system uses a decision-tree-like function based on the non-player opponent's code. It evaluates every possible pair of cards in the player's hand on all possible squares of the board where the player can create a unit, then sorts the resulting units into different tiers based on various factors (e.g., if the unit could kill an enemy when created on a certain square). It also prioritizes units that have powerful abilities with a second pass through the results.

[1]Attached as supplemental material.

4.2 Procedures and Applied Measures

We conducted a within-participants [6] study where all participants played the implemented game, Joker, twice: once using the base version and once with the help of the AI-supported suggestion system. The order of conditions was counterbalanced across participants to reduce the impact of condition order on their experience. We recruited participants through university mailing lists and research centres, with eligible participants required to be: 1) 18 years of age or older; 2) comfortable being audio and screen recorded; 3) comfortable using a computer with a keyboard and mouse; 4) comfortable sitting down for the duration of the study; and 5) familiar with video games and/or AI.

All participants played the game on a desktop computer with a mouse, keyboard, and two monitors. After filling out the consent form and demographics sections of the study survey, participants were introduced to the study. They were then instructed to take as much or as little time as they normally would when approaching a new game to go through the game's rulebook (meaning that participants could skip reading the rulebook entirely if they desired). Once a participant finished with the rulebook they played one round of the game corresponding to their first condition. Afterwards, they participated in a brief semi-structured interview about their first experience. The participant then played the second round of the game with the other condition and shared their opinions in a longer semi-structured interview comparing their experiences with both conditions. The gameplay of each session was screen-recorded to

Table 1: The primary topics covered in the two semi-structured interviews with exemplary questions from each topic. The full set of interview questions is provided in Appendix A.

	Topic	Example Questions
Interview 1	General Reflection	*What are your thoughts on the game you just played?*
Interview 2	General Reflection	*What are your thoughts on the game you just played?*
	Comparison of Conditions	*How would you compare your experiences with the two versions of the game you played? What are your thoughts on the suggestions the game provided you in the [first/second] game?*
	Perceptions and Expectations Regarding Onboarding	*What are your thoughts on video games providing new players suggestions during gameplay to help with decision-making? When you pick up a new game, what do you expect to get out of the onboarding process?*
	Perceptions on AI-Supported Suggestions	*What are your thoughts on AI-supported suggestions in video games?*

collect time data and to track which games participants won or lost. At the end of the interview participants were awarded $20 CAD in cash as remuneration for their participation. Each session took an average of 60 minutes and was not time-limited at any point.

To answer our research questions we collected qualitative data through two semi-structured interviews: a shorter interview after the participant completed their first round of the game and a longer interview after their second round that focused on comparing their experiences. The first author created the initial draft of interview questions based on our analysis of existing literature and our research questions. These questions asked about the participant's experience in both of the study conditions and encouraged them to share their expectations, perspectives, and concerns regarding player-AI interactions, AI-supported suggestion systems in onboarding, and onboarding experiences in video games. This initial draft was later revised through discussion with the other authors. The overarching topics of the semi-structured interviews are provided in Table 1. Please refer to Appendix A for the full set of interview questions.

We used a six-step process for thematic analysis originally proposed by Braun and Clarke [7] to analyze the participant interview data. This method emphasizes researchers taking an active role in analysis and has flexibility well-suited to this study's data (both its homogeneity and the number of participants) [14, 50]. Reflexive thematic analysis is an iterative process where codes can evolve and change over the course of analysis [9]. While reflexive analysis distinguishes itself from the "codebook" and "coding reliability" methods through its flexible and organic process [8], we additionally incorporated aspects of both of these methods in our approach: multiple researchers coded each transcript independently (i.e., coding reliability) and iteratively revised the resulting codes (i.e., codebooks). The participant interviews reached saturation—the point where subsequent interviews produced little to no new information—within the 20 sessions. This was expected, because prior research demonstrates that qualitative studies can reach saturation with as few as 9–17 interviews, especially when the participant group is more homogeneous [2, 28].

We used the online platform Dovetail[2] to transcribe and code the interview recordings. The first author cleaned the automated transcriptions before analysis and was the first coder on all 20 transcripts, while two other coders coded 11 transcripts each. To start the coding process, the first author used an inductive approach on 10% of the data to create the initial codebook. Three coders then independently coded another 10% of the data with the initial codebook and met to discuss new codes, resolve coding differences, and revise the codebook. We then reduced the number of coders per transcript from three to two and continued this iterative process in three more phases to code all remaining transcripts (unifying the codebook after each phase). Additionally, we re-coded the initial 10% of the data so that at least two coders coded all transcripts. See Figure 2 for a diagram of the coding process and refer to our supplemental materials for the final codebook. The first author then used an affinity clustering process to construct the initial themes. Afterwards, they discussed and revised the results with the other authors to create our final set of six themes. Overall, we found that players expect AI-supported onboarding systems to provide **tailored** learning experiences **upfront** that **enhance participation** during the onboarding process without compromising **active learning**, player **agency**, or **trust**.

4.2.1 Positionality Statement. We understand that our social positions shape our research perspective. As researchers who work at the HCI Games Group, our team offers a diverse perspective on games user research. We all have strong backgrounds in qualitative research methods, particularly thematic and content analysis. The first author additionally has experience as an indie game developer and has worked directly with players to incorporate feedback into games. Throughout our research we acknowledged any potential biases we hold as individuals and have taken steps to mitigate these effects. We intentionally used the aforementioned coding reliability method in our analysis to allow multiple researchers to bring their unique perspectives to every transcript. Furthermore, we kept a player-centric perspective across all research stages to prioritize players' needs and expectations in our results.

5 Results

Twenty participants (seven female, 12 male, one non-binary, M=25.5 years old, SD=5.5 years) based in North America were recruited

[2] https://dovetail.com/

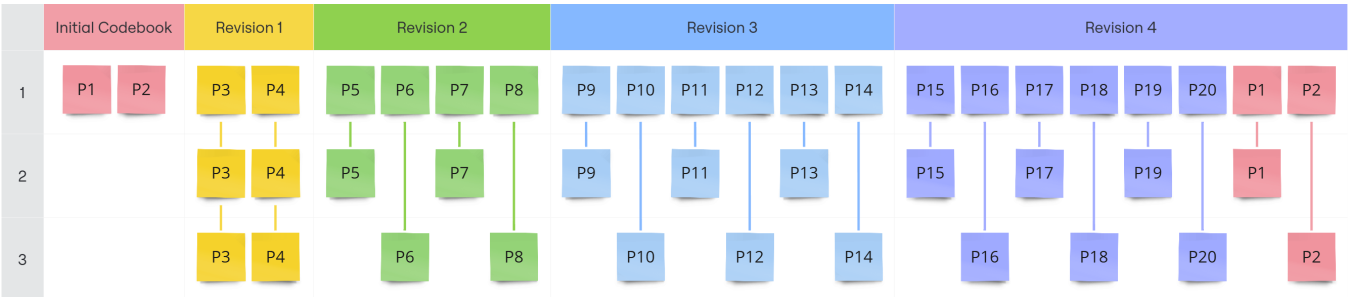

Figure 2: Diagram to visualize the coding process. Vertical connections mean that the coders coded the same transcripts, discussed any coding differences, and agreed on a final coding. At least two coders coded all transcripts.

for our study. All participants had completed some form of post-secondary education (one up to an associate degree, 11 up to a bachelor's degree, and eight up to a postgraduate degree); 19 participants self-identified as a student, while one participant self-identified as being employed. Additionally, all participants either had experience with video games and/or with AI.

5.1 Session Recordings

After spending an average of 4m 40s (*SD*=2m 05s) reading and familiarizing themselves with the rulebook, participants played two rounds of Joker and completed two semi-structured interviews. When asked during the second interview which condition they preferred to experience as a new player, 12 participants preferred the *AI-Assisted* condition, four participants preferred the *Self-Guided* condition, and four participants did not have a distinct preference.

Table 2: Average, minimum, and maximum times based on study phase, outcome, and condition.

	Mean	SD	Min	Max
Reading Rulebook	4m 40s	2m 05s	1m 05s	9m 25s
Playthrough 1	7m 50s	5m 28s	2m 31s	25m 34s
Interview 1	5m 50s	1m 36s	3m 46s	9m 51s
Playthrough 2	6m 45s	5m 19s	0m 34s	21m 31s
Interview 2	17m 31s	3m 24s	11m 54s	22m 21s
Outcome: Win	9m 45s	5m 07s	4m 08s	21m 31s
Outcome: Loss	6m 14s	5m 11s	0m 34s	25m 34s
Cond: Self-Guided	8m 16s	5m 41s	0m 34s	25m 34s
Cond: AI-Assisted	6m 19s	4m 57s	0m 39s	21m 31s

Each round of gameplay lasted on average 7m 18s (*SD*=5m 21s). The first interview took an average of 5m 50s (*SD*=1m 36s), while the second interview took an average of 17m 31s (*SD*=3m 24s). See Table 2 for the full time statistics, Table 3 for the win percentages in each condition and playthrough, and Figure 3 for how often participants followed suggestions during the *AI-Assisted* condition.

The within-participants study design means that any learning that occurs or strategies that develop in the first game could carry over to the second. Indeed, the difference between the combined

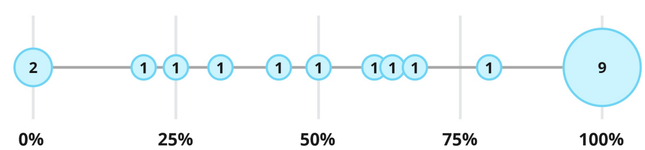

Figure 3: Visualization of the frequency participants followed suggestions during the *AI-Assisted* condition, ranging from 0% (the participant never followed suggestions) to 100% (the participant always followed suggestions).

win percentages displays a slight increase from the first game to the second game (25% to 35%). The win percentage also increases from 20% to 50% for those starting with the *Self-Guided* round and playing the *AI-Assisted* condition afterwards. However, the win percentage actually decreases among participants who played the *AI-Assisted* condition before the *Self-Guided* condition (30% to 20%). Additionally, all participants who won their first game but lost their second game played the *AI-Assisted* condition first. Finally, eight of the nine games where participants followed suggestions 100% of the time ended in a loss.

Table 3: Participant win percentages. There were 10 games per condition–game pair (40 total).

	Game 1	Game 2	All Games
Self-Guided	20%	20%	20%
AI-Assisted	30%	50%	40%
Combined	25%	35%	30%

5.2 Semi-Structured Interviews

In this section we present the six themes we identified within the data through thematic analysis (summarized in Table 4).

Theme 1: Players prefer to learn through lived game experience. All participants (n = 20) preferred to learn through hands-on experience with a game. Some even preferred to jump into gameplay before experiencing any onboarding—in these cases, participants

Table 4: Table of the six main themes extracted from the data alongside their related subthemes, separated by research question.

Themes		Subthemes
(1)	Players prefer to learn through lived game experience	*Losing is learning* *Players gain lived experience through similar games* *Onboarding should feel like part of the game* *Onboarding should not overstay its welcome*
(2)	Upfront guidance in onboarding is necessary for learning	*Structure improves onboarding experiences* *Low-quality upfront guidance is a reason to quit*
(3)	AI can provide onboarding experiences tailored to individual players	*Tailored onboarding enhances discovery*
(4)	AI-supported guidance should prioritize player agency	*Players want to rely on their own abilities* *Low sense of agency in onboarding frustrates players* *AI-supported guidance should be opt-in*
(5)	AI-supported suggestions in video games are safe to use	*Accurate AI-supported suggestions are trustable* *Transparency increases trust in AI*
(6)	Suggestions remove players' incentive to actively learn	*"Give a fish" vs. "teach to fish"* *Players need to understand why an AI makes a suggestion* *Reduced cognitive load reduces learning*

wanted the ability to choose when they would receive guidance: "*I don't read rules, I just start playing and then just figure out how to play.*"***(P18)***. It was important to them and their learning experience that they could try to learn on their own first, but that they still had onboarding methods such as tutorials or rulebooks they could return to when they needed help: "*Usually when I would play a game, [...] I would just try it out for a couple of rounds and then if I keep losing, then maybe I go back to the rulebook and see what's going on.*"***(P17)***. Additionally, participants expressed a preference for interactive learning when going through video game onboarding. In particular, they mentioned methods such as trial-and-error, improving through practice, and training modes. All of these methods are designed to target specific gameplay mechanics.

Subtheme: Losing is learning. Most participants (n = 14) did not perceive failure as negative during the learning process. While they were still primarily motivated by the desire to succeed, they pointed out that losing provided them with an opportunity to assess their knowledge of the game and improve—for example, one participant still felt accomplished in their loss because they learned more about the game in the process: "*I felt like, okay, even if I lost, I had some sense of accomplishment that okay, I understood the game better maybe.*"***(P13)***. Other participants also thought of failure as a natural part of the learning process and felt it was important for new players to accept that they might fail if they wanted to use their failure as a learning experience.

Subtheme: Players gain lived experience through similar games. Video games often expect new players to already have some familiarity with basic game controls, especially if the relevant knowledge is applicable across game genres: "*Newer games expect you to have some proficiency in terms of moving around and controlling the camera and so on.*"***(P17)***. In Joker, many participants (n = 15) drew upon their knowledge of existing game elements, such as playing cards and chess, and applied their existing knowledge of these elements to learn. Some participants used their prior experience to analyze their performance in Joker: "*The moving patterns were so much similar to chess, and in a chess game, I wouldn't have done this.*"***(P1)***. This shows not only recognition of a familiar mechanic in an unfamiliar game, but also successful application of knowledge to learn what to do—or in this case, what *not* to do—in a future game. Lived game experience is therefore not limited to individual games. It is instead a collective experience that players apply to all games they play.

Subtheme: Onboarding should feel like part of the game. Boredom was frequently mentioned in relation to the length of onboarding. Some participants (n = 11) who wanted shorter onboarding experiences attributed this desire to becoming disengaged when trying to finish a game's tutorial. Participants wanted onboarding to still feel like a game, not a classroom, and wanted the learning process to feel as fun as possible within the constraints of learning the game's mechanics. These participants pointed out that they played games to *play a game*, not to read: "*[The] onboarding process, first it has to be fun. Reading the rulebook has no joy in it.*"***(P4)***. They preferred lived, interactive teaching methods over text-based learning methods to increase their sense of engagement during the learning process.

Subtheme: Onboarding should not overstay its welcome. A majority of participants (n = 17) also showed a strong preference for shorter onboarding and expressed a desire to get into "real gameplay"—or, lived experience—as soon as possible. Some participants wanted onboarding to last as short as 1–2 minutes. Other participants mentioned they would skip tutorials if the option was provided to them. However, participants also recognized that different genres of games have different onboarding needs. They did not mind a longer onboarding process if they felt it was necessary to understand a game's mechanics: "*If I'm playing [...] a car simulator, I want to get into a car as quick as possible. But if I'm playing an RPG that's gonna take 100 hours, I don't mind having to sit through 10, 15 hours of onboarding.*"***(P17)***. This highlights the idea that onboarding is proportional to the game itself. Participants did not expect every game to immediately provide them with opportunities for lived experience, but rather that onboarding would only delay their lived experience for an amount of time relative to the game's complexity and length.

Theme 2: Upfront guidance in onboarding is necessary for learning. All participants (n = 20) expressed a desire for upfront guidance during the onboarding process. Even when participants wanted the freedom to explore a game, they also pointed out that it is impossible to properly explore without direction. In the context of Joker with its rulebook-only guidance, some participants immediately opened the rulebook when the game started even though they had just finished reading it moments prior. This lack of guidance in the initial moments of gameplay left participants wondering what they were supposed to do first: "*I'd say I had freedom, but it was kind of useless because I didn't know how to strategize or what to do. So I feel like I could do anything, but it wasn't really going anywhere.*"***(P16)***. Furthermore, participants used the AI's suggestions not only as instructions to follow, but also as encouragement to interact with the game. Displaying the suggested cards visually "pulsing" helped participants understand how to use their cards to create a new unit and how card combinations connected to the descriptions in the rulebook.

Subtheme: Structure improves onboarding experiences. Some participants (n = 10) expressed a need for not just upfront guidance, but also a greater amount of structure during the onboarding process. The absence of a traditional tutorial in Joker overwhelmed many participants and left them unsure of how to manage their cognitive load: "*A more guided tutorial would have made a lot more sense, versus just bombarding you with all the information and expecting you to remember it as you're playing the game.*"***(P14)***. Note that *structure* is used here as a different concept than *freedom*; participants mainly felt a lack of freedom in games when they could not do what they wanted in a particular moment (i.e., they could not skip a tutorial, or they had to perform a specific action to proceed rather than have the freedom to make progress independently). Their idea of structure instead refers to the method of translating information from the game to the player rather than the concept of restricting a player's freedom.

Subtheme: Low-quality upfront guidance is a reason to quit. Finally, some participants (n = 7) felt that if a game's onboarding was too boring or too long, they might quit playing the game altogether: "*If it's more than five minutes, I don't think I would play it.*"***(P2)***. These participants treated onboarding as a preview of the actual game. A boring tutorial implied a boring game, and therefore they could not trust that their experience would improve after they completed the onboarding process: "*It has to be fun or people may get worried. People may just choose not to believe in the game is going to be good and just abandon that.*"***(P4)***. This shows the impact of onboarding on a new player's first impression of a game, as well as how vital it is to create engaging experiences that attract and retain new players from the beginning. Games must make sure that the onboarding process provides players with an experience that makes them want to play more of the game, not less.

Theme 3: AI can provide onboarding experiences tailored to individual players. Most participants (n = 14) felt that AI had the potential to make onboarding more dynamic: "*In older sorts of games, you would have a very constrained tutorial where [there] is a hard-coded scenario and you just go through it. But with AI I feel it can create a much more dynamic setting.*"***(P5)***. They also recognized that individual onboarding preferences are not easy to generalize across different types of players, and that it is important to support as many types of players as possible. Other participants brought up accessibility—for example, the impact of dyslexia on text-based onboarding—and felt that giving players access to multiple onboarding methods allowed them to choose which method worked best for them. Additionally, participants thought that using AI to personalize each player's onboarding experience would reduce the friction from games not meeting their onboarding needs: "*If you use AI, it possibly can just personalize instructions to the player. Because if you see this player losing every time, maybe you can give them other instructions.*"***(P18)***. Some participants also liked the idea of an AI guidance system that was tailored to them as an individual. They described AI systems that would learn alongside them as they played and make suggestions that matched their playing style. Not only do players want onboarding to be tailored at a broad level, such as through different learning methods or accessibility controls, but they additionally want onboarding to be tailored at the narrow level of individual player differences.

Subtheme: Tailored onboarding enhances discovery. As well, some participants (n = 6) felt that AI-supported guidance was most useful at the beginning of a game because it could guide players if they did not know what to do next: "*When you have no clue what to do, you may think that okay, maybe there is a reason that this computer is suggesting such a move.*"***(P1)***. Providing guidance through decision paralysis subsequently helps players discover more of the game rather than grow frustrated with their perceived lack of progress. Participants also felt that AI-supported guidance could promote curiosity alongside discovery if its suggestions were presented in an indirect manner. They wanted the AI to nudge them in the right direction instead of giving them an answer right away. With this method, tailored AI-supported onboarding can provide guidance based on what an individual player needs at a certain point in time while still leading them to discover more of the game on their own.

Theme 4: AI-supported guidance should prioritize player agency. All participants (n = 20) felt that AI-supported guidance should be implemented in games as an additive onboarding method (i.e., a temporary "scaffolding" that should be removed once a player surpasses the need for additional support). They pointed out that existing games often provide guidance only during onboarding and expressed that they would not feel like they were playing the "real" game until the AI's suggestions were removed: "*In general, most* *games that we play, [suggestions] don't really occur in the gameplay as much. But if so, they usually occur right in the beginning of the game just for a few minutes, and then they're gone."(**P6**).* Some participants even preferred if the AI could be removed after playing for a few minutes, while others wanted to disable forms of guidance as soon as they possibly could.

Subtheme: Players want to rely on their own abilities. A majority (n = 18) of participants' main motivation for removing AI-supported guidance was the desire to rely on their own abilities to succeed: "*I should feel that I am in charge of making decisions as [a] player."(**P10**).* Many of the participants who enjoyed the *Self-Guided* condition more than the *AI-Assisted* condition attributed the difference to their perceived agency—their actions were the sole reason why they had won or lost a game. Some participants felt that even when they won a game, they did not really deserve it if they had used the AI's suggestions. Even if participants did not achieve optimal results, the challenge of testing themselves and improving their skills was a more important motivator than just winning the game. This lack of agency was not a lack of freedom for players to do what they wanted, but rather the removal of what incentivizes players to play video games in the first place.

Subtheme: Low sense of agency in onboarding frustrates players. Some participants (n = 9) also pointed out that onboarding could become frustrating when they felt it took away too much of their agency. This frustration often occurred in situations where players did not have the freedom to make their own decisions, or when players were forced to complete onboarding even if they already felt ready to play: "*If [...] they treat everyone as completely new to the game, I kind of get frustrated."(**P4**).* These participants also felt that while AI-supported guidance was more freeing than mandatory choices, the prompt automatically appearing at the beginning of their turn actually provided them with a lesser amount of freedom. They felt that providing the suggestion right away did not give them the opportunity to think for themselves.

Subtheme: AI-supported guidance should be opt-in. Many participants (n = 15) wanted to control whether they had AI-supported guidance or not. The most common participant suggestions on how to implement an AI-supported guidance method were for the AI system to only provide guidance if the player actively requested it, or for the AI system to provide guidance only after a certain amount of time had passed: "*Maybe there should be [an] option button. Where you show a turn hint, click on hint and show you something, [...] or maybe after a couple of seconds if something is not happening and then hints appear."(**P10**).* These kinds of opt-in implementations retain players' freedom to access additional information while also increasing their freedom to choose whether they want to use a suggestion at all. Maintaining the feeling that AI-supported guidance is voluntary across all aspects of the system's implementation helps to maintain players' perceived level of agency within the game.

Theme 5: AI-supported suggestions in video games are safe to use. A majority of participants (n = 19) believed AI-supported suggestions in the context of video games were inherently usable (i.e., that a player could follow a suggestion to achieve a desired result in-game): "*I would assume the suggestion it was giving me is a good suggestion for the specific state of my game."(**P16**).* Participants also felt that because an AI system is capable of manipulating large quantities of data quickly, its results would be more accurate. One participant mentioned that they expected an AI to be "more correct" than a human because it would have data to support its conclusions: "*Because we have such an expectation of AI to always be more correct [...] I would expect it to be pretty bang on."(**P11**).* The context of video games also influenced participants' perceptions of AI systems. Participants felt that if a system was designed for a game and limited to that game's context, then there was little risk of it affecting other aspects of their lives: "*I think I trust the system here because it's not something that is related to me academically or it is not something which is serious to me. This is for fun, right?"(**P13**).* No participants were concerned about using Joker's AI-supported suggestion system; the context of a video game did not increase any participant's concerns with AI, and in some cases it even decreased them.

Subtheme: Accurate AI-supported suggestions are trustable. Most participants (n = 14) also felt that the competency of AI-supported suggestions could influence their trust in the overall system. These participants believed that recent advancements in AI technology demonstrated how a computer's abilities can surpass a human's. Therefore, while most participants were cognizant of the fact that absolute perfection is not a realistic expectation for AI-supported suggestions, they still expected accurate suggestions anywhere from 60%–90% of the time. Many participants felt that an inaccurate suggestion would cause them to distrust future suggestions, and some participants indicated they would stop using the system altogether if the AI caused them to lose: "*[Imperfection] definitely lowers my trust in the systems, and that might be a reason that next time I would double check the answer I get from the AI."(**P7**).* This demonstrates a relationship between the accuracy of an AI-supported suggestion and a player's level of trust in the system, which in turn relates to perceived usability. If an AI-supported suggestion is *accurate*, then a player is more willing to *trust* that suggestion and *use* it during a game.

Subtheme: Transparency increases trust in AI. Many participants (n = 13) thought that an increase in transparency would increase their trust in an AI system: "*If I know why they suggested these cards then maybe if they are trying to help me, then I can trust them."(**P3**).* They felt that if they could understand the "thought process" behind the system's suggestion, then they could compare it with their existing knowledge to determine whether the AI's suggestion was trustable: "*You would build trust only once you understand what the system is trying to do for you, right?"(**P5**).* Even if participants thought that an AI knew more than them as a human, they felt they could only increase their trust beyond their initial threshold if an AI system provided reasoning for its decisions. This shows that players' desire for transparency in an AI-supported system is not just to increase their knowledge of a game, but also so they can build a greater level of trust in that system overall.

Theme 6: Suggestions remove players' incentive to actively learn. Almost all participants (n = 18) felt that receiving a suggestion negatively impacted their incentive to learn during the game. Some participants did not realize that the suggestions were optional and followed the AI's suggestions throughout the entire game. This blind adherence meant that the participants did not actively interact with the game and its rules to discover mechanics for themselves: "*Since the AI was showing me what kind of troops I should play or I can play, it took away my curiosity.*"*(**P9**)*. A few participants commented that they did not understand why the AI had made a suggestion *after* they had followed it. For example, one participant read the description of the unit the AI suggested and did not understand its ability. Despite this, they still created the unit even though they had no idea how to use it. As a consequence of this lack of active interaction, players also did not increase their understanding of the game's rules by using the suggestions. One participant felt there was no benefit to having suggestions available because they did not think about the game when they followed a suggestion: "*Because [...] someone told me, 'okay, pick this one, pick this one drop there', that's mechanical. There isn't any thought process in it.*"*(**P10**)*. Other participants echoed this concept of feeling "mechanical." Some commented that it might as well have been the AI playing the game, not them.

Subtheme: "Give a fish" versus "teach to fish." Most participants (n = 16) felt that receiving suggestions did not set them up for future success. When they blindly followed a suggestion without thinking on their own, they did not actually learn why the AI system had suggested that combination: "*I was using the suggestion card, but I didn't pay attention to how they are created. So my learning experience in the creation of units doesn't improve.*"*(**P8**)*. Another participant compared having suggestions available to not using all of their senses. They felt that when the game did not provide them with support, they were forced to think about the game and form a proper strategy: "*If you have suggestions, you don't use all your senses [...] but if you're just on your own, [...] then you actually start thinking that, okay, what should I do if I have to go in?*"*(**P13**)*. AI-supported onboarding cannot just give players answers; it must additionally make sure it incorporates *teaching* within the suggestion process.

Subtheme: Players need to understand why an AI makes a suggestion. Many participants (n = 13) felt that receiving a suggestion with no explanation did not help them learn the game. Even if they wanted to understand it, the game itself did not provide them with an avenue to learn: "*If the AI does not give the reason why [it's] making this suggestion, it will not help the player to know how to play it in a good way.*"*(**P15**)*. One participant emphasized that understanding an AI would allow them to evaluate their own understanding of a game alongside the AI's suggestion: "*Why are they suggesting it versus what I'm gonna do? So, is their suggestion actually better than what I want to do?*"*(**P11**)*. They wanted to learn actively, but without access to enough information regarding their decision, they were unable to make comparisons between their strategies and the AI's. This again plays into the idea of *giving* versus *teaching*: suggestions without explanations reduced players' incentives to think for themselves and did not support the players who wanted to learn from such explanations.

Subtheme: Reduced cognitive load reduces learning. Some participants (n = 8) explained that they experienced less mental effort when they were provided a suggestion because they did not need to think about the rules beforehand: "*I'd say [the effort] was less because I had something to start with.*"*(**P5**)*. Participants also felt the game was easier when they were provided with additional support, despite the fact that the difficulty had not changed. However, while reducing new players' cognitive load is a worthy goal for AI-supported onboarding systems to target, this subtheme also highlights a potential risk of too little cognitive load. If participants do not need to think about their actions in-game at all, then they are not actually learning.

6 Discussion

The results in Section 5 summarize our findings on player expectations for both general onboarding experiences and AI-supported onboarding, as well as the impact of AI-supported suggestions on player experience. In this section we expand on these findings to further discuss the interpretation and application of our results, and we additionally highlight important takeaways for video game designers to consider when implementing AI-supported systems within onboarding.

6.1 RQ1: What do players expect from an ideal onboarding experience in video games?

Theme 1 suggests that lived game experience is the most preferred learning method for new players. Existing literature supports this concept: one of the most significant onboarding challenges is engaging players during their initial gameplay experience [13, 41]. While designers might feel the urge to provide players with as detailed instructions as possible to fully prepare them before they start the "real" game, players in our study showed a clear preference for *interaction* during onboarding—i.e., *lived experience*. This makes intuitive sense: if players perform an action in-game, they are involved with the input and the output simultaneously. There is a clear difference between telling a player to press a button to attack versus the player pressing a button and attacking. Directly involving the player in the learning experience makes it easier for them to understand how their actions influence what happens in the game. This finding is in line with prior work by Gajos and Mamykina [24], who found that the best learning gains are achieved by engaging with the subject matter and arriving at decisions through one's own thought process. However, **Theme 2** also identifies that guidance is a necessary part of onboarding. Indiscriminately sacrificing guidance in the name of lived experience is not beneficial to the learning process. Players will always need some amount of upfront instruction—though not necessarily everything—so that they can familiarize themselves with the basics of the game. Despite their more restrictive nature, tutorials [56] can meet this need for guidance when they are well-designed, and they additionally are what players expect to receive at the beginning of a game.

6.1.1 *Let Them Play, Let Them Lose, Let Them Cook.*

Theme 1 identifies how players use all types of lived experiences to improve their understanding of games. Many games share common knowledge that is not always necessary to teach explicitly. Not every game mechanic deserves the same level of detail, so designers must prioritize unfamiliar mechanics during the onboarding process. For example, Joker does not spend time explaining the basic characteristics of playing cards because most people are familiar with card suits and values. Focusing on a game's unique mechanics can also contribute to a memorable and engaging onboarding experience, which in turn will help avoid player perception of onboarding being boring or unnecessary.

Additionally, even though game designers may want players to experience as much success in-game as possible, players are perfectly willing to use losing as a learning method. This finding aligns with existing research on how lived experiences of failure within interactive media increase cognitive engagement more than observed experiences [31]. **Theme 1** as a whole shows a perspective of gradual learning, even in losses, because each lived experience contributes to a player's overall knowledge regardless if they win or lose. Again, there is a difference between telling a player "you lose if the enemy checkmates your king" and having a player experience a loss by checkmate. If players understand the reason they lost, then the loss itself becomes a stepping stone on their journey to in-game success. In the same way that experiencing a thrilling victory motivates players to play another round, making a game-ending mistake is the strongest motivator for them to never make that mistake again.

Players also value onboarding that is *fast* and *fun*. **Theme 1** identifies boredom as the primary reason that players skip onboarding methods such as tutorials—they either take too long or are not as engaging as the actual game. When learning feels just as fun as gameplay, players are much more willing to engage with onboarding methods. However, players only prefer brief onboarding methods when they are able to learn the rest of a game by playing it. If the complexity or length of a game demands a more in-depth onboarding experience, players are willing to sit through a longer onboarding session to make sure they are prepared to play. While there is no exact method to calculate what length of onboarding is most appropriate, it is important to make sure that a game's onboarding experience is kept proportional to both its complexity and its overall length.

6.1.2 *Guidance is the Face of a Game.*

Theme 2 also demonstrates the importance of upfront guidance during the onboarding experience. Players seek structured guidance from all types of onboarding: the additional instructive support of additive onboarding [17], the simplified learning environments of subtractive onboarding [29], and the contextually relevant advice of real-time onboarding [46] all provide forms of structure to improve a player's learning experience. This structure familiarizes players with the rules of a game and builds their confidence with game mechanics. Additionally, structured information can help video games provide players with feedback on their progress. Without some type of structured guidance method, it is difficult for new players to track if they know "enough" about the game to be successful. However, this theme also cautions that if a game's upfront onboarding experience is low-quality, then that initial experience is also enough reason for players to quit. Even though players recognize the importance of upfront guidance, they also place importance on games delivering that guidance in an engaging and interactive way. Our results confirm prior work [13] and underscore the necessity to create an enjoyable onboarding experience. A game's onboarding method acts like a trailer for the "real" game, so if players do not enjoy the initial onboarding experience, then they have no reason to believe that the real game will be any different.

6.2 RQ2: What do players expect from AI-supported onboarding systems in video games?

Players have two key expectations for AI-supported onboarding systems: *personalization*, discussed in **Theme 3**, and *agency*, discussed in **Theme 4**. These expectations demonstrate an optimistic outlook toward the implementation of AI in video game onboarding. Players believe that AI systems are capable of providing them with support that is tailored to their own needs as individuals. However, they also do not want games to include AI-supported guidance at the expense of their agency as a player. **Theme 4** also emphasizes that players perceive AI-supported guidance as a temporary support. Even though the system itself is a real-time support method, the temporary implementation of an AI-supported onboarding system is similar to additive support methods such as scaffolding. The end goal of scaffolding is to eventually remove the extraneous information once a player is ready to play on their own [17, 19]; temporary guidance from an AI system in the early stages of a game fulfills the same purpose. Ensuring that players are able to *choose* when they use AI-supported guidance—and, more importantly, that they are able to choose not to use it at all—is crucial for maintaining a player's sense of agency during the learning process.

6.2.1 *Onboarding is Not One-Size-Fits-All-Players.*

Theme 3 demonstrates that players want an increased level of personalization in their onboarding experiences that they currently do not receive from static methods. As Lai [35] discusses, personalized guidance is a highly desirable benefit of incorporating AI-supported systems into learning experiences. We found that players believe AI-supported player profiles [57, 60] have the most potential to support dynamic onboarding because an AI system could adapt to their play style and provide them with guidance methods that match how they best learn. Tailoring onboarding to players as individuals would also alleviate frustration caused by static onboarding methods because AI systems can consider player differences, such as experience and aptitude, that static onboarding systems cannot. For example, players feel that AI-supported guidance would reduce the number of times they would get "stuck" on how to proceed because the system could read the situation and provide a possible direction for them to investigate. Additionally, players believe that AI can provide more dynamic onboarding experiences through adaptive opponents [47, 49]. One restriction of static onboarding involves opponents that are programmed to respond in a specific way. In these scenarios players are forced to make certain actions to continue through a linear chain of events. Adaptive opponents instead have the potential to respond to the player's choices while still finding opportunities to teach the required actions. This not only reduces the amount of restriction present in a game, but also increases a player's sense of agency during the onboarding process.

6.2.2 *Agency is the End Goal.*

Theme 4 identifies the clear prioritization of player agency within video games: players want to feel that *they* are in control of their in-game actions, not the AI. Agency is part of what motivates players to engage with games at all. The appeal of video games is that they are interactive media. Unlike static media such as movies or books, the player is directly involved with what happens in a game. When the game itself tells players exactly what to do and when to do it, the appeal of interaction is removed entirely. Section 2 examined how restrictive onboarding methods such as tutorials can negatively impact the onboarding experience [1, 41, 48] through reduced player agency, especially when tutorials have mandatory interactions that prevent players from choosing what they actually want to do. Even when players are "stuck," they want to use their own abilities to overcome these challenges. Success is meaningless if they need to rely on external support to achieve it.

Theme 4 also expands on the concept of player agency in two ways: freedom of choice and freedom of information. Since suggestions are voluntary by definition, players feel AI-supported suggestions provide a greater amount of freedom than tutorialized support methods because they can choose what to do with a suggestion after they receive it. However, Joker's method of providing a suggestion at the start of every turn did not increase freedom of choice. Players not only need the freedom to use suggestions *how* they want, but also to receive suggestions *when* they want. Providing an optional suggestion when the player does not want it cannot increase their freedom of choice because they did not choose to receive the suggestion in the first place. Players additionally feel that suggestions can provide increased freedom of information when given at appropriate times. For example, when a player needs to make a complex decision, suggestions can add valuable information for them to consider alongside their existing knowledge of the game. Preserving the freedom of information during onboarding helps mitigate player frustrations with decision-making while simultaneously enabling greater access to information when players want additional support.

6.3 RQ3: How does the presence of an AI-supported suggestion system affect a player's onboarding experience?

People who play video games are no strangers to AI. As discussed in Section 2, video games have implemented various types of AI-supported systems for decades [59]. This familiarity lends support to the findings of **Theme 5**, where personal experience with AI in existing games influenced participants' expectations for Joker's suggestion system. Video games are "for fun," so implementations of AI-supported suggestion systems within onboarding are perceived as novel—systems designed to fulfill a limited purpose with no potential to impact a player's life outside their contexts.

6.3.1 The Trust Experience. Since players inherently expect an AI system in a game to function "properly," they enter games with an existing level of trust dependent on the quality of an AI-supported system. **Theme 5** describes how low-quality results impact trust in AI-supported onboarding systems and demonstrates that while players may start with an existing quality-trust relationship, even a single low-quality output has the potential to destroy it. However, the opposite is also true: starting with an existing amount of trust in an AI's quality means that video games do not need to take the time to build trust in the same way as other AI implementations. The rise of generative AI in recent years has sparked much debate regarding the legality, ethics, and privacy of AI-supported systems [23], but at the moment the three main types of AI in video games [58, 60, 61] generally do not seem to fall under the same scrutiny as language models or image generators.

Theme 5 also demonstrates an amount of trust on the human-to-human level between players and game designers. Players expect designers to create good games; designers expect players to interact with their games. It is actively detrimental for designers to create an AI-supported onboarding system that causes the player to lose—players waste time following the AI's suggestions, designers waste time making the system, and the critically important first-time experience [13] is wholly negative. This sort of symbiotic relationship between players and designers reinforces trust and provides an explanation as to why video games are held to different standards than other AI-supported systems. If players perceive that video games have less incentive to violate their ethical standards than other implementations of AI, then there is less of a reason to distrust implementations of AI in video games. In this regard, video games seem to be less affected by common criticisms associated with the use of AI for learning purposes [32, 42]. However, players are also hesitant to blindly trust AI, even if they feel that the people who made the AI are trustable. Providing a reason for the output of an AI—such as *why* an AI system made a suggestion—not only builds a player's trust through increased transparency, but additionally creates another avenue they can use to learn.

6.3.2 The Cognitive Experience. The AI-supported onboarding system implemented in Joker is rooted in cognitive load theory [40]. **Theme 6** identifies a relationship between reduced cognitive load and the presence of the AI's suggestions, where some participants even perceived a difference in difficulty between conditions that did not exist. Managing large amounts of information is the core concept of cognitive load [38], which contributes to mental demand and can cause frustration if a player cannot handle the load. However, the win percentage data shown in Table 3 also supports the primary idea of **Theme 6**: that suggestions did not actually help participants learn. While measuring learning was not a goal of this study, it is interesting that the suggestion-based onboarding system in Joker did not seem to have supported participant learning. In fact, eight of the nine games where participants followed the AI's suggestions 100% of the time ended in a loss. The win percentage also decreased among all participants who played the *AI-Assisted* condition first (30% to 20%), and all participants who won their first game but lost their second game played the *AI-Assisted* condition first. By contrast, the win percentage of participants who played the *Self-Guided* condition first increased (20% to 50%). This suggests that participants who relied on suggestions in their first game may not have learned from them or were unable to translate their experience to the *Self-Guided* playthrough. This reflects Wang et al. [54]'s findings on involvement during the learning process: even though participants were involved in making card combinations, passively following suggestions did not increase their in-game performance. Again, while the AI's suggestions did influence how players perceived Joker's cognitive complexity, they did not demonstrate that reducing cognitive load provided players with a better onboarding experience. It is still important to make sure new players can manage the amount of information they need to process, but AI-supported onboarding must make sure to find a careful balance between *help* and *hindrance* during the learning process.

Theme 6 also demonstrates that players want AI-supported guidance methods to provide a reason alongside each suggestion. If they are told to make an action, then they want to know *why* the action is good so they can evaluate if the AI's suggestion connects to their existing knowledge. Without the "why" component, it is impossible for players to perform a complete evaluation—are they moving a piece to set up for checkmate many turns in the future or only to get it out of danger? Providing a clear reason also helps players better understand if the AI is making suggestions that align with their own plans. However, since providing a reason for a suggestion also increases the amount of information available to a player, it is important that explanations have an appropriate level of complexity [53] so as to not contribute to cognitive overload. An optimal explanation in an AI-supported onboarding system should improve a player's learning experience, not impair it.

6.4 Game Design Considerations

To summarize our discussion, we present four actionable design recommendations game designers should consider when including AI-supported onboarding systems in their games:

1. **Personalize.** We recommend using the flexibility of AI-supported systems to fill the learning gaps static onboarding cannot.
2. **Build for Agency.** We encourage providing players with a degree of agency in AI-supported onboarding that is equal to or greater than existing onboarding methods.
3. **Foster Trust With Reliability.** We suggest giving players reliable ways to build trust in the guidance from AI-supported onboarding systems.
4. **Avoid Overinvestment.** We propose investing an amount of resources into AI-supported onboarding that is appropriate for a temporary learning system.

6.5 Limitations and Future Work

As our participant demographics were very homogeneous, we acknowledge that there is no guarantee that the presented results are applicable to a general population. We also acknowledge that some amount of bias is inevitable when using within-participants designs. Since this study focuses on player experience, it was important that participants could compare their experiences with the two game versions during the interview. However, we also note that two participants did not notice the AI's suggestions in the *AI-Assisted* condition, so they therefore could not fully compare their two experiences. To address this, future studies examining the impact of AI-supported onboarding systems could consider between-participants study designs instead.

Additionally, while Joker's suggestion system was sufficient for this study, the use of machine learning algorithms could allow AI-supported onboarding systems to become more individualized and adaptive. Joker's decision-tree-like implementation was still presented to participants in the same way that a machine learning algorithm would have been, but future studies on AI-supported onboarding systems should compare different types of AI systems to explore their feasibility, performance, and use cases. It may be necessary to conduct longitudinal studies to assess how AI-supported onboarding systems evolve and improve over time as they adapt to individual player behaviours. Alternatively, future research could test dynamic adjustments within AI-supported guidance systems based on real-time player performance and examine how to best implement AI-supported systems in onboarding methods other than just-in-time suggestions. This could involve developing algorithms that detect when a player needs more or less guidance. It may also be useful to study the impact of various adaptive onboarding methods on the long-term retention of skills and knowledge acquired through AI-supported onboarding.

7 Conclusion

This study implemented an AI-supported suggestion system in the custom-built video game Joker to examine the impact of AI-supported onboarding on player experience. Our analysis found that players primarily learn from lived experience with games—including losses, prior experiences, and common knowledge—and prefer to take an active role in their learning experience. Accordingly, players expect AI-supported onboarding systems to provide guidance personalized to them as individuals that facilitates engaging learning experiences while still providing enough upfront structure to support them when they feel confused, lost, or overwhelmed. However, to maintain player agency during the onboarding process and prevent the frustration that occurs when onboarding does not give players the freedom to play games in their own way, AI-supported onboarding must also let players control how and when they receive guidance. Finally, while we found that players believe AI-supported onboarding systems in video games are safe to use, we also found that the transparency of a system influences players' trust in its results as well as the system's ability to support active learning. AI-supported guidance that does not provide a way for players to understand its decisions hinders players who are trying to learn from it. This can even lower players' overall trust in the AI. Thus, AI-supported onboarding must go beyond simply instructing players on how to play the game. Instead, it should offer transparent guidance that increases their understanding of the game and encourages active engagement with the game's mechanics. Ultimately, effective video game onboarding must incentivize players to continue learning throughout their onboarding experience.

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A Interview Script

A.1 First Interview

(1) **What are your thoughts on the game you just played?**
  (a) Was there anything you specifically liked? Why?
  (b) Was there anything you specifically disliked? Why?
  (c) What are your thoughts on:
    (i) The rulebook?
    (ii) Placing the joker?
    (iii) Combining cards?
    (iv) Moving units?
    (v) Attacking enemies?
  (d) How much effort did it take you to play the game?
    (i) Why do you think that is?
  (e) What are your thoughts on the difficulty of the game?
  (f) How much freedom did you feel you had? Why?
    (i) What parts of the game affected your sense of freedom?
  (g) What are your thoughts on the amount of information the game provided you?
  (h) How well did the game help you learn to play? Why?
  (i) How confident did you feel after playing? Why?
  (j) How interested are you in playing the game again? Why?

A.2 Second Interview

(1) **What are your thoughts on the game you just played?**
  (a) Was there anything you specifically liked? Why?
  (b) Was there anything you specifically disliked? Why?
  (c) What are your thoughts on:
    (i) The rulebook?
    (ii) Placing the joker?
    (iii) Combining cards?
    (iv) Moving units?
    (v) Attacking enemies?
  (d) How much effort did it take you to play the game?
    (i) Why do you think that is?
  (e) What are your thoughts on the difficulty of the game?
  (f) How much freedom did you feel you had? Why?
    (i) What parts of the game affected your sense of freedom?
  (g) What are your thoughts on the amount of information the game provided you?
  (h) How well did the game help you learn to play? Why?
  (i) How confident did you feel after playing? Why?
  (j) How interested are you in playing the game again? Why?

(2) **How would you compare your experiences with the two versions of the game you played?**
  (a) Did you notice any differences between the two versions?
  (b) Did you notice any similarities between the two versions?
  (c) Did you find yourself playing differently in the second version compared to the first?
    (i) If so, why do you think that was?

(d) How would you compare the effort it took to play each version?
   (i) Did one version take more effort than the other? Why is that?
(e) How would you compare your confidence after playing each version?
(f) Did you enjoy one version more than the other? Why or why not?
(g) Which version would you prefer to experience as a new player? Why?

(3) **What are your thoughts on the suggestions the game provided you in the [first/second] game?**
   (a) Did you like or dislike them? Why?
   (b) How would you compare the difficulty of the two versions?
      (i) If the difficulty is different between the two, why is that?
   (c) Did the suggestions affect your sense of freedom? Why or why not?
      (i) Are suggestions different from actually performing the action for the player? Why or why not?
   (d) Did the suggestions affect your learning experience? If so, how?

(4) **How would you compare the gameplay of the two versions?**
   (a) Did it feel like you were playing a tutorial? Why or why not?
   (b) Did it feel like you were playing the same game? Why or why not?

(5) **What are your thoughts on video games providing new players suggestions during gameplay to help with decision-making?**
   (a) How does your opinion change based on certain aspects of the game?
      (i) Single player vs multiplayer?
      (ii) Casual vs competitive?
      (iii) Genre?
   (b) How does your opinion change based on if the player is new to video games or not?
   (c) How do you think providing suggestions would impact the onboarding process for new players?
   (d) Have you played any games that have implemented a similar strategy in their onboarding processes? If so, which ones?
   (e) Do you have any other thoughts on this topic?

(6) **What are your thoughts on AI-supported suggestions in video games?**
   (a) How much transparency do you want regarding the results of an AI-supported system?
      (i) Do you prefer to understand why an AI-supported system made a decision? Why or why not?
   (b) What affects your trust in an AI-supported system?
   (c) How accurate do you expect the suggestions generated by AI-supported systems to be?
      (i) Perfect? Good enough?
      (ii) Would imperfect suggestions affect your trust in the system? Why or why not?
   (d) Do you have any other thoughts on this topic?

(7) **When you pick up a new game, what do you expect to get out of the onboarding process?**
   (a) How soon do you want to get into "real" gameplay? (I.e., not onboarding-related gameplay)
   (b) How prepared do you like to feel before "real" gameplay?
   (c) How much freedom do you like to have during onboarding?
   (d) How much information do you want a game to provide you upfront?
   (e) How accessible do you want information about the game to be during gameplay?

(8) **Do you have any other comments you'd like to make?**