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## **Game Interaction Primitives**

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## Resumo

A indústria dos videogames tem vindo a crescer exponencialmente nas últimas décadas, estabelecendo-se como uma das formas de entretenimento mais influentes à escala global. Com milhões de jogadores ativos diariamente, são gerados volumes enormes de dados de interação que oferecem oportunidades únicas para estudar padrões de comportamento humano. A análise desses dados permite compreender não apenas como os jogadores respondem a estímulos visuais e auditivos dentro do jogo, mas também como desenvolvem estratégias motoras e cognitivas para superar desafios, gerir recursos e maximizar o desempenho. Compreender estas interações é essencial para identificar estratégias individuais de jogo, agrupar perfis de jogadores, prever comportamentos e explorar a relação entre desempenho, experiência subjetiva e características motor-cognitivas. A diversidade de jogadores, níveis de experiência, estilos de interação e a ampla variedade de mecânicas de jogo tornam a análise comparativa particularmente desafiante, exigindo métricas e frameworks que sejam consistentes e generalizáveis entre contextos distintos.

Estudos prévios na área têm focado-se em diferentes vertentes da análise de comportamento de jogadores. Uma das abordagens consiste na identificação de clusters e tipos de jogadores, que permite agrupar perfis semelhantes dentro de um mesmo jogo, revelando padrões de desempenho, estilos de interação e estratégias preferenciais. Outra linha de investigação tem explorado a formalização de interações de jogo, utilizando frameworks como as *Core Tasks* para categorizar as tarefas e ações dos jogadores nos jogos. Este tipo de abordagem facilita a comparação entre jogos distintos, fornecendo uma base estruturada para analisar comportamentos recorrentes. Paralelamente, várias pesquisas têm demonstrado o potencial de utilizar dados de interação para monitorizar desempenho e saúde, incluindo estudos sobre cognição ou sobre a deteção precoce de declínios de saúde. Finalmente, o campo de *Game Analytics* oferece diversas ferramentas e metodologias para extrair insights a partir de grandes volumes de dados de gameplay, permitindo análises complexas com métricas de jogos e possibilitando a identificação de padrões comportamentais.

Neste contexto, o presente trabalho propõe o conceito de Game Interaction Primitives (GIPs), padrões de interação dos jogadores que podem ser mensurados, comparados e analisados de forma consistente entre diferentes jogos. Estas primitivas procuram oferecer uma visão granular do comportamento do jogador, complementando frameworks existentes como as *Core Tasks*, ao permitir a definição de métricas objetivas e comparáveis. Em particular, este estudo focou-se na primitiva Predictive Tap, que se caracteriza por toques no ecrã realizados pelo jogador de forma antecipatória, em vez de reagir a um alvo constante ou reativo. Esta primitiva foi escolhida devido à

sua frequência elevada em jogos móveis disponíveis, facilidade de operacionalização e relevância para compreender estratégias motor-cognitivas individuais.

Para estudar o Predictive Tap, foram selecionados jogos móveis com objetivos claros e que permitiam isolar interações fundamentais. Cada jogo foi instrumentado para registrar dados detalhados de interação, incluindo a posição do toque, a área de contacto, a duração, o sucesso do toque e métricas contextuais, como intervalos de tempo e orientação do dispositivo. Adicionalmente, foi desenvolvido um jogo específico, *Hopfury*, um platformer 2D, com níveis graduais e mecânicas de toque e swipe, concebido para capturar interações de forma controlada e precisa. Outros jogos, como *Jumping Ball* e *Spinning Around*, foram adaptados para permitir a recolha de dados sem alterar significativamente a jogabilidade original, garantindo que os comportamentos observados refletissem interações naturais dos jogadores. O design experimental incluiu a implementação de colliders invisíveis, sistemas de registo de eventos e métricas contextualizadas para capturar detalhes de cada toque, sem comprometer a essência do jogo.

O estudo principal envolveu 23 participantes provenientes de três países diferentes, com idades compreendidas entre 20 e 57 anos. Cada participante jogou os três jogos em sessões controladas de aproximadamente nove minutos por jogo, intercaladas com intervalos de um minuto. Durante as sessões, todos os toques e eventos de interação foram registados e processados, permitindo a extração de métricas derivadas. Os dados foram limpos e padronizados, removendo toques inválidos ou inconsistentes, garantindo a qualidade e comparabilidade das métricas.

As análises realizadas incluíram modelos lineares mistos, aplicados para avaliar o efeito do jogo nas métricas de interação, considerando cada participante como fator aleatório, o que permitiu controlar variações individuais e focar nas diferenças atribuíveis à mecânica de cada jogo. Foram também calculadas correlações de Spearman para verificar a consistência de métricas derivadas entre jogos, permitindo explorar se padrões individuais se mantêm em contextos distintos. Para analisar a variabilidade temporal, foram realizadas análises *bin-wise*, que examinam intervalos de tempo específicos, e análises por blocos de toques, que avaliaram a evolução do comportamento ao longo do tempo, identificando possíveis adaptações e estratégias emergentes.

Os resultados indicam que, enquanto métricas de tempo de reação e intervalos entre toques podem variar conforme a mecânica do jogo e o tipo de desafio apresentado, métricas relacionadas diretamente com o toque, como duração e área do tap, assim como métricas compostas derivadas destas, podem apresentar padrões relativamente estáveis entre jogos, refletindo possivelmente estratégias motor-cognitivas individuais. As análises por blocos sugerem que, especialmente nas fases iniciais de cada jogo, existe uma clara variação no comportamento, mas que, com a progressão do jogo, os jogadores tendem a adaptar-se às exigências específicas, ajustando o timing e a duração do toque, embora sem convergência completa entre títulos. Estas observações indicam que o Predictive Tap é uma primitiva influenciado tanto pela habilidade individual como pelas características do jogo.

O estudo apresenta limitações importantes. O número de participantes foi relativamente reduzido, o que limita a generalização das conclusões e a robustez estatística dos modelos aplicados.

A quantidade de toques recolhidos variou significativamente entre jogos, devido à frequência de estímulos e ao design de cada título, o que pode ter introduzido viés na comparação de métricas. A ausência de métricas adicionais, como pressão de toque, limita a compreensão completa do comportamento motor do jogador. Por fim, a liberdade de interação com o dispositivo introduziu variabilidade adicional nas medições de área e precisão, que poderia ter sido minimizada com restrições experimentais.

Apesar das limitações, este estudo fornece um roteiro para instrumentar jogos de forma a capturar padrões consistentes de interação dos jogadores. Os resultados destacam a importância de métricas de toque e de análises detalhadas de comportamento, oferecendo insights úteis para investigação acadêmica, design de jogos e potenciais aplicações em monitorização cognitiva e motora.

Para trabalhos futuros, seria recomendável aumentar o número de participantes e incluir uma maior diversidade etária e de perfis de experiência em jogos. A incorporação de métricas adicionais, como pressão de toque ou análise da área de contacto ao longo da duração do toque, permitiria caracterizar com maior detalhe os padrões motor-cognitivos. Explorar uma maior variedade de géneros e plataformas, incluindo desktop, consola ou jogos com sequências de mecânicas mais complexas, poderia fornecer uma visão mais abrangente da consistência de primitivas. Adicionalmente, estudos futuros podem investigar a aplicação destas métricas em contextos competitivos ou colaborativos, bem como em ambientes de treino cognitivo ou motor, possibilitando intervenções personalizadas baseadas em padrões de interação individuais. A análise de primitivas de interação como o Predictive Tap pode também ser integrada em sistemas de gamificação ou em plataformas de monitorização de saúde, contribuindo para a deteção precoce de alterações motoras ou cognitivas ao longo do tempo.

Em suma, este trabalho apresenta uma contribuição relevante para a formalização e análise de Game Interaction Primitives, sugerindo que padrões recorrentes, podem ser capturados de forma sistemática e comparados entre jogos diferentes. O estudo integra conceitos de *GameAnalytics*, frameworks de interações e métricas contextuais para compreender padrões individuais de comportamento, oferecendo um ponto de partida que pode servir para futuras investigações sobre interações de jogadores e aplicações em áreas ligadas ao desempenho, cognição e saúde.

**Palavras-chave:** design de jogos, core tasks, comportamento do jogador, primitivas de interação, recolha de dados

## Abstract

The gaming industry has witnessed exponential growth, becoming one of the most influential forms of entertainment worldwide. With millions of active players, an enormous amount of interaction data is generated, offering a unique opportunity to analyze behavioral patterns. This thesis proposes and explores the concept of Game Interaction Primitives, core behavioral patterns that remain consistent across different gaming environments.

The central hypothesis is that such primitives, such as tactical movements or reaction times, play a crucial role in maintaining player equivalence across diverse games. The research began with an analysis of multiple digital games to identify recurring interaction patterns. From this analysis, a recurring primitive, named Predictive Tap, was selected, frequently observed in mobile games. This primitive represents a form of anticipatory interaction, where players tap in time with predictable gameplay events.

A proof-of-concept game was developed to embed and capture this primitive during gameplay, allowing its assessment in a controlled environment. A user study will be conducted to validate this approach and assess its effectiveness in detecting and analyzing the primitive.

The results of this work showed that the Predictive Tap primitive captures some consistent anticipatory patterns in player behavior across mobile games, although substantial variability remains and cross-game generalization continues to be a challenge. The project also provides a practical guide for implementing logging of interaction metrics, offering a foundation to support further analysis of Game Interaction Primitives in future studies.

This work aims to contribute to a deeper understanding of player behavior, with potential applications in game design, user experience personalization, and long-term monitoring of cognitive and motor capabilities.

**Keywords:** game design, core tasks, player behavior, interaction primitives, data collection

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# Chapter 1

## Introduction

The gaming industry has grown exponentially over the past decades, becoming one of the most popular forms of entertainment worldwide. Millions of people engage in digital play, generating extensive personal interaction data [13]. This wealth of data offers a unique opportunity to analyze and understand the range of player actions, from decision-making to skill-based mechanics, which are fundamental for characterizing the gaming experience. Moreover, studying these patterns has implications beyond entertainment, as it can reveal trends in cognitive and motor performance over time, potentially supporting early detection of performance shifts or cognitive decline [5]. Digital games have also been shown to enhance cognitive functions, such as working memory [3, 4], and may serve as valuable tools for monitoring skill changes throughout life [37].

However, the increasing complexity of game systems and the diversity of players pose significant challenges for both designers and researchers. Understanding how people interact with games, how they engage with mechanics, adapt to challenges, and interpret feedback, requires frameworks that can generalize across different titles. Despite the richness of player data and behavioral insights, standardized models for comparing interactions across diverse game contexts remain largely absent, limiting our ability to draw broad conclusions about player behavior and skill development.

### 1.1 Motivation

Digital play generates vast amounts of interaction data, yet we currently lack systematic methods to collect, formalize, and compare behavioral patterns across different games.

We propose the concept of *Game Interaction Primitives* (GIPs) which are recurring patterns of interaction that capture a player’s behavior in a given context. Each GIP is defined by a set of measurable metrics (e.g., hold time, pointer speed), the input modality (e.g., touchscreen, mouse), and the gameplay context that elicits the interaction (e.g., jumping to avoid an obstacle, steering a vehicle). By creating a catalog of GIPs with varying levels of abstraction, we believe we can identify consistent behaviors across games and provide a foundation for cross-game comparison.

Our approach builds on the framework of *Core Tasks* by Refai et al. [21], which identifies common, task-level interactions such as aiming, steering, and navigation. While core tasks pro-

vide a high-level structure, they do not capture the full richness or granularity of player behavior. GIPs complement this by focusing on precise, measurable microbehaviors that recur across games, allowing us to characterize player equivalence in diverse contexts.

The establishment of GIPs can enable multiple potential applications. First, it can support longitudinal monitoring of motor and cognitive performance, potentially contributing to the early detection of performance shifts or cognitive decline. Second, it can provide a data stream for personal informatics, allowing players to reflect on their own interaction patterns. Third, it can inform adaptive game design, where games may adjust dynamically to a player's interaction style. Overall, this research is motivated by the need to bridge the gap between rich player interaction data and the lack of standardized frameworks for interpreting that data.

## 1.2 Goals

The primary goal of this thesis was to identify a potential game interaction primitive, define it, and evaluate it. In this work, we propose and evaluate the **Predictive Tap** primitive. To achieve this, the thesis establishes a framework to systematically investigate player interactions across different games, focusing on three main objectives:

- **Identify common interaction patterns:** Analyze player actions in a diverse set of games to extract recurring behavioral patterns. For instance, moving pieces left or right in *Tetris* [53] can be abstracted as a steering behavior, which may have equivalents in other games, such as character navigation or aiming.
- **Instrumentalize Games to collect GIP:** Develop methods to capture the same pattern across multiple games, including adapting existing games and developing a new game to systematically log interactions.
- **Evaluate the consistency of the identified primitive:** Conduct a user study to collect quantitative metrics (e.g., radius of the tap, valid interval time) and examine correlations across games, complemented with semi-structured interviews and questionnaires for contextual qualitative feedback.

## 1.3 Contributions

The main contributions of this thesis are:

- **Identification and formalization of game interaction primitives:** A method is proposed to identify potential interaction primitives by analyzing recurring player behaviors in games. Each primitive is described in terms of both game-contextual factors and measurable player input metrics.

- **Methodological framework for instrumenting games and analyzing metrics:** A systematic approach is outlined for adapting or designing games to capture Predictive Tap interactions without altering core gameplay. This includes the implementation of logging mechanisms and the collection of tap-specific and contextual data, such as start time of the tap or reaction time, for reproducible analysis across different games.
- **Guidelines for cross-game analysis:** This study demonstrates how collected metrics can be analyzed to provide insights into their relationships across games. This includes relating individual and composite metrics to identify patterns, similarities, and differences in player interactions.
- **Recommendations and potential applications:** This work highlights how interaction primitives and their associated metrics can serve as a foundation for multiple areas. Potential directions include supporting systematic analysis of player behavior across games, providing insights for game design by revealing common interaction models, and contributing to health-related research through the detection of cognitive or motor performance indicators (e.g., fatigue, stress).

## 1.4 Structure of the Document

This document is organised as follows:

- Chapter 2 – **Related Work:** reviews literature on understanding players, the formalization of game interactions and frameworks, the role of player data in health and performance assessment and approaches in game analytics.
- Chapter 3 – **Identifying Interaction Primitives:** describes the set of games analyzed, the methodology of exploratory observation, and the identification of proposed interaction primitives. It also presents a cross-game mapping table that summarizes which primitives are present in each game, and introduces the Predictive Tap primitive in more detail.
- Chapter 4 – **Collecting the Interaction Primitive:** describes the selected games, the data collection procedures and their implementation. It also covers in more detail the modifications made to existing games, the development of the original game, and the preliminary tests conducted to identify and correct bugs.
- Chapter 5 – **User Study:** explains the main study evaluating the consistency of the Predictive Tap interaction primitive. It includes a participant overview, the analysis of metrics and composite metrics, qualitative analysis to validate specific aspects, and a discussion including its limitations.
- Chapter 6 – **Conclusion:** summarises the main contributions of the thesis and outlines directions for future research.



## Chapter 2

# Related Work

Understanding player behavior and interaction within games has attracted attention across multiple research domains. This section synthesizes key contributions that are directly or indirectly relevant to the identification of interaction primitives. The reviewed works encompass both behavioral studies and methodological approaches used to model, analyze, or formalize gameplay. We begin by discussing behavioral analyses that classify player types based on in-game actions and decision-making patterns. We then explore various frameworks proposed for formalizing game interactions and identifying core gameplay tasks. Subsequently, we review studies that leverage player data to evaluate cognitive and motor skills. Finally, we examine contemporary game analytics techniques that provide data-driven insights into player behavior and interaction patterns.

### 2.1 Understanding players

Since the beginning of computer games, player actions have been continuously logged and analysed, with real-time responses generated by the software. Evaluating how players interact with a game is essential in game development industry, whether to assess if players engage with game elements as intended [10], to refine gameplay experiences or to uncover relationships between player types and game genres [36]. To support some of these analyses, clustering is a statistical technique that groups players based on behavioral similarities, frequently used to identify patterns and differentiate player interaction styles in both traditional gaming [10, 11, 12, 38, 34] and in serious games analytics [19, 24].

Drachen et al. [10] modeled player behavior based on data from 1,365 players who completed *Tomb Raider: Underworld* [51]. The gameplay data was harvested and included completion time, total number of deaths, Help-on-Demand usage and causes of death (i.e., from opponents, environmental threats, or falls). The initial analysis employed k-means clustering, a method that later studies indicate is simple and often results in similar profiles [12], followed by Ward's hierarchical method to minimize variance within each cluster. The four identified clusters of player behavior were: Veterans, who complete the game quickly with few deaths mainly due to environmental factors; Solvers, who frequently die from falls but excel at puzzles; Pacifists, who mostly die from opponents, finish below average, and request little help; and Runners, who die often from both

opponents and environmental hazards but complete the game swiftly. The existence of these four behavioral clusters, even in a relatively linear game like *TRU* [51], highlights the diverse strategies players employ, rather than relying on a single approach to get through the game [10]. This raises an interesting question about player equivalence: if a player is identified as a Runner in *Tomb Raider: Underworld* [51], will they maintain this pattern in another game? Whether these interaction styles are equivalent across different gaming environments should be further explored.

Drachen et al. [11] later investigated player interactions in two distinct games: *TERA* [48], a MMORPG, and *Battlefield 2: Bad Company 2* [52], a first-person shooter. Utilizing k-means clustering and Simplex Volume Maximization (SIVM), the study analyzed over 260,000 characters to create behavioral profiles. The findings indicated that k-means effectively identifies general player behavior distributions (e.g., average performance, resource utilization), while SIVM is adept at detecting extreme behaviors (e.g., cheaters, bots). In *TERA* [48], k-means clustering identified behavior clusters such as Elite and Stragglers, while SIVM categorized players as Planters and Miners. Similarly, in *Battlefield 2: Bad Company 2* [52], k-means identified clusters like Assassins and Veterans, with SIVM categorizing players into groups like Assault-Recon and Medic-Engineer.

Expanding on these behavioral classifications, the application of educational theories to gaming has also revealed distinct profiles of achievement-oriented players. For instance, Heeter et al. [19] applied achievement goal theory to games, identifying four types of players based on mastery and performance goals: Super-achievers, who excel in both self-improvement and outperforming others; Mastery-only players, focused on self-improvement but uninterested in competition; Performance-only players, motivated by competition but avoiding difficult challenges; and Non-achievers, showing low engagement in both mastery and performance motivations. These classifications provide further insight into how motivations shape player preferences, such as mastery-oriented players gravitating toward harder challenges, while performance-oriented players prioritize competitive environments [19].

In a different analysis, Sifa et al. [36] examined player interactions using data from the Steam platform, finding that most players focus on one or a few games, while about a third evenly distribute their playtime across multiple titles. This clustering reveals distinct engagement patterns, such as Customizers, who dedicate themselves to specific games like *Team Fortress 2* [49] and *DOTA 2* [57], and Active Steam Players, who explore various genres.

These tendencies are particularly relevant for understanding and identifying equivalent interaction patterns across games, offering valuable insights into how players choose to engage [10, 11] and which types of gameplay capture their interest [19, 36]. This concern aligns with the goals of this thesis, which aims to investigate whether consistent patterns of player interaction can be abstracted and formalized as game interaction primitives across different games and contexts. Although each game genre has its own unique mechanics and context, notable patterns emerge in how players interact, revealing similarities in engagement styles that persist across different gaming environments.

## 2.2 Formalizing game interactions and frameworks

Human-computer interaction (HCI) research provides foundational insights into how players intuitively engage with digital systems, offering principles that guide the design of responsive and accessible game interfaces [6, 7].

Formal frameworks for modeling game elements, mechanics, and player interactions provide essential structure for both design and analysis. By introducing consistent terminology and organization, these models enable researchers to compare gameplay systems across different titles and identify underlying patterns of interaction [23, 25]. In particular, such frameworks support the categorization of core gameplay tasks [21] and the systematic evaluation of player actions [18]. This section first introduces basic HCI concepts to frame how players generally interact with games, then reviews formal frameworks and core gameplay task categorizations, which are central to analyzing player behavior in this thesis.

### 2.2.1 Human-Computer Interaction in games

Principles of human-computer interaction (HCI) [6] and research on player engagement [7, 23] provide foundational insights into the design of player-game interactions, demonstrating how games can captivate players. Cai [6] emphasizes that player interactions follow a continuous cycle (Figure 2.1) designed to be immersive and intuitive, ensuring players can focus on gameplay rather than on managing complex interface mechanics.

The study [6] translates general HCI theories into four core principles. The *Simplicity Principle* focuses on reducing unnecessary complexity in the interface, allowing players to focus on the gameplay rather than on understanding or managing complicated controls or features. The *Natural Principle* emphasizes that the controls and feedback within the game should feel familiar or instinctive, minimizing the cognitive load required from the player to figure out how to interact with the game. The *Friendly Principle* aims to create an environment where players feel comfortable and motivated to interact with the game. Lastly, the *Consistency Principle* ensures that similar interactions across the game interface follow predictable patterns, allowing players to build familiarity and confidence with the game mechanics (e.g button placement, control schemes).

In a broader context, Caroux et al. [7] analyzed 72 articles focusing exclusively on entertainment games to explore player experiences more holistically. The study stated that "player–video game interactions are interactions in which technical aspects of video games have influence on players' engagement and enjoyment" emphasizing the intricate relationship between player experiences and video game aspects such as input/output, content and multiplayer features. These technical elements, when carefully designed, significantly enhance the immersive experience. For instance, visual displays (background color, camera viewpoint) and auditory feedback (sound, music) deeply influence aspects like player immersion, emotional state, and flow [7]. This aligns

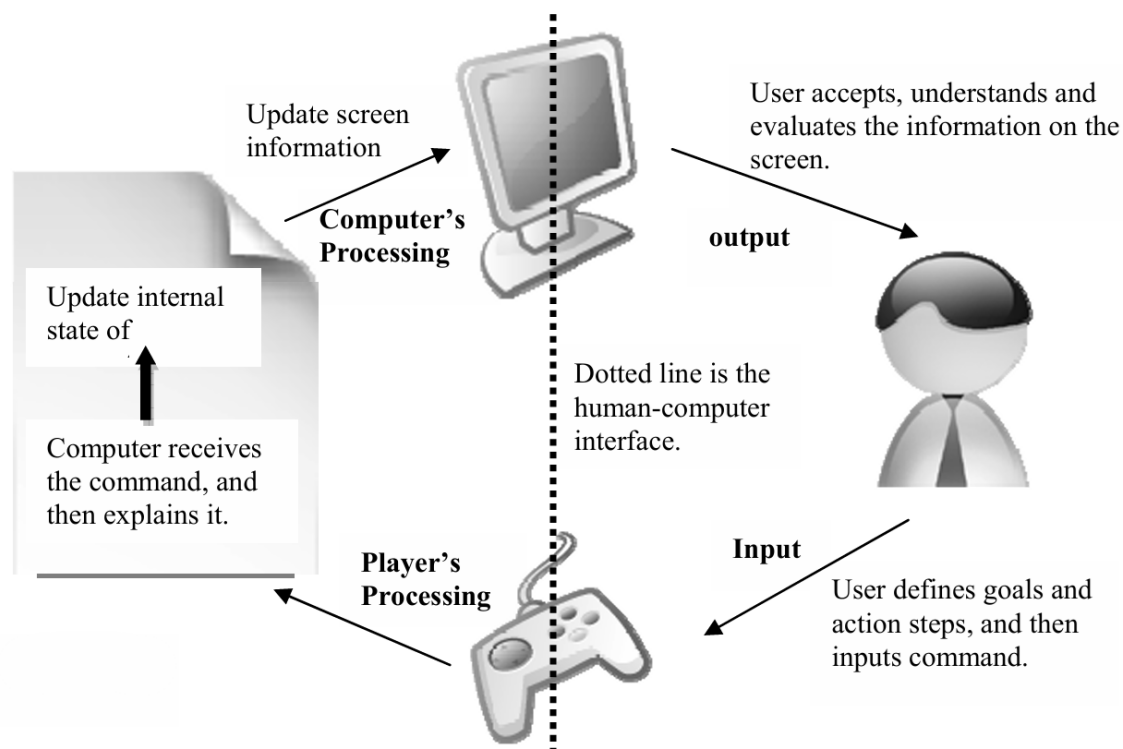


Figure 2.1: Image from Cai [6] illustrating the Human-Computer Interaction (HCI) cycle in gaming. The player sets objectives and provides input via a controller, prompting the computer to process these inputs, update the game state, and reflect changes on screen. The player then observes, evaluates and responds, creating a feedback loop that sustains engagement.

with the *Natural Principle* [6] by fostering an intuitive interaction between the player and the game environment.

## 2.2.2 Structured Elements and Playable Concepts

Nacke and Deterding [30] point out how gamification research has evolved and matured over time, with researchers advocating for a deeper understanding of how individual game elements interact. Moving beyond traditional elements like points, badges, and leaderboards, the study highlights the need for a more structured and thorough examination of these components. It was later conducted a deeper investigation into these game elements, where Hallifax et al. [18] offers insights by analyzing 280 research papers and identifying 15 frequently used elements (e.g., achievement, avatar, badges, feedback). Despite these elements' prevalence in gamified systems, significant inconsistencies were revealed in how they are defined. Only six of the elements have clear, cohesive identities, while others, such as feedback and social, have varied definitions across studies. This inconsistency complicates efforts to create a unified understanding and application of these elements, yet the study provides initial descriptions that may serve as a foundation for future standardization. For instance, elements such as power-ups, even in their placebo form, have been shown to influence player immersion and autonomy [9]. These elements go beyond simply reacting to player input, many of these elements are designed to guide and shape player behavior in

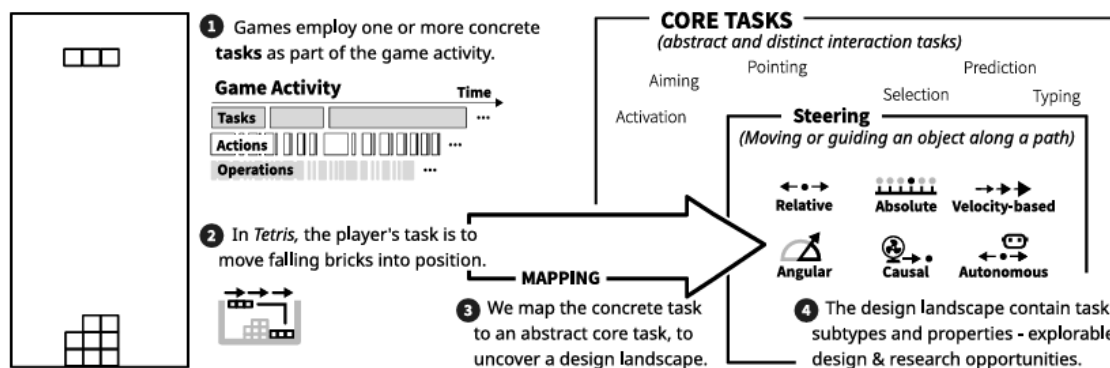


Figure 2.2: Image from Hougaard and Knoche [21], illustrating how gameplay mechanics in Tetris are mapped to the abstract core task of *Steering*. This highlights how player actions, such as moving falling bricks into position, are categorized and analyzed to explore task subtypes and properties, uncovering new design opportunities.

specific directions. This approach mirrors strategies used in other fields, where behavioral data is harnessed to influence user choices and improve outcomes [1]. Given the variability in how these elements are defined and applied, there is a clear need to formalize their conceptualization and implementation.

The use of small and focused games embedded within broader educational or media contexts has proven to be an effective way to convey gameplay concepts [23, 25]. These *Playable Concepts* are based on five key principles: *Partiality*, where each game focuses on a specific gameplay element without trying to be a complete experience; *Embeddedness*, meaning these games are connected with other content, for instance, being part of a website, a text, or a presentation; *Simplicity* and *Immediacy*, which ensure the gameplay is easy to understand and can be quickly engaged with; and *Reusability*, allowing the elements of these games to be used in different projects [23]. This approach focuses on integrating the games into broader materials, making them flexible and practical tools for game design, as highlighted by Kultima et al. [23]. Building on these foundational ideas, a later study by Lyu et al. [25] applies this design approach to explore goal-oriented gameplay patterns specifically, creating 26 playable concepts, each demonstrating a different pattern of goal-setting and achievement. The study follows the original design values closely—particularly *Partiality*, with each mini-game focusing on a single goal structure [25]. While the model of using playable concepts to explore gameplay patterns, particularly goal-related structures [25], offers valuable insights into game design [23], it remains somewhat abstract.

The framework effectively helps identify and categorize design patterns, making it a useful tool for initial exploration and prototyping. Building on the concept of structured game elements and playable concepts, this thesis focuses on systematically studying a single interaction primitive, the Predictive Tap, while also attempting to identify broader interaction patterns across games.

### 2.2.3 Core Tasks

The idea of core tasks emerged as a means of formalizing essential actions within gameplay that players frequently engage in. Flatla et al. [14] were among the first to introduce core tasks. The primary aim of their work was to address the repetitive and often tedious nature of calibration tasks, which are necessary to set up systems like eye trackers or motion sensors accurately. Flatla et al. [14] created calibration games that transformed typical calibration steps into enjoyable activities by incorporating game-like elements. This gamification approach relied on a structured set of core tasks, which are foundational actions that could support calibration goals while keeping players motivated. For instance, reaction time measures the time needed to initiate a response to a perceptual stimulus, while visual search assesses the ability to locate a specific target within a field of distractors. Pattern matching focuses on the ability to determine if a given perceptual pattern aligns with a target, and aiming tests the player's accuracy in pointing a device, such as a virtual rifle, at a target without directional feedback. These tasks collectively target various essential perceptual and motor skills crucial to effective gameplay interaction.

Refai et al. [33] further developed the concept of core tasks by refining the original set of 14 tasks [14] down to 10. This refinement process involved a grounded theory study of 54 games, which enabled the merging of conceptually similar tasks and arrive at a streamlined set. This final set aimed to simplify the application of assistance techniques, thus supporting fundamental motor and perceptual skills without delving into higher-level cognitive tasks such as strategic planning or decision-making.

Further extending the understanding of tasks, Stafford and Vaci [15] explored how specific tasks in games align with certain game mechanics. In this context, tasks are the specific problems or objectives that players must solve or perform in the game, while mechanics refer to the rules and structures that guide how players interact with the game to achieve these tasks. The study categorizes tasks into two main types: generative tasks, which aim at generating new artifacts as the solution to the problem at hand (e.g., labeling, segmenting, ontology linking), and decision tasks, which involve making judgments about existing data (e.g., preference elicitation, ordering). For instance, object recognition is paired with the Agreement mechanic, where players collaborate to identify items, as seen in the ESP Game<sup>1</sup>. Clustering tasks align with the Tile Placement mechanic, used in games such as Phylol<sup>2</sup>. This provides valuable insights into how specific game mechanics can be strategically aligned with distinct tasks, guiding the design of more effective and engaging GWAPs [15].

Hougaard and Knoche [21] focused on analyzing core tasks in greater detail, specifically exploring how they can be used to study and design interactions within games. The goal is to provide a framework for decomposing and analyzing the interaction work players engage in, in order to

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<sup>1</sup>ESP Game is a collaborative game where two players independently provide tags for the same image. The goal is to agree on the same tags, based on the shared visual hint of the image. This approach generates semantic annotations through player agreement.

<sup>2</sup>Phylo is a puzzle game in which players optimize DNA sequence alignments by visually arranging nucleotide patterns. The game leverages human pattern recognition to improve alignments, often surpassing algorithmic results.

better understand game design. The concept and definition of tasks has been underexplored in game studies, and has created an opportunity for the development of a formal structure. To address this gap, Hougaard and Knoche [21] incorporated the *Task Cube*, a model originally developed by Rind et al. [35], which organizes tasks along three key dimensions: *Abstraction*, *Composition*, and *Perspective*. *Abstraction* distinguishes between more concrete (specific) tasks and more abstract (general) ones. *Composition* refers to how tasks can be broken down into smaller, hierarchical subtasks. *Perspective* differentiates tasks based on whether they are defined by the sequence of actions required to achieve them (how) or by the intended outcome (why). In addition to these dimensions, Hougaard and Knoche [21] introduced a new one: *Modality*. This dimension examines how tasks are experienced through various input and output devices, such as controllers, touchscreens and haptic feedback systems. This helps designers understand how different devices affect task performance and how game mechanics should adapt to various interaction methods [21].

In some contexts, tasks are viewed from a goal-based perspective, where broad goals are broken down into smaller, manageable tasks [35]. However, in game design, interactions are carefully structured to guide players toward specific outcomes [7, 15, 33], requiring a clearer definition of tasks. Tasks are therefore defined as units of work consisting of specific actions or subtasks, each directed by a “task goal” [21].

By incorporating earlier efforts [14, 15, 33] the framework by Hougaard and Knoche [21] established a list of 14 core tasks that are commonly found in different types of games. These tasks cover physical actions (aiming, pointing, steering, drawing, activation, typing) and mental actions (selection, configuration, memory, spatial memory, detection, discrimination, prediction, search). For instance, *Aiming* involves aligning a cursor or device with a target, where difficulty can be adjusted with parameters such as target size and speed; *Steering* (Figure 2.2) requires the player to guide a character along a path, with challenge levels influenced by path width, speed and obstacles; *Selection* requires the player to pick specific items from a set, with complexity controlled by factors such as the number of items, spacing and visual differences between choices.

The Core Task Toolkit [21] presents a systematic approach to analyzing and improving gameplay through four key steps. The process begins with *Identification*, where designers focus on identifying the fundamental tasks players must perform. The *Sequencing* phase organizes these tasks in a logical order, considering when and how frequently the tasks occur within the game. Next, *Composition* breaks complex tasks down into subtasks, actions and operations, focusing on how they are ordered or repeated. Finally, the *Examination* phase evaluates each core task using interaction design principles, such as feedback, control, and immersion. This stage also draws on insights from frameworks such as Wensveen et al. [40], which explore how user actions and product functions are coupled through feedback and feedforward mechanisms. Their work outlines key aspects of coupling, such as time, location, and modality, which are essential for ensuring that player actions are intuitively linked to the system’s responses.

Despite the advancements made in structuring core tasks for game design, challenges persist in clearly distinguishing tasks and applying them effectively to more complex game environments.

For instance, the distinction between *Aiming* and *Pointing* remains unclear and still a subject of ongoing debate [21], illustrating the difficulty in capturing the nuanced differences between actions that appear similar but serve different purposes in gameplay. While the Core Task framework represents a significant step forward, it still requires further refinement to address the complexities of dynamic player interactions [21].

These frameworks and analyses provide a foundation to systematically study player interactions, guiding the identification and comparison of recurring patterns across different games.

### 2.3 Using player data for understanding health and performance

Over the past decades, the idea that video games can offer cognitive benefits [4, 32] and serve as effective tools for 'brain training' [3, 5] has gained considerable traction.

Quiroga et al. [32] investigated whether playing casual video games requires general intelligence, using *Big Brain Academy* as its experimental foundation. The study reveals that different minigames within casual gaming contexts demand varying levels of general intelligence. For instance, while the game *Train*<sup>3</sup> showed a growing correlation with general intelligence over time, *Calculus*<sup>4</sup> exhibited a decreasing correlation, suggesting the reliance on specific skills rather than overall cognitive ability. These findings suggest that while casual games may strengthen certain cognitive skills, they do not consistently require (or necessarily improve) a broad range of cognitive abilities [32]. This opened the door for further exploration into which specific cognitive skills, such as working memory, fluid intelligence and attention, are engaged by casual games, as well as whether these games can lead to improvements in these areas—a direction pursued in depth by Baniqued et al. [4, 3]. For instance, the findings reveal that games involving problem solving and working memory have significant potential to enhance these capacities. Notably, fluid intelligence emerges as the most significant predictor of performance in these games, especially in those that involve planning and reasoning. Baniqued et al. [3] naturally lead to the idea of integrating these games into a training program to evaluate their efficacy in improving targeted cognitive skills. Earlier research by Basak et al. [5] supports this idea, suggesting that cognitive training through video games can help mitigate age-related cognitive decline, particularly in executive functions such as working memory and task switching. In their study, Baniqued et al. [3] found that participants in the working memory-reasoning training demonstrated significant improvements in divided attention tasks, although no notable enhancements were observed in fluid intelligence, episodic memory, or perceptual speed. The effectiveness of cognitive training may vary significantly depending on the type of game played and the specific cognitive skills being targeted, rather than simply the act of playing video games [3]. While games requiring similar cognitive skills may lead to comparable performance outcomes, it does not thoroughly address this connection. Further research

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<sup>3</sup>Train is a minigame in which players must select the correct directional pieces to guide a train to its destination as quickly as possible.

<sup>4</sup>Calculus is minigame in which players must quickly discard numbers so that the sum of the remaining numbers matches a target value.

is needed to explore how performance might vary across different gaming contexts, especially for the same individual.

Various other studies have highlighted the importance of tracking user performance over time to better understand and address specific challenges faced by different user groups [22, 29, 2]. For instance, Montague et al. [29] examined the touchscreen interactions of motor-impaired users through a Sudoku app, identifying significant challenges with gesture accuracy and consistency. Their work underscores not only the need to support user improvement through adaptive interfaces, but also the value of detecting and understanding interaction difficulties as they emerge.

Different game genres engage diverse cognitive skills and often stimulate multiple abilities together [4, 3], suggesting that games can support complex skill development [32, 3]. While existing research has primarily focused on accessibility [17, 22, 29] and dynamic difficulty adjustment [28, 2] to enhance performance, it is also important to track an individual's performance over time across various games. This approach helps identify performance patterns and any potential declines, offering valuable insights into whether cognitive and physical gains are maintained or lost across different contexts.

## 2.4 Game Analytics

Game analytics refers to the systematic collection, analysis, and interpretation of data generated during gameplay. As observed earlier, game analytics has been used to identify and model player types [10, 28, 11, 24, 38] and to derive health-related and performance insights [29, 37]. However, its applications extend far beyond these examples. This section focuses on the methodologies and metrics central to game analytics, beginning with an exploration of how data is collected—whether through automatic systems embedded in games or manual approaches requiring player input. It then categorizes the key metrics used to analyze player behavior, performance, and engagement, illustrating their application through real-world examples from game studies.

There are various methods to gather information or collecting data, and it can vary significantly depending on the game's design, the goals of the analysis, and the type of data that needs to be captured. These methods can be divided into two categories: automatic data collection and manual or non-automatic data collection.

Automatic data collection is the most commonly used method in game analytics and it involves embedded systems within the game that capture player actions in real-time. For instance, in the *Guild Wars 2* [47] work by [31] detailed action logs were automatically collected from 175,099 players over a period of 18 months. These logs provided rich data about various player behaviors, including skill usage, positioning, and boss encounter strategies, enabling developers and researchers to perform deep analytics on gameplay trends. In the case of the *Tomb Raider: Underworld* [51] study by Drachen et al. [10], the gameplay data was harvested through the EIDOS Metrics Suite, a game metrics logging system used by EIDOS. The data collection process was completely unobtrusive since data was gathered directly from the game engines of players playing

TRU [51] via the Xbox Live! web service, capturing player behavior in real-time within their natural environment, rather than a controlled laboratory setting. More recently, Chitale et al. [8] demonstrated the use of automatic data collection in mobile games to capture fine-grained swipe gesture interactions. In their study, raw swipe events were first cleaned to remove unintended touches and outliers, then aggregated into meaningful metrics such as swipe speed, duration, and fingertip contact area. These metrics were subsequently analyzed through Spearman rank correlations with standardized measures of anxiety and depression, revealing significant associations. This methodology highlights how event-based logging can produce a rich, high-quality dataset suitable for statistical analysis, and illustrates the potential of leveraging detailed in-game interaction data to uncover patterns in user behavior and psychomotor or cognitive processes. Such an approach is directly relevant to this thesis, where similar event-based metrics are analyzed across games to investigate the consistency and structure of the primitives.

On the other hand, manual or non-automatic data collection involves gathering information directly from players. This often requires them to provide feedback or input voluntarily, though it can also be employed in controlled environments where specific observations or subjective insights are needed. For instance, Gielis et al. [16] employed manual data collection during the recruitment process, where participants were initially screened through questionnaires that gathered demographic information, lifestyle factors, and gaming habits. This non-automatic approach allowed the researchers to assess participant eligibility, ensuring they met certain criteria, such as age range and gaming experience, before the study began. In the case of *Guild Wars 2* [47], while Pfau and El-Nasr's work [31] leveraged automatic data collection through action logs provided rich insights into player behaviors, the researchers also incorporated manual data collection as part of the validation process. After analyzing gameplay data, they further validated their findings by gathering player feedback through surveys and questionnaires. This allowed them to assess the effectiveness of their framework and ensure it aligned with the players' perceptions and experiences.

Metrics provide a structured way to understand player behavior, decision-making, and engagement. The most commonly used metrics can be categorized based on the type of data they capture and they can include: *Performance Metrics*: Focused on evaluating player outcomes and achievements, such as scores (e.g., points, levels completed [18, 16]), completion time (e.g., time taken to finish a task, level, or game [10, 11, 16]), and success or error rates (e.g., percentage in completing objectives, number of mistakes during a task [16, 27]); *Behavioral Metrics*: Capturing in-game actions and decision-making processes, such as action patterns (e.g., sequences of moves or rotations during gameplay [31]), choices under uncertainty (e.g., decision-making in "snacking trials" [27]), and goal-orientation tendencies (e.g., classifying players as explorers, fulfillers or runners, depending on how they navigate and interact with the game environment [10, 11]); *Development Metrics*: Used to track how players develop skills over time, such as learning curves (e.g., progression in skill acquisition [37]), reaction times (e.g., speed of player responses to in-game stimuli [4, 5]), and accuracy rates (e.g., precision when hitting a target or selecting the correct option

during challenges [29, 5, 16]); *Engagement Metrics*: Assessing player interaction and involvement, such as session duration (e.g., how long players stay in the game during a session [36, 16]), help usage (e.g., frequency of using in-game assistance features like Help-on-Demand [10]), and dropout behavior (e.g., players who quit or leave the game prematurely [36, 24]).

By systematically collecting and analyzing metrics, game analytics provides valuable insights into player behavior and interaction dynamics. In this thesis, such metrics are crucial for identifying and characterizing Game Interaction Primitives (GIPs) across different game contexts. Our approach relies primarily on automatic data collection, enabling the capture of detailed, real-time information about player inputs, responses, and performance. We focus on one GIP extensively, compiling a comprehensive set of metrics, in order to understand its structure and function across games. These metrics not only support a deeper understanding of the selected primitive but also serve as the foundation for comparing it across gameplay scenarios, helping to refine and concretize the concept of GIPs within game interaction studies.



## Chapter 3

# Identifying Interaction Primitives

This chapter presents the process followed to identify and formalize recurring player interaction patterns, referred to as **Interaction Primitives**, within a curated set of mobile games. The analysis is grounded in empirical observation and iterative refinement, focusing on minimalistic games with intuitive control schemes that allow for the isolation of fundamental interactions.

The methodology is based on exploratory observation of player interactions across a curated set of mobile games, from which recurring patterns were identified and systematically formalized. While multiple primitives were identified, this chapter concentrates extensively on a single primitive, the **Predictive Tap**. This focus enables a thorough investigation of its expression across different gameplay contexts, along with a concrete method for data collection and a set of tailored metrics to measure its use and variation.

### 3.1 Game Set Overview

The analysis focused on a curated set of 20 mobile games (Figure 3.1). These games feature clear objectives and the interaction paradigms are straightforward, often relying on single-touch inputs, swipes, or hold gestures. The games incorporate a variety of challenges across multiple styles, including puzzle solving, platforming, and endless runners.

This specific set was chosen for two main reasons: firstly, the games were readily available as part of a Unity Asset Pack [39], ensuring full access to source code and implementation details; and secondly, their varied gameplay styles and design provide a broad yet controlled context for analyzing recurring interactions.

### 3.2 Methodology of Exploratory Observation

To explore the concept of interaction primitives, we adopted an empirical and observation-driven methodology. In the initial phase, we played through each game multiple times without involving external participants. This internal and exploratory approach focused on observing the interaction techniques required to progress through the games.

We paid particular attention to the **nature of the input** (e.g., tapping, swiping) and the **game-**



Figure 3.1: Image available from the Unity Asset Pack [39] used to source the mobile games in the study.

**play context** in which it occurred (e.g., timed action, aiming task). These observations served as the foundation for identifying recurring and interaction patterns.

Once the initial patterns were proposed, we held multiple meetings with the research team to discuss and iteratively refine the definitions and characteristics of each identified pattern. This process involved playing each game multiple times and carefully observing recurring interaction patterns. For each candidate primitive, we documented its input type, gameplay effect, contextual variations, and frequency of occurrence. Ambiguous or inconsistent patterns were discussed to arrive at clear definitions, aiming to make each primitive as generalizable and transferable across games as possible. The final set was then organised into a taxonomy to support structured cross-game comparison.

### 3.3 Proposed Interaction Primitives

Through our analysis, we identified six distinct interaction primitives that emerged across the game set. Each primitive was derived from direct observation of input behaviour and gameplay function, focusing on how actions translated into outcomes. It is important to note that these primitives do not represent an exhaustive catalogue of possible interactions, nor the only way to categorise them. Rather, they constitute a proposal for the systematic formalisation of recurring interactions observed in this study, providing a structured basis for subsequent analysis.

- **Hold-to-shift:** The player presses and holds their finger on the screen to shift the background, either horizontally or vertically. This shift indirectly controls the position of the

main object relative to obstacles or pathways. Releasing the hold causes the background to stop moving, requiring careful timing and positioning. *Example: In **Connect Balls** [45], the player rotates the environment by holding input, aligning red and blue balls so they connect through gravity (Figure 3.2).*

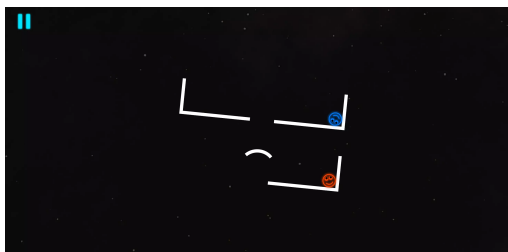


Figure 3.2: Screenshot of **Connect Balls** [45].

- **Predictive Tap:** Involves tapping the screen at the right moment to trigger a specific action, such as jumping or activating a mechanism. This primitive relies heavily on precise timing and the player's ability to anticipate and react to a stimulus, often a moving or emerging element within the game environment. *Example: In **Fill The Cups** [46], the player taps to release balls with precise timing, ensuring they fall into cups for points (Figure 3.3).*

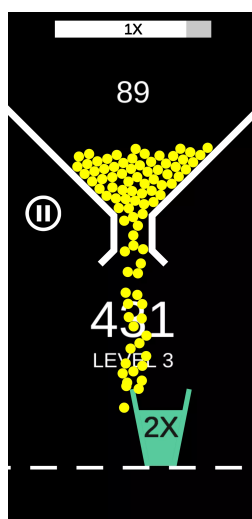


Figure 3.3: Screenshot of **Fill The Cups** [46].

- **Hold-to-steer:** Allows the player to hold their finger on the screen to initiate lateral movement of the object. The movement continues as long as the finger remains in contact and stops when released. This form of input grants continuous but simple directional control. *Example: In **Color Run** [43], the player drags their finger to steer the character, matching same-color obstacles while avoiding others (Figure 3.4).*
- **Position-Based Tap:** Characterised by tapping on specific locations of the screen, where the spatial position of the tap itself determines the resulting action. This primitive is context-sensitive, often used in scenarios where left-right distinction or target-specific tapping is

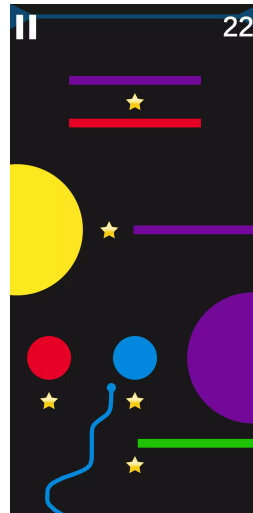


Figure 3.4: Screenshot of **Color Run** [43].

essential. Example: In **Color Blocks** [41], the player taps on groups of adjacent blocks of the same color to destroy them, with outcomes tied to the tapped position (Figure 3.5).

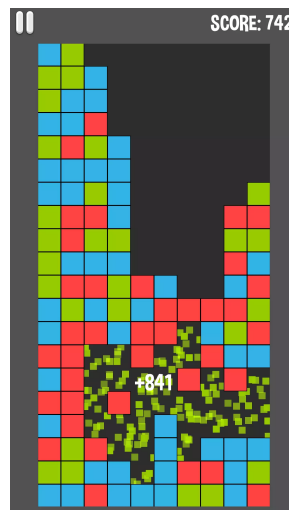


Figure 3.5: Screenshot of **Color Blocks** [41].

- **Swipe-to-move:** Based on directional swipe gestures. The player swipes in the desired direction to move the object accordingly, typically used for dodging, lane switching, or directional changes. Example: In **Color Swipe** [44], the player swipes to move the ball across tiles, progressively filling its path with color until the level is complete (Figure 3.6).
- **Hold-to-aim:** Involves holding input to adjust the aim of an object. A visual indicator often provides feedback during aiming, and releasing executes the action. Example: In **Aim** [42], the player drags to align the trajectory and then releases to shoot, strategically bouncing the ball off obstacles to clear the level (Figure 3.7).

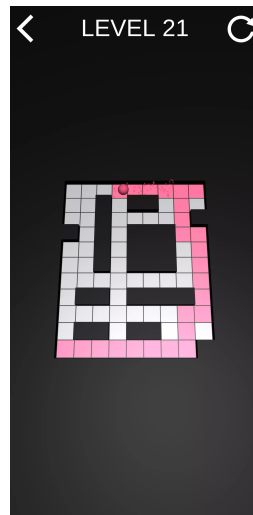


Figure 3.6: Screenshot of **Color Swipe** [44].

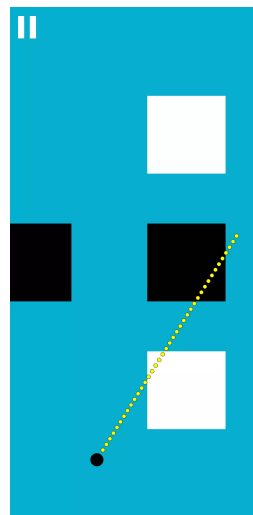


Figure 3.7: Screenshot of **Aim** [42].

### 3.3.1 Cross-Game Mapping

To better understand the distribution of interaction types, we created a cross-reference matrix [3.1] that maps each primitive to the games in which it appears. This visualisation helps to identify which primitives are more prevalent and which are more specific to certain types of gameplay.

## 3.4 Predictive Tap

The Predictive Tap primitive was identified during the exploratory observation phase as a recurring interaction pattern across multiple games. This primitive refers to actions where the player taps on the screen in anticipation of a stimulus, rather than in response to a constant or reactive target. It implies a degree of learned timing or predictive behavior based on visual or rhythmic cues.

This concept is partially grounded in the *Core Tasks Framework* [21], which categorizes game

Table 3.1: Mapping of interaction primitives across games. Legend: H-S = Hold-to-shift, P-T = Predictive Tap, H-St = Hold-to-steer, P-BT = Position-Based Tap, S-M = Swipe-to-move, H-A = Hold-to-aim.

Game	H-S	P-T	H-St	P-BT	S-M	H-A
000 Endless Maze						
Aim						X
Color Blocks				X		
Color Lines				X		
Color Run			X			
Color Swipe					X	
Connect Balls	X					
Fill The Cups		X				
Finger Football						X
Fast Finger			X			
Jumping Ball (/Platform Jumper)		X				
Level Rotator	X					
Neon Yellow Ball						
Rolling Maze						
Skillful Driver			X			
Spikes Everywhere		X				
Spinning Around		X				
Follow The Path						
Zig Zag		X				

interactions based on perceptual and cognitive goals. In this model, Predictive Tap aligns most closely with a *Detection Task*, described as the conscious perception of a stimulus (e.g., sound, light, or vibration). However, Predictive Tap goes beyond mere detection, it requires the player to anticipate the correct moment to initiate the tap in order to achieve a successful outcome, introducing a predictive dimension to the interaction where the effect of the action is not immediate.

While the *Core Tasks Framework* [21] offers a solid theoretical base for classifying actions, it does not define how such interactions should be measured or recorded. This thesis expands on that work by proposing a set of relevant metrics that can be used to empirically analyze this primitive across different gameplay contexts. These metrics are intended to capture both the player's input and the surrounding game state at the moment of the interaction.

The tap-specific parameters focus on the player's direct input, whereas the contextual parameters provide a broader view of the game state, allowing researchers to interpret the interaction within its environment. These metrics were chosen as a starting point based on their recurrence in the observational analysis and their potential to offer insight into player behavior.

As the analysis progressed, it became evident that additional metrics might be necessary depending on the game's design and mechanics. For example, some games include varying tap targets or environmental distractions, which can affect the timing or intention behind a tap. Therefore, the metrics listed here serve as a core foundation, while game-specific extensions are introduced

Table 3.2: Tap-specific and contextual metrics for Predictive Tap

Tap-specific metrics	Contextual metrics
Coordinates (X, Y)	Stimulus appearance timestamp
Radius	Time interval Start
Radius Variance	Time interval End
Touch Down	Device orientation (portrait/landscape)
Touch Up	
Hold Duration	
Result (hit/miss)	

later in the chapter to accommodate different gameplay contexts.

The selection of Predictive Tap as the focal primitive for further study was guided by both its frequency across games and its potential for detailed behavioral analysis. Its presence in diverse mechanics made it a promising candidate for cross-game comparison and for examining player consistency. While multiple GIPs were identified and considered, we concentrate extensively and comprehensively on a single primitive. This focus allows us to deeply investigate its expression in various games, outlining a concrete method for data collection and defining a set of metrics tailored to assess its use and variation across contexts. Among the identified primitives, Predictive Tap was chosen for closer examination because, compared to other primitives that involve multiple simultaneous factors (such as speed or acceleration dynamics), it is more concrete and easier to operationalize through clear performance metrics. Its design centres on timing and anticipation, which can be measured consistently across games without the added complexity of compound gesture features. Furthermore, its presence in several of the analysed games provides a broader comparative ground for studying how players interact with the same primitive in different gameplay contexts. For these reasons, Predictive Tap offers the most suitable entry point for deeper analysis.

**Tap-specific metrics** capture the raw intent and execution of the tap:

- **Coordinates (X, Y)** – reflect the physical location of the user’s tap on the screen, which may provide insights into habitual finger positioning, grip style, or comfort zones when reacting to a stimulus.
- **Radius** – captures the area of contact of the touch on the screen, providing information about how precisely the player taps.
- **Radius Variance** – measures the variability of the touch radius across taps. A low variance indicates consistent, controlled tapping, while a high variance may suggest uncertainty or adjustment in the player’s input.
- **Temporal metrics** – capture the timing of the tap:
  - *Touch Down* – timestamp when the finger touches the screen;

- *Touch Up* – timestamp when the finger lifts off;
- *Hold Duration* – total duration of the press, calculated as the difference between *Touch Up* and *Touch Down*.

These metrics allow us to assess response timing and how long players commit to their input.

- **Result (hit/miss)** – confirms whether the tap was successful, anchoring the interaction as effective or not.

**Contextual metrics** provide insight into the environment in which the tap occurs:

- **Stimulus appearance timestamp** – indicates the exact moment the visual stimulus becomes visible on screen, marking the point from which the player could start perceiving and preparing for the interaction.
- **Time intervals** – define the window during which the tap should ideally occur, composed of:
  - *Start* – the moment when the relevant stimulus becomes actionable, i.e., the earliest point at which a correct tap could be made;
  - *End* – the last valid moment for a meaningful response, after which the tap is considered late or invalid within the context of the task.
- **Device orientation (portrait/landscape)** – provides context for interpreting tap coordinates, as the screen layout and tap zones may vary significantly depending on the orientation. Some games enforce a fixed orientation, while others allow both.

Together, these metrics define not only *what* the player did, but also *when*, *where*, and *under what circumstances*, offering a holistic foundation for identifying and comparing Predictive Tap across games. In some situations, supplementary contextual data must also be collected, not necessarily as standalone metrics, but as auxiliary information required to compute or interpret the core ones. These included internal game variables, visual markers, or timing references specific to each game's design.

## Chapter 4

# Collecting the Interaction Primitive

### 4.1 Selected Games

To further investigate the Predictive Tap primitive, we selected two games from the available set: *Spinning Around* [55] and *Jumping Ball* [54]. These two games were chosen because they present significantly different gameplay structures while both relying on the same core primitive, making them ideal candidates for comparing how the Predictive Tap manifests across varied contexts.

Other games were excluded for various reasons: *Platform Jumper* due to its high similarity with *Jumping Ball* (being essentially a 3D variation), while *Fill The Cups*, *Spikes Everywhere* and *Zig Zag* were left out due to time constraints and the study's scope.

In addition to these existing titles, we also included *Hopfury*, a game specifically developed for the purpose of this thesis. While it equally builds on the Predictive Tap primitive, *Hopfury* introduces an additional swipe mechanic, making it the only game in the set with more than one core interaction. This addition allows us to collect richer data and examine whether the presence of multiple mechanics influences player behaviour in comparison to the other two games, where the only input required is the tap.

Across all three games, several methodological and design choices were made to support the primary objective of this study: analyzing the Predictive Tap primitive and understanding player consistency across different game contexts. First, modifications to *Spinning Around* and *Jumping Ball* ensured detailed behavioral logging without altering the fundamental gameplay. The use of JSON-based logging allowed the capture of temporal and spatial metrics for every tap, supporting subsequent analysis of performance and consistency. These design choices maintained the core gameplay experience while providing rich experimental data. *Hopfury*, while sharing the same Predictive Tap primitive, introduced additional visual and interactive elements, including music, enemies, and animated effects. This provided a more commercially representative game environment, though these elements were considered supplementary rather than experimental variables. Importantly, the inclusion of a second mechanic, the swipe to launch fireballs, did not serve as a focus of the study. Swipes were logged using the same metrics as taps, with the `isTap` flag set to `false`, allowing us to differentiate between taps and swipes. This approach enabled the examination of whether the addition of another primitive influenced the consistency of player performance

on the Predictive Tap, without analyzing the swipe itself. The structuring of *Hopfury* levels, with some levels featuring only taps and others combining taps and swipes, allowed observation of the Predictive Tap both in isolation and in combination with another action, again supporting the study's core objective.

## 4.2 Common Data Collection Procedures

All games collected a set of common metrics, including player's: **name**, **startTime**, **endTime**, **timeOfDeath**; obstacle's: **id**, **name**, **timeStimuli**, **timeIntStart**, **timeIntEnd**; and tap's: **id**, **x**, **y**, **timeStart**, **timeEnd**, **timeHold**, **radius**, and **radiusVariance**; to ensure that data could be compared across games during analysis. Ideally, finger pressure would also be recorded; however, due to device constraints, this metric was not reliably available, an issue also reported in similar studies [8]. To address this limitation, we collected **radius** and **radiusVariance** as proxy measures. These proxies approximate finger contact area, allowing us to capture aspects of tap consistency that could otherwise be reflected by pressure measurements.

To collect detailed behavioral data in all three games, an automatic logging system was implemented. This system stores structured information in a local `.json` file on the participant's device, capturing temporal and spatial metrics associated with player interactions. The hierarchical structure represents each player's gameplay history, with top-level `PlayerData` objects containing a list of gameplay sessions (`SessionData`). Each session corresponds to a single gameplay attempt and records metadata such as **startTime**, **endTime**, **timeOfDeath**, and, where applicable, level information. These values allow us to measure the overall playtime, the number of attempts a participant had on the same level, and indications of progression, which can be interpreted as indicators of increasing skill.

Within each session, a list of obstacles (`PlatformData`, `SpikeData` or `ObstacleData` depending on the game) stores information about each obstacle encountered, including **id**, **name**, **timeStimuli**, **timeIntStart**, and **timeIntEnd**. Each obstacle also contains a list of taps performed by the player between the previous and current obstacle. Tap entries record **id**, **x**, **y**, **timeStart**, **timeEnd**, **timeHold**, **radius** and **radiusVariance**.

Overall, the game modifications, logging structures, and experimental design choices across all three games were carefully implemented to ensure valid and comparable data collection while preserving the integrity of the original gameplay experiences. The following sections describe the game-specific implementations for each title, including unique metrics and gameplay modifications that complement the common data collection procedures outlined above.

### 4.2.1 Implementation Overview

Across all three games, the data collection system was built around a centralized manager responsible for controlling the logging process. This manager coordinated the creation, organization, and storage of all gameplay data, ensuring consistency across sessions while capturing all player

interactions. Gameplay sessions were initiated at the start of a run or attempt and concluded when the player character died or the attempt ended. Upon session completion, all accumulated data were serialized and stored locally in JSON format, preserving each session as an independent unit for later analysis.

Obstacles or platforms encountered during gameplay were automatically registered, and all taps or touch inputs performed by the player were associated with the corresponding game objects, regardless of whether they occurred inside or outside the valid interaction interval. Auxiliary colliders or algorithms were employed in all games, where applicable, to define precise windows for capturing valid interactions, ensuring accurate alignment between stimulus presentation and player input.

Unity's Input System, specifically the *EnhancedTouch API*, was employed across all games to capture precise touch events. This setup allowed detection of the exact moment a tap began or ended, as well as additional parameters such as touch radius and touch positions. A dedicated component centralized the handling of these events and forwarded them to the session manager, allowing modularity and consistency.

Finally, in each game, the settings interface included a field for entering the player's name and a save button, allowing the test coordinator to manually assign identifiers. All sessions played by a participant were recorded under this entry in the JSON file, maintaining consistent player tracking across multiple attempts.

### 4.3 Spinning Around

*Spinning Around* [55] is an endless circular runner where the player controls a white ball that automatically travels along a circular track. The main objective is to avoid randomly placed spikes while collecting stars, which can be used to unlock new balls in the shop menu (Figure 4.1). The only player interaction consists of tapping the screen to make the ball switch between the inner and outer circles of the track, allowing it to dodge upcoming spikes (Watch this [Video](#)).

As the game progresses, difficulty increases: spikes start to appear closer to the ball's position, requiring increasingly faster and more precise taps. This structure emphasizes the importance of anticipation and timing, as players must act just before danger appears. The ultimate goal is to survive as long as possible and beat one's own high score. To support this loop, the game includes a pause menu, which allows the player to either continue the run, restart from the beginning, or exit to the main menu.

#### 4.3.1 Modifications to Spinning Around

Next, we outline the changes made to the original game *Spinning Around* in order to enable better data collection and support the analysis of the primitive.

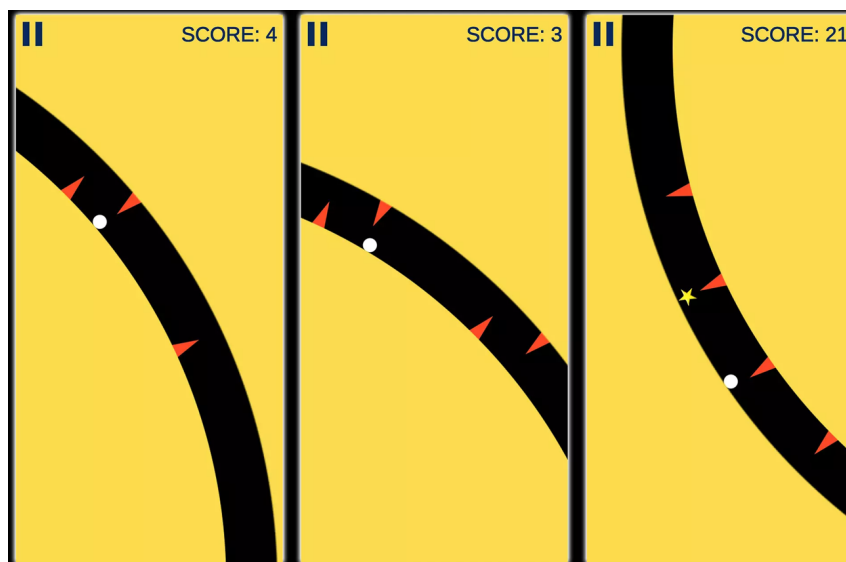


Figure 4.1: Gameplay from *Spinning Around* [55], where the player taps to switch between inner and outer tracks to avoid spikes and collect stars.

### Metrics Collection

In addition to the common metrics collected across all games, *Spinning Around* recorded extra data specific to its gameplay mechanics. Each spike (`SpikeData`) stores information about its position, whether it belonged to the `innerCircle` or `outerCircle`, and the `landedTime`, representing the moment the ball landed on a circle platform just before attempting to pass that spike. This timing can influence the valid tap interval and was therefore included to support later temporal analyses.

Each spike also includes a list of all taps performed by the user between the previous spike and the current one. This ensures that both intentional and unintentional taps (e.g., those aimed at collecting stars or accidental touches) are recorded, providing a complete record of user interaction.

Additionally, for each tap, the ball's position immediately before and after the tap (`beforeBallPos`, `afterBallPos`) was stored. Although these values are typically redundant—for example, if the ball was in the `innerCircle` before a valid tap, it is expected to transition to the `outerCircle` afterwards—they were included to ensure the correctness of the data recording process.

### Game-Specific Implementation Details

In *Spinning Around*, the manager controlled the lifecycle of gameplay sessions: each session began when the player started a run and ended upon death by a spike. Once a session concluded, all accumulated data were immediately serialized and stored locally in JSON format.

A buffering mechanism was implemented to correctly associate taps with the relevant spikes. Since spikes appear sequentially and the interaction window is not instantaneous, all taps per-

Table 4.1: Fields used in the local JSON file for *Spinning Around*. Fields shown in **bold** are those that are common and identical across the other games.

<b>Field</b>	<b>Description</b>	<b>Type (possible values)</b>	<b>Root</b>
<b>players</b>	List of players recorded on the device.	List<PlayerData>	PlayerList
<b>name</b> (Player)	Identifier for the player.	string (e.g., "P7")	PlayerData
<b>sessions</b>	List of gameplay sessions.	List<SessionData>	PlayerData
<b>startTime, endTime</b>	Start and end timestamps of the session.	string (e.g., "26/06/2025 15:10:45")	SessionData
<b>timeOfDeath</b>	Time when the player died in the session.	float	SessionData
<b>spikes</b>	List of spikes in the session.	List<SpikeData>	SessionData
<b>id</b> (Spike)	Unique identifier for the spike	string (e.g., "4", "5")	SpikeData
<b>name</b> (Spike)	Name assigned to the spike	string (e.g., "27", "08")	SpikeData
position	Position of the spike in the circle.	string ("InnerCircle", "OuterCircle")	SpikeData
<b>timeStimuli</b>	Time the spike appeared.	float	SpikeData
<b>timeIntStart</b>	When it's valid to start tapping.	float	SpikeData
<b>timeIntEnd</b>	When the valid tap interval ends.	float	SpikeData
isActive	Whether the spike is currently active.	bool (true, false)	SpikeData
landedTime	Time the ball landed in a circle before the spike.	float	SpikeData
<b>taps</b>	List of taps associated with the spike.	List<Tap>	SpikeData
<b>id</b> (Tap)	Unique identifier for the tap.	int	Tap
<b>x, y</b>	Tap screen coordinates.	float	Tap
<b>timeStart, timeEnd</b>	When the tap began and ended.	float	Tap
<b>timeHold</b>	Duration of the tap.	float	Tap
<b>radius</b>	Radius of the touch input.	float	Tap
<b>radiusVariance</b>	Variance in the radius during the tap.	float	Tap
beforeBallPos	Ball's position before tap.	string ("InnerCircle", "OuterCircle")	Tap
afterBallPos	Ball's position after tap.	string ("InnerCircle", "OuterCircle")	Tap

formed between the previous spike's end and the current spike's interaction window were linked to the current spike.

Additional invisible colliders without physics were placed around each spike to delimit the interaction interval (Figure 4.2), precisely defining when the ball entered and exited the critical interaction zone. The stimulus onset for each spike was determined by the moment it first became visible on the screen, either when it spawned outside the camera view or when instantiated directly within the visible area.

Upon death, the game over UI presented options to either exit or restart the run. For the purposes of the study, however, the restart option was removed to avoid branching data paths that could complicate session analysis and compromise the consistency of logged interactions. This ensured that every new attempt consistently originated from the main menu, streamlining the experimental procedure and avoiding branching paths in the data collection flow.

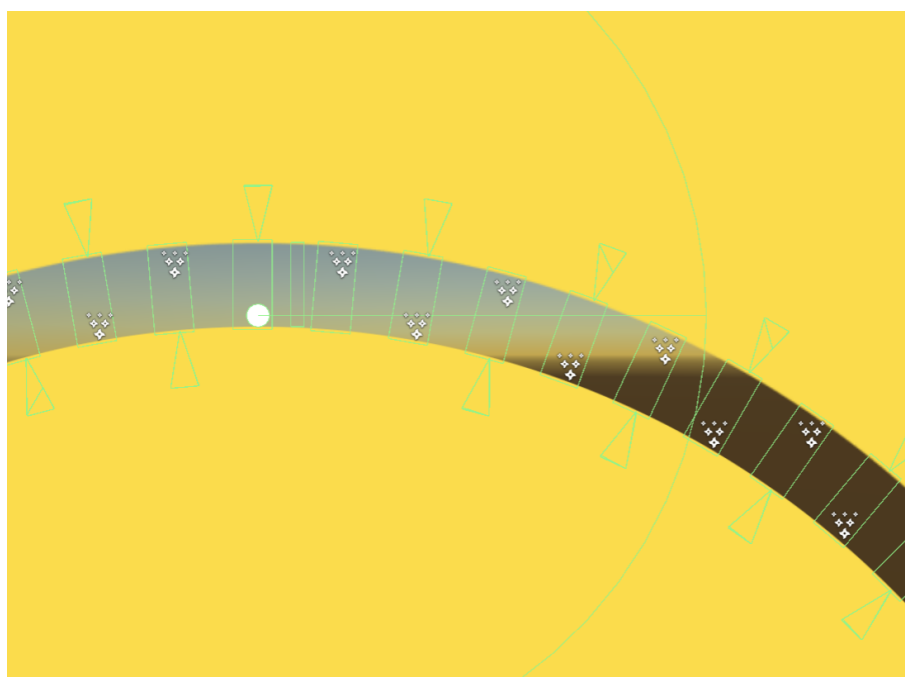


Figure 4.2: Spike with invisible colliders used to define the interaction interval in *Spinning Around* [55].

#### 4.4 Jumping Ball

Jumping Ball [54] is a vertical-scrolling platformer where a white ball moves automatically from side to side on each platform, bouncing between walls (Figure 4.3). The player interacts only by tapping the screen to make the ball jump to the platform above. The main goal is to reach the top of each level by landing safely on the next platform while avoiding falling off the edges (Watch this Video).

The game consists of 51 levels that gradually increase in difficulty. In the initial levels, most platforms are already visible on screen, allowing players to anticipate their movements more eas-

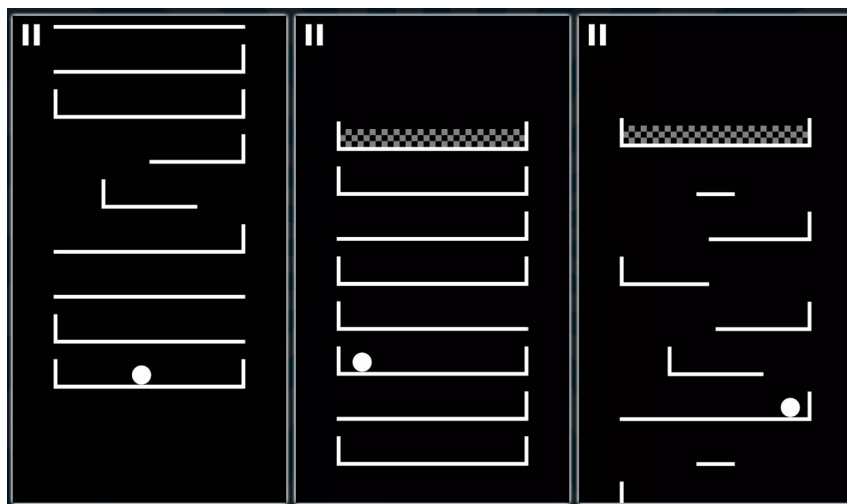


Figure 4.3: Gameplay from *Jumping Ball* [54], where the player taps to make the ball jump between platforms while avoiding falling.

ily. In later levels, however, platforms may only appear as the player ascends, requiring quick reactions and constant adjustment. Moreover, some levels feature wall arrangements that reduce the time window available to perform a jump, demanding faster decision-making and even more precise timing. A pause button is available, offering options to resume, restart, or quit the level. In addition, the game includes dedicated statistics pages, where players can review performance metrics across levels (e.g., total playtime, number of attempts).

#### 4.4.1 Modifications to *Jumping Ball*

This subsection outlines the changes made to the original game *Jumping Ball* in order to enable better data collection and support the analysis of the primitive. To support detailed behavioral analysis, *Jumping Ball* was instrumented to locally store gameplay data using the JSON format.

##### Metrics Collection

In addition to the common metrics collected across all games, *Jumping Ball* recorded extra data specific to its gameplay mechanics. Each platform (`PlatformData`) stores information about its position in the level, including the coordinates of its left and right edges (`xLeft`, `xRight`) and its vertical position (`y`). To clarify, `xLeft` represents the horizontal position of the platform's leftmost point, while `xRight` represents the rightmost point.

To support analysis of tap success, valid horizontal ranges (`xMinMoveLeft`, `xMaxMoveLeft`, `xMinMoveRight`, `xMaxMoveRight`) are included, defining areas where a tap can successfully make the ball land on the next platform depending on ball movement direction. Most of these variables are not directly used to describe the Predictive Tap itself; rather, they capture the game mechanics or player actions that later allow precise calculation of tap timing and intervals. The exact usage of these metrics for analyzing player behavior is explained in detail in the next section.

Table 4.2: Fields used in the local JSON file for *Jumping Ball*. Fields shown in **bold** are those that are common and identical across the other games.

Field	Description	Type (possible values)	Root
<b>players</b>	List of players recorded on the device.	List<PlayerData>	PlayerList
<b>name</b> (Player)	Identifier for the player.	string (e.g., "P7")	PlayerData
<b>sessions</b>	List of gameplay sessions.	List<SessionData>	PlayerData
level	Name of the level played in the session.	string (e.g., "Level1")	SessionData
<b>startTime, endTime</b>	Start and end timestamps of the session.	string (e.g., "26/06/2025 15:10:45")	SessionData
<b>timeOfDeath</b>	Time when the player died in the session.	float	SessionData
<b>platforms</b>	List of platforms encountered in the session.	List<PlatformData>	SessionData
<b>id</b> (Platform)	Unique identifier for the platform	string (e.g., "0", "4")	PlatformData
<b>name</b> (Platform)	Name assigned to the platform	string (e.g., "Platform4", "Finish Platform")	PlatformData
xLeft, xRight, y	Horizontal boundaries of the platform and its vertical position in the level.	string	PlatformData
hasLeftBorder, hasRightBorder	Indicates whether the platform has a left or right wall.	bool	PlatformData
moveRight	Indicates the movement direction of the ball when the platform was registered	bool	PlatformData
xMinMoveLeft, xMaxMoveLeft	Minimum and maximum horizontal position of the ball when moving left for a tap to successfully land on the next platform.	float	PlatformData
xMinMoveRight, xMaxMoveRight	Minimum and maximum horizontal position of the ball when moving right for a tap to successfully land on the next platform.	float	PlatformData
<b>timeStimuli</b>	Time the platform appeared.	float	PlatformData
<b>timeIntStart</b>	When it's valid to start tapping.	float	PlatformData
<b>timeIntEnd</b>	When the valid tap interval ends.	float	PlatformData
<b>taps</b>	List of taps associated with the platform.	List<Tap>	PlatformData
<b>id</b> (Tap)	Unique identifier for the tap.	int	Tap
<b>x, y</b>	Tap screen coordinates.	float	Tap
<b>timeStart, timeEnd</b>	When the tap began and ended.	float	Tap
<b>timeHold</b>	Duration of the tap.	float	Tap
<b>radius</b>	Radius of the touch input.	float	Tap
<b>radiusVariance</b>	Variance in the radius during the tap.	float	Tap

### Game-Specific Implementation Details

In *Jumping Ball*, the player is required to jump at specific moments to succeed. However, these moments are not programmatically defined, as they depend on the assembly of the platforms and level design, and are therefore not immediately available for collection.

Therefore, each platform in a level was automatically registered, storing its position, borders, and the movement direction of the ball. Valid horizontal ranges (`xMinMoveLeft`, `xMaxMoveLeft`, `xMinMoveRight`, `xMaxMoveRight`) were calculated for each platform to determine the intervals where the ball's center could be positioned for a tap to result in a successful jump to the next platform. These ranges considered both the current and the platform above, ball radius, jump distance, ball's horizontal direction and any active borders (Figure 4.4). The stimulus onset for each platform was determined by the moment it first became visible on the screen, either when it spawned outside the camera view and entered it, or when it was instantiated directly within the visible area. The interval remained active while the ball moved in a given direction and was reset only when the ball collided with a wall and changed direction.

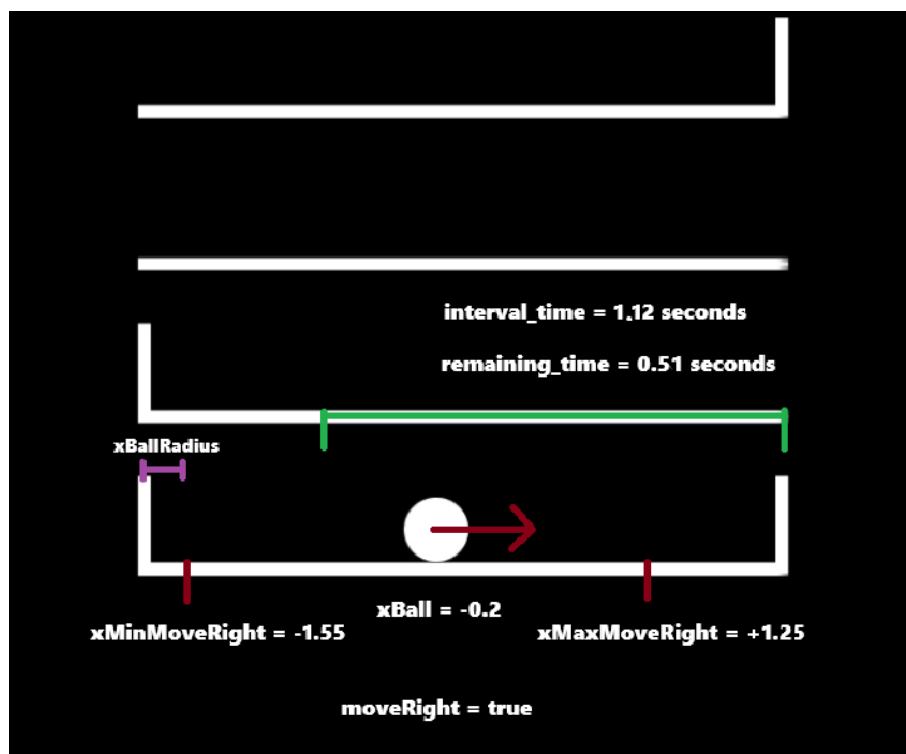


Figure 4.4: Example of metric values during gameplay in *Jumping Ball* [54]. The values are illustrative and do not represent actual recorded data.

Because the ball's movement was frame-dependent by default rather than physically velocity-driven, a 3-second countdown at the start of each level was used to capture timestamps and calculate the average speed of the ball. This average speed was then used to estimate timing for valid tap intervals, ensuring consistency and comparability across devices and framerates. The original interaction design of the game was preserved as much as possible, without altering its intended

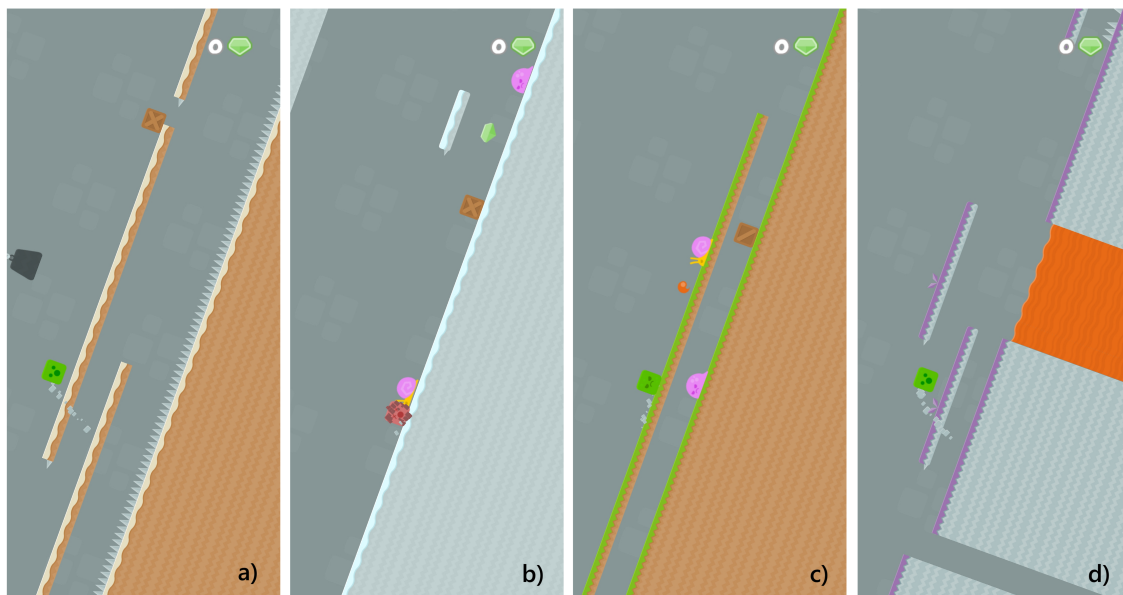


Figure 4.5: Gameplay from *Hopfury*, where the player taps to avoid obstacles by jumping and swipes to kill enemies with a fireball.

mechanics.

Although the original game contained 51 levels, the dataset used for data collection was restricted to 22 levels. The removed levels were those that introduced cases beyond the intended scope of the analysis, such as platforms positioned at the same vertical height as the current one, which would require a distinct jumping model to be considered, or cases where two platforms existed directly above the current one at the same height, creating alternative possible landing targets. Both situations added unnecessary complexity to logging and interpretation of interactions. By focusing on the remaining levels, the dataset was simplified while still capturing a broad variety of scenarios, including platforms of different sizes, with or without walls, and positioned at varying horizontal distances.

## 4.5 Hopfury - Original Game Creation

*Hopfury* is a 2D mobile platformer developed specifically for this research (Figure 4.5). The player controls a green square and must overcome obstacles and enemies to reach the end of each level. The interaction is based on two simple actions, tapping the screen to make the square jump, and swiping up to shoot a fireball that eliminates enemies. The fireball action is subject to a cooldown, meaning that after shooting, the player must wait a short period before being able to shoot again. The game was loosely inspired by popular rhythm-based platformers such as *Geometry Dash* [56], but differs in that its level layout is presented with the screen inclined diagonally rather than strictly horizontal. Its mechanics and pacing were deliberately simplified to fit the study's objectives.

Unlike *Spinning Around* [55] and *Jumping Ball* [54], which feature a more minimalistic visual design, *Hopfury* incorporates a greater number of visual and interactive elements. We decided to

include animated enemies, fireball effects, themed levels synchronized with music, and animations for the green square character corresponding to each action or event. While still maintaining clarity, the visual style was intentionally made more dynamic with visual embellishments which are known to positively affect the player experience [20].

We created a total of 12 levels, with Level 0 and Level 6 acting as tutorials. Level 0 introduces only the tap mechanic and a few core gameplay elements, such as jumping and basic obstacles. The swipe mechanic, used to launch fireballs, is only introduced in Level 6, ensuring a gradual onboarding process and avoiding cognitive overload during the initial stages of play.

Each level is paired with a unique musical beat. As the game progresses, new challenges are introduced, such as moving enemies and more complex obstacle layouts, requiring increased coordination between jumps and fireball attacks.

*Hopfury* was created from scratch to support detailed data logging for research purposes. It records all relevant gameplay interactions, which will be described in detail in the following chapter.

To speed up development and maintain a clean and engaging aesthetic, all assets used in the game, including music tracks, sound effects, environment sprites, and visual elements, were sourced from free-to-use repositories.

### Metrics Collection

In addition to the common metrics collected across all games, *Hopfury* recorded extra data specific to its gameplay mechanics. Each `PlayerData` entry tracks how level progression was achieved, distinguishing whether a level was unlocked manually via the level selection menu (`levelUnlocked`) or automatically through gameplay (`unlockNextLevel`). The attempt number for each session (`tryNumber`) is also recorded. Additionally, the session stores whether the player successfully collected the level's diamond (`gotDiamond`), providing an optional measure of challenge completion.

Each obstacle (`ObstacleData`) records its position in the level (`x`, `y`). This information allows later identification of which obstacle the player was reacting to, enabling the recalculation of merged interaction intervals based on the probability of taps falling within multiple valid intervals of different obstacles. The exact methodology will be described in Chapter 5.1.4.

Each tap within an obstacle also stores the ball's position upon landing (`landedTime`) and includes a flag (`isTap`) to differentiate between simple taps and swipes.

### Game-Specific Implementation Details

The implementation of *Hopfury* involved several design decisions oriented toward supporting reliable data collection rather than optimizing for commercial gameplay. One of the earliest choices concerned the overall layout of the game world. While traditional platformers are typically played in a strictly horizontal or vertical configuration, *Hopfury* was designed with a diagonal ground plane, creating the impression that the square character was constantly moving upwards along a

Table 4.3: Fields used in the local JSON file for *Hopfury*. Fields shown in **bold** are those that are common and identical across the other games.

Field	Description	Type (possible values)	Root
<b>players</b>	List of players recorded on the device.	List<PlayerData>	PlayerList
<b>name</b> (Player)	Player identifier.	string (e.g., "P7")	PlayerData
levelUnlock	Flag indicating if all levels were unlocked.	int	PlayerData
unlockNextLevel	Flag indicating if the next level was unlocked by the 3-try system.	int	PlayerData
<b>sessions</b>	List of gameplay sessions.	List<SessionData>	PlayerData
<b>startTime, endTime</b>	Start and end timestamps of the session.	string (e.g., "26/06/2025 15:10:45")	SessionData
tryNumber	Attempt number for this level.	int	SessionData
gotDiamond	Indicates whether the player collected the level's diamond.	bool	SessionData
<b>timeOfDeath</b>	Time (in seconds) when the player died during the session.	float	SessionData
<b>obstacles</b>	List of obstacles encountered in the session.	List<ObstacleData>	SessionData
<b>id</b> (Obstacle)	Unique identifier for the obstacle.	string (e.g., "4", "5")	ObstacleData
<b>name</b> (Obstacle)	Name assigned to the obstacle.	string (e.g., "Box", "Spikes")	ObstacleData
x, y	X and Y coordinates of the obstacle.	float	ObstacleData
<b>timeStimuli</b>	Timestamp when the obstacle appeared.	float	ObstacleData
<b>timeIntStart</b>	Start time of the valid tap interaction window.	float	ObstacleData
<b>timeIntEnd</b>	End time of the valid tap interaction window.	float	ObstacleData
<b>taps</b>	List of taps associated with the obstacle.	List<Tap>	ObstacleData
<b>id</b> (Tap)	Unique identifier for the tap.	int	Tap
isTap	True if the input was a tap, false if it was a swipe.	bool	Tap
<b>x, y</b>	Tap screen coordinates.	float	Tap
<b>timeStart, timeEnd</b>	Start and end timestamps of the tap.	float	Tap
<b>timeHold</b>	Duration the tap was held.	float	Tap
<b>radius</b>	Radius of the touch input.	float	Tap
<b>radiusVariance</b>	Variation in the touch radius during the tap.	float	Tap
landedTime	Time when the ball landed on a surface.	float	Tap

slope. This arrangement provided several benefits simultaneously: it maintained visual continuity with vertical-style games, allowed participants to anticipate upcoming obstacles earlier, and provided flexibility to hold the device in either portrait or landscape orientation.

The level structure followed a gradual progression: Level 0 and Level 6 acted as tutorials and were excluded from data logging, serving only to introduce mechanics. Level 0 presented the tap action alongside basic obstacles, while Level 6 introduced the swipe mechanic, moving enemies, and the fireball cooldown. Between these two, five levels used taps only, and another five combined taps and swipes, ensuring both mechanics were tested in varied contexts. Early levels were deliberately kept simple and repetitive, using a limited set of obstacles to capture clean baseline interaction data before introducing more complex combinations in later stages.

Progression was adapted to guarantee that all participants advanced to the levels containing both mechanics. A “three-try rule” was implemented: if the player failed a level three consecutive times, the next level was automatically unlocked. Additionally, a button in the main menu, represented by a key icon, allowed all levels to be unlocked manually. This feature, originally created for development and debugging, also provided researchers with a fallback option during testing sessions, ensuring that data could be collected across the entire level set.

Each obstacle was implemented as a prefab containing both standard and auxiliary colliders dedicated to logging. These included colliders that marked when an obstacle entered the player’s field of view, the start and end of the valid interaction interval, and a finishing collider that registered the end of the obstacle event (Figure 4.6). This design allowed each obstacle to store precise information about its reaction window and associate all taps made within and outside that interval with the corresponding event. In cases where the player died by colliding directly with the obstacle before reaching the finishing collider, the obstacle’s own collider acted as the termination point, ensuring the event was still logged correctly with all relevant timestamps. Different obstacle types required tailored setups: for example, colliders for spikes registered lethal contact from any direction, whereas boxes allowed safe landings from above. Platforms were also included not only to diversify the level design but also to extend the available reaction time for subsequent obstacles, giving participants additional opportunities to prepare for their next action.

To sustain engagement, audiovisual elements such as animated enemies, character animations, and themed music tracks were integrated. Some levels were loosely synchronized with the background music to create a sense of flow, but strict rhythm-based design was intentionally avoided, as it would have significantly shortened reaction times and increased difficulty beyond the intended scope. Specific audiovisual cues were added to reinforce gameplay feedback and create a more immersive experience. For instance, distinct sounds were triggered for jumping, launching a fireball, or collecting a diamond, ensuring that players could clearly associate each action with a perceptible outcome. Similarly, animations highlighted key states, such as the cooldown indicator for the fireball ability (Figure c 4.5), the visual trail left by the square while moving and jumping (Figures a, c, and d 4.5), and the death sequence of the character (Figure b 4.5). An additional layer of challenge was introduced through diamonds, designed as optional collectibles that often

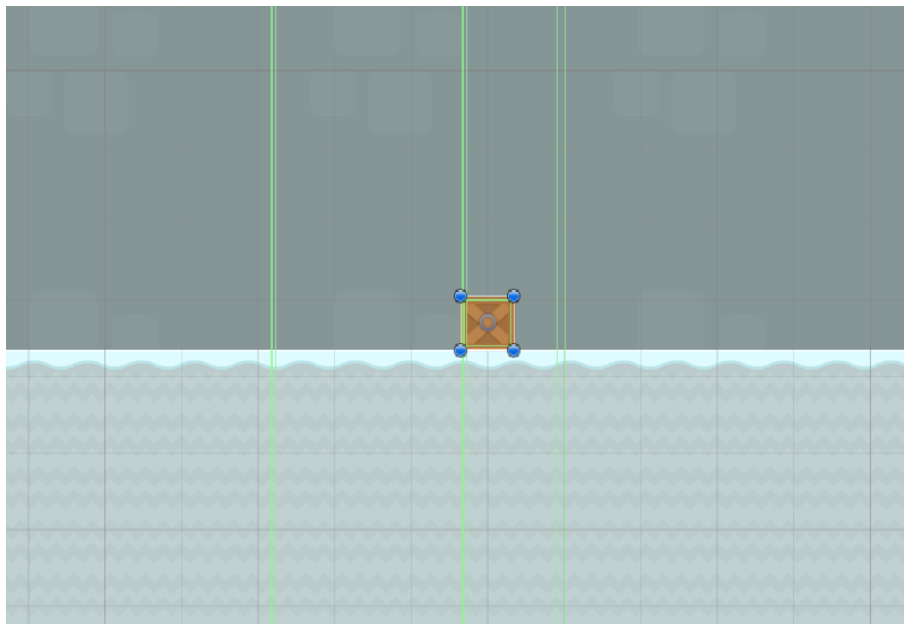


Figure 4.6: Example of colliders in the prefab of an obstacle in *Hopfury*.

required more demanding timing or planning. This offered a secondary performance measure distinguishing players who pursued these challenges from those concentrating exclusively on level completion. By combining optional and mandatory tasks, supported by clear audiovisual cues, the game encouraged both consistent baseline behaviour and opportunities for players to demonstrate higher levels of skill.

## 4.6 Preliminary Tests

Before conducting the main user study, a set of preliminary tests was carried out to validate the data collection process and identify potential issues in the experimental setup. These tests were essential to ensure that the experimental games and logging systems were robust, consistent, and able to capture reliable player interaction data.

The preliminary study focused exclusively on *Spinning Around* and *Jumping Ball*, as *Hopfury* was still under development at the time. A total of 8 participants took part in these sessions. Their role was not to provide final experimental data but to help identify limitations, inconsistencies, and possible improvements in both gameplay design and data collection.

The objectives of the preliminary tests were threefold. First, verification of logging accuracy, ensuring that taps, timings, and platform interactions were being registered correctly without errors. Second, the detection of bugs or inconsistencies in the games, such as crashes, incorrect event triggers, or missing data points. Third, estimation of session length, determining how long participants needed to play each game to generate a sufficiently rich dataset while avoiding fatigue.

Moreover, involving participants at this stage proved valuable beyond technical validation. Their gameplay revealed behaviours that had not been anticipated during development, exposing

situations that the logging system was not initially designed to capture and providing guidance for improving both data accuracy and game interaction consistency.

### 4.6.1 Participants

A total of 8 participants took part in the preliminary tests. The group included 5 females and 3 males. Participants were recruited through a combination of word-of-mouth and personal networks, ensuring a mix of gaming experience and familiarity with similar types of games. While not representative of the full study sample, this group provided sufficient diversity to detect technical and procedural issues in the data collection.

### 4.6.2 Procedure

During the preliminary tests, participants played both *Spinning Around* and *Jumping Ball* in short alternating sessions. Each participant started with one of the games, then switched to the other, and continued alternating until they had completed two rounds with each game. Each session lasted approximately 2 minutes, resulting in a total of 4 minutes of gameplay per game. This design allowed the researchers to gather initial interaction data for both games while keeping session durations short enough to prevent fatigue.

Throughout the sessions, all interactions, including tap locations, timestamps, and platform events, were logged for subsequent inspection. This setup provided an early view of how participants interacted with the games and allowed the team to identify potential issues in data collection and game behavior.

### 4.6.3 Problems Identified and Corrections

The preliminary tests offered crucial insights into the accuracy and reliability of the data collection system, as well as the robustness of game mechanics. Several problems were identified and addressed to ensure that the main study would generate consistent and meaningful results.

#### Spinning Around

We identified three main issues in *Spinning Around*. First, when players completed multiple laps, respawned spikes were sometimes logged as the same instance, which was solved by treating each spike spawn as a separate entity. Second, colliders occasionally caused taps to be missed, which we addressed by resizing and repositioning them to better match the ball's radius. Finally, delayed or long-held taps sometimes caused the game to crash or were ignored after player death; a short timeout was introduced to safely capture these inputs.

#### Jumping Ball

In *Jumping Ball*, a key problem involved the calculation of tap intervals in relation to platform interactions. Originally, the system assumed a fixed ball speed based on previous tests. This approach failed to account for small variations caused by the device's framerate, which could result

in taps being misregistered when the ball ascended and descended across platforms. To address this and as previously described, an initial 3-second calibration phase was added at the beginning of each level to measure the ball's actual speed dynamically. This ensured that subsequent tap intervals were calculated correctly, maintaining accurate logging and preventing unintended deaths due to timing inconsistencies.

Furthermore, an additional issue was identified when the ball ascended to a higher platform and then fell back to a lower one. In these cases, taps associated with the platforms were sometimes misregistered from the point of the fall onwards. This could lead to a situation where the ball would no longer correctly ascend to the next platform, causing the player to die despite having reacted within the expected time. To address this, the tap-interval algorithm was revised so that after a downward fall, subsequent taps continued to be registered correctly. This ensured that platform interactions remained accurate, prevented unintended deaths, and eliminated the majority of unexpected game behaviors in more advanced levels.

### Limitations Identified Across Both Games

During the preliminary tests, a significant limitation was identified regarding touch pressure. Although the system was designed to record touch pressure values, the hardware consistently returned a default or non-informative value, making meaningful analysis impossible. To compensate, proxy measures were collected, namely the touch radius and radius variance, which provided a more reliable basis for analyzing tap intensity and dynamics. These measures were subsequently used to replace direct pressure readings in the main study.

Additionally, an issue was observed with the recording of tap hold times. Initially, timestamps for each tap were registered in a manner that depended on the device's framerate. This sometimes resulted in taps appearing clustered and their hold times being slightly inaccurate. While the differences were on the scale of milliseconds, this could affect analyses that rely on precise temporal data. To address this, the tap logging system was restructured to use an event-based approach, ensuring that each tap's start time and duration were recorded accurately. This change was implemented for both *Spinning Around* and *Jumping Ball*, improving the reliability of interaction data across all sessions.

#### 4.6.4 Exploratory Data Analysis

Beyond technical validation, the preliminary tests also enabled an exploratory inspection of the logged data. The JSON logs were processed into structured DataFrames, where new metrics were derived to complement the existing ones. Two additional measures were introduced: *remaining time*, defined as the amount of valid interaction time still available when a tap was performed (i.e., how much of the allowed interval remained), and *reaction time*, defined as the delay between the start of the valid interval and the moment the tap was executed. Preprocessing also included adjustments for special cases. When extra taps occurred within an expected interval, the interval was recalculated so that it only became valid after the most recent *landed time* on the circle opposite

to the reacting spike. This refinement ensured that measures such as reaction time and remaining time reflected the correct temporal context of each tap.

These new metrics were combined with existing data such as *hold time*, *radius*, and *radius variance* for exploratory analysis. Correlations between them were inspected (e.g., between remaining time and hold time, or between radius and remaining time), but no strong relationships were found at this stage. It should be noted that this analysis was preliminary and conducted without extensive data cleaning, serving primarily as a first glance at the data rather than a rigorous evaluation.

A series of visualisations was produced to compare participants and games. Stripplots and scatterplots of hold time, radius, and reaction time were used to observe player-specific patterns. Comparisons across games suggested that the same player could exhibit slightly different interaction profiles between *Spinning Around* and *Jumping Ball*. However, it is important to note that these observations were made on data that, while not corrupted, were not yet fully accurate due to the limitations identified in the preliminary tests, such as misregistered taps, collider issues, and uninformative pressure readings. As such, the exploratory analysis primarily served to guide improvements in data collection and planning for a more precise and structured analysis in the main study.

Overall, the exploratory analysis highlighted the diversity of play styles among participants and demonstrated the potential of the collected data to reveal interaction patterns once the identified issues were addressed. These insights were instrumental in informing adjustments to the games and logging systems, ensuring that subsequent data collection in the main study would be both reliable and suitable for rigorous analysis.



# Chapter 5

## User Study

### 5.1 Evaluating Predictive Tap Consistency

The study was conducted in a controlled environment, where participants played three experimental games: *Spinning Around*, *Jumping Ball*, and *Hopfury*, for approximately nine minutes each, including a one-minute break in-between. During the sessions, participants completed several questionnaires about the experience with the games. Finally, a semi-structured interview was conducted to gather qualitative feedback from participants regarding the games, including their perceptions of similarities and differences between them, as well as their views on the potential use of game interaction data beyond gaming.

The main objective of this study was to collect a large set of quantitative interaction data in order to analyse the proposed game interaction primitive and explore potential correlations between its underlying metrics. By examining these correlations across different games, the study aimed to evaluate the hypothesis that players exhibit consistent behaviour when interacting with games that share the same mechanics or primitives.

The research question guiding this study was as follows:

**RQ:** To what extent are players' gameplay patterns consistent across games sharing the Predictive Tap interaction primitive?

The study was approved by the Ethics Committee of our university.

#### 5.1.1 Participants

A total of 23 participants took part in the main user study, coming from 3 countries and aged between 20 and 57 years ( $M = 25.9$ ,  $SD = 8.5$ ), of which 11 were female and 12 were male (Table 5.1). Participants were recruited through announcements in several departments of our university, as well as via Discord groups and online forums, with the recruitment form (Appendix A) shared directly within these channels, aiming to reach individuals aged 18 or older with varying levels of gaming experience.

The sample included a mix of expert gamers, casual gamers, and individuals with little prior gaming experience, with the majority (except P6) reporting experience in mobile gaming, which

aligned with the target profile for this study (Table 5.1).

Table 5.1: Participant demographics and gaming experience.

ID	Age	Gender	Country	Player Type	Avg. Mobile Session	Touch Control Comfort
P1	23	F	Portugal	Semi-serious	< 1 hours	5
P2	23	F	Portugal	Casual	< 1 hours	4
P3	22	F	Portugal	Casual	< 1 hours	4
P4	22	M	Portugal	Hardcore	< 1 hours	5
P5	24	M	Portugal	Semi-serious	1-2 hours	4
P6	45	M	Andorra	Casual	< 1 hours	3
P7	23	F	Portugal	Casual	< 1 hours	5
P8	22	M	Portugal	Casual	< 1 hours	5
P9	24	F	Portugal	Casual	1-2 hours	5
P10	26	M	Portugal	Hardcore	< 1 hours	4
P11	28	M	Portugal	Semi-serious	< 1 hours	5
P12	24	M	Portugal	Semi-serious	< 1 hours	5
P13	24	M	Portugal	Hardcore	2-4 hours	5
P14	24	F	Portugal	Casual	1-2 hours	5
P15	20	F	Portugal	Casual	2-4 hours	3
P16	57	F	Portugal	Casual	1-2 hours	5
P17	22	F	Portugal	Don't know	< 1 hours	4
P18	23	M	Brasil	Semi-serious	1-2 hours	5
P19	28	M	Portugal	Semi-serious	< 1 hours	1
P20	26	F	Portugal	Casual	< 1 hours	4
P21	23	M	Portugal	Semi-serious	< 1 hours	4
P22	22	F	Portugal	Semi-serious	< 1 hours	5
P23	20	M	Portugal	Hardcore	1-2 hours	5

### 5.1.2 Apparatus

The study was conducted in a controlled indoor environment, with participants seated and a table available for support if needed. Participants played the three experimental games (*Spinning Around*, *Jumping Ball*, and *Hopfury*) on a Black Shark Android smartphone, with the volume increased to ensure audibility. Questionnaires were completed on a Lenovo Legion laptop, which was also used by the researcher to take notes on contextual aspects of the participants' interactions and other relevant behaviours observed during gameplay. In addition, all semi-structured interviews were audio-recorded using the iPhone 15 Pro with the Dictaphone app. This recording facilitated later transcription and analysis of qualitative feedback.

### 5.1.3 Procedure

The first session (P1) was conducted as a pilot test (Table 5.1), in which all three games were played while simultaneously trialling the study script and overall flow of the session. This allowed us to identify and adjust minor issues in the procedure before running the main study.

Sessions were arranged in advance through direct communication with each participant (e.g., via email or Discord), with a mutually agreed time scheduled for the study. Prior to attending

the session, participants were provided with an informative document (Appendix [B](#)) detailing the study, which they were asked to read in advance to understand the general purpose, procedures, and expectations. Each session lasted approximately 45 minutes and took place in a controlled indoor environment, where a chair and table were available for optional use.

Before starting gameplay, the researcher followed the study script (Appendix [I](#)) to ensure that each session was conducted in a controlled and consistent manner across participants. Several preparatory steps were carried out to ensure a smooth testing process. The smartphone used for the study was fully charged, with all three experimental games installed, volume increased, and the participant's ID entered in the appropriate field for each game. Additionally, an online document on the Lenovo Legion laptop was prepared for note-taking. Throughout the sessions, the researcher recorded contextual observations not captured by the game logs, such as any bugs, unexpected behaviours, or interruptions that occurred during the sessions, to be considered later in the analysis.

Participants were firstly asked to complete the Informed Consent Form (Appendix [C](#)) and then the Demographic Questionnaire (Appendix [D](#)) to provide contextual information regarding their background, gaming experience, and familiarity with mobile devices.

Before each game, the basic objectives, controls, and rules were explained to participants to ensure they understood how to interact with the game without influencing their natural behaviour. Participants were instructed to play naturally and independently, while the researcher remained silent except to provide pre-planned instructions or clarify procedural points if necessary. Importantly, no constraints were imposed on how participants held or interacted with the device. They were free to adopt whichever grip, hand usage, or finger input felt most natural to them, replicating the conditions of everyday mobile gameplay. This design choice contrasts with what would happen if a strict interaction protocol were enforced (e.g., holding the device in one hand and tapping with the index finger of the other), which could help reduce potential confounding variables, but may fail to capture authentic player behaviour [\[8\]](#).

For each experimental game, participants played for approximately nine minutes, including a one-minute break at the halfway point. During this break, participants completed a short questionnaire regarding their experience so far (Appendix [E](#)). At the end of each game, an additional questionnaire was administered to assess the experience specific to that game (Appendix [F](#)). The games were played in a fixed order: *Spinning Around*, *Jumping Ball*, and *Hopfury*. The mid-session breaks also helped mitigate fatigue, since the straightforward mechanics of the games often resulted in repetitive interactions.

Following the completion of all three games, a final questionnaire (Appendix [G](#)) was administered to compare experiences across games and gather overall feedback. Finally, a semi-structured interview (Appendix [H](#)) was conducted to collect qualitative insights regarding participants' experiences and perceptions of the games. With prior consent, the interview was audio-recorded and typically lasted between five and ten minutes. It allowed participants to elaborate on their performance, reflect on difficulties encountered, and provide subjective feedback and overall gameplay experience, as well as share their opinions and interest regarding the collection of gameplay met-

rics in commercial games.

### 5.1.4 Data Analysis and Preprocessing

The analysis was conducted in Python using Jupyter Notebook, where each game session was logged in JSON format. The raw JSON files were converted into pandas DataFrames, allowing the data to be structured and processed systematically. Each tap was treated as an independent event.

#### Data Cleaning

In total, 29,679 taps were initially extracted across all players and sessions. After systematic cleaning and filtering, the final dataset contained 19,345 taps, which formed the basis of all subsequent analyses. The discarded events included:

- taps from the “Teste” player, used exclusively by the researcher for debugging and testing purposes;
- obstacles with no associated taps (cases where players successfully passed the obstacle without needing to react);
- records with invalid or inconsistent values (e.g., `timeIntEnd=-1` or `0`), resulting from data collection failures or unexpected behaviors.
- for *Hopfury*, taps with `isTap=false` were also excluded, as these corresponded to swipes rather than actual taps.

In *Hopfury*, a single tap could be simultaneously associated with multiple overlapping obstacles, since their interval times often overlapped. To resolve this, a custom function was implemented in Jupyter Notebook that merged overlapping intervals into a single valid obstacle instance. Each tap was then reassigned to the corrected interval, ensuring that only one valid event per tap was kept.

The three games generated heterogeneous JSON schemas, with different columns and event structures. To address this, unified DataFrames containing a shared set of variables were constructed across games. From these standardized datasets, several derived metrics were computed directly from the raw logs (Table 5.2). Both the individual game DataFrames and the combined DataFrame were utilized in the analysis.

#### Data Aggregation and Feature Engineering

Beyond the per-tap metrics, a `global_score` was developed for each player-game instance as an approximate composite measure of performance. The scoring functions were defined as follows:

- **Spinning Around** – 50% weight on the session score (average survival time, capped at 45 seconds) and 50% on the maximum number of obstacles cleared.

- **Jumping Ball** – 40% weight on the highest level reached, and 60% on attempts per level, penalizing earlier failures based on the average completion times of other players.
- **Hopfury** – 40% from the average level scores (penalized by early deaths, with bonus points for collecting diamonds), 40% from the average maximum horizontal position reached per level, and 20% from the number of levels completed.

For each player-game instance, the raw global score was normalized to a standardized index ranging from 0 to 1. This ensured comparability across games despite their different mechanics and scoring systems.

Table 5.2: Common variables across games and derived metrics.

Variable	Description
<i>Raw variables (common across games)</i>	
player	Identifier of the player.
session_start	Timestamp of session start.
session_end	Timestamp of session end.
timeOfDeath	Timestamp when the player died in the session.
obstacle_id	Unique identifier of the obstacle.
name	Name of the obstacle.
timeStimuli	Timestamp of the obstacle’s appearance.
timeIntStart	Start timestamp of the valid interval for the obstacle.
timeIntEnd	End timestamp of the valid interval for the obstacle.
tap_id	Unique identifier of the tap within the session.
tap_timeStart	Timestamp when the tap started.
tap_timeHold	Duration of the tap.
tap_timeEnd	Timestamp when the tap ended.
tap_x	X-coordinate of the tap on the screen.
tap_y	Y-coordinate of the tap on the screen.
<i>Derived metrics (engineered from raw variables)</i>	
global_score_norm	Standardized global performance index for each player-game instance, normalized to range between 0 and 1.
reaction_time	Latency between the start of the valid interval and the tap moment. Ignores visual stimulus onset.
interval_time	Duration of the valid reaction window ( $\text{timeIntEnd} - \text{timeIntStart}$ ).
tap_success	Binary indicator if the tap occurred within the valid interval (1 = success, 0 = failure).
tap_radius_metric	Combined measure of finger contact area and its stability during the tap ( $\text{tapRadiusNorm} * (1 - \text{tapRadiusVarianceNorm})$ ).

## Data Analysis

The gameplay data from the three games was analyzed to explore and characterize the Predictive Tap game primitive. Our analysis approach was partially inspired by Chitale et al. [8], who captured fine-grained swipe interactions in mobile games, aggregated them into interpretable metrics, and analyzed their relationship with psychological measures using Spearman rank correlations.

Following a similar philosophy, we logged all tap events, collected a wide range of per-tap metrics, and aggregated them (mean, std, min, max, var). We then compared these aggregated metrics across different games using Spearman rank correlations to identify cross-game consistency. In addition, we analyzed the original per-tap metrics by computing per-player averages and correlating them across games, ensuring that each participant contributed equally, accounting for inter-player variability. Analyses were further stratified by temporal bins to examine performance across different tap intervals. Separate block-wise analyses were conducted to investigate how player performance evolved within each game and to identify stable patterns indicative of predictive tapping. Finally, mixed linear models were applied to assess the effects of game context on individual metrics. Participant feedback was transcribed and analyzed alongside the quantitative results to provide additional insights into player experience and perceptions of the games.

## 5.2 Results

### 5.2.1 Player context

#### Rankings

To contextualize the skill levels of the participants in the study, player rankings were computed based on two complementary performance indicators: mean reaction time across all three games and the normalized global scores per game. Reaction time provides an objective measure of anticipatory and predictive motor behavior, while the global scores offer a broader view of overall gameplay performance across different mechanics.

Table 5.3 presents the ranking of players according to their mean reaction times, with lower values reflecting fast and more consistent responses. Table 5.4 shows the ranking based on the average global score across the three games, which reflects overall performance considering multiple aspects of gameplay. While both rankings highlight high-performing players, the reaction time ranking emphasizes speed and consistency, whereas the score ranking captures broader success across different game mechanics. Players self-identified as hardcore tend to occupy higher ranks in terms of average scores across games, suggesting that their gaming experience corresponds with overall performance. However, reaction time alone does not clearly differentiate between gaming types, as both hardcore and semi-serious players are distributed across the ranking, indicating that faster reactions are not necessarily indicative of better overall skill. This highlights that overall performance is influenced by multiple factors, including game-specific strategies and composite skills, rather than raw reaction speed alone.

These rankings provide a contextual baseline for subsequent analyses of the Predictive Tap game primitive. By understanding individual differences in skill and performance, we can better interpret the observed anticipatory behaviors, composite metrics, and temporal patterns discussed in the following sections.

Table 5.3: Player ranking by mean reaction time, including player type. Lower values indicate faster and more consistent responses.

Rank	Player	Reaction Time Mean	Std	Taps	Player Type
1	P4	0.333	0.377	1000	Hardcore
2	P14	0.344	0.362	877	Casual
3	P19	0.347	0.477	840	Semi-serious
4	P3	0.357	0.458	934	Casual
5	P13	0.360	0.398	932	Hardcore
6	P9	0.364	0.407	989	Casual
7	P8	0.372	0.370	910	Casual
8	P15	0.379	0.496	1037	Casual
9	P12	0.380	0.475	1099	Semi-serious
10	P23	0.381	0.489	873	Hardcore
11	P5	0.390	0.448	820	Semi-serious
12	P1	0.391	0.427	802	Semi-serious
13	P2	0.393	0.410	693	Casual
14	P10	0.406	0.581	975	Hardcore
15	P21	0.408	0.491	929	Semi-serious
16	P6	0.413	0.501	633	Casual
17	P20	0.435	0.551	665	Casual
18	P22	0.435	0.527	864	Semi-serious
19	P11	0.452	0.592	986	Semi-serious
20	P7	0.452	0.560	820	Casual
21	P16	0.459	0.431	472	Casual
22	P18	0.518	0.843	617	Semi-serious
23	P17	0.566	0.783	578	Don't know

### Player Experience

The participants' subjective experiences were assessed using two sets of questionnaires: one administered during a mid-session break and another at the end of each game session. The results are summarized in Tables 5.5 and 5.6.

The clarity of objectives was rated consistently high across all games (Table 5.5), indicating that players generally understood what they were expected to do. Participants frequently noted that the majority of the games involved simple interactions such as tapping or jumping: *"Yes, all of them were for jumping."* (P12). However, they also emphasized that, while the core mechanics were consistent, the games diverged notably in their objectives, structure, and difficulty. For example, one participant stated: *"I found all of them different. Ah, even though they were all tapping games, they were quite different in terms of objectives, [...] which is why I liked some more than others."* (P2) and another participant described these contrasts more specifically: *"The first one [Spinning Around] was about switching sides, the second [Jumping Ball] was basically just jumping up through each level, and the third [Hopfury] was basically a platformer, always moving and just avoiding obstacles."* (P21). Players also highlighted how these distinctions affected challenge and cognitive effort: *"Besides visual differences, difficulty was the main difference between them."*

Table 5.4: Player ranking by average global score across the three games, including player type. Higher values indicate better overall performance.

Rank	Player	<i>Spinning Around</i>	<i>Jumping Ball</i>	<i>Hopfury</i>	Average	Player Type
1	P12	87.4	90.8	81.9	86.7	Semi-serious
2	P21	61.6	99.0	78.4	79.7	Semi-serious
3	P15	64.9	92.1	75.3	77.4	Casual
4	P10	60.5	86.3	80.5	75.8	Hardcore
5	P4	61.8	94.0	68.9	74.9	Hardcore
6	P13	60.6	91.8	66.7	73.1	Hardcore
7	P23	39.3	94.2	81.2	71.6	Hardcore
8	P11	46.4	86.8	79.3	70.8	Semi-serious
9	P3	42.1	91.5	77.7	70.4	Casual
10	P8	42.2	94.9	73.1	70.1	Casual
11	P14	51.8	92.0	64.2	69.3	Casual
12	P1	51.5	90.4	55.6	65.8	Semi-serious
13	P22	40.1	84.3	72.3	65.6	Semi-serious
14	P2	37.2	90.3	68.5	65.3	Casual
15	P7	44.5	67.1	84.4	65.3	Casual
16	P19	60.3	64.5	69.9	64.9	Semi-serious
17	P5	43.8	90.0	43.3	59.0	Semi-serious
18	P18	27.4	70.4	68.9	55.6	Semi-serious
19	P9	50.6	70.1	40.2	53.6	Casual
20	P6	33.9	65.8	45.6	48.4	Casual
21	P17	18.2	26.8	69.2	38.1	Don't know
22	P20	35.0	22.2	51.2	36.1	Casual
23	P16	19.7	37.7	37.3	31.6	Casual

Table 5.5: Break questionnaire results (mean  $\pm$  SD).

Game	Enjoyment	Challenge	Objectives clear	Focus
<i>Spinning Around</i>	3.61 $\pm$ 1.20	4.13 $\pm$ 0.63	4.96 $\pm$ 0.21	4.52 $\pm$ 0.95
<i>Jumping Ball</i>	3.87 $\pm$ 1.06	4.70 $\pm$ 0.47	4.78 $\pm$ 0.52	4.57 $\pm$ 0.84
<i>Hopfury</i>	3.91 $\pm$ 0.95	4.13 $\pm$ 0.87	4.87 $\pm$ 0.46	4.30 $\pm$ 1.06

(P22), and "I'd say in the second and third games you have to think more, while the first is more intuitive, and the third is also slightly more intuitive than the second." (P15).

In greater detail, regarding the cognitive demands required, in *Spinning Around*, difficulty was often associated with the continuous need for input in a short time: "In the first game [*Spinning Around*], the spikes.. required us to keep tapping constantly because of the fast pace, and if something appeared we would lose right away and have to restart." (P16). This game was also rated as less enjoyable ( $M = 3.61$ ,  $SD = 1.20$ ) due to its repetitiveness and limited variation: "The first was the least engaging. . . it didn't have much content and didn't motivate me to play." (P17). Participants frequently preferred *Jumping Ball* ( $M = 3.87$ ,  $SD = 1.06$ ), because it was perceived as more strategic and demanding of higher-level skills ( $M = 4.70$ ,  $SD = 0.47$ ): "The most engaging for me was the second, *Jumping Ball*, because I really like the strategy part, thinking ahead and

Table 5.6: End-of-session questionnaire results (mean  $\pm$  SD).

Game	Gameplay smooth	Focus	Visual style	Play longer
<i>Spinning Around</i>	3.96 $\pm$ 1.02	4.52 $\pm$ 0.95	3.87 $\pm$ 0.81	3.52 $\pm$ 1.53
<i>Jumping Ball</i>	4.09 $\pm$ 0.95	4.43 $\pm$ 0.84	4.22 $\pm$ 0.74	3.78 $\pm$ 1.35
<i>Hopfury</i>	3.70 $\pm$ 1.06	4.09 $\pm$ 1.12	4.43 $\pm$ 0.99	3.61 $\pm$ 1.44

trying to anticipate the taps I had to make.” (P3), and “I found the second game the most enjoyable because the difficulty was balanced, I could progress gradually and maintain my motivation.” (P18). For *Hopfury*, players highlighted the challenge of timing jumps precisely (M = 4.13, SD = 0.87): “I didn’t know when exactly I had to tap to jump, it had to be really close or not.. I thought it was earlier and then I fell into the box.” (P13), while also noting its immersive environment (M = 3.91, SD = 0.95): “The third, of course, was the most enjoyable, because it had full graphics and sound, which made it more interesting.” (P10).

These remarks illustrate that, despite all games sharing the same core primitive, the Predictive Tap, players perceived each game as distinct and requiring different skill sets. As one participant reflected, “the first [*Spinning Around*] was high score, the second [*Jumping Ball*] involved levels [...] and the third [*Hopfury*] seemed almost like a mix of the two [...]” (P12).

Participants were asked to rank each game from 1 (most) to 3 (least) for difficulty, immersion, and likelihood of playing in short sessions (Figure 5.1). The analysis of these rankings corroborates the trends observed in the break and end-of-session questionnaires.

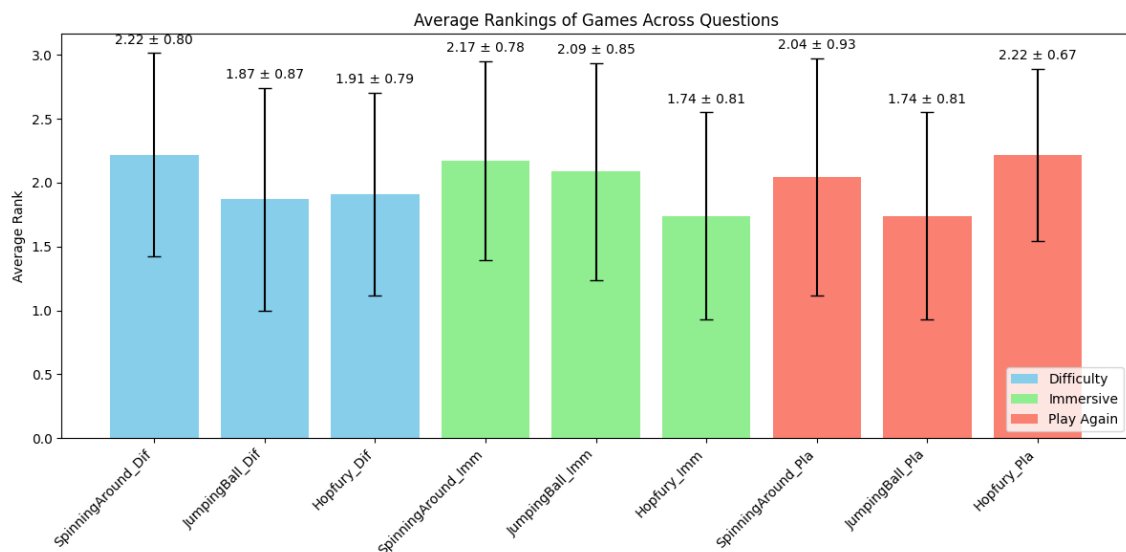


Figure 5.1: Average rankings of the three games across difficulty, immersion, and likelihood of playing at a bus stop. Rankings were given from 1 (most) to 3 (least). Error bars represent standard deviations.

Participants generally expressed conditional support for commercial games collecting interaction data. Many considered it beneficial when used to improve games or enhance the user experience: “Yes, if it’s to improve games or the user experience, I think it’s a good thing.” (P3)

and *"I'm not against it because it can help develop new mechanics and improve the game itself."* (P8). However, concerns were raised about transparency and potential invasiveness: *"I think it depends on how the data is used [...] For that data to be collected, people must be informed"* (P5) and *"It can get a bit invasive, right? [...] if it's for malicious purposes, that's where the limit is."* (P17) and *"It depends. If it's in partnership with a healthcare organization and the purpose is clear and transparent, that makes sense"* (P12).

Regarding potential clinical applications of interaction data, participants generally viewed this positively, provided the purpose was clear and ethically sound: *"In that sense, okay, I wouldn't mind."* (P20), *"Even better, yes, I think it's definitely beneficial."* (P3), and *"Yes, that's a good use of those metrics."* (P22). As for the type of data players were willing to share, all types of interaction metrics and general gameplay behavior were widely accepted: *"Yes, reaction times, the force with which you tap the screen... I have nothing to hide."* (P14) and *"Metrics? Anything necessary. If it's anonymous, you can collect everything."* (P8). Participants also emphasized the importance of consent, anonymity, and user control: *"Don't share any additional personal data that could compromise anonymity."* (P16) and *"For these games... tapping, swiping, etc., could make sense for clinical purpose. It should never be mandatory, people should be able to play without providing behavior data."* (P12).

### Tap Metrics in Successful vs. Failed Attempts

To explore how tap characteristics relate to success, we analyzed four key metrics: `reaction_time`, `reaction_time_div_interval_time`, `tap_timeHold`, and `tap_radius_metric`; across all players and games. For each player and metric, we computed the mean value for successful taps and the mean value for failed taps, and then calculated the difference as:

$$\Delta = \text{mean}(\text{success}) - \text{mean}(\text{fail})$$

Positive values indicate that successful taps had higher values than failed taps, while negative values indicate that successful taps had lower values. A Mann–Whitney U test was applied to compare the distributions of successful and failed taps, with significance considered at  $p < 0.05$  (Table 5.7).

Overall, the patterns indicate that the relationship between tap metrics and success varies across players. For `reaction_time`, many players were more successful when reacting more slowly, such as P3 ( $\Delta = +0.302$ ,  $p < 0.001$ ), P9 ( $\Delta = +0.281$ ,  $p < 0.001$ ) and P19 ( $\Delta = +0.274$ ,  $p < 0.001$ ), while others performed better with quicker reactions, such as P18 ( $\Delta = -0.153$ ,  $p = 0.004$ ) and P12 ( $\Delta = -0.132$ ,  $p = 0.021$ ).

The comparison between `reaction_time` and `reaction_time_div_interval_time` provides additional insight. While `reaction_time` measures the absolute delay between the start of the valid interval and the tap, `reaction_time_div_interval_time` normalizes this delay by the total interval length. This makes `reaction_time_div_interval_time` a relative metric that accounts for how much of the available reaction window a player used. For

Table 5.7: Difference between successful and failed taps for each metric and player, with Mann–Whitney U test results.

Player	Reaction Time	Tap Time Hold	Tap Radius Metric	Reaction Time Relative
P1	0.156 (p=0.000, sig)	0.004 (p=0.132, ns)	-0.020 (p=0.378, ns)	0.139 (p=0.390, ns)
P2	0.206 (p=0.000, sig)	-0.012 (p=0.049, sig)	0.006 (p=0.229, ns)	0.145 (p=0.699, ns)
P3	0.302 (p=0.000, sig)	-0.012 (p=0.024, sig)	0.002 (p=0.639, ns)	0.272 (p=0.000, sig)
P4	0.233 (p=0.000, sig)	0.006 (p=0.031, sig)	0.001 (p=0.272, ns)	0.291 (p=0.000, sig)
P5	0.259 (p=0.000, sig)	0.005 (p=0.060, ns)	-0.006 (p=0.491, ns)	0.208 (p=0.000, sig)
P6	0.043 (p=0.152, ns)	0.017 (p=0.000, sig)	0.016 (p=0.642, ns)	-0.003 (p=0.000, sig)
P7	0.212 (p=0.000, sig)	-0.008 (p=0.386, ns)	-0.015 (p=0.660, ns)	0.375 (p=0.967, ns)
P8	0.104 (p=0.000, sig)	-0.005 (p=0.626, ns)	-0.048 (p=0.008, sig)	0.063 (p=0.318, ns)
P9	0.281 (p=0.000, sig)	0.017 (p=0.000, sig)	-0.001 (p=0.620, ns)	0.129 (p=0.013, sig)
P10	0.060 (p=0.000, sig)	0.009 (p=0.000, sig)	0.010 (p=0.494, ns)	0.064 (p=0.870, ns)
P11	-0.272 (p=0.466, ns)	0.006 (p=0.022, sig)	0.004 (p=0.269, ns)	0.201 (p=0.000, sig)
P12	-0.132 (p=0.021, sig)	0.002 (p=0.149, ns)	-0.035 (p=0.066, ns)	0.130 (p=0.015, sig)
P13	0.056 (p=0.000, sig)	-0.014 (p=0.153, ns)	-0.030 (p=0.701, ns)	0.034 (p=0.260, ns)
P14	0.234 (p=0.000, sig)	0.003 (p=0.050, sig)	0.032 (p=0.044, sig)	0.822 (p=0.000, sig)
P15	0.136 (p=0.000, sig)	0.007 (p=0.001, sig)	0.002 (p=0.352, ns)	0.333 (p=0.037, sig)
P16	0.011 (p=0.836, ns)	-0.009 (p=0.061, ns)	-0.025 (p=0.371, ns)	-0.116 (p=0.000, sig)
P17	-0.047 (p=0.904, ns)	-0.011 (p=0.113, ns)	-0.002 (p=0.834, ns)	-0.116 (p=0.000, sig)
P18	-0.153 (p=0.004, sig)	-0.005 (p=0.099, ns)	0.004 (p=0.509, ns)	-0.788 (p=0.531, ns)
P19	0.274 (p=0.000, sig)	0.009 (p=0.054, ns)	0.001 (p=0.636, ns)	0.195 (p=0.110, ns)
P20	0.046 (p=0.020, sig)	-0.014 (p=0.103, ns)	0.004 (p=0.358, ns)	0.124 (p=0.011, sig)
P21	0.099 (p=0.000, sig)	-0.008 (p=0.262, ns)	-0.002 (p=0.952, ns)	0.407 (p=0.000, sig)
P22	0.061 (p=0.000, sig)	-0.000 (p=0.329, ns)	-0.005 (p=0.452, ns)	0.197 (p=0.098, ns)
P23	0.187 (p=0.000, sig)	0.007 (p=0.011, sig)	-0.047 (p=0.002, sig)	0.281 (p=0.000, sig)

example, P14 was more successful with slower reactions ( $\Delta = +0.234$ ,  $p < 0.001$ ) for `reaction_time`, but showed an even larger difference ( $\Delta = +0.822$ ,  $p < 0.001$ ) for `reaction_time_div_interval_time`, indicating that, relative to the interval, successful taps were considerably more delayed. In contrast, P12 performed better with quicker absolute reactions for `reaction_time`, but still showed a positive value ( $\Delta = +0.130$ ,  $p = 0.015$ ) for `reaction_time_div_interval_time`, suggesting that although successful taps were faster in absolute terms, they still occupied a larger fraction of the available interval.

For `tap_timeHold`, players like P6 ( $\Delta = +0.017$ ,  $p < 0.001$ ) and P9 ( $\Delta = +0.017$ ,  $p < 0.001$ ) tended to hold their taps slightly longer on successful attempts, whereas P2 ( $\Delta = -0.012$ ,  $p = 0.049$ ) and P3 ( $\Delta = -0.012$ ,  $p = 0.024$ ) were more successful with shorter holds.

Regarding `tap_radius_metric`, differences were generally small, but there were some exceptions: P14 ( $\Delta = +0.032$ ,  $p = 0.044$ ) achieved more success with inconsistent taps, while P8 ( $\Delta = -0.048$ ,  $p = 0.008$ ) and P23 ( $\Delta = -0.047$ ,  $p = 0.002$ ) did better with more precise, smaller ones.

Taken together, these results suggest that success is influenced by multiple factors and that no single metric can fully predict performance. While some players succeed with slower or longer taps and others with faster or shorter ones, many differences are small or not statistically significant. This indicates that each player may adopt their own strategy to achieve success, highlighting the variability in tapping behavior across individuals.

## 5.2.2 Mixed Models: Cross-Game Metrics

To investigate whether the game influenced player performance, we applied mixed linear models to the collected data (Tables 5.8, 5.9 and 5.10). In these models, the fixed effect is the *game* and the random factor is the *participant*, in order to account for inter-individual variability. This approach allows us to test whether the values of each metric, including both the basic measures and the composite ratios derived from them, differ significantly between games. The analysis was performed separately for each metric, using the data in long format (`|Metric|Game|Participant|`), where each row represents a single measurement from one participant.

Across all three games, `tap_radius_metric` did not show a statistically significant effect, likely due to its limited scale and low variability; this indicates that no significant difference between games was detected for this metric. Overall, the majority of metrics exhibited statistically significant differences across the three games, while some measures showed only slight differences or did not reach significance.

In the comparison between *Spinning Around* and *Jumping Ball* (Table 5.8), `reaction_time` was lower in *Jumping Ball* (`game[T.Jumping]` coef = -0.253), reflecting a shorter average reaction time compared to *Spinning Around*. Similarly, `interval_time` was smaller in *Jumping Ball* (`game[T.Jumping]` coef = -0.230), indicating a reduced average interval for successful taps. While most metrics and composite measures are significantly affected by the game, the differences are smaller for `tap_timeHold` (`game[T.Jumping]` coef = -0.014), indicating only a minor decrease in hold duration.

Table 5.8: Mixed Linear Model Regression Results: *Spinning Around* vs *Jumping Ball*

Metric	Intercept (coef)	game[T.Jumping] (coef)	Group Var (coef)	p-value
<code>reaction_time</code>	0.255	-0.253	0.000	<0.001
<code>interval_time</code>	0.084	-0.230	0.000	<0.001
<code>tap_timeHold</code>	-0.028	-0.014	0.000	<0.001
<code>tap_radius_metric</code>	-1.257	-0.001	0.000	0.737
<code>reaction_time_div_interval_time</code>	0.699	-0.263	0.001	<0.001
<code>reaction_time_div_tap_timeHold</code>	0.527	-1.914	0.000	<0.001
<code>reaction_time_div_tap_radius_metric</code>	0.342	-1.095	0.000	<0.001
<code>tap_timeHold_div_tap_radius_metric</code>	0.444	-0.065	0.000	<0.001
<code>tap_timeHold_div_interval_time</code>	0.133	0.182	0.000	<0.001
<code>tap_radius_metric_div_interval_time</code>	-0.130	0.515	0.000	<0.001

In the comparison between *Spinning Around* and *Hopfury* (Table 5.9), `reaction_time` was higher in *Hopfury* (`game[T.Hopfury]` coef = 0.164), reflecting a slightly longer average reaction time compared to *Spinning Around*. `interval_time` was also higher in *Hopfury* (`game[T.Hopfury]` coef = 0.060), indicating a slightly wider average window for successful taps. The composite measure `reaction_time_div_interval_time` was not statistically significant (`game[T.Hopfury]` coef = 0.011), indicating that the analysis did not detect a significant difference in the relative ratio between reaction time and interval time between the two games. Differences were smaller for `tap_timeHold` (`game[T.Hopfury]` coef = 0.010), reflecting only a minor increase in average hold duration.

Table 5.9: Mixed Linear Model Regression Results: *Spinning Around vs Hopfury*

Metric	Intercept (coef)	game[T.Hopfury] (coef)	Group Var (coef)	p-value
reaction_time	0.124	0.164	0.000	<0.001
interval_time	0.136	0.060	0.000	<0.001
tap_timeHold	0.007	0.010	0.000	<0.001
tap_radius_metric	-0.138	-0.008	0.000	0.015
reaction_time_div_interval_time	0.701	0.011	0.001	0.432
reaction_time_div_tap_timeHold	0.296	1.084	0.000	<0.001
reaction_time_div_tap_radius_metric	0.150	0.794	0.000	<0.001
tap_timeHold_div_tap_radius_metric	0.080	0.036	0.000	<0.001
tap_timeHold_div_interval_time	0.256	0.153	0.002	<0.001
tap_radius_metric_div_interval_time	-0.051	0.272	0.000	<0.001

In the comparison between *Jumping Ball* and *Hopfury* (Table 5.10), `reaction_time` was higher in *Hopfury* (`game[T.Hopfury]` coef = 0.414), representing a positive estimated effect of the game on reaction time relative to *Jumping Ball*. `interval_time` was also higher in *Hopfury* (`game[T.Hopfury]` coef = 0.287). The composite measure `reaction_time_div_interval_time` showed a significant positive effect (`game[T.Hopfury]` coef = 0.273). Differences were smaller for `tap_timeHold` (`game[T.Hopfury]` coef = 0.024) and for `tap_timeHold_div_tap_radius_metric` (`game[T.Hopfury]` coef = 0.102). The composite measure `tap_timeHold_div_interval_time`, which showed significant differences in previous comparisons, did not reach statistical significance here (`game[T.Hopfury]` coef = -0.028), indicating that no significant effect of the game was detected for this metric between *Jumping Ball* and *Hopfury*.

Table 5.10: Mixed Linear Model Regression Results: *Jumping Ball vs Hopfury*

Metric	Intercept (coef)	game[T.Hopfury] (coef)	Group Var (coef)	p-value
reaction_time	-0.000	0.414	0.000	<0.001
interval_time	-0.000	0.287	0.000	<0.001
tap_timeHold	-0.000	0.024	0.000	<0.001
tap_radius_metric	0.000	-0.006	0.000	0.057
reaction_time_div_interval_time	-0.000	0.273	0.000	<0.001
reaction_time_div_tap_timeHold	1.796	3.024	0.410	<0.001
reaction_time_div_tap_radius_metric	-0.000	1.891	0.000	<0.001
tap_timeHold_div_tap_radius_metric	0.526	0.102	0.014	<0.001
tap_timeHold_div_interval_time	0.000	-0.028	0.000	0.149
tap_radius_metric_div_interval_time	0.000	-0.235	0.000	<0.001

Taken together, the mixed linear model results indicate that the game (fixed effect) affects player behaviour in most measures. Metrics showing a significant effect differ across games, indicating that their values are not equivalent, without implying any specific relationship between them. Across the three games, the majority of metrics present statistically significant differences, while some measures show only slight differences or did not reach significance, suggesting varying sensitivity of player interaction metrics to the game context.

### 5.2.3 Correlation Analysis: Cross-Game Metrics

#### Global Correlation

To investigate the consistency of player behavior across different games, we conducted a correlation analysis of core gameplay metrics between game pairs. We employed Spearman’s rank correlation coefficient ( $\rho$ ), which ranges from -1 to 1 and indicates the strength of the monotonic relationship between two sets of ranks. Although Spearman does not require averaging, we computed per-player averages for each metric within each game to ensure that each participant contributed equally to the analysis. This prevents players with more attempts from disproportionately influencing the correlations and allows us to focus on inter-player consistency rather than trial-by-trial variability. The analysis provides insights into which player behaviors are stable across games, but limitations include the fact that averaging can obscure intra-player variability.

The correlation analysis between *Spinning Around* and *Jumping Ball* (Table 5.11) reveals several very strong relationships across multiple gameplay metrics. In particular, `tap_timeHold` ( $\rho = 0.752964$ , p-value = 0.000034), `tap_radius_metric` ( $\rho = 0.766798$ , p-value = 0.000020), `global_score_norm` ( $\rho = 0.556324$ , p-value = 0.005837), `reaction_time_div_tap_radius_metric` ( $\rho = 0.659091$ , p-value = 0.000625), `tap_timeHold_div_tap_radius_metric` ( $\rho = 0.713439$ , p-value = 0.000132), and `tap_radius_metric_div_interval_time` ( $\rho = 0.604743$ , p-value = 0.002237) exhibit high Spearman correlation coefficients, indicating statistically significant monotonic relationships. All remaining metrics exhibit weak correlations, indicating that player performance in these measures does not appear consistent across these games.

Table 5.11: Spearman Correlation: *Spinning Around* vs *Jumping Ball*

Metric	$\rho$	p-value	Strength
<code>reaction_time</code>	-0.271739	0.209731	weak
<code>interval_time</code>	-0.021739	0.921571	weak
<code>tap_timeHold</code>	0.752964	0.000034	very strong
<code>tap_radius_metric</code>	0.766798	0.000020	very strong
<code>global_score_norm</code>	0.556324	0.005837	very strong
<code>reaction_time_div_interval_time</code>	0.053360	0.808931	weak
<code>reaction_time_div_tap_timeHold</code>	0.378458	0.074958	weak
<code>reaction_time_div_tap_radius_metric</code>	0.659091	0.000625	very strong
<code>tap_timeHold_div_tap_radius_metric</code>	0.713439	0.000132	very strong
<code>tap_timeHold_div_interval_time</code>	0.365613	0.086233	weak
<code>tap_radius_metric_div_interval_time</code>	0.604743	0.002237	very strong

The correlation analysis between *Spinning Around* and *Hopfury* (Table 5.12) reveals very strong correlations in the following gameplay metrics: `tap_timeHold` ( $\rho = 0.753953$ ,  $p = 0.000033$ ), `tap_radius_metric` ( $\rho = 0.812253$ ,  $p = 0.000003$ ), `tap_timeHold_div_tap_radius_metric` ( $\rho = 0.742095$ ,  $p = 0.000050$ ), and `tap_radius_metric_div_interval_time` ( $\rho = 0.632411$ ,  $p = 0.001204$ ), indicating statistically significant and consistent monotonic trends. Notably, `reaction_time_div_tap_radius_metric` has slightly decreased

from very strong to strong compared to Table 5.11, while `tap_timeHold_div_interval_time` has slightly increased from weak to strong, being the only metric that is strong (while in the other two game-pair comparisons it was very strong), indicating minor changes in the stability of this measure. All remaining metrics continue to exhibit weak correlations.

Table 5.12: Spearman Correlation: *Spinning Around* vs *Hopfury*

Metric	$\rho$	p-value	Strength
<code>reaction_time</code>	0.084980	0.699851	weak
<code>interval_time</code>	-0.057312	0.795060	weak
<code>tap_timeHold</code>	0.753953	0.000033	very strong
<code>tap_radius_metric</code>	0.812253	0.000003	very strong
<code>global_score_norm</code>	0.334980	0.118181	weak
<code>reaction_time_div_interval_time</code>	-0.377470	0.075784	weak
<code>reaction_time_div_tap_timeHold</code>	0.350791	0.100767	weak
<code>reaction_time_div_tap_radius_metric</code>	0.484190	0.019223	strong
<code>tap_timeHold_div_tap_radius_metric</code>	0.742095	0.000050	very strong
<code>tap_timeHold_div_interval_time</code>	0.451581	0.030537	strong
<code>tap_radius_metric_div_interval_time</code>	0.632411	0.001204	very strong

The correlation analysis between *Jumping Ball* and *Hopfury* (Table 5.13) reveals several very strong correlations across multiple gameplay metrics. Specifically, `tap_timeHold` ( $\rho = 0.578063$ , p-value = 0.003864), `tap_radius_metric` ( $\rho = 0.894269$ , p-value = 8.85e-09), `reaction_time_div_tap_timeHold` ( $\rho = 0.528656$ , p-value = 0.009502), `tap_timeHold_div_tap_radius_metric` ( $\rho = 0.735178$ , p-value = 0.000064), and `tap_radius_metric_div_interval_time` ( $\rho = 0.701581$ , p-value = 0.000191) exhibit strong Spearman correlation values. Notably, this is the only game pair where `reaction_time_div_tap_timeHold` reaches a very strong correlation, while `reaction_time_div_tap_radius_metric` shows only a strong correlation ( $\rho = 0.436759$ , p-value = 0.037180), similar to Table 5.12. All remaining metrics continue to exhibit weak correlations.

Table 5.13: Spearman Correlation: *Jumping Ball* vs *Hopfury*

Metric	$\rho$	p-value	Strength
<code>reaction_time</code>	-0.026680	0.903820	weak
<code>interval_time</code>	-0.087945	0.689877	weak
<code>tap_timeHold</code>	0.578063	0.003864	very strong
<code>tap_radius_metric</code>	0.894269	8.84805e-09	very strong
<code>global_score_norm</code>	0.352767	0.098731	weak
<code>reaction_time_div_interval_time</code>	-0.066206	0.764075	weak
<code>reaction_time_div_tap_timeHold</code>	0.528656	0.009502	very strong
<code>reaction_time_div_tap_radius_metric</code>	0.436759	0.037180	strong
<code>tap_timeHold_div_tap_radius_metric</code>	0.735178	0.000064	very strong
<code>tap_timeHold_div_interval_time</code>	0.223320	0.305699	weak
<code>tap_radius_metric_div_interval_time</code>	0.701581	0.000191	very strong

Overall, several core gameplay metrics and derived measures appear to maintain consistent

correlations across different game pairs, although some variations are observed. These results suggest that certain aspects of player behavior, particularly tapping patterns and derived ratios, are relatively stable across different game contexts, while others, such as raw reaction times or interval-based measures, are more variable.

### Bin-Wise Correlation

To evaluate player behavior across different games, we conducted a bin-wise correlation analysis, grouping trials according to *interval\_time*, the time window in which a tap is considered valid in the game (Tables 5.14, 5.15 and 5.16). Trials were divided into three bins based on their *interval\_time* values: short ]0.0003,1] s, medium ]1,2] s, and long ]2,11] s. Each bin contains all taps whose *interval\_time* falls within the corresponding range, allowing us to explore whether correlations between gameplay metrics vary depending on the temporal context of the taps. This allowed us to observe potential patterns in player consistency and explore whether certain metrics remain correlated under different temporal conditions.

The results show that in short bins (Table 5.14), many metrics, for example *tap\_timeHold*, exhibit strong correlations across all game pairs, suggesting high consistency when taps occur within shorter intervals. In medium bins (Table 5.15), some correlations remain strong, especially between *Spinning Around* and *Jumping Ball*, but a larger number of metrics show weak correlations, indicating reduced stability. In long bins (Table 5.16), most metrics display weak correlations, although a few measures related to *reaction\_time* and *reaction\_time\_div\_interval\_time* show strong correlations, which were not present in shorter bins. These findings suggest that player behavior is generally more consistent for taps occurring in shorter valid intervals, while longer intervals introduce greater variability.

### Aggregated Metrics Correlation

To further investigate player behavior across games, we analyzed aggregated metrics across all games and computed pairwise correlations. The tables presented (Tables 5.17, 5.18 and 5.19) have been simplified to include only medium and strong correlations, omitting weak correlations for clarity.

From the results, we can observe that *Spinning Around* and *Jumping Ball* tend to be the most aligned in terms of aggregated metrics, showing stronger correlations across several aggregated measures. Notably, the metrics *tap\_timeHold* and *tap\_radius\_metric* consistently exhibit strong or medium correlations across different game pairs, suggesting that these aspects of player interaction are relatively stable regardless of the game context.

Other metrics, such as *reaction\_time* or *interval\_time*, show more variation between games. While some correlations are still present (e.g., *reaction\_time\_min* in Table 5.17), in general these measures fluctuate more and are less consistent across different game pairs. This indicates that while certain aspects of player behavior remain stable, others are more sensitive to the specific mechanics and timing demands of each game.

Table 5.14: Short Bin Correlation Analysis Across Games

(a) *Spinning Around vs Jumping Ball*

<b>Metric</b>	$\rho$	<b>p-value</b>	<b>Strength</b>
reaction_time	0.301383	0.162256	weak
interval_time	0.100791	0.647250	weak
tap_timeHold	0.715415	0.000124	very strong
tap_radius_metric	0.762846	0.000023	very strong
global_score_norm	0.556324	0.005837	very strong
reaction_time_div_interval_time	0.025692	0.907367	weak
reaction_time_div_tap_timeHold	0.501976	0.014659	strong
reaction_time_div_tap_radius_metric	0.751976	0.000035	very strong
tap_timeHold_div_tap_radius_metric	0.700593	0.000197	very strong
tap_timeHold_div_interval_time	0.372530	0.080015	weak
tap_radius_metric_div_interval_time	0.572134	0.004336	very strong

(b) *Spinning Around vs Hopfury*

<b>Metric</b>	$\rho$	<b>p-value</b>	<b>Strength</b>
reaction_time	-0.143281	0.514267	weak
interval_time	0.202569	0.353941	weak
tap_timeHold	0.658103	0.000641	very strong
tap_radius_metric	0.796443	0.000005	very strong
global_score_norm	0.334980	0.118181	weak
reaction_time_div_interval_time	-0.307312	0.153748	weak
reaction_time_div_tap_timeHold	0.539526	0.007885	very strong
reaction_time_div_tap_radius_metric	0.594862	0.002754	very strong
tap_timeHold_div_tap_radius_metric	0.756917	0.000029	very strong
tap_timeHold_div_interval_time	0.559289	0.005527	very strong
tap_radius_metric_div_interval_time	0.668972	0.000483	very strong

(c) *Jumping Ball vs Hopfury*

<b>Metric</b>	$\rho$	<b>p-value</b>	<b>Strength</b>
reaction_time	-0.040514	0.8543766	weak
interval_time	0.213439	0.328142	weak
tap_timeHold	0.499012	0.015352	strong
tap_radius_metric	0.910079	0.00000001735	very strong
global_score_norm	0.352767	0.098731	weak
reaction_time_div_interval_time	0.019763	0.928683	weak
reaction_time_div_tap_timeHold	0.635375	0.001123	very strong
reaction_time_div_tap_radius_metric	0.680830	0.000349	very strong
tap_timeHold_div_tap_radius_metric	0.736166	0.000062	very strong
tap_timeHold_div_interval_time	0.135375	0.537975	weak
tap_radius_metric_div_interval_time	0.691700	0.000256	very strong

Table 5.15: Medium Bin Correlation Analysis Across Games

(a) *Spinning Around vs Jumping Ball*

<b>Metric</b>	$\rho$	<b>p-value</b>	<b>Strength</b>
reaction_time	0.091729	0.700516	weak
interval_time	-0.396992	0.083071	weak
tap_timeHold	0.500752	0.024519	strong
tap_radius_metric	0.648608	0.001978	very strong
global_score_norm	0.345865	0.135252	weak
reaction_time_div_interval_time	0.120301	0.613418	weak
reaction_time_div_tap_timeHold	0.124812	0.600074	weak
reaction_time_div_tap_radius_metric	0.470677	0.036215	strong
tap_timeHold_div_tap_radius_metric	0.723308	0.000313	very strong
tap_timeHold_div_interval_time	0.589474	0.006233	very strong
tap_radius_metric_div_interval_time	0.581955	0.007104	very strong

(b) *Spinning Around vs Hopfury*

<b>Metric</b>	$\rho$	<b>p-value</b>	<b>Strength</b>
reaction_time	-0.224308	0.303507	weak
interval_time	-0.073123	0.740213	weak
tap_timeHold	0.609684	0.002011	very strong
tap_radius_metric	0.292490	0.175626	weak
global_score_norm	0.334980	0.118181	weak
reaction_time_div_interval_time	-0.163043	0.457288	weak
reaction_time_div_tap_timeHold	0.161067	0.462834	weak
reaction_time_div_tap_radius_metric	0.315217	0.142899	weak
tap_timeHold_div_tap_radius_metric	0.399209	0.059147	weak
tap_timeHold_div_interval_time	0.618577	0.001653	very strong
tap_radius_metric_div_interval_time	0.296443	0.169593	weak

(c) *Jumping Ball vs Hopfury*

<b>Metric</b>	$\rho$	<b>p-value</b>	<b>Strength</b>
reaction_time	0.130827	0.582473	weak
interval_time	0.652632	0.001814	very strong
tap_timeHold	0.631579	0.002818	very strong
tap_radius_metric	0.232506	0.323912	weak
global_score_norm	0.195489	0.408819	weak
reaction_time_div_interval_time	-0.042105	0.860095	weak
reaction_time_div_tap_timeHold	0.249624	0.288513	weak
reaction_time_div_tap_radius_metric	0.144361	0.543701	weak
tap_timeHold_div_tap_radius_metric	0.230075	0.329138	weak
tap_timeHold_div_interval_time	0.643609	0.002199	very strong
tap_radius_metric_div_interval_time	0.192481	0.416206	weak

Table 5.16: Long Bin Correlation Analysis Across Games

(a) *Spinning Around vs Jumping Ball*

<b>Metric</b>	$\rho$	<b>p-value</b>	<b>Strength</b>
reaction_time	-0.466667	0.173939	weak
interval_time	-0.066667	0.854813	weak
tap_timeHold	0.236364	0.510885	weak
tap_radius_metric	0.214740	0.551325	weak
global_score_norm	0.381818	0.276255	weak
reaction_time_div_interval_time	-0.648485	0.042540	strong
reaction_time_div_tap_timeHold	-0.284848	0.425038	weak
reaction_time_div_tap_radius_metric	0.054545	0.881036	weak
tap_timeHold_div_tap_radius_metric	-0.090909	0.802772	weak
tap_timeHold_div_interval_time	-0.115152	0.751420	weak
tap_radius_metric_div_interval_time	-0.163636	0.651477	weak

(b) *Spinning Around vs Hopfury*

<b>Metric</b>	$\rho$	<b>p-value</b>	<b>Strength</b>
reaction_time	-0.275692	0.202916	weak
interval_time	-0.334980	0.118181	weak
tap_timeHold	0.430830	0.040137	strong
tap_radius_metric	0.510870	0.012734	strong
global_score_norm	0.334980	0.118181	weak
reaction_time_div_interval_time	-0.106719	0.627922	weak
reaction_time_div_tap_timeHold	0.174901	0.424754	weak
reaction_time_div_tap_radius_metric	0.173913	0.427416	weak
tap_timeHold_div_tap_radius_metric	0.274704	0.204606	weak
tap_timeHold_div_interval_time	0.380435	0.073328	weak
tap_radius_metric_div_interval_time	0.565217	0.004947	very strong

(c) *Jumping Ball vs Hopfury*

<b>Metric</b>	$\rho$	<b>p-value</b>	<b>Strength</b>
reaction_time	0.648485	0.042540	strong
interval_time	-0.006061	0.986743	weak
tap_timeHold	0.321212	0.365468	weak
tap_radius_metric	0.300636	0.398644	weak
global_score_norm	0.515152	0.127553	weak
reaction_time_div_interval_time	0.709091	0.021666	strong
reaction_time_div_tap_timeHold	0.842424	0.002220	very strong
reaction_time_div_tap_radius_metric	0.551515	0.098401	weak
tap_timeHold_div_tap_radius_metric	0.418182	0.229113	weak
tap_timeHold_div_interval_time	0.321212	0.365468	weak
tap_radius_metric_div_interval_time	0.139394	0.700932	weak

Table 5.17: Correlation: *Spinning Around* vs *Jumping Ball*

Metric	$\rho$	p-value	Strength
global_score_norm_mean	0.556324	0.00583747	Medium
tap_radius_metric_mean	0.766798	1.97336e-05	Strong
tap_radius_metric_min	0.424945	0.0432507	Medium
tap_radius_metric_std	0.417984	0.0471749	Medium
tap_radius_metric_var	0.417984	0.0471749	Medium
tap_timeHold_mean	0.752964	3.38076e-05	Strong
reaction_time_min	-0.412055	0.050731	Medium
interval_time_min	0.532609	0.00888495	Medium

Table 5.18: Correlation: *Spinning Around* vs *Hopfury*

Metric	$\rho$	p-value	Strength
tap_radius_metric_mean	0.812253	2.51478e-06	Strong
tap_radius_metric_std	0.494071	0.0165641	Medium
tap_radius_metric_var	0.494071	0.0165641	Medium
tap_timeHold_mean	0.753953	3.25697e-05	Strong
tap_timeHold_std	0.519763	0.0110211	Medium
tap_timeHold_var	0.519763	0.0110211	Medium

Table 5.19: Correlation: *Jumping Ball* vs *Hopfury*

Metric	$\rho$	p-value	Strength
tap_radius_metric_max	0.452381	0.0302068	Medium
tap_radius_metric_mean	0.894269	8.84805e-09	Strong
tap_timeHold_mean	0.578063	0.00386383	Medium

## 5.2.4 Block-Based Analysis of Taps

To explore how player performance evolves over the course of each game, we conducted a block-based analysis. The sequence of taps for each player was divided into blocks of 20 consecutive taps, and the mean value of each metric was then computed for each block.

### Evolution of Taps Across Blocks

For this analysis, we focused on two key metrics: `tap_timeHold` (Figure 5.3) and `reaction_time_div_interval_time` (Figure 5.2). As the valid intervals for successful taps vary slightly between games, we chose to focus on this normalized metric for a fairer cross-game comparison. These metrics were selected as they provide the most relevant insights into performance evolution, while other metrics did not reveal clear or consistent trends across games.

It is worth noting that the number of taps varies across games: *Spinning Around* contains a larger number of taps per player, whereas *Hopfury* has relatively fewer taps. Despite this, the block-based comparison allows a standardized view of performance progression across the three games.

This analysis highlights clear differences in player behavior between games, particularly dur-

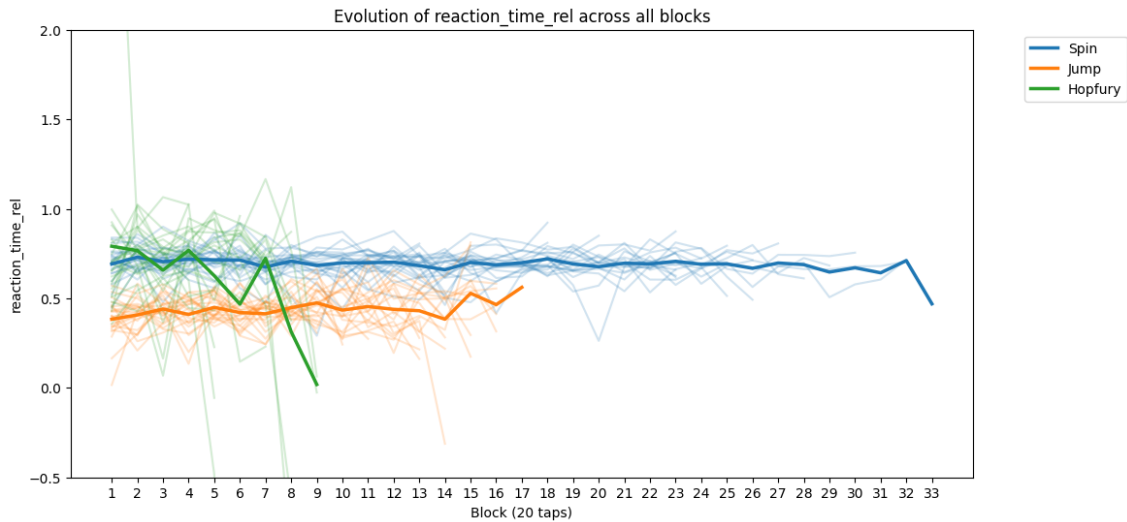


Figure 5.2: Evolution of *reaction\_time\_rel* over blocks of 20 taps for each game. Transparent lines represent individual players, while the bold lines show the average per game.

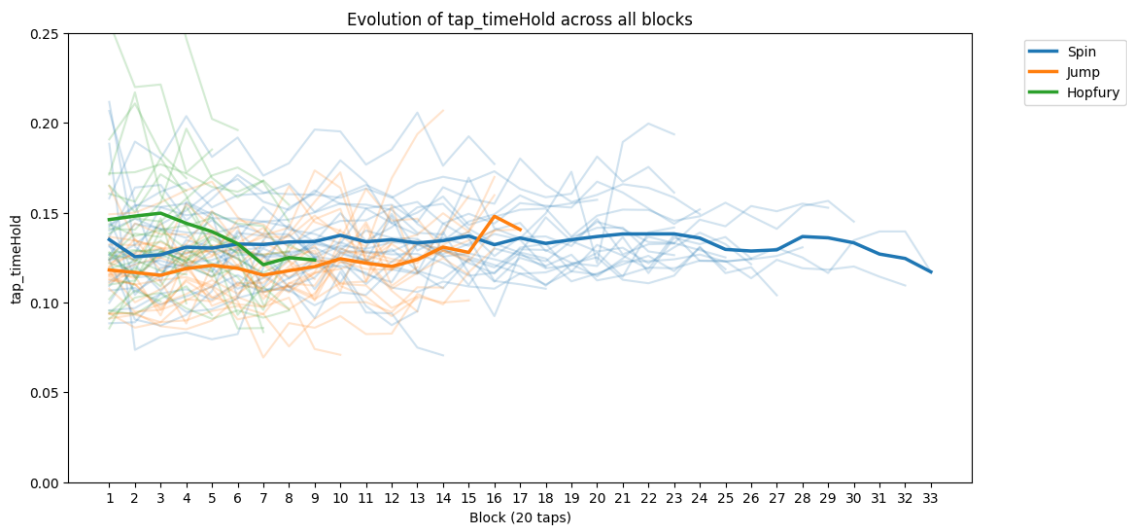


Figure 5.3: Evolution of *tap\_timeHold* over blocks of 20 taps for each game. Transparent lines represent individual players, while the bold lines show the average per game.

ing the initial phases. For instance, in *Hopfury*, players consistently exhibited longer tap durations (Figure 5.3). This can be associated with the fact that the game registers a tap either when the player lifts their finger or after a timeout if the tap is held too long. In contrast, the other games react immediately when the screen is touched. In *Jumping Ball*, the relatively lower *reaction\_time\_div\_interval\_time* can be explained by the game mechanics (Figure 5.2), where success often required repeatedly tapping in rapid succession to clear multiple platforms. As gameplay progressed, players adapted to the specific requirements of each game, with minor changes in tap duration and relative reaction time observed within each title. However, in both cases, these adaptations did not lead to convergence between games. Metrics evolved differently depending on the game, and cross-game similarities were limited over time.

## Repeated Measures Correlation Across Blocks

To examine cross-game consistency in tapping behavior over the course of gameplay, we conducted a repeated measures correlation analysis using the previously computed block-averaged metrics. For fair comparisons, the number of blocks considered per player in each pairwise comparison was constrained by the game with the fewer total taps, ensuring that only comparable portions of gameplay were analyzed (Table 5.20).

In general, most metrics exhibit weak or non-significant correlations. Some metrics, such as *reaction\_time* relative to other tap characteristics, suggest potential for moderate consistency across games, although these patterns are not uniformly strong across all comparisons. Comparisons involving *Hopfury* generally display weaker correlations, which may partly reflect the reduced number of taps per player in this game and the consequently smaller number of blocks available for analysis. Notably, *Jumping Ball vs Hopfury* shows particularly low correlations, indicating limited consistency between these two games throughout gameplay.

## 5.3 Discussion

### 5.3.1 Implementing Game Interaction Primitives: Predictive Tap

The implementation of Predictive Tap logging requires dedicated attention, as it involves adapting existing games to capture precise behavioral data without compromising their original design. To achieve this, games must be instrumented to record timing, touch events, and success intervals in a way that seamlessly integrates with the gameplay loop. This process typically demands the addition of invisible colliders, logging managers, buffering systems, and adjustments to frame-dependent movement or interaction windows.

These modifications highlight the non-trivial challenges of using games as research tools. At the same time, they reveal opportunities for methodological standardization. Centralized session managers, modular logging components, and enhanced input APIs can all contribute to ensuring consistent data capture across different devices and game contexts.

By documenting these modifications, this study provides guidance on how future researchers and developers might implement Predictive Tap (and other primitives) logging in a way that preserves the game's original design.

### 5.3.2 Predictive Tap Consistency Across Games

Having addressed the implementation challenges of logging Predictive Tap in games, we turned to the analysis of player data collected across three different titles, with the goal of identifying and characterizing the Predictive Tap primitive. To approach this, we employed complementary methods designed to capture different aspects of player behavior: contextualizing individual differences through player metrics, mixed linear models to examine the influence of game context on timing and tap metrics, correlation analyses to assess cross-game consistency of taps and derived measures, bin-wise analyses to explore the effect of temporal intervals on metric stability, aggregated

Table 5.20: Repeated Measures Correlation Analysis Across Blocks

(a) *Spinning Around vs Jumping Ball*

<b>Metric</b>	$\rho$	<b>p-value</b>	<b>Strength</b>
reaction_time	-0.120454	0.045968	strong
interval_time	0.091178	0.131483	weak
tap_timeHold	0.074027	0.221073	weak
tap_radius_metric	-0.052765	0.383408	weak
reaction_time_div_interval_time	-0.151431	0.011928	strong
reaction_time_div_tap_timeHold	-0.145014	0.016103	strong
reaction_time_div_tap_radius_metric	-0.091225	0.131285	weak
tap_timeHold_div_tap_radius_metric	-0.021953	0.717028	weak
tap_timeHold_div_interval_time	0.113078	0.061117	weak
tap_radius_metric_div_interval_time	0.034846	0.565021	weak

(b) *Spinning Around vs Hopfury*

<b>Metric</b>	$\rho$	<b>p-value</b>	<b>Strength</b>
reaction_time	-0.118356	0.197926	weak
interval_time	-0.090737	0.324327	weak
tap_timeHold	0.085082	0.355511	weak
tap_radius_metric	0.132238	0.149935	weak
reaction_time_div_interval_time	-0.054227	0.556368	weak
reaction_time_div_tap_timeHold	-0.224144	0.013852	strong
reaction_time_div_tap_radius_metric	-0.058958	0.522401	weak
tap_timeHold_div_tap_radius_metric	0.007687	0.933591	weak
tap_timeHold_div_interval_time	0.037390	0.685150	weak
tap_radius_metric_div_interval_time	0.035658	0.699013	weak

(c) *Jumping Ball vs Hopfury*

<b>Metric</b>	$\rho$	<b>p-value</b>	<b>Strength</b>
reaction_time	0.042839	0.642235	weak
interval_time	-0.070114	0.446681	weak
tap_timeHold	0.020190	0.826748	weak
tap_radius_metric	0.004897	0.957664	weak
reaction_time_div_interval_time	0.118048	0.199101	weak
reaction_time_div_tap_timeHold	0.006774	0.941464	weak
reaction_time_div_tap_radius_metric	0.036835	0.689587	weak
tap_timeHold_div_tap_radius_metric	-0.051392	0.577221	weak
tap_timeHold_div_interval_time	0.127532	0.165108	weak
tap_radius_metric_div_interval_time	-0.036814	0.689754	weak

metrics correlations to identify stable behavioral patterns across games, and block-based analyses to examine how player behavior evolves over time within each game. Together, these exploratory analyses allowed us to observe how touch metrics and contextual game metrics can be combined to approximate the definition of the Predictive Tap.

The comparison between reaction time and overall score revealed that response speed alone is not a reliable predictor of performance. While fast reaction times reflect quicker responses, they do not necessarily correspond to higher scores, as players employ different strategies to achieve success. Consequently, reaction time must be considered alongside other touch metrics, such as tap duration and precision, to accurately capture individual anticipatory behavior.

Across all analyses, tap-related metrics—particularly `tap_timeHold` and `tap_radius_metric`, along with derived ratios combining these measures, consistently show strong cross-game stability. These findings suggest that core motor behaviors related to tapping are largely preserved regardless of game context. In contrast, raw timing measures such as `reaction_time` and `interval_time` are more sensitive to game mechanics, showing greater variability across games and temporal conditions. Interval bin analyses further clarify these patterns. Strong correlations are observed at short valid intervals, where taps are required within tight timing windows to be considered successful. In these intervals, players' responses are more consistent and reveal reliable patterns of anticipatory behavior. In contrast, medium and long intervals show weaker correlations and often yield inconsistent or missing data, likely due to fewer valid opportunities or greater variability in timing requirements. These findings indicate that Predictive Tap is perhaps best captured by taps executed within these short, critical intervals, rather than by aggregated metrics over longer periods. Aggregated metrics confirm that tapping patterns remain reliable indicators of consistent player interaction, whereas timing measures fluctuate depending on the game and temporal context.

It shows that the primitive does not depend solely on the objective outcome of a tap (whether it is valid or invalid), but rather on the player's individual motor-cognitive behavior. Each player exhibits their own characteristic patterns, as reflected in differences in reaction timing, tap duration, and precision. This highlights the importance of considering intra-player variability when trying to define primitives.

The analysis of tap evolution across blocks shows that player behavior differs clearly between games, especially early on. Players adapt over time to each game's demands, with minor changes in tap duration, precision, and relative reaction time, but these adaptations do not lead to convergence between games. Overall, cross-game similarities remain limited.

These findings collectively reinforce that primitives are a reflection of the player's individual motor-cognitive strategies. The primitive emerges most clearly from short-term microbehaviors, where timing, tap duration, and precision interact to produce anticipatory touch responses. Consistent patterns observed in metrics such as the ratio of tap duration to tap radius metric across games suggest that certain behavioral signatures are stable and can serve as reliable indicators of the primitive.

### 5.3.3 Limitations

Despite the insights provided by this study, several limitations should be acknowledged. First, the sample size was relatively small, with only 23 participants. For analyses with a strong quantitative focus and an exploratory nature, a larger number of players would likely be necessary to capture the full range of individual strategies and to strengthen the generalizability of the findings.

Another limitation relates to the number of taps collected across games. *Spinning Around* produced a substantially higher number of taps per session compared to *Hopfury* and *Jumping Ball*. This discrepancy is primarily due to the frequency of short valid intervals in *Spinning Around*, which generated many more taps within the same playtime. In contrast, the level-based design of the other two games, with fewer required taps per session and cooldowns, resulted in considerably fewer data points. Extending playtime for these games could have increased the number of taps, but this might have introduced greater player fatigue. Alternatively, we could have designed additional games more similar to *Spinning Around* to collect more taps, yet this would have shifted the focus away from exploring the same primitive across distinct game mechanics. It is also worth noting that the first two games were selected from a set of 25 available titles, and future work could certainly explore other games, as the primitives investigated here were defined solely based on this limited set.

A further limitation was the inability to collect pressure data. Pressure is a potentially informative metric that could have provided richer correlations and more nuanced characterizations of touch behavior than tap radius or its variance, which are constrained to relatively coarse values (e.g., 0.25, 0.50, 0.75). Capturing continuous pressure information, or even tracking the touch area throughout the duration of each tap, could have enabled additional analyses relating hold time, precision, and force, offering a more detailed view of the motor-cognitive patterns underlying Predictive Tap.

Another limitation is that players were allowed to interact with the device freely, using their preferred hand, finger, or device orientation. This variability may have influenced tap radius measurements, as different fingers (e.g., thumb versus index) cover different contact areas, and players who changed hands or grip between games or within a game could have affected the results. Ideally, players whose interaction behavior was observed to be inconsistent would have been filtered and analyzed separately, but due to time constraints, this was not performed.

Overall, these limitations suggest that while the study provides valuable exploratory insights into game interaction primitives in general, future work should aim to increase participant numbers, balance the quantity of taps across games, incorporate additional metrics such as pressure, and examine a broader set of game mechanics to validate and extend the current findings.



## Chapter 6

# Conclusion

Prior research on game interaction primitives has often focused on specific cognitive or conceptual aspects of player behavior, without providing systematic methods to capture interactions across games or formal frameworks to generalize these patterns. This lack of standardized approaches limits the ability to compare behaviors across diverse game contexts. To address this gap, this work introduced the Predictive Tap primitive, a recurrent player action capturing anticipatory touch responses, enabling cross-game analysis of player motor-cognitive strategies.

Our analyses suggest that Predictive Tap may be most consistently expressed through tapping behaviors rather than raw reaction times, with metrics such as tap duration and tap radius potentially serving as stable cross-game indicators. Timing-related measures, including reaction time and interval time, appeared more variable and sensitive to game context, although derived ratios combining these with tap characteristics may partially stabilize the patterns.

Ultimately, this work illustrates both the practical challenges and potential solutions for instrumenting existing games for behavioral research. Implementing logging systems, invisible colliders, algorithms and buffering mechanisms without altering gameplay demonstrates the effort required, but also provides a roadmap for future studies aiming to capture fine-grained interaction data. By standardizing such approaches, researchers can study player behavior across diverse games while preserving the intended player experience.

### 6.1 Future Work

Several avenues exist for extending this work and further exploring the Predictive Tap primitive. One promising direction is the inclusion of additional metrics, particularly touch pressure. Capturing more metrics could allow for a more precise understanding of motor-cognitive strategies, especially in controlled environments where finger usage or grip can be constrained to investigate detailed behavioral patterns. Such setups might reveal insights that are harder to detect in fully naturalistic gameplay.

Another direction involves broadening the range of game genres and platforms. While this study focused on mobile games due to the relative simplicity of capturing discrete interactions, future work could explore desktop or console games, as well as more complex sequences of me-

chanics, for instance combining actions like tap–swipe–tap across multiple games. Analyzing these sequences as cohesive interaction events could deepen our understanding of recurrent player patterns beyond single taps.

Additionally, expanding the participant pool and balancing the number of interactions across games would improve the robustness of statistical analyses. Investigating Predictive Tap in diverse gameplay contexts, including competitive or multiplayer scenarios, could also reveal how anticipatory behaviors manifest under varying cognitive and motor demands.

Another important limitation of this study is that no correction for multiple comparisons was applied in the correlation analysis. This decision was made due to the preliminary and exploratory nature of the work, where the goal was to surface potentially relevant behavioral metrics rather than to provide confirmatory evidence. As such, the reported results should be interpreted with caution. Future confirmatory studies, particularly those built on prespecified hypotheses and reduced feature sets, will be essential to validate these preliminary findings and ensure their robustness.

Finally, there is potential to translate these insights into applied domains such as health monitoring. By systematically capturing and analyzing interaction primitives, it may become possible to detect early signs of cognitive or motor decline in players, opening avenues for using games as tools for longitudinal monitoring of skill and performance. Overall, these directions highlight the broad applicability of the Predictive Tap primitive and its potential to inform both game design and human-computer interaction research.

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# Appendix A

## Recruitment Form

### Participation in the Game Interaction Primitives Study

You are invited to participate in a research project conducted by the Faculty of Sciences at the University of Lisbon, as part of a Master's thesis entitled "Game Interaction Primitives."

This study aims to analyze common interaction patterns across different games.

You should only participate in this study if you meet the following criteria:

- Be 18 years of age or older
- Have some prior experience with games (mobile, computer, or console)

Participation involves playing three small games on a provided mobile device and answering a few questions about the experience. The session will be conducted in person and will last approximately 45 minutes.

At this time, we are collecting sign-ups and will contact you only if additional participants are needed. Submission of this form does not automatically guarantee selection, but it will be considered for future sessions.

If you are interested in signing up for the study, please enter your email: \_\_\_\_\_



# Appendix B

## Participant Information Sheet

**Project: Game Interaction Primitives**

**Principal Investigator: André Rodrigues**

You are invited to participate in our research study focused on understanding fundamental interactions between players and different types of games. The aim of this research is to identify consistent patterns in player interactions, analyzing how they perform core tasks within games.

Before deciding, we would like to present the details of this research, its purpose, potential usefulness, and the implications of your participation. A member of the research team will accompany you in reading this leaflet and answer any questions you may have.

### **1 - What is the study “Game Interaction Primitives”?**

Hello, my name is Inês Marques and I am conducting this study as part of my Master’s thesis at the Faculty of Sciences, University of Lisbon. My research focuses on Game Interaction Primitives, which are fundamental interaction patterns in games. The work is conducted at the LASIGE Research Center at the Faculty of Sciences, University of Lisbon. More information about our group can be found at: <https://techandpeople.github.io>. This study aims to analyze how players interact with mobile games. The collected data will help us understand common interaction patterns across different games. We are recruiting participants over 18 years old to play three different games in short sessions during which we will record their interactions.

### **2 - Do I have to participate in this study?**

Participation is entirely voluntary. We will describe the study and present the contents of this information sheet, including the details of your participation. If you agree to participate, you will sign a Consent Form. Copies of this document and the informed consent form will be provided to you.

### **3 - Can I withdraw from the study?**

You are free to withdraw at any time without providing any reason or explanation.

### **4 - What will I do as part of the study?**

You will participate in two four-minute sessions for each game (three games in total). The maximum duration will be 45 minutes, with no minimum required. At the end, you will answer a brief interview about your gaming experience. The aim is to analyze player interactions with different types of games, focusing on behavioral patterns and consistency of actions. This study does not aim to evaluate you personally. All suggestions for improvements are welcome.

### **5 - What are the risks of participating?**

No risks are anticipated, and we expect the sessions to be an enjoyable experience.

### **6 - What are the potential benefits?**

Participants often enjoy engaging with researchers. Your involvement will help us better understand player behavior patterns across different game contexts, contributing to identifying Game Interaction Primitives and ultimately informing game design.

### **7 - What happens when the study ends?**

Data analysis will conclude on 31-07-2025. Results will be published in academic conferences and journals. If you wish, you will receive a copy of the study report after 31-09-2025.

### **8 - Who do I contact if there is a problem?**

If you have any concerns about the study, contact Prof. André Rodrigues ([afrodrigues@ciencias.ulisboa.pt](mailto:afrodrigues@ciencias.ulisboa.pt)). Complaints can be addressed to the Director of the Faculty of Sciences, University of Lisbon ([di-reccao@fc.ul.pt](mailto:di-reccao@fc.ul.pt)).

### **9 - Will my information be kept confidential?**

Yes. All ethical and legal practices will be followed. Your personal information will remain confidential. Only the principal investigator and necessary team members will access the data. Data used in publications will be anonymized. Any photos or videos used will require your prior consent. You may request access or deletion of your data at any time ([afrodrigues@ciencias.ulisboa.pt](mailto:afrodrigues@ciencias.ulisboa.pt)).

## 10 - Has the study been reviewed?

Yes. The study has been reviewed by the Ethics Committee of Sciences (<https://ciencias.ulisboa.pt/pt/comissao-etica-ciencias>) with no ethical objections.

## 11 - Who can I contact regarding this study?

- Prof. André Rodrigues; Faculty of Sciences, University of Lisbon; [afrodrigues@ciencias.ulisboa.pt](mailto:afrodrigues@ciencias.ulisboa.pt)
- Prof. Rúben Gouveia; Faculty of Sciences, University of Lisbon; [rhgouveia@ciencias.ulisboa.pt](mailto:rhgouveia@ciencias.ulisboa.pt)
- Inês Marques; Faculty of Sciences, University of Lisbon; [fc62839@alunos.fc.ul.pt](mailto:fc62839@alunos.fc.ul.pt)

Feel free to contact them in any matter related to this study. Thank you for your time and for considering participating in this study.

**Principal Investigator:** André Rodrigues



# Appendix C

## Informed Consent Form

**Project: Game Interaction Primitives**

**Principal Investigator: Inês Marques**

**Supervisors: André Rodrigues, Rúben Gouveia**

We appreciate your interest and collaboration in this study. Please complete the following form.

**Participant Name:** \_\_\_\_\_

**Date:** \_\_\_\_\_

1. I confirm that I understood the information about how the study works, as presented.
  - a) Yes
  - b) No
  
2. I was given the opportunity to read and consider the information presented, and to ask questions, which were satisfactorily answered.
  - a) Yes
  - b) No
  
3. I understand that my participation is voluntary and that I am free to withdraw from the study at any time without giving reasons and without any consequences.
  - a) Yes
  - b) No
  
4. I understand that the data collected during the study may be accessed by members of the research team when necessary for the study. I authorize such access.
  - a) Yes
  - b) No
  
5. I understand that, if this research is published, all data will be anonymized and no information will be identifiable as mine.

- a) Yes  
b) No
6. I would like to receive the final report of the study.  
a) Yes  
b) No
7. My email address to receive the final report is: \_\_\_\_\_
8. I would like to be contacted at the above address about additional sessions or studies related to this study.  
a) Yes  
b) No
9. I declare that I have not communicated any potential reason of any kind that could constitute a risk factor for my health or physical integrity.  
a) Yes  
b) No
10. I participate in this study without any remuneration or compensation, except for reimbursement of expenses incurred or symbolic compensation for my time.  
a) Yes  
b) No
11. I consent to my test sessions and interviews being recorded in audio and files for player behavior analysis.  
a) Yes  
b) No
12. I make my decision entirely voluntarily.  
a) Yes  
b) No
13. I agree to participate in this study.  
a) Yes  
b) No

# Appendix D

## Demographic Questionnaire

**Project: Game Interaction Primitives**

**Principal Investigator: Inês Marques**

**Supervisors: André Rodrigues, Rúben Gouveia**

This questionnaire aims to collect demographic information and details about your gaming experience to support our research at the Faculty of Sciences, University of Lisbon.

Your participation is completely voluntary and anonymous. No personally identifiable information will be stored or shared.

Completing this form will take approximately 3 minutes.

If you have any questions, you can contact the lead researcher at [fc62839@alunos.fc.ul.pt](mailto:fc62839@alunos.fc.ul.pt).

### 1) Personal Information

1.1) Participant ID: \_\_\_\_\_

1.2) Name (first and last): \_\_\_\_\_

1.3) Age: \_\_\_\_\_

1.4) Gender:

a) Male

b) Female

c) Non-binary

d) Prefer not to say

e) Other: \_\_\_\_\_

1.5) Country/Region: \_\_\_\_\_

**1.6) Occupation:** (Select all that apply)

- a) Student
- b) Full-time employment
- c) Part-time employment
- d) Self-employed/Freelancer
- e) Unemployed
- f) Other: \_\_\_\_\_

**2) Gaming Experience****2.1) How long have you been playing video games?**

- a) Less than 1 year
- b) 1-3 years
- c) 4-7 years
- d) 8-10 years
- e) 10+ years

**2.2) How often do you play video games?**

- a) Less than once a week
- b) 1-2 times a week
- c) 3-4 times a week
- d) Daily

**2.3) On average, how long are your gaming sessions?**

- a) Less than 1 hour
- b) 1-2 hours
- c) 2-4 hours
- d) 4+ hours

**2.4) What kind of player are you?**

- a) Casual
- b) Semi-serious
- c) Hardcore
- d) Don't know

### 3) Experience with Mobile Video Games

#### 3.1) Do you usually play on mobile devices?

- a) Yes, it's my main platform
- b) Yes, but I mainly play on other platforms
- c) Occasionally
- d) No, I don't play mobile games

#### 3.2) On average, how long are your gaming sessions on mobile devices?

- a) Less than one hour
- b) 1-2 hours
- c) 2-4 hours
- d) 4+ hours

#### 3.3) What type of mobile games do you play the most? (Select all that apply)

- a) Action
- b) Puzzle
- c) Strategy
- d) Endless Runner
- e) Rhythm games
- f) Other: \_\_\_\_\_

#### 3.4) Have you played games that require touch gestures such as tapping, swiping, or holding?

- a) Yes, frequently
- b) Yes, sometimes
- c) Rarely
- d) No

#### 3.5) How comfortable are you with touchscreen controls? (Scale 1-5)

- 1 a)
- 2 b)
- 3 c)
- 4 d)
- 5 e)

#### 3.6) Do you use any accessibility settings or assistive tools while gaming?

- a) No
- b) Yes, I use enlarged buttons/text or simplified controls

c) Yes, I use vibration settings

d) Other: \_\_\_\_\_

**3.7) Do you use external controllers to play on your mobile device (e.g., Bluetooth controllers)?**

a) Yes, frequently

b) Yes, occasionally

c) Rarely

d) Never

# Appendix E

## Break Game Questionnaire

**Project: Game Interaction Primitives**

**Principal Investigator: Inês Marques**

**Supervisors: André Rodrigues, Rúben Gouveia**

This questionnaire is part of the in-game break evaluation. Please answer the following questions regarding your gameplay experience.

**Participant ID:** \_\_\_\_\_

1. I'm enjoying this game. / Estou a divertir-me com este jogo.

Strongly disagree / Discordo totalmente    1    2    3    4    5    Strongly agree /  
Concordo totalmente

2. The game is challenging. / O jogo está a ser desafiante.

Strongly disagree / Discordo totalmente    1    2    3    4    5    Strongly agree /  
Concordo totalmente

3. The objectives of the game are clear. / Os objetivos do jogo são claros.

Strongly disagree / Discordo totalmente    1    2    3    4    5    Strongly agree /  
Concordo totalmente

4. I feel focused while playing this game. / Sinto que estou focado/a no jogo.

Strongly disagree / Discordo totalmente    1    2    3    4    5    Strongly agree /  
Concordo totalmente



# Appendix F

## End-Game Questionnaire

**Project: Game Interaction Primitives**

**Principal Investigator: Inês Marques**

**Supervisors: André Rodrigues, Rúben Gouveia**

This questionnaire is part of the end-of-game evaluation. Please answer the following questions regarding your gameplay experience.

**Participant ID:** \_\_\_\_\_

1. The gameplay was smooth and responsive.

Strongly disagree / Discordo totalmente    1    2    3    4    5    Strongly agree /  
Concordo totalmente

2. I was fully focused on the game.

Strongly disagree / Discordo totalmente    1    2    3    4    5    Strongly agree /  
Concordo totalmente

3. The game had a nice visual style.

Strongly disagree / Discordo totalmente    1    2    3    4    5    Strongly agree /  
Concordo totalmente

4. I would like to play this game for longer.

Strongly disagree / Discordo totalmente    1    2    3    4    5    Strongly agree /  
Concordo totalmente



# Appendix G

## Final Games Questionnaire

**Project: Game Interaction Primitives**

**Principal Investigator: Inês Marques**

**Supervisors: André Rodrigues, Rúben Gouveia**

Thank you for participating in this study! This short final questionnaire helps us understand your overall opinion about the three games you played.

**Participant ID:** \_\_\_\_\_

1. Rank the following games from most difficult to least difficult. / Ordena os seguintes jogos do mais difícil ao menos difícil.  
a) Spinning Around      b) Jumping Ball      c) Hopfury
2. Rank the following games from most immersive to least immersive. / Ordena os seguintes jogos do mais imersivo para o menos imersivo.  
a) Spinning Around      b) Jumping Ball      c) Hopfury
3. Rank the following games from most likely to least likely to play while waiting at a bus stop. / Ordena os seguintes jogos do mais provável ao menos provável de jogares numa paragem de autocarro.  
a) Spinning Around      b) Jumping Ball      c) Hopfury



# Appendix H

## Final Interview Questions

**Project: Game Interaction Primitives**

**Principal Investigator: Inês Marques**

**Supervisors: André Rodrigues, Rúben Gouveia**

Thank you! We will now move on to some quick questions about your overall experience. I will start the audio recording. [START AUDIO RECORDING]

1. Were the games different? (If yes), how would you describe the differences between them?
2. Were the games similar in any way? (If yes), in what way?
3. Which of the three games did you find the least engaging and which did you find the most engaging? Why?
4. How difficult did you find each game? Which elements contributed to that difficulty?
5. Do you think your performance was consistent across all games? (If not), why?
6. If you had to guess, where do you think you ranked compared to other players? (We are imagining around 20 other participants in the study with varying expertise).
7. Would you like to know any metrics about your performance in these games? (If yes), which metrics would you like to know? (e.g., average reaction time, total taps, effective taps).
8. Overall, did you enjoy playing these games or not? Why?
9. What is your opinion about commercial games collecting interaction data? And knowing that in the future this data could potentially be used as approximations of clinical motor and cognitive assessments? What kind of data would you be willing to share? What protections should be guaranteed to the players?
10. If there is anything else you would like to share about your experience, feel free to do so!



# Appendix I

## User Test Script

### Preparation

- Phone charged and with the 3 games installed (Spinning Around, Jumping Ball and Hop-fury).
- Volume turned on for both phone and games.
- Correct player selected in the game settings.
- Click “Save” after choosing the name.
- Pen and paper / online document ready for taking notes.

Before starting the test, make sure the participant fills in the following forms:

- **Informed Consent Form:** <https://forms.gle/cEXG7kRGFnHa3mxcA>
- **Demographic Questionnaire:** <https://forms.gle/eq9bzn5S3farUf2y9>

### Introduction

“Hi! Thank you for participating in this study. I want you to imagine you’re at home relaxing, or waiting for a bus, and you opened a game just to pass the time. The idea is to play in a casual and comfortable way. You’ll be playing 3 different games, each for about 9 minutes. After 4 minutes, we’ll take a short break for a quick question, and then you’ll continue. At the end, I’ll do a brief interview with you. Sound good?”

### Notes for the Test Supervisor

- Remain silent during gameplay, except when giving planned instructions.
- Do not encourage or criticize the participant while they play.
- Do not mention how much time is left (unless the participant seems frustrated or asks).

- Observe and take notes on how the participant holds the phone (portrait/landscape, fingers used, one or both hands) and whether this changes.
- If the participant seems frustrated, let them know how much time remains.

## Game 1 – Spinning Around

### Preparation

- Open the **Spinning Around** app.

### Instructions to Say

“In this first game, your goal is to control a white ball that spins along a circular path, and avoid the spikes that appear. Everything is controlled by tapping the screen. When you’re ready, you can start.”

### Gameplay Flow

- **4 minutes of gameplay.**
- Pause (**1 minute**).

### Break Questionnaire

“Let’s take a quick break. Please fill out this short questionnaire with a few quick questions about your experience so far.”

Questionnaire link: <https://forms.gle/EEXH4YR8aBB7qgXn6>

### Resume Gameplay

- **4 more minutes of gameplay.**

### End-Game Questionnaire

“That’s the end of the session. Before we move on to the next game, please take a moment to fill out this short questionnaire about your experience.”

Questionnaire link: <https://forms.gle/Cbm5GKJLsaTL94sA9>

### Transition

“Alright, let’s continue with the next game.”

## Game 2 – Jumping Ball

### Preparation

- Open the **Jumping Ball** app.

### Instructions to Say

“In this second game, you control a white ball that jumps from platform to platform. The goal of each level is to reach the top. Everything is controlled by tapping the screen. When you’re ready, you can start.”

### Gameplay Flow

- **4 minutes of gameplay.**
- Pause (**1 minute**).

### Break Questionnaire

“Let’s take a quick break. Please fill out this short questionnaire with a few quick questions about your experience so far.”

Questionnaire link: <https://forms.gle/xASghYVi5eTADtDW8>

### Resume Gameplay

- **4 more minutes of gameplay.**

### End-Game Questionnaire

“That’s the end of the session. Before we move on to the next game, please take a moment to fill out this short questionnaire about your experience.”

Questionnaire link: <https://forms.gle/QVwXRtBMve4kv5UU7>

### Transition

“Alright, let’s continue with the next game.”

## Game 3 – Hopfury

### Preparation

- Open the **Hopfury** app.

## Instructions to Say

“This last one has multiple levels, and your goal is to reach the end of each one. You play as a square, and there are built-in tutorials that will explain how things work as you go (note: we will not time the tutorials). You have 3 attempts per level, and the game will automatically unlock the next level so you can keep progressing. Just like the other games, it’s controlled through screen gestures. When you’re ready, you can start.”

## Gameplay Flow

- **4 minutes of gameplay.**
- Pause (**1 minute**).

## Break Questionnaire

“Let’s take a quick break. Please fill out this short questionnaire with a few quick questions about your experience so far.”

Questionnaire link: <https://forms.gle/RVhFz8uJkE5nsEVN9>

## Resume Gameplay

- **4 more minutes of gameplay.**

## End-Game Questionnaire

“That’s the end of the session. Before we move on, please take a moment to fill out this short questionnaire about your experience.”

Questionnaire link: <https://forms.gle/ZknnpqRcwofpYDv19>

## Transition

“Alright, let’s continue. If you want to stop at any time, just let me know.”

## Final Interview

“Now that you’ve finished all three games, I’d like you to fill out a quick questionnaire about your experience with the games. This will help us better understand how you felt about each one.”

Questionnaire link: [https://docs.google.com/forms/d/e/1FAIpQLScGddky1bSr7FWb1Y82es9I5ZGsb\\_eg/viewform](https://docs.google.com/forms/d/e/1FAIpQLScGddky1bSr7FWb1Y82es9I5ZGsb_eg/viewform)

“Thank you! Now, I’d like to ask you a few quick questions about your overall experience. Is it okay if I record the audio of this interview?”

- Start recording only after getting consent.
- Ask the prepared interview questions.
- Record responses.

## **Closing**

“Thank you for your participation! Your help is very valuable to my research. If you’d like, I can send you the results once the study is completed.”