Perceptual Distraction and its Effects on Difficulty and User Experience in Digital Games

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Abstract

Modern video games often feature rich visual worlds, with many aesthetic elements not essential to gameplay. As our brains are limited in capacity, such task-irrelevant elements can increase cognitive load and lead to distraction, which affects working memory - a key cognitive function in gaming. Little is known about which visual characteristics have the potential to distract and what consequences distraction has on player experience. A better understanding of these interactions can advance the design of more enjoyable, engaging, and accessible games. The present thesis therefore aims to uncover the relationship between perceptual distraction, game difficulty, and user experience in digital games, following an interdisciplinary approach. Three traditional cognitive experiments investigated how basic visual characteristics affect working memory accuracy. Participants were asked to retain and recall an array of black target circles. Compared to trials without distractors, grey circle distractors impaired recall accuracy, whereas other distractor types did not, underscoring the target-distractor similarity account, which states that stimuli that are visually closer to target items are more distracting. Utilising a custom-designed video game, two subsequent studies revealed that performance gradually decreased as target-distractor similarity in terms of brightness contrast increased. While distractor difficulty per se did not impact player experience, success rates in distractor trials correlated with enjoyment, highlighting the importance of providing adequate challenges and progress feedback in games. Finally, since individuals differ substantially in cognitive abilities, the effects of game difficulty based on players' working memory capacity and ability to ignore distraction on player experience were studied. Contrary to expectations, personalising difficulty based on individual player skills did not improve player experience. In sum, these findings emphasise the importance of considering both task-relevant and task-irrelevant visual elements in video game design and suggest a complex interplay between the visual design of game elements, performance and PX.

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Declaration

I declare that the research described in this thesis is original work, which I, Madeleine Frister, undertook at the University of York during 2020 - 2024 under the supervision of Dr Fiona McNab and Prof Paul Cairns. Except where stated, all of the work contained within this thesis represents the original contribution of the author. This work has not previously been presented for a degree or other qualification at this University or elsewhere. All sources are acknowledged as references.

Some of the material in this thesis has been submitted to the following academic journal:

- Madeleine Frister, Fiona McNab, Maximilian Croissant, Paul Cairns, "Examining the influence of target-distractor similarity on difficulty in a working memory game." [Submitted to Entertainment Computing], 2024.

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Chapter 1

Introduction

The video games field is becoming increasingly competitive, with over 14,000 games released alone on Steam in 2023, the number increasing each year [1]. Ensuring a good Player Experience (PX) that engages and immerses players is therefore crucial for the success of a video game. Since video games are highly interactive forms of media and mainly operate through the visual channel, particular consideration has to be given to the visual elements that make up a game. Modern video games are often extremely high in visual complexity, which has been driven by technological advancements in computer graphics over the past decades. From abstract pixel art back in the 1970s, many of today's games feature almost photo-realistic or highly stylised 3D imagery, remarkably detailed game worlds, and sophisticated special effects. A popular example is the first-person shooter *Overwatch 2* with its highly detailed characters and game environments, and abundance of visual effects (see Figure 1.1).

Figure 1.1: Screenshot of the video game Overwatch 2. Source: [2]

Such visual embellishments, which often have no functional purpose and are as such not necessarily task-relevant, but rather reinforce player actions, feedback, and game events, are in the games industry as well as literature often referred to as "juiciness" or "polish" [e.g., 3]–[5]. Juiciness has been shown to improve PX by increasing immersion and visual appeal [4]. Zhou and Forbes [6] further suggest that visual effects can facilitate interpreting the game world and reinforce game mechanics. However, there appears to be a limit as to how juicy a game should be: Extreme levels of juiciness have been demonstrated to negatively influence performance and PX [3]. This could be due to the heightened cognitive load that can occur with excessive use of visual effects [7], [8]. Since our cognitive system is limited in the amount of information it can efficiently process [9], a high level of cognitive load can increase the risk of perceptual distraction [10], which is a state in which an individual's attention is diverted by the presence of distracting stimuli in the (visual) environment. Our brains do not process everything that surrounds us but generally employ a selective approach by only focusing on information that may help complete a current task, and ignoring everything else. In cognitive-psychological literature, this is known as *Selective Attention* [11]. Yet, under some circumstances, irrelevant information can enter our cognitive system and divert attention from what we are currently doing, disrupting the efficient completion of a current task. Factors that increase the risk of distraction are highly salient or distinct visual features of task-unrelated elements [12] or the similarity between task-relevant and -irrelevant items [13]. In many modern video games, such circumstances are very common, particularly in action games that feature highly detailed game worlds and plenty of visual effects, such as the aforementioned game *Overwatch 2*. Considering that games like this often also require a high degree of attention and cognitive effort, players may be easily distracted. Visual complexity in video games has indeed been demonstrated to impair performance and therefore increase difficulty [14]–[16]. But what does this increased difficulty factor mean for players and are the consequences necessarily negative?

Since distraction can hinder efficient task completion, User Experience (UX) guidelines generally recommend that any information that is irrelevant to the task at hand should be eliminated [17], [18]. While these guidelines are often applied to video games with regards to the design of the user interface [e.g., 19], it has to be acknowledged that games are somewhat different from other types of interactive software such as productivity tools [20]. The principal goal of almost every game is not to efficiently accomplish a task, but rather to elicit a certain experience. Therefore, such guidelines may not necessarily apply to games, particularly when taking into account that challenge is considered a key element of games that can improve PX [20]–[22]. However, it has indeed been shown that games that are too difficult may reduce enjoyment [23], and many researchers believe that game difficulty needs to be adjusted to players' individual skills in order to elicit enjoyable experiences and prevent negative feelings such as frustration [24]–[27]. Aside from research about "juicy" game elements, which refer more to visually embellished feedback rather than the presence of potentially distracting task-irrelevant game elements, the effects of perceptual distraction on PX have not been researched in much detail. Anecdotal evidence from social media and blog posts surrounding topics about clutter in video games, however, do suggest that many players have issues with the visual complexity such games offer, which may leave them overwhelmed and frustrated [e.g., 28], [29].

In order to avoid such negative consequences and to increase the chance of providing enjoyable gaming experiences, examining players' motivations, perceptions, and feelings toward the game is imperative. This is particularly important in light of inter-individual differences: It is known that cognitive abilities such as attention, Working Memory (WM), and the ability to ignore distracting stimuli differ substantially from individual to individual [30]–[33]. In addition, PX is also known to vary from individual to individual [34]:

While some players enjoy the increased cognitive demand that comes along with visual clutter in the game world, others may feel overwhelmed or discouraged. More research is needed that addresses open questions around how players process goal-relevant and -irrelevant visual elements present in the game world, how this affects difficulty and PX, and any inter-individual differences related to such associations. Drawing on theories and evidence from cognitive science relating to attention, WM, and the ability to ignore distraction could help answer these questions and ultimately aid game designers in creating more engaging and enjoyable games for all players.

The current thesis therefore adopts a cognitive-scientific approach in order to further our knowledge of how the visual characteristics of game elements affect distractibility, game difficulty, and PX. A better understanding of these matters can assist game design in a variety of ways. Since video games often contain many elements that are not necessarily relevant for the task at hand, but are rather used for aesthetic purposes or to add juice, distraction can easily occur. Game designers may benefit from clear principles concerning the design of goal-relevant and -irrelevant elements. For instance, insights about the distractibility of certain visual features can be leveraged to effectively highlight elements that are crucial to advance in the game and to tone down or eliminate elements that are not currently task-relevant. On a different take, potentially distracting visual characteristics could be purposefully applied to modulate the challenge level of games, which in turn could increase engagement and enjoyment.

Insights from this research project can also have broader implications for other domains beyond game design: A better understanding of what determines the processing of task-relevant and -irrelevant material can be useful for a variety of situations where we are prone to be distracted, and which require us to be focused, such as driving or studying. For example, being able to predict what captures drivers' attention and eliminate these sources may decrease the risk of critical accidents. Knowing what distracts us from performing leisure activities such as reading, watching movies, or playing video games can help us stay focused and improve our well-being. Having a better understanding of what elements may divert attention away from a current task can improve the usability of interfaces, educational software, and other interactive systems for which attentional focus on a task at hand is crucial. Finally, researching perceptual distraction in video games can advance the understanding of cognitive processes more generally in an ecologically valid setting.

1.1 Research Aims and Questions

The main goal of this PhD project is to contribute knowledge that allows game designers to create more engaging, accessible, and enjoyable games by improving our understanding of the visual characteristics of game elements, their potential to distract from a current task, and the consequences for difficulty and PX. This thesis therefore addresses the following overarching Research Question (RQ):

How do perceptual characteristics of task-relevant and -irrelevant elements affect difficulty and PX in video games?

To answer this question, the following four specific RQs will be addressed by collating theories and empirical evidence from cognitive science, Human-Computer Interaction (HCI), and video games research, and by conducting a series of experimental studies:

1. What visual characteristics make items distracting?
2. How does perceptual distraction affect game difficulty?
3. What consequences does perceptual distraction have on PX?
4. How does a personalised gaming experience, based on players' Working Memory Capacity (WMC) and their ability to ignore distraction, affect PX?

The first RQ is addressed in a series of three experiments described in Chapter 3. In these experiments, distractors with different visual characteristics are directly compared, and their effects on information processing in a memory task are investigated. Since video games often require players to keep information such as game controls or target locations in mind, examining visual features in the context of a memory task can tell us more about how video game performance may be affected by distracting visual stimuli, while keeping the setting fairly controlled. Building upon the outcomes of this experiment, Studies 4 and 5, which are described in Chapter 4, take a closer look at how distractors that have been identified to impact memory performance in the first three experiments affect performance and difficulty in a simple memory game, addressing RQ 2. While the effects of game difficulty induced by perceptual characteristics on performance have been investigated to some extent [14]–[16], the focus has been on visual search tasks and not on WM, which is, as mentioned above, a capability required in many video games. For instance, action or shooter games require players to memorise enemy attack patterns; in open-world games, players frequently need to remember locations and quest targets. While Study 4 adopts a within-subjects design that allows us to examine how performance in trials with varying appearance of distractors in relation to targets affects PX, in Study 5, a between-subjects approach is adopted in order to make direct conclusions about associations between game difficulty and PX, addressing RQ 3. Finally, since distractor filtering abilities vary from individual to individual and since it is believed that game difficulty and player skill need to be balanced in order to provide positive gaming experiences, a last study, which is described in Chapter 5, investigates how adapting game difficulty to players' WMC and their individual ability to ignore distraction affects PX, contributing to RQ 4.

Taken together, the studies conducted within this PhD project aim to contribute novel information about both fundamental cognitive mechanisms relating to distractor processing and WM, as well as the interplay between these mechanisms and video gaming. Ultimately, the findings of this thesis should help game designers make more informed choices about the visual presentation of goal-relevant and -irrelevant game elements as well as about game difficulty choices that could improve PX.

1.2 Thesis Outline

To address the above-mentioned research objectives, the following chapters first discuss existing background literature about PX, cognitive psychology, and the interplay between cognition and gaming, followed by empirical studies that take a closer look at the specific research questions. Finally, the outcomes of the conducted studies and their contributions to the fields of games research and cognitive psychology, as well as their implications for game design are discussed.

In Chapter 2, a detailed literature review discusses principal topics that are of relevance to answering the present research questions. This chapter first delves into the concept of PX, its main components, and its basis in psychological theories. Subsequently, fundamental insights from cognitive psychology, particularly with respect to attention, WM, and distractor filtering are discussed. Finally, Chapter 2 presents literature about the interplay between cognition and gaming, including the cognitive abilities that different types of video games demand from players, and the effects of visual complexity in games on PX.

Following the literature review, Chapter 3 describes three empirical studies that address the first RQ: *What makes a distractor distracting?* Within these studies, a range of primitive visual variables and their effect on WM performance are investigated in a traditional cognitive task. Each experiment examines a specific set of visual characteristics, which in combination contribute to a better understanding of how perceptual characteristics of task-irrelevant stimuli affect information processing.

Building upon the previous three studies, Chapter 4 describes two empirical studies that use a simple custom-made WM game to investigate the effects of perceptual characteristics of task-irrelevant game elements not only on performance and game difficulty but also on PX. These studies will further explore associations between performance and a range of PX metrics to shed more light on what predicts a good UX in video games.

Subsequently, and again building upon the previous studies, Chapter 5 describes a final empirical study that examines the effects of adapting game difficulty to players' individual WMC and ability to ignore distraction on PX. This study therefore takes into account individual differences and provides insights as to how personalizing video games based on individual abilities may shape PX.

Finally, Chapter 6 provides a summary of the conducted studies and their main outcomes, along with discussing implications and outlining contributions for game design, games research, and cognitive-psychological research. Chapter 6 also discusses the limitations of the current work and presents potential avenues for future research that further help advance our understanding of the interplay between human information processing and UX.

Chapter 2

Literature Review

In order to understand how Player Experience (PX) is shaped by the visual design of any particular video game, it is not only important to consider evidence from HCI and video game research but also to draw upon fundamental psychological concepts, particularly with regard to aspects of human information processing, such as attention and Working Memory (WM). Integrating these disciplines can ultimately help create more enjoyable and engaging games by improving our understanding of the complex interaction between the idiosyncrasies of our mind and the visual characteristics of video games, and how this interplay affects the overall experience players have while playing games. The following chapter therefore first discusses the concept of PX, with a focus on its integral components enjoyment and challenge, as well as its roots in psychological theories. Subsequently, a closer focus will be placed on the fundamental aspects of human information processing, including Working Memory (WM) and attention, that can help inform game design principles. Finally, existing evidence on the interplay between cognition and gaming will be laid out in more detail, focusing particularly on how cognitive load in the form of visual complexity can influence player performance and experience. This literature review aims to provide a comprehensive overview of the complex interaction between PX and cognition and to point out any existing gaps in knowledge that when addressed can advance our understanding of this interaction and ultimately assist in creating better games.

2.1 Player Experience

With the video game market becoming increasingly competitive, it is getting more and more important for game designers to craft compelling experiences for players. This not only requires ensuring the functionality and usability of a *game*, but also understanding the *player*, including their motivations, perceptions, and emotional reactions. The field of Player Experience (PX) research, which has evolved from the broader concept of User Experience (UX), aims to shed light on the player-game interaction and attempts to explain why players engage with games. The following paragraphs define and discuss PX and related concepts in more detail and explain the central aspects that constitute it.

2.1.1 Definitions and Concepts

The idea of employing a user-centred approach when designing interactive products has been around since at least the 1950s, and has evolved into a fastly growing discipline which is today known as "User Experience", or shortly, UX design [35]. UX is a complex construct that encompasses aspects of the user, such as their motivation or needs, of the product, such as its functionality, and of the surrounding context the interaction occurs in [36]. An integral part of UX is usability, which concentrates more on task accomplishment and efficiency, and less on the experiential component - including users' emotions and feelings - that many digital applications entail [37]–[39]. Jakob Nielsen [40] for instance characterises a usable system or application as one that is easy to learn, efficient to use, easy to remember, has a low error rate, and is pleasant to use (note that some of these criteria, and especially the last one, do indeed contain some form of experiential qualities, yet they are are rather vaguely defined and not at the centre of usability). To fulfil these criteria, knowledge about human psychology, and particularly about the capabilities and limitations of human information processing need to be taken into account when designing interactive software [41], [42]. These aspects are recognised in common UX and usability guidelines. For example, Jakob Nielsen's usability heuristics [17] or Ben Shneiderman's Eight Golden Rules of Interface Design [18] emphasise the importance of reducing cognitive load and focusing on minimalist design, which implicates the prioritisation of information required to accomplish a task and to eliminate any unnecessary and potentially distracting elements irrelevant to the task at hand.

While UX and usability are arguably important for any interactive product, video games feature particular characteristics related to gameplay that are not accounted for by common UX models [43]. Video games are often compared to productivity applications when describing their unique properties. While the main focus of productivity software is to enable users to solve tasks quickly and efficiently, the primary goal of video games is to entertain and elicit pleasurable experiences like fun, without necessarily focusing on task accomplishment [20], [43], [44]. PX research aims to shed light on these experiential qualities that are unique to video games.

PX has been described and evaluated based on a variety of components related to the subjective experience a player has while interacting with a game [45]. These components include for instance immersion, flow, enjoyment, presence, and challenge. The range of dimensions or components that have been suggested to form part of the PX construct underlines its complexity. Accordingly, there is no single model that describes the concept in its completeness. Instead, many different models have been developed that concentrate on more or less specific aspects of PX [see 34]. The following sections describe some of the most important dimensions of PX, their roots in psychological theories, and how they have been integrated into theories of PX.

2.1.2 Central Aspects of Player Experience

2.1.2.1 Enjoyment

Enjoyment is arguably one of the most important experiences video game designers strive to elicit in players [46] and has also been cited as one of the key motives for playing games [47]. Hence, the growing popularity and ubiquity of video games have spurred an increased interest in better understanding what constitutes and predicts the enjoyment experience. There are many different terms that refer in some way to enjoyment, with entertainment, engagement, fun, or pleasure as some frequently used examples. Along with the various terms used to describe the presumably same experience, there is also no unified definition of enjoyment. Yet, many scholars agree that enjoyment is a complex concept that involves not only affective but also physiological, behavioural and cognitive dimensions [48]–[51]. Several models have been proposed for the construct of enjoyment, focusing on different game aspects and underlying psychological theories. Some of the most prominent models are discussed in more detail in the following sections.

Flow and GameFlow

One of the most frequently discussed concepts in relation to enjoyment is *flow* - a deep sense of pleasure that arises from being fully absorbed or immersed in a task. The term flow was coined by Mihaly Csikszentmihalyi and originated from his studies of the creative process in artists [52]. Flow has since been researched in various contexts, including sports, art, and education [52], but also video gaming [46]. The experience of flow itself relies on two main conditions: first, the challenges of the task shall not exceed or fall behind one's skills, and second, clear and immediate progress feedback must be given [52]. If these conditions are met, a state of flow is reached, which is characterised by an intense concentration on the present task, a loss of awareness and self-consciousness, a sense of control over one's actions, a distorted experience of the passage of time, and the experience of intrinsic reward [52].

In its application to video games, the GameFlow model has been introduced by Sweetser and Wyeth [46] with the goal of better understanding the enjoyment experience in games. The GameFlow model consists of the eight elements concentration, challenge, skills, control, clear goals, feedback, immersion, and social interaction, which - with the exception of the latter - largely mirror the components of flow proposed by Csikszentmihalyi [53]. Sweetser and Wyeth provide a variety of criteria for each component that should be fulfilled in order to provide enjoyment. For instance, games should grab players' attention, have a high but not too high cognitive load, and avoid distraction in order for players to be able to concentrate on the game. Games should also provide challenges that match the players' skill level and support their skill development. When all prerequisites are fulfilled, players should experience a deep sense of immersion in the game, which is characterised by the elements of the flow experience described before.

Psychological Need Satisfaction

Flow is in many aspects related to another famous psychological model, which is Self-Determination Theory (SDT) [54]. SDT posits that people have three basic psychological needs - the need for competence, the need for autonomy, and the need for relatedness, all of which are essential for motivated behaviour and psychological well-being [54]. Competence refers to a sense of achievement or efficacy and is only fulfilled when attributed to oneself rather than to some external factor such as a reward. The need for autonomy is satisfied when people have a choice or opportunities to direct their own actions, as opposed to a controlling environment. Finally, relatedness refers to a sense of security and belonging with others. Both flow theory and SDT place a strong focus on intrinsic motivation, that is the motivation to perform an activity not based on any external rewards or goals, but out of an inherent drive or interest for the activity itself. Another main point where both theories converge is the aspect of optimal challenge. SDT, like flow theory, requires a task to be at an optimal challenge level tuned to one's skills. Only then a true sense of competence can occur [55].

Just like flow theory, which has been applied to video gaming in the form of the GameFlow model, SDT has found its way into PX research. Video game enjoyment has been proposed as the result of the satisfaction of the three needs of autonomy, competence, and relatedness [56], [57]. A measure has been developed to assess the satisfaction of the three basic needs specifically from video game play - known as the Player Experience of Need Satisfaction (PENS) scale [56]. The PENS model consists of five dimensions: in-game autonomy, in-game competence, in-game relatedness, presence, and intuitive controls. The PENS dimension of presence - a sense of being engulfed in the game world - bears resemblance to the experience of immersion described by the GameFlow model. Also similar to the GameFlow model, the PENS dimension of in-game competence highlights the importance of an appropriate balance between player skill and the challenges of the game. One element that repeatedly emerges in theories about video game enjoyment, including the above-mentioned PENS and GameFlow models, is challenge. The next section explores the concept of challenge in more detail and discusses its relation to player skill and PX.

2.1.2.2 Difficulty and Challenge

Challenge is often described as being situated at the core of the enjoyment experience [46], [58], [59], and is also a main aspect in which games differ from productivity software [20], [43], [44]. Challenge has been defined as the perceived or subjective difficulty of a game [21] - a definition that emphasises that challenge is unique for each player and not an objective characteristic of the game. Thus, subjective difficulty may include motivations, attitudes, and feelings that can differ from individual to individual. In contrast, objective difficulty, which is stable across players, directly relates to aspects of the game itself and can be measured for instance with the likelihood of winning or losing [60].

Generally, challenge is seen as a desirable quality in games [20], [22], and has been associated with a number of positive experiential consequences including enjoyment, flow, and immersion. In a systematic review, Mekler and colleagues [49] identified challenge as an important precursor of game enjoyment. As described in the last section, challenge is also a central aspect of flow theory, and empirical studies investigating the relationship between challenge and the enjoyment of intrinsically motivated activities have shown that challenge was indeed a strong predictor of enjoyment [61]. Increasing challenge, specifically in the cognitive domain, has also been shown to lead to higher levels of immersion [62].

Since the subjective difficulty or challenge is unique to the player, the player's individual skill is an important factor to consider when looking at the difficulty-enjoyment relationship. While a game should indeed provide challenges, care should be taken that these do not become too difficult for a specific player. Otherwise, the enjoyment experience may suffer and negative experiences like frustration may even occur [26]. This is substantiated by a number of empirical studies. For instance, Schmierbach and colleagues [23] found that in general, players enjoyed difficult games less, which was mediated by a reduced feeling of competence and a lower perceived challenge-skill balance. Notably, this was also the case for players who indicated a preference for particularly hard games. Similarly, Klimmt et al. [63] examined game enjoyment in players experienced in playing first-person shooter (FPS) games and found significant differences in enjoyment across three groups of different difficulty levels, with the easy version being enjoyed more than the difficult version. These findings suggest that higher performance (or skill) leads to increased enjoyment, a relationship which, according to the authors, may be mediated by players' own perception of the game's difficulty and their performance [63]. Jin [64] also reported increased enjoyable game experiences when performance was higher, and further established an interaction with challenge, reporting that highly skilled players experienced a higher level of flow in challenging gameplay situations compared to players with lower levels of skill, highlighting the importance of providing stimulation through adequate challenges in games.

Adjusting Game Difficulty

Game designers commonly apply technologies to provide adequate challenge levels for players. While the more traditional approaches entail difficulty selection menus or a linear increase in difficulty as the player advances in the game, modern approaches tend to dynamically adjust difficulty to player performance. This technique is known as Dynamic Difficulty Adjustment (DDA). DDA is usually motivated by flow theory, which, as described before, assumes an optimal balance between the challenge level of the game and the player's skills. This "optimal" state is also known as the flow channel. Accordingly, as the player's expertise and skills are growing, the challenge level of the game should also increase to keep the player inside the flow channel and avoid boredom or frustration.

DDA is generally applied by continually measuring the game's difficulty level and evaluating it against metrics such as win and death rates, points, or time to complete tasks [27]. Some researchers suggest that rather than adjusting to performance metrics, PX may be enhanced by adapting game difficulty to players' affective states, such as anxiety or boredom [e.g., 65], [66], or to players' personality [67]. The application of DDA frameworks has been shown to increase engagement rates [68], and in-game performance [25]. Positive effects on PX have also been reported [24], [67], [69]–[71]. Yet, in some cases simple difficulty selection made by the player may be as effective as DDA [72].

One problem associated with DDA is that it assumes an "optimal" level of challenge, which is hard to determine and may vary from player to player [73]. In addition, rather than a performance measure such as a win/loss ratio, other aspects of the player, such as their experience, play style, or motivation, may be better suited to determine the difficulty level the player actually wants in a specific moment [74]. This seems particularly relevant when considering that failure is a central aspect of most video games, and although failing may evoke negative emotions, players happily decide to play video games regardless or even seek this specific experience [75]. So, while applying player-centric methods such as DDA in determining a game's difficulty is a promising way to enhance the PX, there is an increasing interest to focus on metrics beyond mere in-game performance, and also consider individual differences in gaming preferences, emotions, and cognitive skills [76], [77].

2.1.3 Summary

In sum, the construct of PX is very complex, consisting of a variety of sub-components. With enjoyment and challenge considered as two of the most central aspects of the gaming experience, a lot of research exists that addresses these concepts. Enjoyment and challenge are not independent, and a balance between the difficulty of the game and the skills of the player is often considered crucial to provide enjoyment. Consequently, techniques have been developed to balance the difficulty of the game with the player's skill. One such technique is the so-called Dynamic Difficulty Adjustment (DDA), which continuously alters the difficulty of the game based on the player's current performance. Yet, emerging evidence suggests that the optimal difficulty level may not depend on the player's skill as measured by their performance, but may rather rely on other factors such as their play style, difficulty preferences, or motivations. As it stands, the relationship between game difficulty, player performance, challenge, and enjoyment is not well understood. More research is needed that provides a better understanding of how these aspects interact with each other, which can help make more informed choices when it comes to game difficulty which may increase the enjoyment value of a game.

2.2 Lessons from Cognitive Psychology

Even though our brains can accomplish remarkably complex tasks, there are certain limitations as to how much information the human mind is capable of processing [9], [78]. This is not necessarily a negative quality but rather enables us to perform tasks very efficiently by only considering what is currently relevant and disregarding anything else. However, in some situations, information that is not necessarily relevant to the task at hand can enter our cognitive system, distracting us from what we are currently doing. In video games, which often not only feature highly complex visual environments, but also place substantial demand on cognitive capabilities such as perception, attention, and working memory, distraction can easily happen. Being distracted is known to impair performance [79] and may even lead to negative consequences such as reduced perceived usability [80]. Drawing upon theories and evidence from cognitive psychology can shed light on the circumstances under which we are prone to be distracted, which can then provide guidance for better design of task-unrelated visual elements in video games. The following sections discuss theories and evidence relating to distraction and its effects on information processing in more detail, along with reviewing fundamental concepts of the human cognitive system, including WM and attention.

2.2.1 Working Memory

One of the key cognitive capacities that are prone to distraction is Working Memory (WM). WM is defined as a limited capacity brain system for the temporary storage and manipulation of information that is considered necessary for accomplishing complex cognitive tasks, such as learning and reasoning [81], [82]. WM has been associated with a variety of other cognitive abilities, including intelligence [83]–[85], multi-tasking abilities [86]–[89], language comprehension [90]–[92], and attention [93]–[95], which highlights its role as a central aspect of human cognition. The term *Working Memory* was introduced by Miller, Galanter, and Pribram [96] in 1960, and since then, a plethora of studies have been published about the topic. While WM is commonly understood as a system that allows for the simultaneous storage and manipulation of information, there are still some inconsistencies regarding a clear definition of the construct, and also how to distinguish it from short-term storage [97]. Therefore, the current work will refer to a more general definition of WM which will be sufficient for the present purposes: “the temporarily heightened availability of information about a small number of recent events and thoughts” [98, p. 536].

That WM cannot contain an unlimited amount of information has been acknowledged for a long time now and has widely been researched under the term Working Memory Capacity (WMC) [99]. Back in 1956, Miller [99] postulated that we can hold about seven items or chunks of items in mind, which he famously referred to as the “magical number seven”. Alternative amounts of items that can be stored in immediate memory have later been proposed [e.g., 9], and other researchers have suggested a mental capacity limit not only based on the number of items or chunks but also with respect to a temporal aspect [100]. Baddeley and colleagues [100] for instance suggested a time-based articulatory rehearsal loop that supplements an item-based executive WM system. More recent theories propose that (visual) WMC is not fixed by the number of items or by a time limit, but rather represents a limited resource that can be flexibly shifted between all objects that are currently perceived [101]. Whether resources are allocated to a specific item is thought to be biased by selective attention [101] - a mechanism which is discussed in more detail in the next section.

2.2.2 Selective Attention and Working Memory

WM is closely intertwined with attention [93]–[95], [101]. Attention is fundamentally related to human cognition and might explain the wide range of interactions between WM and other cognitive functions as has for instance been suggested for intelligence [85] and language processing [102].

Recent evidence suggests that a key determinant of WMC may be the ability to only attend to relevant information and to filter out irrelevant distraction [103]–[106]. It is for instance commonly reported that individuals with higher WMC are more efficient in directing their attention to task-relevant information compared to individuals with low WMC, who are more likely to also attend to irrelevant material [107]–[111], or disengage slower from distraction [112]. This process is also known as selective attention, describing the "differential processing of simultaneous sources of information" [11, p. 44]. Selective attention is often referred to as a "spotlight" of attention [113], [114] that determines what is processed further, and is thus thought to operate as a "gatekeeper" for WM [93]: Allowing irrelevant information to enter would occupy invaluable space that limits efficient execution of currently relevant tasks. Vogel and colleagues [115] for instance argue that the available storage in low-capacity individuals is more occupied by irrelevant information, even though they may be able to store more information than high-capacity individuals. Their conclusions were based on a study in which they recorded storage-relevant event-related potentials (ERPs) of participants performing a visual WM task that required memorizing only a few relevant items within an array. For high-capacity individuals, they found that ERP amplitudes in conditions with two target items and two distractor items were smaller than in conditions with four target items alone, but similar to conditions with two target items alone, suggesting that these individuals processed only the targets and not the distractors. By contrast, for low-capacity individuals, ERP amplitudes in conditions with two targets and two distractors were larger than in conditions with two target items alone, but similar to conditions with four target items - suggesting the aforementioned larger occupation of mental storage with unnecessary information in these individuals. Similar conclusions were drawn by Conway et al. [108] who investigated the relationship between WMC and the *cocktail party phenomenon*, which describes situations in which attention is captured by a salient stimulus, such as one's own name, in an otherwise noisy environment. They found that individuals who detected their own name in an unattended message had lower WMC than those who did not, again suggesting that low-capacity individuals have more difficulty filtering out unnecessary information.

2.2.2.1 Attentional Selection at Different Stages of Processing

The link between WMC and selective attention appears to be not only present when information is encoded, but also during subsequent processing and retrieval. Awh, Vogel, and Oh [93] for instance suggest that attention can shift internally towards one object representation in WM which limits the processing of another item stored in WM. In a similar vein, other studies have concluded that selective attention operates both at early perceptual stages as well as at later stages as a control mechanism to handle distractor interference [116], [117].

For instance, Vogel, Woodman, and Luck [117] conducted a study in which they manipulated perceptual load (early stage) and memory load (postperceptual stage) and found that only when the cognitive system is overloaded, attention is operating to select relevant information and filter out distraction. Similarly, Allen and colleagues [118] investigated how visual WM is influenced by perceptual distraction and by executive load induced by a demanding cognitive task. Across seven experiments with different kinds of objects to remember, varying types and numbers of distractors, and varying task demands, they found that both perceptual distractors as well as internal executive load limit WM performance. Gazzaley and Nobre [119] extend this perspective even further and argue that WM and selective attention share a top-down modulatory mechanism that operates throughout all stages of processing from the expectation of a stimulus to the retrieval of information.

2.2.3 Attentional Guidance and the Questions of What Makes a Distractor Distracting

In order to determine what factors can make an item distracting and thus impair information processing, it is important to understand how visual attention is guided through a currently observed scene. Generally, two types of mechanisms are assumed to contribute to attentional guidance: bottom-up and top-down processes [12], [120]–[122]. Top-down attentional guidance is a volitional process that relies on prior knowledge or current goals. For instance, searching for a specific item helps find that object by selectively attending to features that define this target item. Instead, bottom-up guidance represents an automatic process that solely depends on the visual properties of a stimulus. Some famous models of visual search incorporate both bottom-up as well as top-down mechanisms. For instance, the Feature-Integration Theory by Treisman and Gelade [123] suggests an early, preattentive stage during which basic visual features are quickly processed in a bottom-up fashion, and a later stage of focused attention, where individual features are combined into a coherent object. This later stage of object identification can be influenced by previous knowledge, where the perceived object is matched with a familiar object representation in a top-down manner. An alternative account was proposed by Wolfe [124], known by the term Guided Search. Wolfe argues that top-down factors can also influence the preattentive process, whereby visual attention is guided (see also Wolfe's most recent version of the model [125]).

2.2.3.1 Visual variables

Most studies on attentional guidance utilise primitive visual features such as colour, shape, or orientation to investigate how attention is directed within the visual field and how this affects information processing. A useful categorisation comes from Jacques Bertin, a graphic designer and cartographer, whose main area of interest lay in uncovering how information can be effectively conveyed by visual means. In his *Image Theory* [126], which is often cited in the area of data visualisation and cartography, he organised perceptual features into so-called *visual* or *retinal variables.* These variables are size, value, texture, colour, orientation, and shape. In design literature, value is often also referred to as "lightness" [127] or "brightness" [128] and describes the amount of light reflected by the stimulus [127]. These variables have different levels of organisation, which specify whether they are able to represent nominal, ordered, or interval-scaled data. For instance, different colours or shapes are usually easily perceived as representing different but equal groups, whereas different brightness values or sizes are usually perceived to also indicate some form of rank or importance. Size instead allows us to extract information about ratios between data values. According to Bertin, the visual variables are differently well suited to indicate the relationship of elements to each other based on how humans perceive these variables in a pre-attentive or automatic manner, similar to what Treisman and Gelade suggest in their Feature-Integration Theory [123]. Although Bertin did not base his theory on empirical evidence, it is in large part supported by vision research [128]. Apart from Treisman and Gelade's Feature-Integration Theory [123], who propose similar mechanisms of automatic bottom-up processing of primitive visual features, and a slower focused attention state in which features are combined into coherent objects, many theories described in the following sections use a similar categorisation of basic visual features and their relation to information processing.

2.2.3.2 Bottom-up Attentional Guidance

Bottom-up attentional guidance is often associated with an object's saliency. Saliency can be defined as the "capability of important or arousing stimuli to interrupt the current cognitive focus and [...] elicit an attentional or behavioural switch" [129, p. 977], which highlights the consequences for information processing arising from the characteristics of a stimulus. Constant and Liesefeld [130] characterise an object as being salient when at least one of its features stands out against other objects in a scene. In fact, an abundance of visual search studies reports that it is easier to detect a target item when it can be differentiated by any feature from surrounding elements compared to when targets and distractors share features [123], [124], [131]. In order to objectively determine the saliency of visual elements, computational models are often applied. A popular model that was presented by Itti et al. [132] extracts low-level visual features such as colour, intensity, and orientation in order to define the most relevant regions of a scene, represented by a so-called *saliency map*. This saliency map can then be used to determine where attention will be directed next, mirroring how the human visual system would prioritise and attend to certain features.

It has been suggested that some features such as colour are more capable of guiding attention in perceptual selection than others [133], [134]. Fan and colleagues [133] for instance found attentional guidance effects when colour or a conjunction of colour and shape of the visual WM representation matched distractors and not when only shape matched. They concluded that the more salient feature *colour* actively guided attention. While the guidance effects in this study as well as in their previous study [e.g., 135] were only found for reaction times, there is also evidence of guidance effects on WM accuracy. For instance, Fine and Minnery [136] report a positive correlation between an item's saliency and participants' ability to memorise its spatial location. Similarly, Constant and Liesefeld [130] systematically manipulated stimulus saliency and found that recall performance was best for the most salient stimuli, indicating stronger guidance effects for highly salient objects as compared to less salient items. Such guidance effects can be helpful when the salient item is relevant to the current task but can be sub-optimal when the salient object is task-unrelated, i.e., a distractor. In such a case, memory for actual targets that are less salient compared to other items in a scene can be disrupted. Melcher and Piazza [137] for instance found that memory performance was poorer for items that had a low relative saliency compared to surrounding distractors in terms of visual contrast as opposed to when target items had an increased relative saliency to distractors.

2.2.3.3 Top-down Attentional Guidance

However, it has been argued that there are cases in which salient stimuli do not necessarily capture attention. Instead, attentional guidance is also thought to depend on the search strategy employed by the observer [138]. This is where top-down processes come into play. The Contingent Capture Theory (CCT) for instance postulates that attentional capture depends on a match between a stimulus and top-down attentional control settings [139]–[142]. In other words, if a task-irrelevant item has matching features with the target item that is searched for, attention is drawn towards the task-irrelevant item and away from the target, resulting in reduced search efficiency. It is assumed that suppression or enhancement mechanisms are in place that guide attention in a top-down fashion, with the goal of eliminating disruption by distractors.

One such mechanism is Dimension-Weighting (DW), according to which the visual system up-weighs or down-weighs certain feature dimensions, based on previous experience or current goals [143]–[145]. Down-weighing feature dimensions by which a task-irrelevant object is characterised can eliminate distractor interference. If targets and distractors however share featural characteristics, DW becomes inefficient and distractors can interfere with information processing [144]. Prioritizing certain feature dimensions or values is a central aspect of the Feature-Based Attention (FBA) theory, which describes the enhancement of certain image characteristics that helps find an object with that particular characteristic within the visual field [143], [146]–[148]. Apart from guiding attention towards prioritised features in the visual field, FBA has also been shown to operate within visual WM by enhancing specific features of the object representation held in memory [149], [150]. FBA can improve recognition for certain features, as is reported in a study by Cutting, Cairns, and Kuhn [151], who conducted a set of experiments in which participants either played a colour-matching or an image-matching version of the classic game *Two Dots*. They found that recognition for images was higher in the image-matching condition since the images were task-relevant here, as opposed to the colour-matching condition, where colour was the only relevant feature. This can have real-life implications in areas such as learning. Cutting and Iacovides [152] for instance found that promoting attentional focus on specific visual features related to the learning material improved recognition of said material in a video game setting, supporting the idea of drawing upon attentional mechanism to promote learning in educational games.

2.2.3.4 Target-Distractor Similarity

To disentangle purely stimulus-driven (bottom-up) processes from goal-driven (top-down) mechanisms, Van Zoest and Donk [153] manipulated not only the saliency of distractors, but also the similarity between targets and distractors. They presented two sets of displays to participants that contained either a vertical target line or a tilted distractor line, surrounded by a series of tilted non-target lines. Participants had to indicate whether the target was present or not. The distractor line varied in orientation difference from the vertical target line as well as from the tilted non-target lines, so that it was either salient in relation to the surrounding elements or not, and either similar to the target or not. Results showed that saliency and target-distractor similarity independently affected search performance, with higher performance in cases where the distractors were not salient but also in cases where the distractors were dissimilar from the target. In a similar vein, Barras and Kerzel [154] found that in cases where the similarity between targets and surrounding non-targets was low, a salient distractor could be ignored, but when the similarity between targets and non-targets was high, a salient distractor captured attention, leading to disruptions in visual search.

The similarity between targets and distractors has long been regarded as a factor that influences search efficiency [13], [155]–[157], yet there is also evidence that a high featural overlap between a to-be-remembered stimulus and a distractor distorts WM performance, and this not only during the encoding of material but also during memory retention. For instance, participants' memory for faces was found to be lower when the target face was followed by another image of a face as compared to images of scenes [158], [159] or shoes [160]. Memorizing low-level perceptual features such as spatial frequency has also been shown to be impaired by distractors that differ in spatial frequency but not in orientation [161]–[163]. Similarly, Nicholls et al. [164] found that distractors that differed in colour and shape from previously displayed target items eliminated the memory debilitating effect that was found for distractors that were identical in colour and shape to the target items. Similar results were obtained by Nemes [165], with memory for colours only being impaired by a masking stimulus with a hue that fell within a narrow range of the reference stimulus' colour space and not if the hue of the masking stimulus differed to a larger extent from the reference stimulus.

2.2.4 Summary

To summarise, both bottom-up processes like saliency, as well as top-down processes like goal-driven attention, appear to influence whether a stimulus is distracting and thus affect visual search and subsequent information processing. However, research is lacking that directly and systematically compares visual characteristics of task-irrelevant and task-relevant stimuli, and investigates the conditions under which task-irrelevant items may be distracting and affect information processing. Pinpointing specific visual features that make a stimulus distracting has important implications for the design of video games, which often feature an abundance of visual elements and effects, and in addition, often place substantial cognitive demand on players. A more informed choice of the visual features of task-irrelevant game elements may result in reduced cognitive load, and consequently, less frustration that may occur as a consequence of distraction from an in-game goal. Studies 1 - 3 therefore attempt to work towards closing this research gap by comparing stimuli with different visual characteristics such as shape, contrast, colour, and texture in relation to target items, and how they affect memory for these targets. A detailed description of the conducted experiments can be found in chapter 3.

2.3 The Interplay between Cognition and Gaming

Any meaningful interaction with a system requires the coordination of a variety of skills. Even for a seemingly mundane task such as reading, we need to pay attention to the text, perceive and recognise patterns that constitute syllables or words, and make meaning of the contents. Video games are no exception. Instead, since they usually allow players to exert a high level of control, they are thought to also put considerable demand on the player, not only in the cognitive domain, but also with regard to emotional, physical, and social aspects, all of which shape the PX [166], [167]. The following sections focus on cognitive demand, and discuss what consequences increased cognitive demand may have on performance, difficulty, and PX.

2.3.1 Cognitive Load in Video Games

Compared to more passive forms of media, such as television, video games are highly interactive technologies. Consequently, they demand considerable resources from the player [166]. While some argue that this increased level of control on the player-side is a key reason for the entertainment value of video games [168], the heightened demand that comes along with it may also have adverse consequences on player experience [169], [170]. In their video game demand scale, Bowman, Wasserman, and Banks [166] identified cognitive demand as a key source of demand, which they describe as the extent to which the game engages the player's mental capacities or attentional resources. Since our mental capacities are limited [9], [78], too much cognitive demand may be overwhelming and frustrating for the player. However, Bowman et al. [166] found that cognitive demand was associated with autonomy, competence, and even enjoyment, providing support for the notion of challenge as a key element in video games [46], [58], [59] (see also Chapter 2.1.2.2). Yet, to avoid making universal claims, how PX is affected by the demands of a particular game likely depends on its unique characteristics. Today's landscape of video games is extremely versatile, ranging from very simple and minimalist games like *Mini Metro* to sophisticated 3D action or open-world games like *Red Dead Redemption 2*. Naturally, these games differ considerably in gameplay and thus also in the skills they demand from the player. While there are a few capabilities that are shared across games such as hand-eye coordination, other skills are thought to be more specific to certain types of games. Spence and Feng [171] list a variety of perceptual and cognitive skills they believe to be tapped by different video game genres. According to them, puzzle games place demands on mainly analytical skills, whereas action games are thought to require multiple aspects of attention, visuo-motor abilities, WM, spatial and emotional cognition, as well as visual detection of target elements among cluttered surroundings. For instance, FPS games, which belong to the action game genre, require rapid reactions from the player, such as quickly identifying hazards that appear in visually complex game worlds, choosing appropriate weapons and tools, discriminating enemies from allies under difficult and dynamic viewing conditions, and coordinating their movements accordingly [171].

The claim that video games place this varied cognitive demand on players originates from repeated reports of enhanced cognitive abilities in players who regularly play such games. One of the most influential works in this area comes from Green and Bavelier [172], who demonstrated that playing action video games can improve a range of visual skills, including attentional capacity and sustained attention over rapid presentation of several items. Other researchers have extended their work by establishing links between video gaming and improvements in visual WM [173], [174], executive control mechanisms such as task switching [175]–[178], spatial cognition [179], [180], perceptual abilities [181]–[183], decision making [184], and distractor resistance abilities [185]–[187]. Recently, newly evolved game genres that are more specific than the rather broadly defined "action" genre have been proposed to place similar cognitive demands on players, as evidenced by superior cognitive abilities in players with expertise in playing such games. These involve for example action role-playing games (RPGs) [188], strategy games [189], and multiplayer online battle arena (commonly known as MOBA) games [190].

2.3.2 Visual Complexity and Performance

The reason why particularly games with "action" components pose such a varied cognitive demand on players may be the highly complex or even cluttered environments these games often feature, requiring players to focus closely on the current task and ignore the many irrelevant elements and visual effects that surround them over prolonged periods of time. While this may lead to improvements in cognitive functions, the immediate experience for players may suffer, particularly when they cannot keep up with the sustained cognitive demand, leading to frequent failure and hindered progress within the game. In line with evidence from cognitive psychology reporting impaired cognitive abilities under situations of high target-distractor similarity or the presence of salient distractors (see Section 2.2.3), studies in the field of HCI have demonstrated that display clutter reduces performance in tasks requiring abilities such as visual search [191], attention [192], [193], or memory [194]. Moacdieh and Sarter [192], who provide an overview of the concept of display clutter, and who define it as "the presence of performance and attentional costs that results from the interaction between high data density, poor display organisation, and abundance of irrelevant information" (p. 65), argue that the similarity between target elements and distractors and a low target saliency can aggravate the effects of clutter.

Empirical studies have provided evidence for this stance in the context of video games: For instance, Jie and Clark [14] asked participants players to play a shooter game with two difficulty modes. In the easy mode, they positioned task-relevant items (enemies) in positions low in background complexity, and in the hard mode, enemies appeared superimposed on a cluttered background. Results indicated poorer performance in the latter condition, suggesting that a reduced distinctiveness between target and surroundings can increase game difficulty. Very similarly, Caroux and colleagues [15], [16] were able to modulate difficulty in a simple shooter game by varying both background complexity and the visual features of targets and distractors. They found that the game was easier when background clutter was low, and also when targets were distinguishable in both colour and size from distractors as compared to when distractors shared one of those visual features with the target.

In order to improve usability, target elements in video games are therefore often highlighted by using salient colours to make them distinct from their surroundings [6], [195], [196]. Likewise, efforts to improve accessibility, especially with regard to visual impairments, often include the manipulation of visual features such as enhancing contrast between elements or increasing the size of relevant items to facilitate distinguishing relevant from irrelevant elements [197].

2.3.3 Visual Complexity and Player Experience

Although visual complexity can impair performance, failure is a central aspect of many video games [75]. From a game design perspective, it is thus less important to solely focus on how visual characteristics impact performance, but rather on what effects the visual setup of a game may have on PX. Many of today's most popular video games such as *Overwatch 2* or *Apex Legends* feature highly detailed game worlds and sophisticated visual effects and animations, offering ample opportunity for a high cognitive load and distraction. While video game graphics can be a powerful way to increase its commercial value, the effects on gameplay and consequently PX have not been researched extensively.

A few studies have looked at the overall visual style or complexity of a game and PX. For instance, Gerling et al. [198] have demonstrated that highly stylised graphics can lead to a more positive impression of the game, including increased immersion and a higher positive affect. However, further evidence suggests that the graphical style in itself does not affect PX. Smeddinck, Gerling, and Tiemkeo [199] for example compared different levels of visual complexity ranging from an abstract style over simple and stylised 2D to detailed 3D graphics. They found that graphical detail did not influence enjoyment in older adults. Similarly, Cheng and Cairns [200] did not find that more realistic game graphics enhance immersion. Rather than the overall graphical style, a more specific design concept that has gained attention in both academia and industry is *juiciness*, which is widely considered an important precursor of game enjoyment. Juiciness is a game characteristic that emanates from the use of design elements that reinforce feedback or game events but serve otherwise no functional purpose regarding gameplay [26], [201]. Juicy game elements are not restricted to the visual modality, but may also include audio and haptic effects such as vibrations. The video game *Tetris Effect: Connected* is a good example to illustrate the concept (see Figure 2.1). While the principal gameplay and mechanics remain largely the same compared to its traditional counterpart, the re-imagined version features audio-synchronised particle effects surrounding the main play area. As such, these effects are not necessarily task-relevant but purely serve aesthetic purposes.

Figure 2.1: Screenshot of the video game Tetris Effect: Connected. Source: [202]

There is some evidence that juiciness can influence PX. For instance, Andersen and colleagues found increased engagement in games with rather than without animations [203]. Hicks et al. [4] report enhanced visual appeal, curiosity, and immersion in a juicy game compared to a version without additional particle effects and animations. Juul [7] however found no significant effects of juiciness on either ease of use, performance, or game quality, indicating that juicy game elements do not automatically make the game better. Instead, the level of juiciness appears to be important: Kao [3] reports negative influences of both no juiciness at all or extreme levels of juiciness on PX and engagement (as measured by playtime). This is also supported by anecdotal evidence from social media platforms like Reddit or YouTube, where players frequently discuss and complain about the visual complexity or clutter that is present in many modern video games and which keeps them from navigating the game world with ease and distinguishing relevant from irrelevant information, leaving them overwhelmed or even frustrated [e.g., 28], [29].

2.3.4 Summary

To summarise, although the addition of task-irrelevant visual design elements can improve PX, under some circumstances, such as in-game scenarios with extreme levels of visual complexity, not only performance but also PX may suffer. To date, there has not been much research about the effects that visual characteristics can have on game difficulty and

PX aside from research surrounding the concept of juiciness, which however focuses more on visually embellished feedback rather than on the mere presence of potentially distracting elements. The current work thus concentrates specifically on how the visual setup of task-irrelevant game elements in relation to target elements can alter game difficulty, performance, and PX.

2.4 Chapter Summary

This literature review discussed theories and evidence surrounding central aspects of PX, including enjoyment and challenge, as well as research from cognitive psychology encompassing fundamental facets of human information processing, including attention and WM. Since video games are highly interactive forms of media and rely on a number of cognitive abilities, integrating insights from cognitive psychology can help understand the appeal of video games and provide appropriate tools to design better and more enjoyable games. Especially research surrounding mechanisms of attention and WM may prove fruitful in this endeavour since video games often require us to concentrate on a specific task or goal, keep goal-relevant information in mind, and ignore any distracting material. Not being able to focus may result in negative gaming experiences, which game designers usually strive to avoid. Distraction is more likely to happen in visually complex environments, which is particularly common in modern video games that make use of the latest technologies in computer graphics and often exhibit highly detailed or even photo-realistic game worlds.

Whilst existing research indicates that increased visual complexity in video games can lead to diminished performance, effects have been mostly shown for tasks that require searching for a target. Yet, visual characteristics can also affect WM, which is a cognitive capability that is also required in many video games. Effects of visual characteristics of task-relevant and -irrelevant elements on WM performance in the context of video games have not yet been investigated systematically. In addition, although in-game performance hints at a game's difficulty, game designers are likely less interested in maximising or controlling performance, but rather in creating games that engage players. The relationship between the visual design of game elements and performance is therefore of limited use for game designers when disregarding the experiential consequences it has on players. Yet, the effects of difficulty induced by visual means on PX have largely been neglected.

The current work therefore attempts to uncover the influence of visual characteristics of task-relevant and -irrelevant game elements on WM performance and further explores the effects of visually induced difficulty and performance on various aspects of PX.

Chapter 3

Studies 1 - 3: What Makes a Distractor Distracting?

3.1 Motivation and Research Questions

As described in the literature review, video games often rely on several cognitive functions including attention and Working Memory (WM) [171]. In addition, they often exhibit a great visual diversity, which increases the risk of distraction by goal-unrelated elements, which can affect both attentional abilities such as searching for specific items [191], as well as memorizing and keeping in mind relevant information [194]. A better understanding of the specific visual features that make goal-irrelevant elements more or less distracting can inform the visual design of game worlds, characters, and visual effects, allowing game designers to keep in check unwanted cognitive demand, which may lead to negative Player Experience (PX).

In order to examine visual features and their potential to distract, applying a cognitive-psychological approach that utilises a controlled experimental setup can be more informative than using fully-fledged video games that may exhibit many confounds due to their complexity, not only visually, but also with respect to their mechanics and goals. The current set of experiments therefore uses a traditional WM task to examine visual features in isolation while relying on cognitive-psychological theories of attention and WM. Cognitive psychology generally suggests that our brains employ a selective approach as to what information to process [11], which means that task-irrelevant information is usually disregarded. Yet, under certain circumstances, attention can be diverted by task-irrelevant stimuli. This may be particularly the case when these task-unrelated stimuli are very similar to a target stimulus [153], [164], [165], [204], or when they pop out from their surroundings [123], [124], [131]. Several theories have been suggested that attempt to explain these effects, including top-down approaches such as Dimension-Weighting (DW; [143]–[145]) or Feature-Based Attention (FBA; [143], [146]–[148]; see also Chapter 2.2.3.3), which assume the enhancement or prioritisation of task-relevant stimulus characteristics on the part of the observer, facilitating the guidance of attention towards the object that is searched for when it is sufficiently distinct from other objects in a scene. In addition, bottom-up approaches propose that the features of the stimulus itself, particularly when they are very salient, have the capability to capture attention ([129]; see also Chapter 2.2.3.2).

While several mechanisms have been suggested for the guidance of attention, it is not very clear which characteristics of task-irrelevant elements influence information processing the most. Researching how basic visual characteristics affect attention and WM can not only further our understanding of fundamental cognitive processes surrounding distractor filtering and WM but also provide a better idea of the circumstances under which visual elements may impact cognition in the context of video games. In a series of three experiments, I therefore examined how task-unrelated stimuli (i.e., distractors) that differ from goal-relevant stimuli based on texture, colour, brightness, or shape affect recall accuracy for these target items. Since distractor filtering processes may differ depending on whether distractors are presented during memory encoding or in a delay period [205], I further investigated how the different types of distractors affect WM recall when presented either simultaneously with the target items, or after the target items have disappeared but before recall.

This set of experiments contributes to answering RQ 1: *Which visual characteristics make items distracting?* More specific questions that are also addressed within this series of experiments and which aim at giving a more comprehensive idea of how potentially distracting stimuli are processed are:

(a) How do different types of distractors affect WM at different stages of processing?

(b) How does distractor filtering at different stages of processing as well as filtering out different types of distractors contribute to overall memory performance?

3.2 Methods

The three studies described in this chapter were approved by the Research Ethics Committee of the Department of Psychology at the University of York. Since the experimental procedure and analyses were identical across experiments, the present section entails the methodology for all three experiments. Where the experiments differ is solely in the types of distractor stimuli that were used: Each individual experiment looked at a particular set of stimulus types, one of which was identical across experiments (Type 1 distractors) to ensure comparability, and the other one acting as a comparison stimulus to Type 1 distractors which was specific to each experiment (Type 2 distractors). The effect of these stimuli on memorizing a target array of black circles, which was also identical across experiments, was then examined.

The utilised stimuli consisted of a set of primitive visual variables that were chosen based on Jacques Bertin's *Image Theory* [126], which includes size, value, texture, colour, orientation, and shape. Since value is often also referred to as "lightness" [127] or "brightness" [128] in design literature, I will adopt the term "brightness" in the following sections as a more descriptive term compared to "value". While *Image Theory* originated from Bertin's experience as a graphic designer and cartographer, the theory can be applied to any kind of data visualisation, including in video games, where visual variables may be used to convey information about threats, resources, or target locations to players. Drawing upon Bertin's idea of different perceptual consequences based on different visual variables, a set of variables was chosen for the current experiments in order to identify which characteristics might render task-irrelevant stimuli distracting in relation to target stimuli. The variables that were used for target and distractor stimuli were brightness, texture, colour, and shape.

The distractor stimuli that were identical across experiments (Type 1 distractors) differed only with regard to brightness from the target stimuli. For Type 2 distractors, Study 1 further examined distractor stimuli that differed in shape, brightness and texture from targets, Study 2 further examined distractor stimuli that differed in shape and brightness from targets, and Study 3 further investigated distractors that only differed in colour from targets. Note that "colour" is a multidimensional construct that includes brightness, hue, and saturation. Thus, the distractors used in Study 3 technically differed in all three of those values from the target stimuli. Figure 3.1 displays the stimuli used in the three experiments.

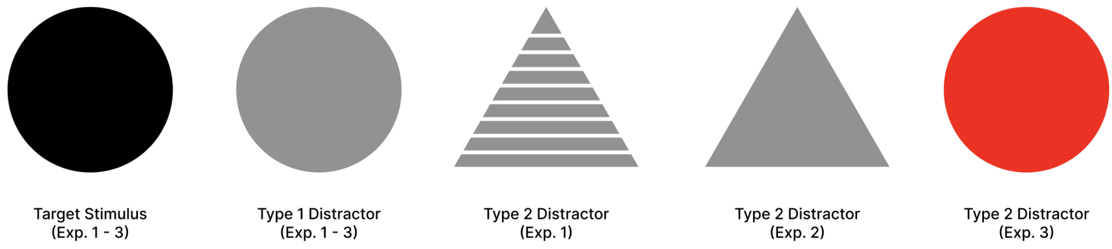

Figure 3.1: The stimulus types used in the three studies. In all three experiments, target stimuli were black circles and Type 1 distractors were grey circles. Type 2 distractors were striped triangles in Study 1, grey triangles in Study 2, and red circles in Study 3.

The distractor stimulus set up across experiments was therefore as follows:

1. Study 1: brightness distractors (Type 1) vs. brightness+shape+texture distractors (Type 2)
2. Study 2: brightness distractors (Type 1) vs. brightness+shape distractors (Type 2)
3. Study 3: brightness distractors (Type 1) vs. colour (brightness+hue+saturation) distractors (Type 2)

Combining the results of all three studies allows us to make conclusions about specific visual variables and how they affect information processing in relation to other visual variables. For instance, if the brightness+shape distractors affect information processing more than the brightness distractors, it can be assumed that the visual variable shape adds distraction costs. Analogously, if the brightness+shape+texture distractors affect memory for target stimuli more than the brightness+shape distractors, texture differences presumably hold additional distracting qualities.

3.2.1 Participants

Participants were excluded according to the exclusion criteria specified in the data analysis section. The final sample considered for analysis for Study 1 consisted of 29 participants between 18 – 20 years (M = 19.50, SD = 0.59). For Study 2, data from 51 participants between 18 – 20 years (M = 19.49, SD = 0.63) was considered for analysis, and for Study 3, the final sample consisted of 49 participants between 18 – 22 years (M = 19.6, SD =

0.79). All participants gave informed consent ahead of the experiment and were debriefed afterwards. Participants received course credit for their participation.

3.2.2 Experimental Design and Task

The studies were set up on the online experiment platform Gorilla. The design and procedure in all three experiments were identical. The chosen task was adapted from McNab and Dolan [205], who were able to demonstrate unique contributions of distractor filtering on WM at the time of encoding and during memory maintenance. Utilizing that same task thus allows us to reliably dissociate the influences of different types of distractors at these separate stages of processing and enhance the validity of the obtained results in the context of previous research. Participants were asked to remember four black circles (target array) presented on a circular grid with 16 possible positions. In half of the trials, distractors were presented either simultaneously with the target array (Encoding Distraction, ED), or in a delay period (Delay Distraction, DD). There were two distractor conditions: one condition with Type 1 distractors which was identical across studies and a comparison condition with distractors that varied across studies (Type 2 distractors).

Each experiment consisted of five within-subject conditions: a No Distraction (ND) condition, an ED condition with Type 1 stimuli (grey circles), a DD condition with Type 1 stimuli, an ED condition with Type 2 stimuli (striped triangles (Study 1), grey triangles (Study 2), red circles (Study 3)), and a DD condition with Type 2 stimuli. In the ND condition, participants were asked to memorise the locations of the target array, presented for 1s. After a delay period of 3s, during which the empty grid was displayed, a response array appeared, requiring participants to indicate whether the array was the same or different from the target array. In the ED condition, four irrelevant distractors were presented with the target array, which participants were instructed to ignore. At least one but no more than two distractors always appeared next to a target position. The remainder of the trial was identical to the ND condition. In the DD condition, after a delay period of 1s after the target array has disappeared, four distractors were presented for 1s, which participants were asked to ignore. After a further delay period of 1s, the response array appeared, and participants were again asked to indicate whether it was the same or different from the target array. In all conditions, the response probe was either the same as the memory probe or differed slightly from the memory probe (one circle in a different position). Participants were asked to indicate by key press whether the response

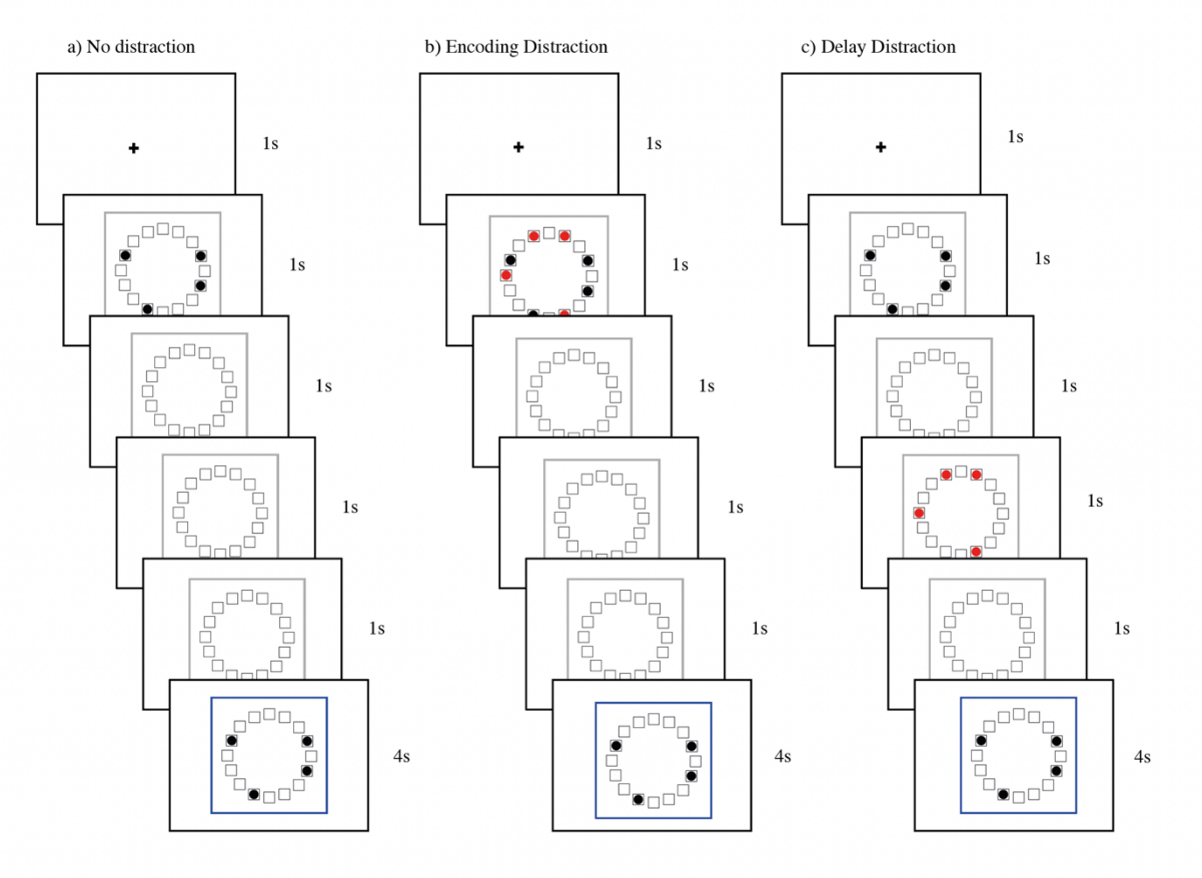

Figure 3.2: Procedure in the three experimental conditions.

probe was the same or different from the memory probe. Half of the trials required a "same" response, whereas the other half required a "different" response. Performance in trials in which no distractors were presented was used as an estimate for Working Memory Capacity (WMC). Each participant completed 160 trials plus 12 practice trials. To rule out stimulus position effects, stimuli were counterbalanced across two groups, such that each set of target stimuli was presented together with distractors (i.e., in ED trials) in one group and in isolation (i.e., in DD trials) in the other group. The experiment was further separated into two blocks, with 80 trials in each block and a break in between blocks. The total duration of the experiment was around 25 minutes. Figure 3.2 illustrates the experimental procedure.

3.3 Study 1

3.3.1 Data Analysis

To obtain an estimate for WMC, the K-value was calculated, a measure of how much information can be stored in WM [9], [115]. The measure was calculated with the formula $K = S * (H - F)$, where S is the size of the array, i.e., the number of black circles to remember, H is the hit rate, i.e., trials in which participants correctly identified a response array as being the same as the memory array, and F is the false alarm rate, i.e., trials in which participants erroneously indicated a response array to be the same as the memory array. For each participant, five K-values were calculated: one for ND trials, one for ED trials with Type 1 distractors (grey circles), one for ED trials with Type 2 distractors (striped triangles), one for DD trials with Type 1 distractors (grey circles), and one for DD trials with Type 2 distractors (striped triangles). Participants with K-values lower than 0.5 in any condition were excluded from the analysis, as this would indicate that less than half an item was correctly remembered, which could potentially hint at inattentiveness during the experiment. These participants' K-values might therefore not accurately represent their actual WMC.

To investigate the effects of different distractor types on WMC as well as any interactions between distractor types and processing period, a one-way repeated measures ANOVA was calculated for stimulus type (Type 1 vs. Type 2 vs. ND) in order to uncover any performance differences between the different distractor types and in relation to trials without any distractors. Moreover, a two-way repeated measures ANOVA with the factors type and condition (ED, DD) was calculated to test the interaction effect with the presentation period, which was only applicable to distractor trials and therefore did not include ND trials. Follow-up comparisons were calculated where appropriate and corrected using the Bonferroni-Holm method. To further determine the unique influences of each distractor type and processing period on WMC, a hierarchical regression analysis was conducted. Performance in the ND condition was hereby used as the dependent variable. In the first regression, performance in both ED conditions was used to predict ND performance (Model 1: $\text{ND} = \beta_0 + \beta_1 \text{ ED\_Type1} + \beta_2 \text{ ED\_Type2}$), and then performance in both DD conditions was added to the model (Model 2: $\text{ND} = \beta_0 + \beta_1 \text{ ED\_Type1} + \beta_2 \text{ ED\_Type2} + \beta_3 \text{ DD\_Type1} + \beta_4 \text{ DD\_Type2}$). R^2 change between the two models was used to determine the unique variability in WMC that could be explained by filtering out distractors at delay. The second regression predicted ND performance first with performance in both Type 1 (grey circles) distractor conditions (Model 1: ND = β_0 + β_1 ED_Type1 + β_2 DD_Type1), and then performance in both Type 2 distractor conditions (striped triangles) was added to the model (Model 2: ND = β_0 + β_1 ED_Type1 + β_2 DD_Type1 + β_3 ED_Type2 + β_4 DD_Type2). R^2 change between the two models was used to determine the unique variability in WMC that could be explained by filtering out striped triangle (Type 2) distractors. In addition, partial correlations between the different conditions were calculated to further characterise the associations between ED and DD filtering as well as between the ability to filter out striped triangles vs. the ability to filter out grey circles. The respective irrelevant conditions were hereby used as control variables. Data was prepared for analysis using Microsoft Excel 365 [206]. All statistical analyses were performed using IBM SPSS Statistics [207].

3.3.2 Results

A visual representation of the obtained K-values per condition and stimulus type is displayed in Figure 3.3.

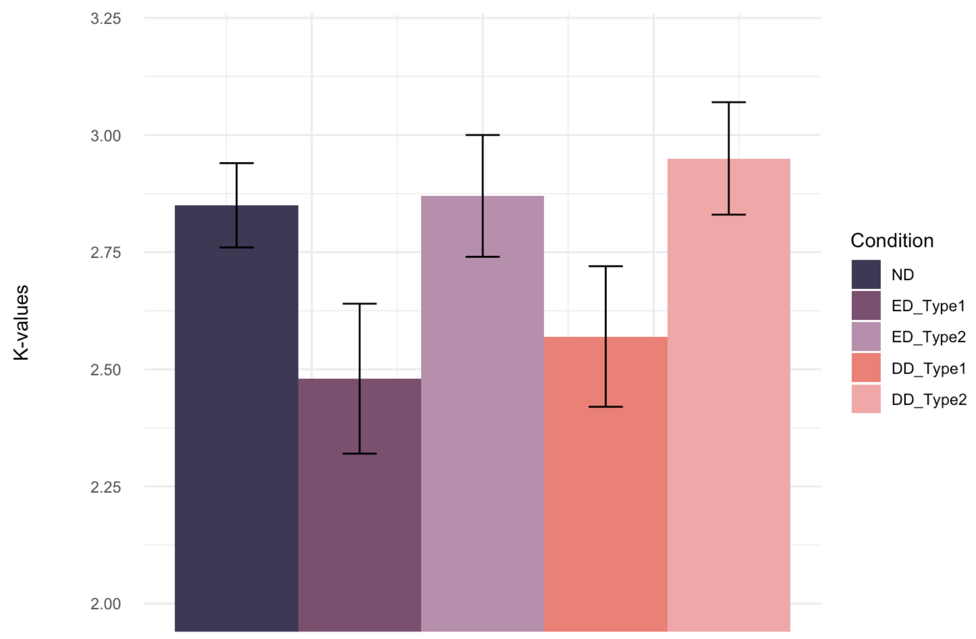

Figure 3.3: Mean K-values per condition and stimulus type. Type 1 distractors are grey circles, Type 2 distractors are striped triangles. Error bars represent +/- 1 standard error.

An overview of the results of the calculated ANOVAs and associated F-tests can be found in Table 3.1. A two-factor repeated measures ANOVA with the factors condition

(ED, DD) and type (Type 1: grey circles, Type 2: striped triangles) revealed a significant main effect for type. No other main effects or interactions were observed. A separate one-factorial ANOVA for the ED condition with the factor type (Type 1, Type 2, no distractors (ND)) revealed a significant main effect. Follow-up pairwise comparisons revealed higher K-values for ND than for Type 1 (p = 0.027), and higher K-values for Type 2 than for Type 1 (p = 0.020). There were no significant differences between Type 2 and ND performance. A further ANOVA was calculated with the factor type (Type 1, Type 2, ND) for the DD condition. A main effect was again found, with pairwise comparisons revealing higher K-values for Type 2 than for Type 1 (p = 0.048). No significant differences were found between performance for ND and either distractor type.

Effect	F-value (df)	p-value	Effect size η_p^2
Condition	0.56 (1, 28)	0.459	0.02
Type	18.04 (1, 28)	0.001**	0.39
Condition x Type	0.00 (1, 28)	$>$ 0.999	0.00
ED Type	5.87 (2, 56)	0.005**	0.17
DD Type	4.61 (2, 56)	0.014*	0.14

Table 3.1: F-test results for each of the calculated ANOVAs. *** $p < .001$; ** $p < .01$; * $p < .05$

To investigate the unique contributions of ED and DD filtering, a hierarchical regression was calculated with both ED conditions predicting performance in ND trials (Model 1), and with all ED and DD conditions predicting performance in ND trials (Model 2). Model 1 was significant (p = 0.001; adj. R^2 = 0.36), i.e., ED performance predicted ND performance, but the addition of DD conditions to the model did not significantly explain more variance. Detailed results as well as standardised β-coefficients can be found in Table 3.2.

To investigate the unique contributions of filtering specific distractor types, a further hierarchical regression was calculated with both Type 1 conditions predicting performance in ND trials (Model 1), and with all Type 1 and Type 2 conditions predicting performance in ND trials (Model 2). Model 1 was significant (p = 0.001, adj. R^2 = 0.38), i.e., performance for Type 1 conditions predicted ND performance, but the addition of Type 2 conditions to the model did not significantly explain more variance. Detailed results as well as standardised β-coefficients can be found in Table 3.3.

Model	Predictor	R^2 change	Standardised β	p-value
1	ED_Type1	0.40**	0.39	0.037
	ED_Type2		0.33	0.076
2	ED_Type1	0.08	0.27	0.167
	ED_Type2		0.23	0.231
	DD_Type1		0.16	0.343
	DD_Type2		0.25	0.178

Table 3.2: Results of the hierarchical regression comparing ED and DD conditions. Model 1 predicts performance in the ND condition from both ED conditions and Model 2 predicts performance in the ND condition from both ED and both DD conditions. Type 1 distractors are grey circles, Type 2 distractors are striped triangles. **** $p < .001$; ** $p < .01$; * $p < .05$*

Model	Predictor	R^2 change	Standardised β	p-value
1	ED_Type1	0.40**	0.48	0.006
	DD_Type1		0.29	0.079
2	ED_Type1	0.08	0.27	0.167
	DD_Type1		0.16	0.343
	ED_Type2		0.23	0.231
	DD_Type2		0.25	0.178

Table 3.3: Results of the hierarchical regression comparing distractor Type 1 and distractor Type 2. Model 1 predicts performance in the ND condition from both Type 1 distraction conditions (grey circles), and Model 2 predicts performance in the ND condition from both Type 1 distraction conditions and both Type 2 distraction conditions (striped triangles). **** $p < .001$; ** $p < .01$; * $p < .05$*

Correlation analyses revealed a significant correlation between ED_Type1 and ED_Type2, when controlling for DD_Type1 and DD_Type2 ($r = 0.40$, $p = 0.040$). No further significant associations were found.

3.4 Study 2

3.4.1 Data Analysis

As in Study 1, five K-values were calculated for each participant to obtain an estimate for WMC: one for ND trials, one for ED trials with Type 1 distractors (grey circles), one for ED trials with Type 2 distractors (grey triangles), one for DD trials with Type 1 distractors (grey circles), and one for DD trials with Type 2 distractors (grey triangles). Again, participants with K-values lower than 0.5 in any condition were excluded from the analysis to avoid potential confounds due to inattentiveness during the experiment.

A one-way repeated measures ANOVA was calculated for stimulus type (Type 1 vs. Type 2 vs. ND) to uncover performance differences between the different distractor types and between trials with and without distractors. A two-way repeated measures ANOVA with the factors type and condition (ED, DD) was conducted to examine the interaction effect with the presentation period. The ND condition was not relevant for this analysis as it did not contain distractors and therefore no factor 'presentation period'. Follow-up comparisons were calculated where appropriate and corrected using the Bonferroni-Holm method. A hierarchical regression analysis was performed to assess the unique influences of each distractor type and processing period on WMC. Performance in the ND condition was used as the dependent variable. In the first regression, performance in both ED conditions was used to predict ND performance (Model 1: ND = β_0 + β_1 ED_Type1 + β_2 ED_Type2). At Stage 2, performance in both DD conditions was added to the model (Model 2: ND = β_0 + β_1 ED_Type1 + β_2 ED_Type2 + β_3 DD_Type1 + β_4 DD_Type2). R^2 change between the two models served as an indicator to determine the unique variability in WMC that could be explained by filtering out distractors during memory maintenance periods. The second regression predicted ND performance with performance in both Type 1 (grey circles) distractor conditions at Stage 1 (Model 1: ND = β_0 + β_1 ED_Type1 + β_2 DD_Type1), and performance in both Type 2 distractor conditions (grey triangles) at Stage 2 (Model 2: ND = β_0 + β_1 ED_Type1 + β_2 DD_Type1 + β_3 ED_Type2 + β_4 DD_Type2). R^2 change between the two models again served as an indicator to determine the unique variability in WMC that could be explained by filtering out grey triangle (Type 2) distractors. Partial correlations between the different conditions were calculated to examine the relationship between ED and DD filtering and between the ability to filter out grey triangles vs. the ability to filter out grey circles. The respective irrelevant conditions were used as control variables. As in Study 1, data was prepared for analysis using Microsoft Excel 365 [206], and statistical analyses were performed using IBM SPSS Statistics [207].

3.4.2 Results

A visual representation of the obtained K-values per condition and stimulus type is displayed in Figure 3.4.

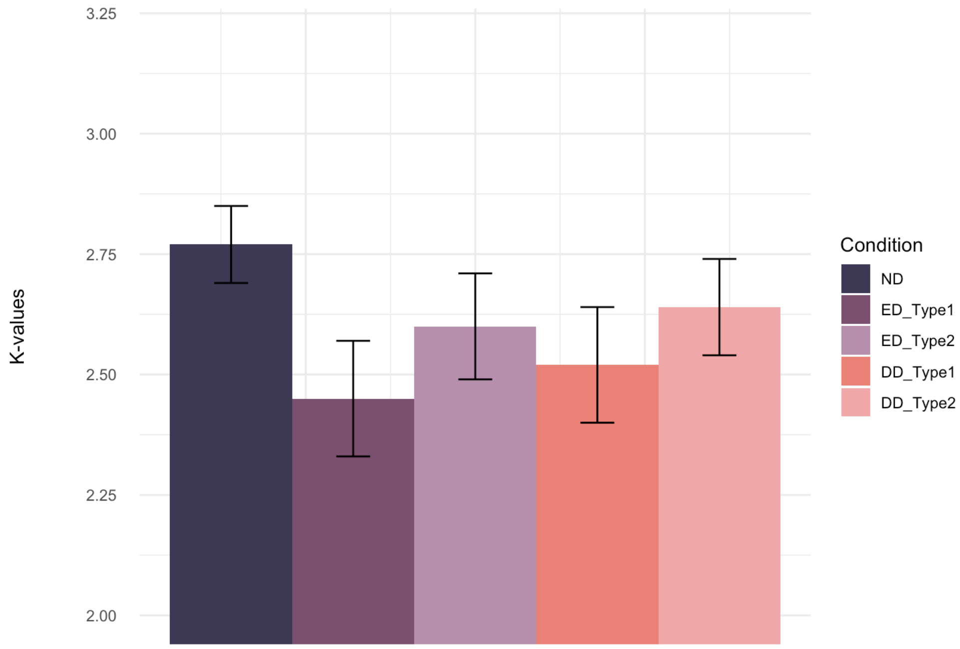

Figure 3.4: Mean K-values per condition and stimulus type. Type 1 distractors are grey circles, Type 2 distractors are grey triangles. Error bars represent +/- 1 standard error.

An overview of the results of the calculated ANOVAs and associated F-tests can be found in Table 3.4. A two-factor repeated measures ANOVA with the factors condition (ED, DD) and type (Type 1: grey circles, Type 2: grey triangles) revealed no significant main effects or interactions. A separate one-factorial ANOVA for the ED condition with the factor type (Type 1, Type 2, ND) revealed a main effect. Mauchly's tests indicated a violation of sphericity assumptions ($\chi^2(2) = 8.12$, $p = 0.017$), therefore Greenhouse-Geisser corrected F- and p-values are reported in Table 3.4. Follow-up pairwise analyses revealed a lower performance for Type 1 distractors than for ND ($p = 0.003$, Bonferroni-Holm corrected), but no significant difference between performance for Type 2 distractors and ND. For the DD condition, a further ANOVA was calculated with the factor type (Type 1, Type 2, ND). Mauchly's tests again indicated a violation of sphericity assumptions ($\chi^2(2)$

= 9.55, p = 0.008), therefore Greenhouse-Geisser corrected F- and p-values are reported in Table 3.4. No main effect was found, indicating that performance did not differ between trials without distractors, Type 1 distractors and Type 2 distractors at delay.

Effect	F-value (df)	p-value	Effect size η_p^2
Condition	0.38 (1, 50)	0.593	0.01
Type	2.33 (1, 50)	0.133	0.05
Condition x Type	0.03 (1, 50)	0.873	0.00
ED Type	4.45 (1.74, 86.76)	0.014*	0.08
DD Type	3.20 (1.70, 84.96)	0.054	0.06

Table 3.4: F-test results for each of the calculated ANOVAs in Experiment 2. **** p < .001; ** p < .01; * p < .05*

To investigate the unique contributions of ED and DD filtering, a hierarchical regression was calculated with both ED conditions predicting performance in ND trials (Model 1), and with all ED and DD conditions predicting performance in ND trials (Model 2). Model 1 was significant ($p < 0.001$; adj. $R^2 = 0.41$), i.e., ED performance predicted ND performance. Model 2 explained an additional 15% of the variance ($p < 0.001$; $f^2 = 0.37$). Detailed results as well as standardised β-coefficients can be found in Table 3.5.

Model	Predictor	R^2 change	Standardised β	p-value
1	ED_Type1	0.43***	0.49	< 0.001
	ED_Type2		0.29	0.019
2	ED_Type1	0.15***	0.32	0.006
	ED_Type2		0.19	0.085
	DD_Type1		0.28	0.014
	DD_Type2		0.27	0.020

Table 3.5: Results of the hierarchical regression comparing ED and DD conditions. Model 1 predicts performance in the ND condition from both ED conditions and Model 2 predicts performance in the ND condition from both ED and both DD conditions. Type 1 distractors are grey circles, Type 2 distractors are grey triangles. **** p < .001; ** p < .01; * p < .05*

To investigate the unique contributions of filtering specific distractor types, a further hierarchical regression was calculated with both Type 1 conditions predicting performance in ND trials (Model 1), and with all Type 1 and Type 2 conditions predicting performance in ND trials (Model 2). Model 1 was significant ($p < 0.001$, adj. $R^2 = 0.47$), i.e., performance in Type 1 conditions predicted ND performance. Model 2 explained an additional 9.7% of the variance ($p = 0.008$; $f^2 = 0.23$). Detailed results as well as standardised β-coefficients can be found in Table 3.6.

Model	Predictor	R^2 change	Standardised β	p-value
1	ED_Type1	0.49***	0.46	< 0.001
	DD_Type1		0.38	0.001
2	ED_Type1	0.10***	0.32	0.006
	DD_Type1		0.28	0.014
	ED_Type2		0.19	0.085
	DD_Type2		0.27	0.020

Table 3.6: Results of the hierarchical regression comparing distractor Type 1 and distractor Type 2. Model 1 predicts performance in the ND condition from both Type 1 distraction conditions (grey circles), and Model 2 predicts performance in the ND condition from both Type 1 distraction conditions and both Type 2 distraction conditions (grey triangles). **** $p < .001$; ** $p < .01$; * $p < .05$*

Correlation analyses revealed no significant associations between performances in any of the investigated conditions.

3.5 Study 3

3.5.1 Data Analysis

Similar to Studies 1 and 2, K-values were calculated to obtain an estimate for WMC. For each participant, a K-value was obtained each for ND trials, ED trials with Type 1 distractors (grey circles), ED trials with Type 2 distractors (red circles), DD trials with Type 1 distractors (grey circles), DD trials with Type 2 distractors (red circles). Again, participants with K-values lower than 0.5 in any condition were excluded from the analysis to limit the risk of participant inattentiveness influencing the results.

To examine performance differences between trials with different distractor types as well as between trials with and without distractors, a one-way repeated measures ANOVA was calculated for stimulus type (Type 1 vs. Type 2 vs. ND). A two-way repeated measures ANOVA with the factors type and condition (ED, DD) further served to investigate the interaction with the presentation period. Since ND trials did not contain distractors, and thus did not contain the factor 'presentation period', the ND condition was not relevant for this analysis. Where applicable, follow-up comparisons were conducted and corrected using the Bonferroni-Holm method. To determine the unique influences each distractor type and processing period has on WMC, a hierarchical regression analysis was performed, with performance in the ND condition as the dependent variable. In the first regression, performance in both ED conditions was used to predict ND performance (Model 1: ND = β_0 + β_1 ED_Type1 + β_2 ED_Type2). At stage 2, performance in both DD conditions was added to the model (Model 2: ND = β_0 + β_1 ED_Type1 + β_2 ED_Type2 + β_3 DD_Type1 + β_4 DD_Type2). R^2 change between the two models served as an indicator to determine the unique variability in WMC that could be explained by filtering out distractors during memory maintenance periods. The second regression predicted ND performance with performance in both Type 1 (grey circles) distractor conditions at Stage 1 (Model 1: ND = β_0 + β_1 ED_Type1 + β_2 DD_Type1), and performance in both Type 2 distractor conditions (red circles) at Stage 2 (Model 2: ND = β_0 + β_1 ED_Type1 + β_2 DD_Type1 + β_3 ED_Type2 + β_4 DD_Type2). R^2 change between the two models again served as an indicator to determine the unique variance in WMC that could be explained by filtering out red circle (Type 2) distractors. In addition, partial correlations between the different conditions were calculated to characterise the associations between ED and DD filtering and between the ability to filter out red circles vs. the ability to filter out grey circles. The respective irrelevant conditions were hereby used as control variables. Data was prepared for analysis using Microsoft Excel 365 [206] and statistical analyses were performed using IBM SPSS Statistics [207].

3.5.2 Results

A visual representation of the obtained K-values per condition and stimulus type is displayed in Figure 3.5.

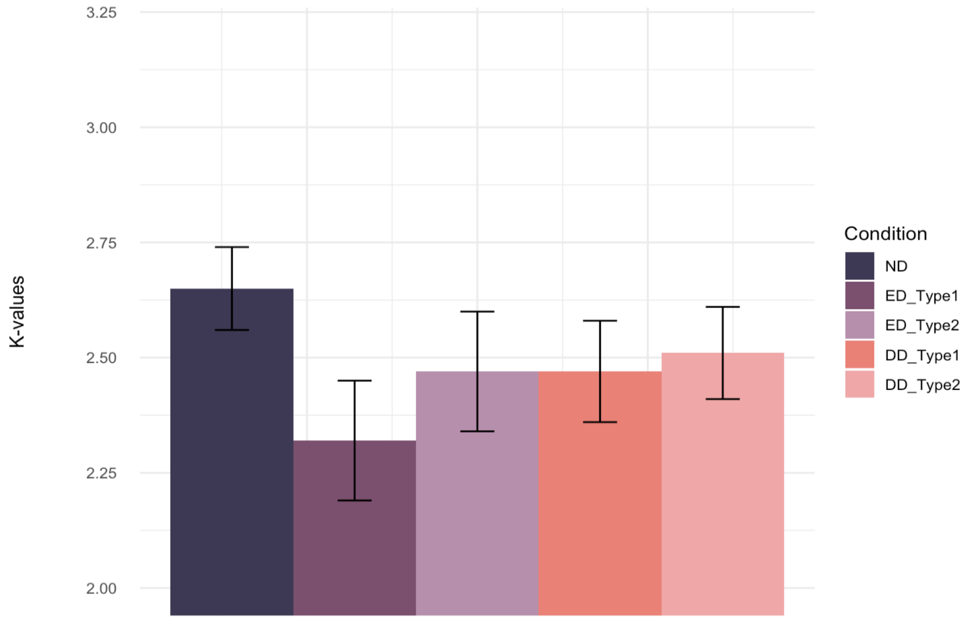

Figure 3.5: Mean K-values per condition and stimulus type. Type 1 distractors are grey circles, Type 2 distractors are red circles. Error bars represent +/- 1 standard error.

An overview of the results of the calculated ANOVAs and associated F-tests can be found in Table 3.7. A two-factor repeated measures ANOVA with the factors condition (ED, DD) and type (Type 1: grey circles, Type 2: red circles) revealed no significant main effects or interactions. A separate one-factorial ANOVA for the ED condition with the factor type (Type 1, Type 2, ND) revealed a main effect. Mauchly's tests indicated a violation of sphericity assumptions ($\chi^2(2) = 12.30$, p = 0.002), therefore Greenhouse-Geisser corrected F- and p-values are reported in Table 3.7. Follow-up pairwise comparisons revealed lower performance for Type 1 distractors than for ND ($p = 0.009$), but no significant difference between performance in Type 2 trials and the ND condition. For the DD condition, a further ANOVA was calculated with the factor type (Type 1, Type 2, ND). No main effect was found, indicating that performance did not significantly differ between the ND condition, the Type 1 condition, and the Type 2 condition during the delay period.

Effect	F-value (df)	p-value	Effect size η_p^2
Condition	0.88 (1, 48)	0.353	0.02
Type	1.23 (1, 48)	0.272	0.03
Condition x Type	0.32 (1, 48)	0.574	0.01
ED Type	4.01 (1.63, 78.04)	0.029*	0.08
DD Type	1.58 (1.63, 78.43)	0.212	0.03

Table 3.7: F-test results for each of the calculated ANOVAs in Experiment 3. **** p < .001; ** p < .01; * p < .05*

To investigate the unique contributions of ED and DD filtering, a hierarchical regression was calculated with both ED conditions predicting performance in ND trials (Model 1), and with all ED and DD conditions predicting performance in ND trials (Model 2). Model 1 was significant ($p < 0.001$; adj. $R^2 = 0.55$), i.e., ED performance predicted ND performance. Model 2 explained an additional 14.7% of the variance ($p < .001$; $f^2 = 0.51$). Detailed results as well as standardised β-coefficients can be found in Table 3.8.

Model	Predictor	R^2 change	Standardised β	p-value
1	ED_Type1	0.57***	0.37	0.001
	ED_Type2		0.52	< 0.001
2	ED_Type1	0.15***	0.23	0.019
	ED_Type2		0.39	< 0.001
	DD_Type1		0.22	0.015
	DD_Type2		0.34	< 0.001

Table 3.8: Results of the hierarchical regression comparing ED and DD conditions. Model 1 predicts performance in the ND condition from both ED conditions and Model 2 predicts performance in the ND condition from both ED and both DD conditions. Type 1 distractors are grey circles, Type 2 distractors are red circles. **** p < .001; ** p < .01; * p < .05*

To investigate the unique contributions of filtering specific distractor types, a further hierarchical regression was calculated with both Type 1 conditions predicting performance in ND trials (Model 1), and with all Type 1 and Type 2 conditions predicting performance in ND trials (Model 2). Model 1 was significant ($p < .001$, adj. $R^2 = 0.47$), i.e., performance for Type 1 conditions predicted ND performance. Model 2 explained an additional 22.2% of the variance ($p < 0.001$; $f^2 = 0.77$). Detailed results as well as standardised β-coefficients can be found in Table 3.9.

Model	Predictor	R^2 change	Standardised β	p-value
1	ED_Type1	0.49***	0.51	< 0.001
	DD_Type1		0.40	< 0.001
2	ED_Type1	0.22***	0.23	0.019
	DD_Type1		0.22	0.015
	ED_Type2		0.39	< 0.001
	DD_Type2		0.34	< 0.001

Table 3.9: Results of the hierarchical regression comparing distractor Type 1 and distractor Type 2. Model 1 predicts performance in the ND condition from both Type 1 distraction conditions (grey circles), and Model 2 predicts performance in the ND condition from both Type 1 distraction conditions and both Type 2 distraction conditions (red circles). **** p < .001; ** p < .01; * p < .05*

Partial correlation analysis revealed a significant correlation between ED_Type1 and ED_Type2, when controlling for DD_Type1 and DD_Type2 ($r = 0.30$, $p = 0.037$). No further significant associations were found.

3.6 Comparison across Studies

The ND condition as well as the ED condition with grey circles (ED_Type1) and the DD condition with grey circles (DD_Type1) were identical in all three studies. To ensure that the results are comparable across studies, an ANOVA with the within-factor condition (ND, ED_Type1, DD_Type1) and the between-factor study was calculated. A significant main effect of condition was revealed ($F(1.62, 203.64) = 11.07$, $p < 0.001$, $\eta_p^2 = 0.08$). Mauchly's tests indicated a violation of sphericity assumptions ($\chi^2(2) = 33.89$, p < 0.001), therefore Greenhouse-Geisser corrected F- and p-values are reported. Pairwise comparisons revealed significantly higher K-values for ND ($M = 2.74$, $SD = 0.58$) than ED_Type1 ($M = 2.40$, $SD = 0.87$) and DD_Type1 ($M = 2.51$, $SD = 0.79$; $p < 0.001$, in both cases, Bonferroni-Holm corrected). No further main effect or interaction was observed, which confirmed that the three studies were comparable.

3.7 Discussion

This first series of studies addressed the question of how task-irrelevant stimuli with different visual characteristics affect WM for an array of four black target circles. Results of all three experiments indicate that simultaneously presented grey circles negatively affect performance, underscoring pervasive evidence of memory-debilitating effects of distraction, which has been classified as a benchmark of WM [79]. Interestingly however, neither performance in trials with striped triangles, grey triangles, nor red circles was found to differ significantly from performance in no-distractor trials, suggesting that these stimuli were effectively ignored.

In some circumstances, an increased perceptual load can reduce distraction effects [116], which might offer an explanation for the present results. Lavie's [116] load theory, which was derived from this observation, postulates the existence of two dissociable mechanisms: a passive perceptual selection mechanism that enables distractor inhibition under high perceptual load conditions, as well as an active cognitive control mechanism that can reduce interference from perceived distractors. Translated to the current experiments, it might have been the case that the used target array consisting of four black circles represented a rather high perceptual load, which could have led to reduced processing of encoding distractors. Consequently, if these items are not processed, they may not have a negative effect on recall accuracy, explaining the absent distraction costs for striped triangles, grey triangles, and red circles. To explain the limited debilitating effects of irrelevant items in the delay period, ample cognitive resources may have been available for a late exclusion of irrelevant material during memory maintenance. Under this assumption, however, the same results should have been observed for grey circles, which was not the case for the encoding period.

These divergent findings may be explained by suppression or enhancement mechanisms, by which task-irrelevant characteristics are inhibited and task-relevant characteristics are enhanced, resulting in so-called priority maps that improve target processing [144], [148], [208]. For instance, FBA theory [148], by which target-relevant features (e.g., the colour red) are prioritised, might account for the current results. For instance, in Studies 1 and

2, it may have been the case that the target-relevant shape value “circle” was enhanced. Accordingly, attention would be directed towards circular items and away from other items, resulting in circular target items being reliably processed and differently shaped items being efficiently ignored. Yet, circular distractors would also be processed, resulting in increased distractor interference. The current results indeed revealed that only grey circles negatively affected WMC, and not striped triangles or grey triangles. In Study 3, however, red circles should have been distracting as well if the feature value “circle” was prioritised. In this experiment, the shape value “circle” is not useful for target selection as all targets and distractors were circular. Instead, colour might be a more appropriate attribute in differentiating otherwise identical distractors from the targets. It is important to note that colour is not a one-dimensional concept [209], which may explain why grey circles, but not red circles interfered with WM performance. Colour can be determined based on the HSB colour model, which has been designed to align with human visual perception and specifies visual perception of colour in terms of hue, saturation, and brightness. The black circles used as target stimuli in the current experiment had saturation and brightness values of 0% (the saturation value of 0% renders any hue value redundant). The grey circles used as irrelevant items had a brightness value of 57%, while saturation was still at 0%. The red circles had a brightness value of 100%, a saturation value of 100%, and a hue value of 0 degrees. Consequently, grey circles differed only with respect to brightness from the black target circles, whereas red circles differed with respect to brightness – and that to a higher extent than grey circles – as well as with respect to saturation from the target stimuli. Thus, in Study 3, a prioritisation or down-weighting of certain colour values might have resulted in only the very distinct red circles being efficiently filtered out, whereas the more similar grey circles were still processed and thus interfered with WM recall accuracy for black target circles.

This is also in concordance with the Contingent Capture Theory (CCT) that states that attentional capture depends on a match between a cue or distractor feature and a target-relevant feature [139], [140], [142]. Likewise, a number of studies have reported distraction effects on WM when target-distractor similarity was increased. Higher distraction costs have for instance been found when target and distractor items were from the same visual category than when distractors were incongruent [159], [160]. Similarly, in a study by Cohen et al. [158], delayed recognition performance was disproportionately affected when all items in a memory array were from the same visual category as compared to a mixed-category condition. Importantly, these congruency effects seem to extend to low-level visual features, which may be more applicable to the current study, where stimuli differed with respect to colour, shape, or texture. For example, memory interference has been found to be only caused by distractors along the relevant stimulus dimension [162], [210]. When participants were for instance required to remember spatial frequencies, only irrelevant spatial frequency changes interfered with memory, and not irrelevant orientation changes [161], [162]. A potential functional architecture that could explain these findings is the existence of feature-specific storage modules in the visual cortex [211]. According to this view, memory is disrupted due to different memory stores maintaining conflicting information about a shared visual feature. This might be related to the previously mentioned FBA account, according to which specific features can be enhanced to facilitate target detection.

It must be noted that in the current experiments, the feature that had to be remembered was the spatial location of target stimuli – the colour and shape of the target items remained constant. Thus, the relevant features for selection that help differentiate between targets and distractors were different from what needed to be remembered, which were the locations of the four target circles. Taking into account theories that explain the guidance of attention based on priority maps, such as the FBA account, remembering additional features (such as the locations) of attended stimuli might be facilitated when attention is guided more efficiently towards those stimuli in the first place. This hypothesis has however not yet been specifically addressed, and it might be the case that a difference between the feature relevant for selection and the feature relevant for memorisation leads to different outcomes that may be explained by different mechanisms.

3.7.1 Distinct Effects of Different Types of Distractors at Encoding and Delay

It has been established that ED and DD filtering have a unique influence on WMC, suggesting two dissociable mechanisms for distractor inhibition in different processing phases [205], [212]. This finding was replicated in Studies 2 and 3. In Study 1, DD filtering did not explain additional variance, which could be due to the smaller sample size and thus limited statistical power. Correlations between performance in encoding and performance in delay conditions in all three experiments remained non-significant, strengthening the assumption of separate mechanisms involved in ED and DD filtering.

Surprisingly, unique effects were found for performance in trials with grey triangles as well as performance for trials with red circles when added to regression models with grey circle trials only, suggesting that there may be separate mechanisms for handling different types of distractors. In different situations, different strategies might be required to reliably differentiate targets from distractors. One possible mechanism could be the aforementioned FBA, according to which specific stimulus features or feature dimensions are prioritised based on current goals or task history. The prioritisation of a certain feature could be helpful for some target-distractor configurations, but not for others. For instance, an implicit enhancement of the shape feature “circle” can be helpful in differentiating triangular distractors from circular targets, but not in differentiating black circle targets from grey or red circle distractors. In this case, an enhancement of the feature “black” might be more appropriate. Additionally, as the colour red, which is commonly used as a signal or warning colour, may capture attention due to a pop-out effect, a more potent mechanism to resist such attentional capture might be relevant in cases where red distractors need to be filtered out. Yet, there was also a correlation between recall accuracy for encoding trials with grey circles and encoding trials with red circles, as well as between encoding trials with grey circles and encoding trials with striped triangles, indicating that handling these different types of distractors is not completely independent and may rely on a shared mechanism as well.

3.7.2 Limitations and Future Directions

It would be interesting to look at reaction times associated with memory recall in different distractor conditions. Previous studies that have investigated attentional guidance effects of irrelevant distractors found increased reaction times when distractors shared a salient feature with a target item, but no effects on recall accuracy [133], [134]. In the present experiments, reaction time was not gathered due to concerns over varying Internet connection speeds and browser environments that may have affected precision. Hilbig [213] argued that these concerns are unwarranted, and Anwyl-Irvine et al. [214], developers of the Gorilla software that was used in the present studies, note that reaction-time sensitive experiments can be conducted on the Gorilla platform. Yet, they also note that there may be some unanticipated factors that can influence reaction times, such as the hardware of the user or the processing load of their device. It was therefore decided to focus on accuracy only, yet future studies with adequate controls of potential external influences may also look at reaction times to address the question of how distractors with varying visual features may influence temporal aspects of WM. Additionally, investigating the effects of different types of distraction on WM on much larger samples could uncover individual differences and generally yield more reliable results. Finally, only a limited set of visual variables was examined in the present set of experiments. Further variables such as size or orientation could be investigated in future studies, which can provide more insights into how different types of visual characteristics may shape attention and WM.

3.8 Conclusions

To conclude, the three studies established that different types of distractors affect memory recall accuracy differently. Results showed that only irrelevant grey circles presented in the encoding period negatively affected memory recall accuracy for black target circles. Such an effect was neither observed for striped triangles, grey triangles, nor red circles, demonstrating that there may be suppression or enhancement mechanisms in place that prioritise task-relevant over task-irrelevant features and thus eliminate distraction effects on recall accuracy. Grey circles may have been too similar to the black target circles so that such mechanisms were rendered inefficient and distraction effects were observed. These mechanisms have been observed only during the encoding period, providing further evidence of separable contributions of encoding and delay distractor filtering in addition to the unique effects of filtering different types of distractors. The divergent results for different types of distractors may be traced back to feature-based attention, where task-relevant features are prioritised, as well as to the relative similarity between to-be-remembered items and distractors, where a lower similarity leads to facilitated filtering efficiency.

The notion that it may be particularly the visual similarity between task-relevant and task-irrelevant items has important implications for game design. Since video games are often very rich in their visual setup, colour and brightness must be carefully applied in order to support players in attaining a certain in-game goal and not to accidentally distract players from reaching that goal. The following studies will move from the presently employed controlled setting of a cognitive-psychological experiment towards examining visual similarity in terms of brightness in a simple video game, allowing for conclusions about how the visual setup of the game world affects performance in a gaming setting and, more importantly, how this shapes PX.

Chapter 4

Studies 4 + 5: How Perceptual Characteristics Influence Difficulty and Player Experience in a Working Memory Game

4.1 Motivation and Research Questions

Empirical evidence described in Chapter 2 as well as the results of Studies 1-3 suggest that visual manipulation of distractor stimuli in terms of their saliency or similarity to target items can increase cognitive demand and affect visual search performance and Working Memory (WM). Increased cognitive demand can be beneficial since it may improve immersion [62] and enjoyment [166], however, excessive cognitive load might also lead to accessibility concerns and negative feelings such as frustration [59]. It is therefore crucial for game designers to design game elements in a way that makes the game exciting and interesting but at the same time does not add excessive cognitive demand that inhibits players from advancing in the game which may leave them overwhelmed.

Most studies that have looked at the effects of saliency and target-distractor similarity in video games have focused on the initial detection of elements [14]–[16], mirroring findings commonly found in cognitive-psychological experiments involving visual search. However, as described before, task-irrelevant stimuli can not only affect target detection but also disrupt contents already stored in memory, providing further opportunities to increase cognitive demand. How the timing of distractors (i.e., during encoding versus during maintenance) affects target processing performance and Player Experience (PX) in a video game that places demand on WM has not yet been empirically investigated. Since many video games however not only require players to search for items but often also ask the player to remember certain information, such as locations or mechanics, a better understanding of how and when certain kinds of distractors affect WM can further inform the visual design of game elements, which may ultimately also help to improve PX. Studies 4 and 5 thus examine how target-distractor similarity influences memory for target stimuli in the presence of distraction at different times of processing. In addition, associations between visual characteristics of task-irrelevant items, performance, and PX are investigated to illuminate potential beneficial as well as harmful consequences of distraction. The relationship between visual features and PX has been studied by only a few [215], [216], and to the best of my knowledge, the association between target-distractor similarity, WM performance, and PX has not yet been interrogated.

A custom-made digital game was utilised that allowed me to investigate Working Memory Capacity (WMC) in the absence of distraction as well as filtering abilities in conditions with distractors of varying similarity to target items. The design and development of the game are described in more detail in section 4.2. In essence, the game required players to memorise a path consisting of grey circles presented for a short time on a rectangular grid. After a brief delay, players were asked to navigate their player character on the empty grid along the memorised path. Distractor presentation conditions were implemented in which either no distractors were presented, distractors were presented simultaneously with the to-be-remembered path, or in the delay period after the path had disappeared (note: in Study 5, the Delay Distractor (DD) condition was removed). For distractor conditions, similarity to the target path was further manipulated. Since contrast is often utilised to highlight game objects and at the same time offers the possibility to gradually alter similarity by increasing or decreasing brightness, brightness contrast was utilised to manipulate target-distractor similarity. In addition, brightness difference between distractors and targets was the only factor that disrupted memory performance in Studies 1-3. Using this visual variable again in the present experiments, together with gradually altering similarity to target stimuli, can thus offer a more granular perspective on the conditions in which WM is disrupted and to what extent, and ultimately provide insights into how the level of distraction affects the experience players have while playing video games.

Three brightness conditions were implemented, with distractors differing either to a large, medium, or small extent from the target path circles. Based on empirical evidence and theories of target-distractor similarity, levels with the smallest brightness difference between targets and distractors were expected to be the most difficult and levels with the largest brightness difference to be the easiest, reflected in player performance. In Study 4, a within-subjects design was implemented, which means that players played each of the three brightness conditions. In contrast, a between-subjects design was used for Study 5: Players were allocated to one of three groups and played the game at either small, medium, or large target-distractor differences. While the within-subject nature of Study 4 thus allows us to investigate how game difficulty can be manipulated by altering perceptual demand through distraction and also how performance is related to enjoyment, a direct link between difficulty and enjoyment can only be established in a between-subjects design, which was for that reason implemented in Study 5. Study 5 further served to replicate the findings of Study 4 by eliminating potential spill-over effects between experimental conditions that could occur in a within-subjects design.

Since there is evidence of individual differences in WMC and the ability to ignore distraction [105], [115], which may influence players' feelings and attitudes towards the game, I further explored several aspects of PX and their association with target-distractor similarity and performance. In particular, I was interested in how game difficulty and performance were related to enjoyment as an overall indicator of positive PX and a key reason why people play video games [47]. Uncovering how task difficulty induced by visual characteristics and performance affect PX can be relevant for a wide range of games that ask players to retain information in the presence of potentially distracting visual stimuli, such as open-world games.

Studies 4 and 5 address RQs 2 and 3 of this thesis:

- RQ 2: How does perceptual distraction affect game difficulty?
- RQ 3: What consequences does perceptual distraction have on PX?

For both studies, game performance was hypothesised to be higher in trials with no distractors than in trials with distractors so as to establish that distractors indeed impact WM. For Study 4 specifically, performance was expected to be higher the larger the perceptual difference between target and distractor stimuli, which would provide evidence for the target-distractor similarity account. Similarly, for Study 5, performance was expected to be highest in the group with the largest target-distractor difference, and poorest in the group with the smallest target-distractor difference. In addition, for Study 5, enjoyment ratings were expected to differ between groups, establishing a direct link between game difficulty induced by visual means and enjoyment. Such associations have been reported before [23], [49], [63], and notably in both directions: While some researchers report that easier games are enjoyed more [23], [74], [217], which may be due to higher elicited feelings of competence [23], [217] and a higher likelihood that player skill and game difficulty are aligned [23], many others report that challenge is an important game element that can increase game enjoyment, suggesting that more difficult games are enjoyed more [49]. This latter hypothesis was therefore non-directional. In addition, there are substantial inter-individual differences in WM and filtering abilities [218], [219], which could also influence the relationship between game difficulty and enjoyment. According to flow theory (see Chapter 2), skill and task difficulty need to be balanced in order to provide an optimal experience or, in other words, a state of flow. Thus, each player's experience while playing a video game depends on both the individual skill and the difficulty of the task. Applied to the current research, players with high distractor filtering abilities may enjoy the game more when filtering is more difficult (when targets and distractors are similar to each other) and may feel bored when filtering is effortless (when targets and distractors are very distinct from each other). Instead, players with low filtering abilities may be left frustrated when there is a high target-distractor similarity, and enjoy the game more when filtering becomes easier due to a higher distinctness between targets and distractors. Further factors that might influence the relationship between difficulty and enjoyment are expectations and gaming expertise [63], as well as difficulty preferences of the player [220]. While such individual differences likely cause different experiences from player to player, the current study allows us to examine whether game difficulty per se has an effect on PX, irrespective of individual differences in WMC, filtering abilities, gaming expertise, or game difficulty preferences.

Lastly, for both studies, associations between game difficulty, performance, and further metrics of PX were explored, which can help improve our understanding of the effects of game difficulty based on perceptual distraction on PX and can provide useful guidance for game designers to design enjoyable games.

4.2 Design and Development of the Video Game

Using video games as research tools may present some challenges that could violate the validity of the observed outcomes [221]. This may be particularly the case for commercially available video games that are often very complex and varied in nature. To that end, a custom game was created to allow for sufficient control in order to eliminate any potential confounds that may come with game elements irrelevant to the present research question. Yet, since the conclusions of the present studies relate to video games in particular, it was also important to include elements that are commonly found in commercial video games. In addition, since the game should be used for multiple studies, enabling relatively straightforward iterations to adjust to new research questions was crucial.

The resulting research game is based on a game originally created in a joint endeavour for the IGGI Game Jam in 2022. The original game featured a comprehensive narrative, a rather detailed art style, as well as a variety of playing mechanics. The main gameplay mechanic involved memorizing a path that needed to be recalled later on. This mechanic was maintained in the game adapted for the present experiments. In order to eliminate any irrelevant game elements in relation to the current research questions, a minimalist style was chosen and art assets were exchanged for simple shapes. Yet, some game elements such as a points system and progress feedback were maintained to preserve a game-like experience.

The main gameplay loop in a typical game level is as follows: The player is presented with a rectangular grid of varying sizes. A path consisting of circles placed in connected fields is presented on this grid, starting in the top left corner and ending in the bottom right corner. Players are asked to memorise this path, which then disappears. In some trials, additional distractor circles are presented in some of the unoccupied fields, either simultaneously with the path, or after the path has disappeared. After the distractors have disappeared as well, the player is faced with an empty grid, and a red rectangle representing the player character in the top left corner. A message saying “Start!” indicates that the player can commence moving along the path they have previously memorised with the arrow or WASD keys on their keyboard. If the bottom right corner is reached, a success message is displayed on the screen and 100 points are added to the point score displayed in the user interface (UI) below the play area. If the player makes an erroneous move off the path, a failure message appears, and 50 points are deducted from the point score. Figure

4.1 displays the gameplay loop of a successfully completed level without any distractor circles, and Figure 4.2 shows the gameplay loop of a successfully completed level with distractor circles appearing simultaneously with the path.

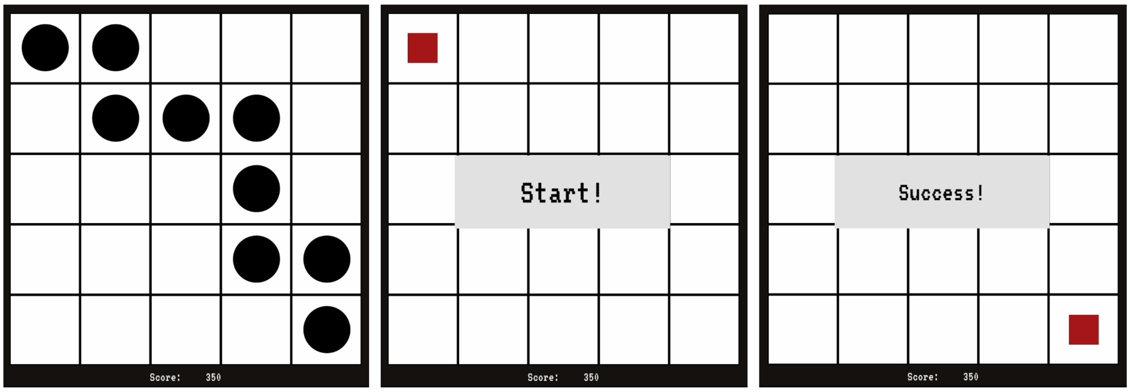

Figure 4.1: Example level of the game without distractor circles. First, a path is presented that players need to memorise (left). The path disappears and a player character appears in the top left cell (centre). After navigating correctly along the memorised path, a success message is displayed (right). Points are added once the next level starts.

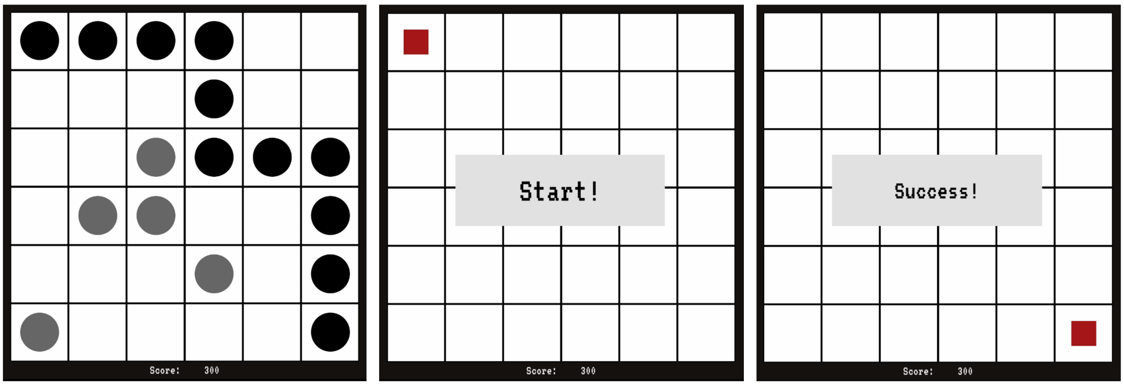

Figure 4.2: Example level of the game with distractor circles. First, a path is presented that players need to memorise, ignoring any other circles that may be presented (left). The path disappears and a player character appears in the top left cell (centre). After having navigated correctly along the memorised path, a success message is displayed (right). Points are added at the beginning of the next level.

The game was developed with Unity and C# as scripting language and was set up so that an easy adjustment of all variables of interest was possible. This included for instance the shade of the targets and distractors, the number of distractors, the grid size, the number of trials, and the distractor presentation period.

4.3 Study 4

4.3.1 Methods

Study 4 was approved by the Ethics Committee of the Department of Psychology of the University of York. The design and procedure, study hypotheses, as well as a data analysis plan were preregistered using the Open Science Framework repository (https://osf.io/2qk3s). Deviations from the preregistration are described at the end of this section.

4.3.1.1 Participants

An *a priori* power analysis using G*Power (version 3.1.9.6) [222] was calculated to determine the minimum required sample size. With expected medium effect sizes, a power of 0.80 and an alpha error probability of $\alpha = 0.05$, the required sample size was $N = 28$. To allow for potential missing or faulty data, the final sample consisted of 36 participants (32 female) aged between 18 and 20 years ($M = 19.2$, $SD = 0.77$). Participants were recruited online via the University participant pool system SONA and received course credit for their participation. No participants were excluded from the main analysis as specified in the preregistration. All participants gave informed consent ahead of the experiment and were debriefed after the study.

4.3.1.2 Experimental Design and Task

The experiment was uploaded and accessed by participants on the website itch.io. The previously described memory game was adjusted so that it contained three phases. The first phase served to identify players' individual WMC in the absence of distraction. Evidence in cognitive research suggests that processing irrelevant items only affects performance when the limited capacity WM system is exceeded and distractors are processed in place of targets, and not when there is enough storage to process both the target and distractor items [103]. Since I was interested in how different types of distractors affect memory performance, it was important to make sure that participants did not have spare capacity to also remember distractors in addition to the target. Ensuring that each player played the game at a level where their baseline WMC was fully occupied allowed me to investigate the sole influence of distraction on performance. On top of that, there is substantial individual variance in the amount of information that can be stored in WM [32] as well as in the ability to ignore distraction [115], [205]. Thus, the calibration procedure also allowed for the investigation of distraction effects irrespective of inter-individual variance in WMC.

Before participants started with Phase 1, circles in different shades of grey were presented on the screen and participants were asked to adjust the brightness and contrast settings of their screens to ensure they could clearly see the difference between the shades. The circles that were presented differed 10% in brightness from each other, which was the highest degree of similarity that could occur in the main part of the experiment. After the screen adjustment, participants proceeded with the adaptation (Phase 1) as follows: they were asked to remember a path consisting of grey circles presented on a grid with the top left cell as the starting point and the bottom right cell as the endpoint. The grey circles had a brightness value of 50% (HSB value of H=0, S=0, B=50). After the path had disappeared, participants were asked to follow the memorised path with a red player character presented in the top left cell, which represented the beginning of the path in every trial. The first trial started with a grid size of 3x3. If participants got at least 2 out of 3 trials correct, the grid size increased by 1 column and 1 row on the next trial (i.e., the player had moved to the next level). If only 1 out of 3 trials were solved correctly, the grid size decreased by 1 column and 1 row (i.e., the player moved down a level). The maximum grid size that could be reached was 7x7. In total, each participant completed 18 trials in this phase. The individual grid size that was used in Phase 2 was determined as the largest grid size at which the participant successfully completed at least 2 out of 3 trials. The procedure for Phase 1 can be seen in Figure 4.3.

The procedure in the second phase of the experiment was similar to Phase 1, and participants were asked to memorise a path on a grid, and after the path had disappeared, follow the memorised path with their player character. However, this time the grid size was fixed to each player's individual level which was determined in Phase 1. In addition, distractor trials were introduced in this phase, and 5 distractor circles appeared either simultaneously with the target path (Encoding Distractor (ED) condition), or in a delay period (Delay Distractor (DD) condition). Where participants reached a grid size of only 3x3, only 4 distractors could be presented as the path already occupied 5 of the 9 possible grid positions. Distractors were grey and had brightness values of 20% (H=0, S=0, B=20), 30% (H=0, S=0, B=30), 40% (H=0, S=0, B=40), 60% (H=0, S=0, B=60), 70% (H=0, S=0, B=70), and 80% (H=0, S=0, B=80), resulting in target-distractor difference values

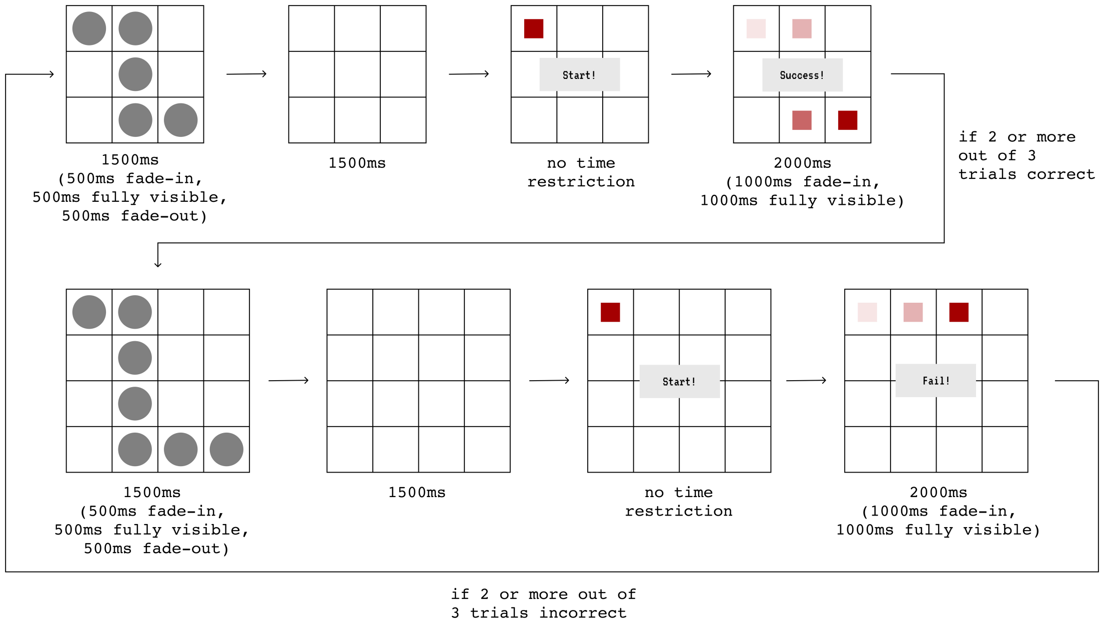

Figure 4.3: Phase 1 of the game. The game started with a grid size of 3x3. If at least two out of three trials were correct, grid size increased by 1 cell size in width and 1 cell size in height. If two or more out of three trials within that grid size were incorrect, grid size decreased by 1 cell size in width and height, respectively. The maximum reachable grid size was 7x7. Where fade effects were used, game elements changed their appearance in a linear manner between fully opaque and fully transparent.

of 10%, 20%, and 30% (hereafter referred to as Diff10, Diff20, and Diff30). Distractors were thus either brighter or darker than the target path circles (which had a brightness value of 50%), in order to account for potential confounds due to stimulus brightness per se and not the relative difference to the target. The results of the analysis comparing brighter and darker distractors compared to target brightness can be viewed in section 4.3.2.6.

In total, there were 7 within-subject conditions: an ND condition, which served as the baseline, an ED condition with Diff10 (ED10), an ED condition with Diff20 (ED20), an ED condition with Diff30 (ED30), a DD condition with Diff10 (DD10), a DD condition with Diff20 (DD20), and a DD condition with Diff30 (DD30). There were 10 trials in each distractor condition (5 with the distractors darker than the target and 5 with the distractors brighter than the target), resulting in 30 ED trials and 30 DD trials. The number of ND trials was 60 to ensure an equal number of trials with and without distractors. Trials were further randomised to limit expectation effects. Figure 4.4 illustrates the experimental procedure in Phase 2.

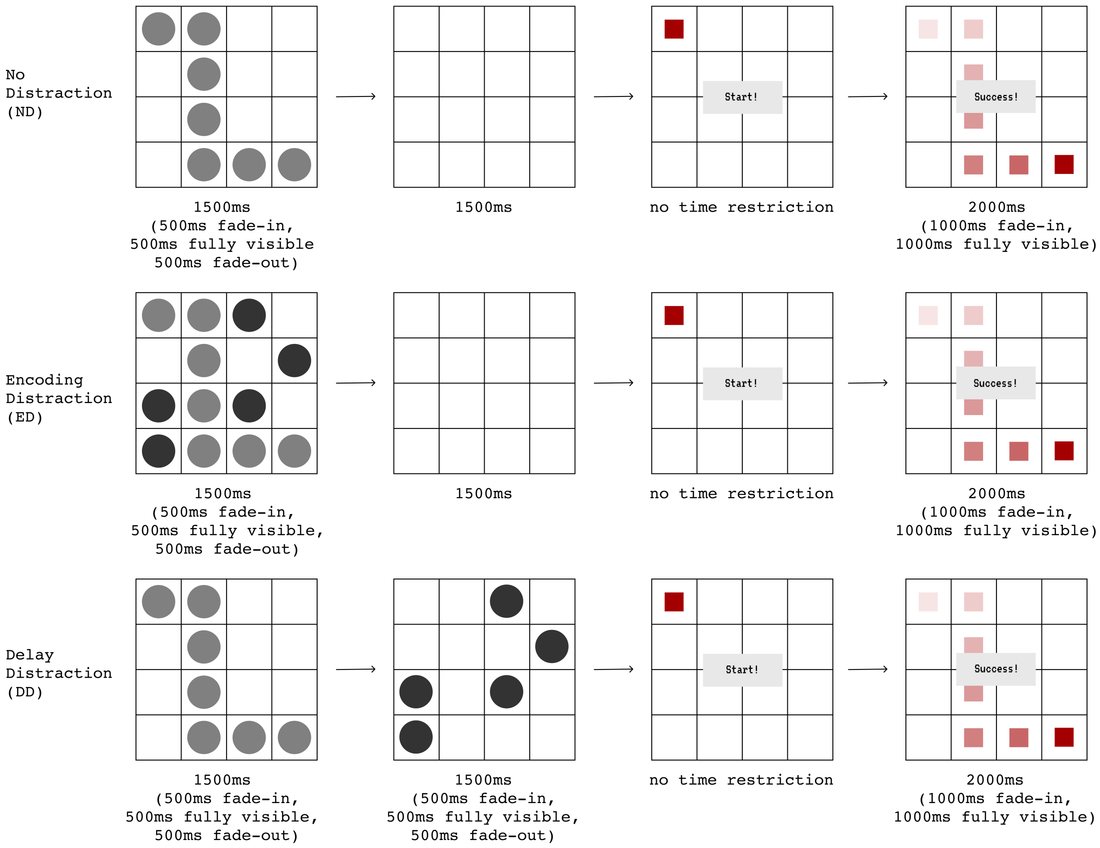

Figure 4.4: Phase 2 of the game. In ND conditions, the path was presented alone. Players responded by following the memorised path after a delay period of 1500ms. In ED conditions, distractors (here: 20% grey) were presented with the path. After a delay of 1500ms, players responded. In DD conditions, the path was first presented alone, and in the delay period, distractors appeared. Then, players responded. Grid size stayed constant for each participant in this phase. Where fade effects were used, game elements changed their appearance in a linear manner between fully opaque and fully transparent.

After this phase, participants' experience playing the game was assessed with the Player Experience Inventory (PXI) [223]. The PXI was chosen since it is an open-access and well-validated PX instrument that is widely used in video gaming research and covers a broad range of PX facets. It consists of 30 questions on a 7-point Likert scale (-3: strongly disagree to +3: strongly agree) and includes the scales meaning, curiosity, mastery, autonomy, immersion, progress feedback, audiovisual appeal, challenge, ease of control, and clarity of goals, allowing for exploring a variety of potential associations between game difficulty, performance, and PX. Since I was also interested in the extent to which players enjoyed the game overall, the three questions for enjoyment that are provided with the inventory but not a construct of the PXI per se were included. Finally, two questions about participants' expertise in playing video games (years playing digital games, hours per week spent playing digital games) were asked. The total duration of the experiment was around 25 minutes.

4.3.1.3 Data Analysis

The main outcome variable in the current study was performance in Phase 2, which was measured in two different ways: success rate and progression. The success rate refers to the overall win-to-lose ratio (a trial is won when players successfully follow the entire path, and a trial is lost when players move to a cell that was not occupied by the path), whereas progression refers to the average number of moves a participant made before failing or succeeding. The number of moves was averaged over the number of trials in each condition. For instance, the progression value for the encoding condition represents the average of a player's number of moves in the 30 encoding trials. Since the presented paths always started in the top left cell and ended in the bottom right cell, all paths within a given grid size were of the same length. The average number of moves thus takes into account the individual grid size and serves as a more fine-grained measure of performance that also considers a person's WMC. Success rate instead allowed for the investigation of distraction effects irrespective of participants' baseline WMC, and may furthermore be more relevant for PX than absolute performance, since it is directly related to the in-game feedback players receive.

For both outcome measures, a one-factorial ANOVA with the three levels ND, ED, and DD was calculated in order to uncover how the presence of distractors at different stages of the WM task affects performance compared to no-distractor trials. Again for each outcome measure, a further 2x3 repeated measures ANOVA with the factors condition (ED, DD) and target-distractor difference (Diff10, Diff20, Diff30) was calculated to directly compare the effects of the two different types of distraction, as well as target-distractor similarity on performance. Follow-up comparisons were calculated where appropriate and corrected using Bonferroni-Holm.

For the measurement of PX, which formed part of the exploratory analysis, means were calculated for every scale of the PXI (including enjoyment), as recommended by Haider et al. [224]. Each scale consisted of 3 questions and since possible answers on each item ranged from -3 to +3, possible mean values for each scale also reached from -3 to

+3. The scale score was treated as missing if at least one item was not completed [see 225]. The PXI scores were correlated with averaged performance for ND, ED, and DD, with performance in each ED10, ED20, ED30, DD10, DD20, and DD30 conditions, and with the variables age and gaming expertise. The latter was measured as number of hours spent playing video games per week. Note that in the following, inspired by a study by Deterding and Cutting [226], the PXI scale "challenge" will be referred to as "perceived balance" since this term reflects to what extent the player felt the challenges of the game aligned with their skill rather than challenge in the sense of game difficulty, two terms which are often used synonymously and might therefore cause confusion.

While the correlation analysis provided insights about how ND, ED, and DD performance are related to each other, these performance measures may also involve combined skills that were required in each ND, ED, and DD condition, such as overall WMC, or the ability to follow instructions or handle game controls. To control for such factors and see how ED resistance and DD resistance specifically and uniquely predict enjoyment, a hierarchical regression analysis was performed. Two hierarchical regressions were conducted using either success rates (Regression 1) or progression (Regression 2) in the ND, ED and DD conditions to predict enjoyment. The regression hierarchy was set up so that at Stage 1, ND performance alone (Enjoyment = β_0 + β_1 ND), at Stage 2, ND and ED performance (Enjoyment = β_0 + β_1 ND + β_2 ED), and at Stage 3, ND, ED and DD performance (Enjoyment = β_0 + β_1 ND + β_2 ED + β_3 DD) were used to predict enjoyment. Having seen how performance is affected by target-distractor similarity, a follow-up analysis was conducted investigating how target-distractor similarity predicts enjoyment, which could provide further support for the importance of considering target-distractor similarity in game design. Thus, where significant associations were found regarding distractor presentation period (ED or DD), further hierarchical regressions were calculated with enjoyment predicted from performance in the ND and each of the three target-distractor difference conditions (Diff10, Diff20, Diff30) of the respective distractor presentation period. Again, this regression was calculated for both success rates and progression. The regression hierarchy was set up so that enjoyment was predicted from ND alone at Stage 1 (Enjoyment = β_0 + β_1 ND), then Diff10 was added at Stage 2 (Enjoyment = β_0 + β_1 ND + β_2 Diff10), then Diff20 was added at Stage 3 (Enjoyment = β_0 + β_1 ND + β_2 Diff10 + β_3 Diff20), and finally, Diff30 was added at Stage 4 (Enjoyment = β_0 + β_1 ND + β_2 Diff10 + β_3 Diff20 + β_4 Diff30). Note that these analyses were also exploratory since I did not have specific hypotheses regarding such associations.

Data was prepared for analysis using Microsoft Excel 365 [206]. Statistical analyses were performed using IBM SPSS Statistics [207] and R Studio [227].

4.3.1.4 Deviation from Preregistration

The analysis deviated from the preregistration in one aspect: for the secondary performance measure (progression), I did not use the ratio between target path length and reached path length, but the number of moves a participant made. This alteration was made as the initial measure would eliminate any baseline WMC differences, which may be an important factor in the relationship between target-distractor similarity, performance, and PX. For instance, the ratio between target path length and reached path length of a participant reaching 3 steps on a grid size of 5 x 5 (target path length = 9) would be the same as for a participant reaching 5 steps on a grid size of 8 x 8 (target path length = 15), although the latter memorised a higher absolute number of target positions, indicating a higher WMC. Utilizing the number of moves a participant makes, averaged across trials, takes into account the person's baseline WMC and may thus be more relevant for addressing the present research questions.

4.3.2 Results

4.3.2.1 Descriptive Statistics

Participants spent on average 4.67 hours per week playing video games ($SD = 8.31$, min: 0, max: 48) and have been playing video games for 10 years on average (min: 4 years, max: 15 years). The maximum reached grid size was 7 (7x7), and the smallest reached grid size was 3 (3x3), with a median of 6 ($IQR = 1$). Only 1 person (2.78% of participants) was at the bottom end, and 2 participants (5.56% of participants) reached the upper end of 7, so floor or ceiling effects were unlikely.

4.3.2.2 Main Effects for Distractor Condition

Success Rate. A one-factorial ANOVA with success rate as the dependent performance variable and condition (ED, DD, ND) as the independent factor revealed a significant main effect ($F(2, 70) = 29.60$, $p < 0.001$, $\eta_p^2 = 0.46$). Follow-up pairwise comparisons revealed a higher ND performance than both ED performance ($M = 0.55$, $SD = 0.17$; $t(70) = 7.41$,

$p < 0.001$) and DD performance ($M = 0.64$, $SD = 0.18$; $t(70) = 3.71$, $p < 0.001$), and a significantly higher DD performance than ED performance ($t(70) = 4.05$, $p < 0.001$).

Progression. Consistent with the analysis for success, a one-factorial ANOVA with progression as the dependent performance variable and condition (ED, DD, ND) as the independent factor revealed a significant main effect ($F(2, 70) = 18.12$, $p < 0.001$, $\eta_p^2 = 0.34$), with pairwise comparisons revealing a better ND performance than both ED performance ($M = 7.20$, $SD = 1.54$; $t(70) = 6.16$, $p < 0.001$) and DD performance ($M = 7.59$, $SD = 1.46$; $t(70) = 2.88$, $p = 0.008$), and a significantly better DD performance than ED performance ($t(70) = 3.06$, $p = 0.008$).

4.3.2.3 Interaction Effects Between Condition and Target-Distractor Difference

Success Rate. A 2x3 ANOVA with the factors condition (ED, DD) and target-distractor difference (Diff10, Diff20, Diff30) and the dependent variable success rate revealed a main effect for condition ($F(1, 35) = 16.76$, $p < 0.001$, $\eta_p^2 = 0.32$), a main effect for target-distractor difference ($F(2, 70) = 5.96$, $p = 0.004$, $\eta_p^2 = 0.15$), as well as an interaction between the two factors ($F(2, 70) = 6.96$, $p = 0.002$, $\eta_p^2 = 0.17$) (see Figure 4.5). Simple main effect analysis revealed a significant effect for target-distractor difference in the ED condition ($F(2, 70) = 13.82$, $p < 0.001$, $\eta_p^2 = 0.28$), but not in the DD condition ($F(2, 70) = 0.05$, $p = 0.955$, $\eta_p^2 = 0.00$). Table 4.1 displays the results of the follow-up pairwise comparisons. Adjusting for multiple comparisons, there were significant differences between ED10 and ED20, between ED10 and ED30, and between ED20 and ED30 while no significant differences were observed between target-distractor difference conditions in the delay period.

Progression. For the dependent variable progression, results revealed a similar pattern: A 2x3 ANOVA with the factors condition (ED, DD) and target-distractor difference (Diff10, Diff20, Diff30) revealed a main effect for condition ($F(1, 35) = 9.35$, $p = 0.004$, $\eta_p^2 = 0.21$), a main effect for target-distractor difference ($F(2, 70) = 7.72$, $p = 0.001$, $\eta_p^2 = 0.18$), as well as a significant interaction between the two factors ($F(2, 70) = 6.29$, $p = 0.003$, $\eta_p^2 = 0.15$) (see Figure 4.6). Simple main effects analysis revealed a significant effect for target-distractor difference in the ED condition ($F(2, 70) = 11.96$, $p < 0.001$, $\eta_p^2 = 0.26$), but not in the DD condition ($F(2, 70) = 0.49$, $p = 0.613$, $\eta_p^2 = 0.01$). Ta-

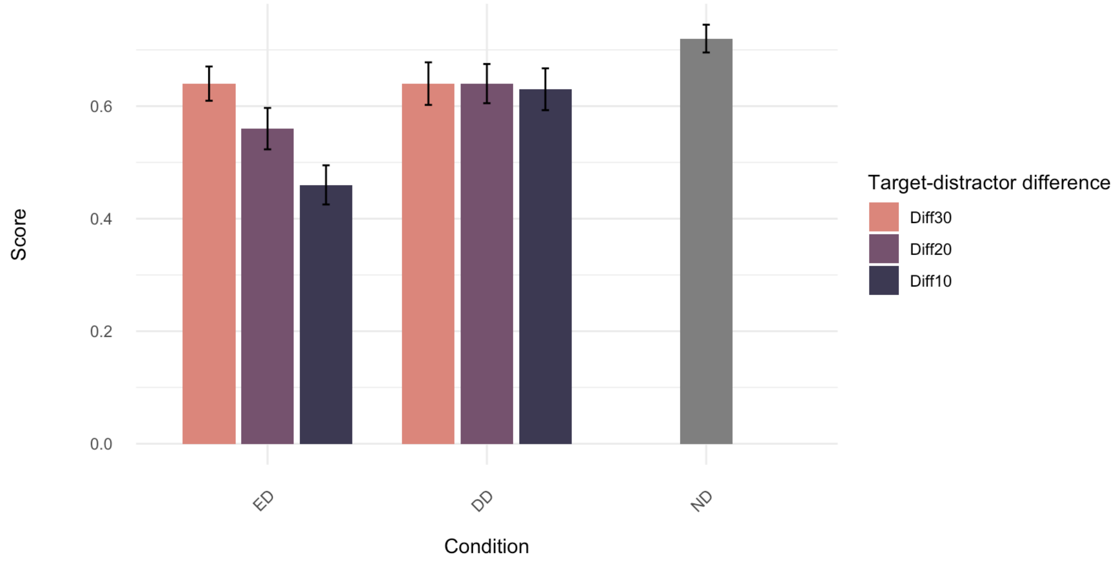

Figure 4.5: Interaction between target-distractor difference (Diff10, Diff20, Diff30) and condition (ED, DD) for the outcome measure success rate. The ND score is displayed for reference. Error bars represent +/- 1 standard error.

Pair	*t*	*df*	*p*-value (Bonferroni-Holm-adjusted)
ED10 - ED20	-3.30	70	0.004**
ED10 - ED30	-4.53	70	< 0.001***
ED20 - ED30	-2.48	70	0.018*
DD10 - DD20	-0.31	70	> 0.999
DD10 - DD30	-0.16	70	> 0.999
DD20 - DD30	0.15	70	> 0.999

Table 4.1: Paired t-test results for success rate. **** $p < .001$; ** $p < .01$; * $p < .05$*

ble 4.2 displays the results of the follow-up pairwise comparisons. As for success rates, there were significant differences between ED10 and ED20, and between ED10 and ED30, and no significant target-distractor differences were observed between the different DD conditions.

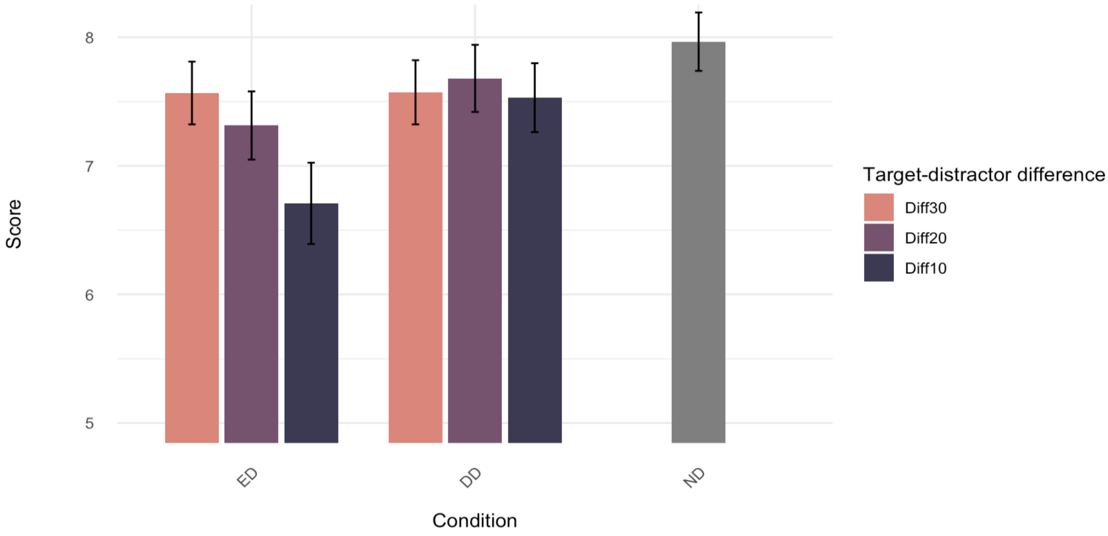

Figure 4.6: Interaction between target-distractor difference (Diff10, Diff20, Diff30) and condition (ED, DD) for the outcome measure progression. The ND score is displayed for reference. Error bars represent +/- 1 standard error.

Pair	t	df	p-value (Bonferroni-Holm-adjusted)
ED10 - ED20	-3.49	70	0.002**
ED10 - ED30	-4.15	70	0.001**
ED20 - ED30	-1.61	70	0.117
DD10 - DD20	-1.08	70	0.864
DD10 - DD30	-0.28	70	> 0.999
DD20 - DD30	0.62	70	> 0.999

Table 4.2: Paired t-test results for progression values. **** p < .001; ** p < .01; * p < .05*

4.3.2.4 Player Experience and Correlation Analysis

Two-tailed Pearson correlations were calculated for the mean scores of the PXI, the performance metrics in the ND, ED10, ED20, ED30, DD10, DD20, and DD30 conditions, performance in the averaged ED and DD conditions, as well as age and gaming expertise for success rate and progression respectively. All Pearson values can be viewed in the correlation matrices for success in Table A1 and for progression in Table A2 in Appendix A.

As expected, all measures of WM were positively correlated. However, some correlations did not reach statistical significance: There were significant and strong positive correlations between ND, ED, and DD performance (all p-values < 0.001). Correlations were also significant and positive between most target-distractor difference conditions regarding success rates ($p < 0.05$), with the exception of ED30 and ED10, and ED20 and DD10, which were not significantly correlated. Regarding progression, all target-distractor difference conditions were highly correlated (all p-values < 0.001).

I did not have *a priori* hypotheses for relations between performance and PX metrics, so the following analyses were exploratory in nature. Figure 4.7 displays a boxplot of the means for each of the PXI scales including enjoyment.

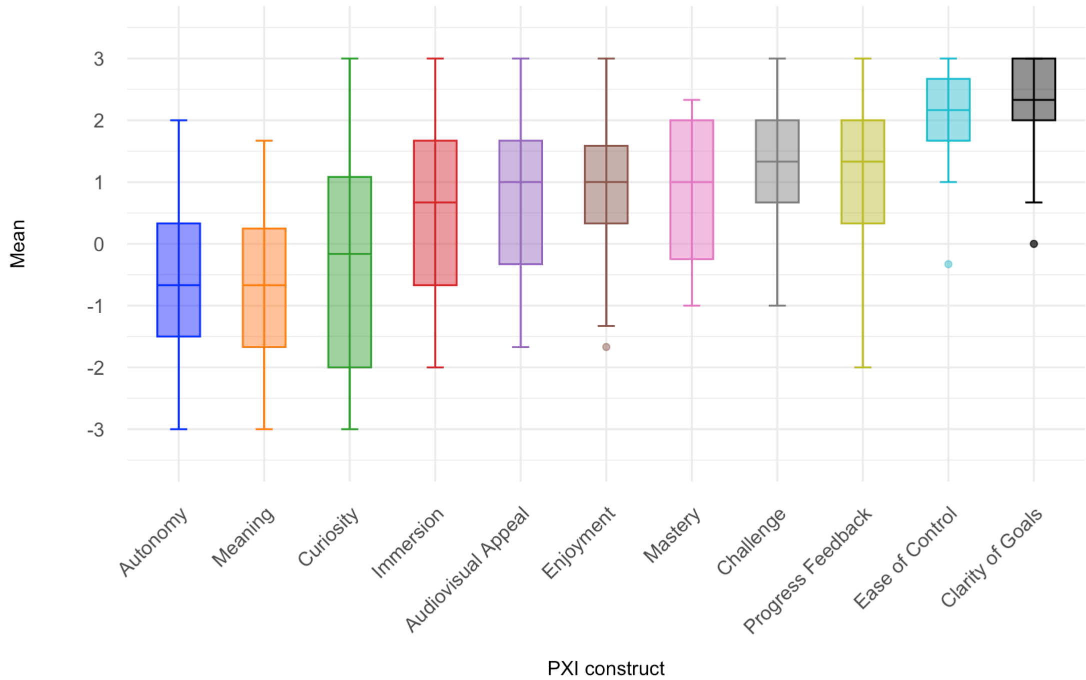

Figure 4.7: Boxplot for each of the scales of the PXI including enjoyment, sorted by mean scores. Boxes represent the interquartile range (IQR) between the third and first quartile (IQR = Q3 - Q1). Lower whiskers extend to Q1 - 1.5 * IQR; upper whiskers extend to Q3 + 1.5 * IQR. Horizontal lines within each box represent the median.

Enjoyment correlated with the averaged success rates for ED ($r = 0.50$, $p = 0.003$) and DD ($r = 0.36$, $p = 0.038$) conditions, and also with success rates in each of the ED conditions (ED10: $r = 0.37$, $p = 0.033$; ED20: $r = 0.49$, $p = 0.004$; ED30: $r = 0.40$, $p = 0.019$). Enjoyment did not correlate with success rate in the ND condition ($r = 0.26$,

$p = 0.135$). Regarding progression, enjoyment correlated with none of the performance metrics (lowest $p = 0.132$ between enjoyment and ED20). Enjoyment correlated with all PXI metrics ($p < 0.05$) except progress feedback ($p = 0.204$) and ease of control ($p = 0.059$).

Similar outcomes were obtained for audiovisual appeal, which correlated moderately to strongly with averaged success rates for both ED ($r = 0.53$, $p = 0.002$) and DD ($r = 0.38$, $p = 0.028$), and also with success rates in each of the ED conditions (ED10: $r = 0.42$, $p = 0.014$; ED20: $r = 0.51$, $p = 0.003$; ED30: $r = 0.38$, $p = 0.030$). Audiovisual appeal also correlated with success rate in the DD30 condition ($r = 0.38$, $p = 0.031$). As for enjoyment, regarding progression, audiovisual appeal did not correlate with any performance metric (lowest $p = 0.409$ between audiovisual appeal and ND).

There were further significant positive correlations between each ND, ED, and DD success rate and mastery ($p < 0.05$), progress feedback ($p < 0.05$), and ease of control ($p < 0.05$). Regarding progression, the only measure to show a significant positive correlation with performance in the ND condition and the averaged performance in ED and DD conditions was clarity of goals ($p > 0.05$). Ease of control further correlated significantly and positively with progression for ED and DD ($p > 0.05$).

Gaming expertise was positively correlated with success rate in the DD20 condition ($r = 0.34$, $p = 0.045$), and with all progression performance metrics except DD30 (ND: $r = 0.50$, $p = 0.002$; ED: $r = 0.45$, $p = 0.006$; DD: $r = 0.40$, $p = 0.015$; ED10: $r = 0.46$, $p = 0.005$; ED20: $r = 0.34$, $p = 0.040$; ED30: $r = 0.44$, $p = 0.007$; DD10: $r = 0.41$, $p = 0.012$; DD20: $r = 0.48$, $p = 0.003$). Age did not correlate with any other observed variable.

4.3.2.5 Regression Analysis

Having seen positive correlations between enjoyment and success rate for the WM task with each type of distraction (ED and DD), but no significant correlation for ND success, I further explored how WMC and distractor resistance may contribute to overall game enjoyment. To that end, a hierarchical regression analysis was calculated for each outcome measure: success rate and performance. Detailed results and standardised β-coefficients can be found in Table 4.3 for success rate and Table 4.4 for progression.

At Stage 1, ND performance was used to predict enjoyment (Model 1), then ED performance was entered at Stage 2 (Model 2), and finally, DD performance was added at Stage 3 (Model 3). Regarding success rates, the model with ND predicting enjoyment alone was not significant (adjusted $R^2 = 0.04$, $F(1, 32) = 2.36$, $p = 0.135$), however adding ED to the model accounted for an additional 19% of variation in enjoyment (adjusted $R^2 = 0.21$, $\Delta F(1, 31) = 7.90$, $p = 0.008$). ED success significantly and uniquely contributed to enjoyment when also taking into account ND success. Adding DD performance to the model at Stage 3 did not explain any additional variance and ED success was still found to make a significant and unique contribution to predicting enjoyment.

Model	Predictor	ΔR^2	β	p-value	Partial correlation
1	ND	0.07	0.26	0.135	0.26
2	ND	0.19**	-0.12	0.553	-0.11
	ED		0.58	0.008**	0.45
3	ND	0.00	-0.13	0.597	-0.10
	ED		0.58	0.029*	0.39
	DD		0.01	0.985	0.00

Table 4.3: Hierarchical regression results predicting enjoyment from success rates in each distractor condition. Model 1 predicts enjoyment from ND performance, Model 2 predicts performance from ND and ED performance, and Model 3 predicts enjoyment from ND, ED, and DD performance. Partial correlations for each predictor while controlling for the other predictor variables are displayed. **** $p < .001$; ** $p < .01$; * $p < .05$*

Regarding progression, Model 1 with only ND as a predictor was not significant (adjusted $R^2 = -0.03$, $F(1, 32) = 0.07$, $p = 0.796$), consistent with the results for success. Adding ED to the model at Stage 2 explained an additional 20% of variation in enjoyment (adjusted $R^2 = 0.15$, $\Delta F(1, 31) = 7.71$, $p = 0.009$). Here, both ND and ED significantly and uniquely predicted enjoyment, with a negative coefficient for ND and a positive coefficient for ED. The addition of DD performance to the model again did not explain any additional variance and both ND and ED continued to significantly and uniquely predict enjoyment.

Model	Predictor	ΔR^2	β	p-value	Partial correlation
1	ND	0.00	-0.05	0.796	-0.05
2	ND	0.20**	-0.86	0.015*	-0.42
	ED		0.92	0.009**	0.45
3	ND	0.01	-0.93	0.018*	-0.42
	ED		0.84	0.040*	0.37
	DD		0.17	0.650	0.08

Table 4.4: Hierarchical regression results predicting enjoyment from progression in each distractor condition. Model 1 predicts enjoyment from ND performance, Model 2 predicts performance from ND and ED performance, and Model 3 predicts enjoyment from ND, ED, and DD performance. Partial correlations for each predictor while controlling for the other predictor variables are displayed. **** $p < .001$; ** $p < .01$; * $p < .05$*

Since ED performance seems to contribute uniquely to enjoyment and target-distractor similarity at the stage of encoding seems to affect performance, I further explored this association by calculating a hierarchical regression with each target-distractor difference level (ED10, ED20, ED30) predicting enjoyment, controlling for ND. Detailed outcomes and standardised β-coefficients can be found in Table 4.5 for success rate and Table 4.6 for progression. At Stage 1, ND was used to predict enjoyment (Model 1), at Stage 2, ED10 was entered (Model 2), at Stage 3, ED20 was entered (Model 3), and at Stage 4, ED30 was entered (Model 4).

Model	Predictor	ΔR^2	β	p-value	Partial correlation
1	ND	0.07	0.26	0.135	0.26
2	ND	0.08	0.12	0.532	0.11
	ED10		0.31	0.106	0.29
3	ND	0.10	-0.06	0.765	-0.06
	ED10		0.12	0.561	0.11
	ED20		0.45	0.055	0.34
4	ND	0.02	-0.14	0.539	-0.12
	ED10		0.15	0.467	0.14
	ED20		0.33	0.205	0.23
	ED30		0.21	0.373	0.17

Table 4.5: Hierarchical regression results predicting enjoyment from ED success rates in each target-distractor similarity condition. Model 1 predicts enjoyment from ND performance, Model 2 predicts performance from ND and ED10 performance, and Model 3 predicts enjoyment from ND, ED10, and ED20 performance. Model 4 predicts enjoyment from ND, ED10, ED20, and ED30 performance. Partial correlations for each predictor while controlling for the other predictor variables are displayed. **** $p < .001$; ** $p < .01$; * $p < .05$*

For success rates, the first model was not significant (adjusted $R^2 = 0.04$, $F(1, 32) = 2.36$, $p = 0.135$). Adding ED10 at Stage 2 did not significantly explain additional variance (adjusted $R^2 = 0.09$, $F(1, 31) = 2.77$, $p = 0.106$), and neither did adding ED20 at Stage 3 (adjusted $R^2 = 0.17$, $F(1, 30) = 4.00$, $p = 0.055$), and ED30 at Stage 4 (adjusted $R^2 = 0.17$, $F(1, 29) = 0.82$, $p = 0.373$).

For progression, Model 1 again remained non-significant (adjusted $R^2 = -0.03$, $F(1, 32) = 0.07$, $p = 0.796$). Adding ED10 at Stage 2 did not significantly explain additional variance (adjusted $R^2 = 0.02$, $F(1, 31) = 2.45$, $p = 0.128$), however adding ED20 at Stage 3 explained an additional 15% of variation in enjoyment (adjusted $R^2 = 0.15$, $F(1, 30) = 5.75$, $p = 0.023$). In addition, at this stage, ND performance uniquely and negatively contributed to enjoyment. Adding ED30 at Stage 4 did not explain additional variance (adjusted $R^2 = 0.12$, $F(1, 29) = 0.17$, $p = 0.684$), and neither ND nor ED20 performance remained significant.

Model	Predictor	ΔR^2	β	p-value	Partial correlation
1	ND	0.00	-0.05	0.796	-0.05
2	ND	0.07	-0.45	0.158	-0.25
	ED10		0.48	0.128	0.27
3	ND	0.15	-0.63	0.043*	-0.36
	ED10		0.03	0.935	0.02
	ED20		0.73	0.023*	0.40
4	ND	0.01	-0.72	0.065	-0.34
	ED10		0.06	0.878	0.03
	ED20		0.64	0.092	0.31
	ED30		0.16	0.684	0.08

Table 4.6: Hierarchical regression results predicting enjoyment from ED progression in each target-distractor similarity condition. Model 1 predicts enjoyment from ND performance, Model 2 predicts performance from ND and ED10 performance, and Model 3 predicts enjoyment from ND, ED10, and ED20 performance. Model 4 predicts enjoyment from ND, ED10, ED20, and ED30 performance. Partial correlations for each predictor while controlling for the other predictor variables are displayed. **** $p < .001$; ** $p < .01$; * $p < .05$*

4.3.2.6 Direction of Target-Distractor Difference

In order to rule out potential effects of stimulus brightness per se rather than the relative distance to the target, two three-way ANOVAs with the factors direction (darker, brighter), target-distractor difference (Diff10, Diff20, Diff30), and condition (ED, DD) were calculated for both success and progression outcome variables. There were no significant main effects for direction regarding success rates ($F(1, 35) = 2.61$, $p = 0.115$) or progression ($F(1, 35) = 1.26$, $p = 0.269$), and no significant interactions between direction and target-distractor difference (success rates: $F(2, 70) = 0.35$, $p = 0.706$; progression: $F(2, 70) = 0.01$, $p = 0.987$) or condition (success rates: $F(1, 35) = 0.23$, $p = 0.638$; progression: $F(1, 35) = 2.02$, $p = 0.165$). The three-way interaction between direction, target-distractor difference and condition also remained non-significant for both success rates ($F(2, 70) = 0.397$, $p = 0.674$) and progression ($F(2, 70) = 0.26$, $p = 0.773$). These results do not suggest that the effects of target-distractor difference on performance are specific to distractors that are brighter or darker than the targets. The conducted analysis therefore focused on target-distractor difference, irrespective of the direction of this difference.

4.3.3 Discussion

The present study was conducted to investigate how target-distractor similarity affects game difficulty and WM performance when distractors are presented during periods of memory encoding and maintenance utilising a custom-designed video game. Associations between difficulty, performance, and PX metrics were further explored to gain initial insights into how the visual design of task-relevant and -irrelevant game elements may impact game difficulty and PX.

Overall, results revealed that distractors, irrespective of their visual characteristics and presentation period (encoding, delay), had a debilitating effect on performance compared to trials without distractors, indicating that the presence of task-irrelevant elements in video games can increase their difficulty. Furthermore, performance was better in conditions where distractors were presented in the delay period compared to when they were presented simultaneously with the path, implying not only that the mere presence of distractors can negatively affect performance, but also that such performance costs appear to depend on the timing of their presentation. On top of that, the hypothesis that performance is higher the larger the perceptual difference between target and distractor stimuli was supported: Performance gradually declined as target-distractor similarity increased, yet only when distractors were presented in the encoding period.

This variance in performance under different distractor conditions, both with regard to when they are presented, as well as with regard to their similarity to target items, emphasises the importance of considering the visual appearance of task-irrelevant elements in video game design, particularly during periods in which players need to encode information. Task-irrelevant stimuli that are very similar to the target information may cause distraction, hindering the effective encoding of the task-relevant material, which may have negative effects on PX.

While the present study did not allow for a direct comparison of PX metrics across different distractor conditions due to its within-subjects design, associations between performance and PX could be investigated. Generally, performance in the ND, ED, and DD conditions correlated highly, suggesting that all conditions required some shared abilities, which likely includes general WMC. Considering PX metrics, results revealed that enjoyment was associated with success rates in both distractor conditions (i.e., ED and DD), and not the ND condition. Furthermore, enjoyment was predicted by success rates in the ED condition, as revealed by the regression analysis. The fact that significant associations between performance and enjoyment were only observed in conditions with distractors, which, as stated above, were more difficult than trials without distractors, suggests that the presence of visual distraction in a video game may increase enjoyment. This could be because distractors also make the game more challenging, and challenge has been named a key element of video games that can improve PX [22]–[24].

Interestingly, except for the significant unique contribution of ED progression to enjoyment, these associations were only observed for success rates and not progression, indicating that it is particularly the successful completion of trials rather than absolute performance (as measured by progression) that may have caused the surge in enjoyment. The positive correlation between the PX metric 'mastery' and success rate but not between mastery and progression also supports this notion and suggests that adequate progress feedback may be an important game element that can lead to feelings of achievement and increase enjoyment.

Taken together, Study 4 revealed that the presence as well as the visual appearance of task-irrelevant game elements can modulate game difficulty. In addition, successfully overcoming trials with distractors was related to enjoyment, suggesting that challenge is an important game element, but particularly effective in eliciting enjoyment when players are also able to overcome it.

4.4 Study 5

4.4.1 Introduction

Study 4 has established a link between game difficulty and the presence of distractors as well as their visual similarity to target items at different stages of WM processing. Key findings indicated that the mere presence of distractors impairs memory performance, and also that performance declined with increasing target-distractor similarity in terms of brightness contrast. In addition, enjoyment appeared to be predicted by success rates in trials with distractors, particularly when they were presented during memory encoding. While Study 4 improved our understanding of the relationship between performance and PX, no conclusions could be made for the association between game difficulty and PX since every player played each game difficulty level, and PX was assessed only once for the entire game.

Yet, considering that the visual appearance of distractors reliably altered game difficulty, examining how difficulty changes due to visual characteristics of game elements are related to PX directly can provide useful insights for game design. Previous studies investigating the association between game difficulty and PX have produced mixed findings. While some argue that lower difficulty leads to higher enjoyment [23], [74], [217], others say that challenge is important for game enjoyment [49]. Since there are individual differences not only in PX and game difficulty preferences [34], but also in WMC and the ability to ignore distraction [30]–[33], difficulty may be a very individual experience, stemming from many different factors unique to each player. Whether there are still general effects of game difficulty related to these factors on PX is investigated in the present experiment. This is particularly important when considering that WM and the ability to ignore distracting information is a key cognitive skill that is required in many video games. Study 5 therefore seeks to examine the relationship between PX and WM-related game difficulty. In addition, it serves to replicate the findings of Study 4 in a between-subjects design which eliminates potential spill-over effects that may have occurred in the previous study and may strengthen the conclusions made previously.

4.4.2 Method

The study was approved by the Ethics Committee of the Department of Psychology at the University of York. The design and procedure, study hypotheses, as well as a data analysis plan were preregistered using the Open Science Framework repository (https://osf.io/pje2x). Deviations from the preregistration are described at the end of this section.

4.4.2.1 Participants

127 participants (77 female, 41 male, 7 other) aged between 18 and 60 years (M = 24.5, SD = 7.79) took part in the experiment. Participants were recruited online via the participant pool system SONA and the online survey platform Prolific, and they received either course credits or monetary compensation of £2.50 for their participation. No participants were excluded from the main analysis as specified in the preregistration. All participants gave informed consent ahead of the experiment and were debriefed after the study.

4.4.2.2 Experimental Design and Task

The experimental procedure was almost identical to the design of Study 4, with a few exceptions. First, difficulty was a between-subjects factor this time. Accordingly, there were three experimental groups that differed in target-distractor similarity. In Group Easy, distractors that were presented differed by 30% in brightness value from the target path, in Group Moderate, distractors differed by 20%, and in Group Hard, distractors differed by 10%. Participants were randomly allocated to one of the three groups. There were 51 subjects in Group Easy, 39 subjects in Group Moderate, and 37 subjects in Group Hard. The second alteration to the previous study was that only ED trials were included in this study since the previous outcomes did not show any significant effects for delay distractors. The current study thus had a 3x2 design, with group as a between-factor with three levels (easy, moderate, hard), and condition as a within-factor with two levels (ND, ED). Finally, the maximum reachable grid size was altered. In Study 4, grid size was limited to 7 fields in width and 7 fields in height to avoid exhaustion effects. Yet, since the results revealed that distractor performance was still very high in people who already reached high grid sizes, ceiling effects in distractor performance could be present for people who reached the maximum grid size. Thus, the maximum reachable grid size was set to 8x8 in order to gain more insights about people at the upper end of the grid size spectrum and their distractor filtering abilities.

Again, participants first completed a calibration procedure, where each participant's optimal grid size when no distractors were present was determined. This grid size was used for the main phase of the experiment. In distractor trials of the main experimental phase, 5 distractor circles appeared simultaneously with the target path. These distractors could either be brighter or darker than the target circles, but always differed by the same amount from the target circles within a group. Distractors were grey and had brightness values of 20% (H=0, S=0, B=20) and 80% (H=0, S=0, B=80) (Group Easy), 30% (H=0, S=0, B=30) and 70% (H=0, S=0, B=70) (Group Moderate), and 40% (H=0, S=0, B=40) and 60% (H=0, S=0, B=60) (Group Hard), resulting in target-distractor difference values of 10%, 20%, and 30%. There were 30 trials in the distractor condition (15 with the distractors darker than the target and 15 with the distractors brighter than the target). The number of ND trials was matched to the trials in the ED condition and so was also 30, and trials were randomised to limit expectation effects. Finally, participants were asked to complete the PXI questionnaire including the three questions for enjoyment [223]. Using the same measure for PX allows for comparisons between Studies 4 and 5. Two questions about participants' expertise in playing video games (years playing digital games, hours per week playing digital games) were further asked. The total duration of the experiment was around 20 minutes.

4.4.2.3 Data Analysis

As in Study 4, performance was examined across groups, which was again measured with the win-to-lose ratio across all trials within the respective condition (1: win, 0: lose; success rate) and as the number of moves participants were able to make before failing (progression). These two measures were used since Study 4 indicated that actual success may have separate effects on PX than mere ability. To calculate the progression measure, averaged game performance over the number of trials in each condition was used. For each of the two outcome measures, a two-factorial repeated-measures ANOVA with the factors condition (ND, ED) and group (easy, moderate, hard) was calculated. Follow-up comparisons were calculated where appropriate and corrected using Bonferroni-Holm. For the measurement of PX, the mean for all PXI scales, which consist of three questions each, was calculated. Cases with missing data within a scale were excluded. For each group, those scores were correlated with success rate and progression for each ND and ED, as well as age and gaming expertise, which was measured with the number of hours spent playing video games per week. For significant correlations of interest, further one-way ANOVAs were calculated to explore how PX measures directly compare across groups. As in Study

4, data was prepared for analysis using Microsoft Excel 365 [206], and statistical analyses were performed using IBM SPSS Statistics [207] and R Studio [227].

4.4.2.4 Deviation from Preregistration

I deviated from the preregistration in the same way as for the previous study: For the measure of progression, I did not use the ratio between target path length and reached path length, but the absolute number of moves a participant made before failing or succeeding. Since the preregistration for the current study was done before it was decided to use a different second outcome measure for Study 4 that takes into account a person's individual WMC, the progression measure for the current study also needs to be adjusted to ensure comparability.

4.4.3 Results

4.4.3.1 Descriptive Statistics

The average time participants spent playing video games per week was 7.87 hours (SD = 11.82; min: 0, max: 100). Participants have been playing video games for 14 years on average (min: 4, max: 44). The smallest reached grid size was 3 (3x3), and the largest reached grid size 8 (8x8), with a median grid size of 6 (6x6; $Mdn = 6$, $IQR = 2$). Reached grid size was roughly normally distributed, with 4 participants reaching the minimum grid size, accounting for 3.15% of the sample, and 12 participants reaching the maximum grid size, representing 9.45% of the sample. No signs of floor or ceiling effects were apparent from the distribution of grid sizes (see Figure 4.8). There were 51 participants in Group Easy, 39 participants in Group Moderate, and 37 participants in Group Hard.

4.4.3.2 Group Differences in Performance

I calculated two-way ANOVAs with the within-factor condition (ND, ED) and the between-factor group (easy, moderate, hard) for each outcome measure (success, progression).

For success, a main effect for condition was found ($F(1, 124) = 139.48$, $p < 0.001$, $\eta_p^2 = 0.53$) with a better performance in ND trials than in ED trials. The analysis also revealed a main effect for group ($F(2, 124) = 4.95$, $p = 0.009$, $\eta_p^2 = 0.07$). Condition and group further interacted ($F(2, 124) = 17.62$, $p < 0.001$, $\eta_p^2 = 0.22$). Simple main effects analysis revealed that while performance in the ND condition did not differ between groups (F(2,

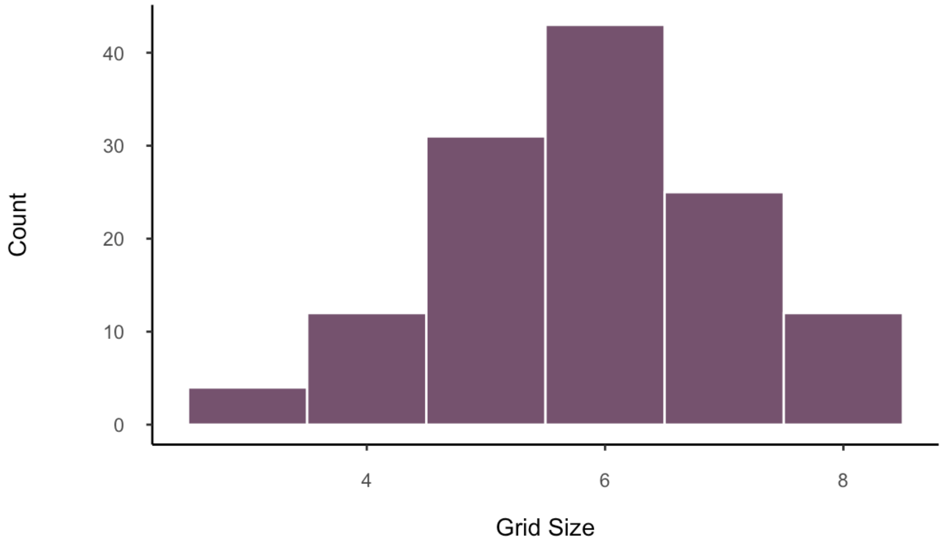

Figure 4.8: Distribution of reached grid sizes across groups.

124) = 1.00, p = 0.371, η_p^2 = 0.02), performance in the ED condition did differ (F(2, 124) = 12.40, p < 0.001, η_p^2 = 0.17) (see Figure 4.9). As pairwise comparisons revealed, performance in this condition was poorer in Group Hard compared to both Groups Easy and Moderate (see Table 4.7).

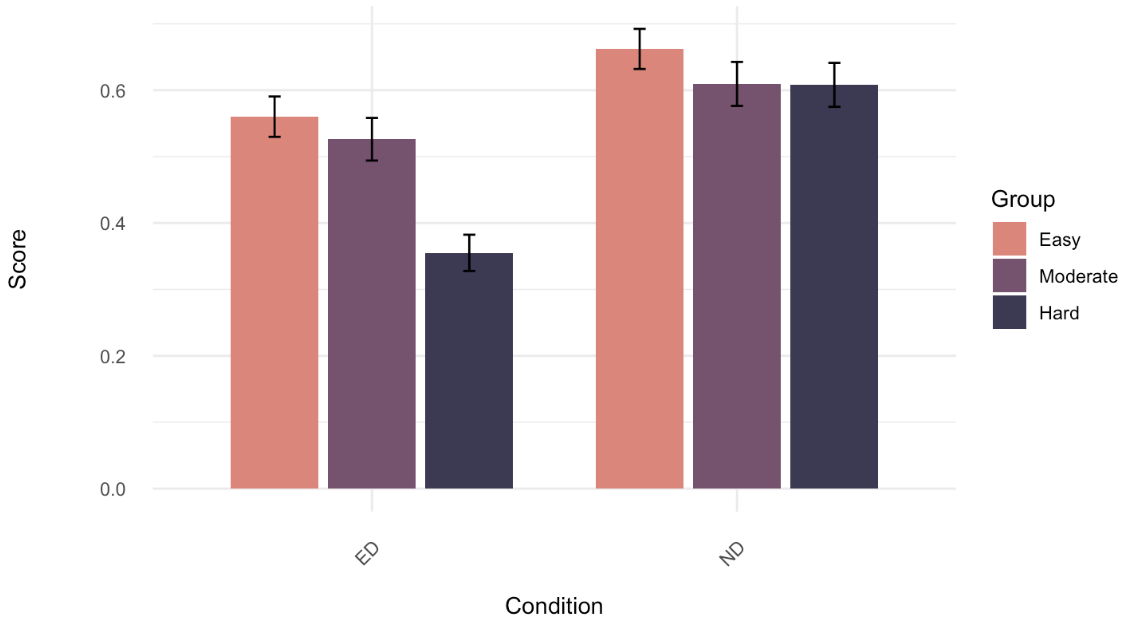

Figure 4.9: Success score by condition and group. Error bars represent +/- 1 standard error.

Pair	Mean Difference	t	p-value (Bonf.-Holm-adjusted)
ND_easy - ND_mod	0.05	1.20	0.696
ND_easy - ND_hard	0.05	1.20	0.696
ND_mod - ND_hard	0.00	0.02	0.977
ED_easy - ED_mod	0.03	0.81	0.421
ED_easy - ED_hard	0.21	4.77	< 0.001***
ED_mod - ED_hard	0.17	3.72	< 0.001***

Table 4.7: Pairwise comparisons for success rate. **** $p < .001$; ** $p < .01$; * $p < .05$*

Similar results were achieved for progression. There was also a significant main effect for condition ($F(1, 124) = 164.25$, $p < 0.001$, $\eta_p^2 = 0.57$), with higher performance in ND trials than in ED trials. There was no main effect for group however ($F(2, 124) = 2.88$, $p = 0.060$, $\eta_p^2 = 0.04$), suggesting that overall performance did not differ between groups. Yet, there was a significant interaction between condition and group ($F(2, 124) = 22.58$, $p < 0.001$, $\eta_p^2 = 0.27$) with simple main effects analysis revealing no effect of group in the ND condition ($F(2, 124) = 0.94$, $p = 0.040$, $\eta_p^2 = 0.02$), but a significant effect in the ED condition ($F(2, 124) = 6.49$, $p = 0.002$, $\eta_p^2 = 0.10$) (see Figure 4.10). Follow-up pairwise comparisons revealed a lower performance in Group Hard compared to Group Easy and Group Moderate in the ED condition (see Table 4.8).

Pair	Mean Difference	t	p-value (Bonf.-Holm-adjusted)
ND_easy - ND_mod	-0.44	-1.15	0.666
ND_easy - ND_hard	0.06	0.16	0.874
ND_mod - ND_hard	0.51	1.23	0.666
ED_easy - ED_mod	-0.38	0.99	0.324
ED_easy - ED_hard	1.04	2.71	0.015*
ED_mod - ED_hard	1.42	3.47	0.002**

Table 4.8: Pairwise comparisons for progression. **** $p < .001$; ** $p < .01$; * $p < .05$*

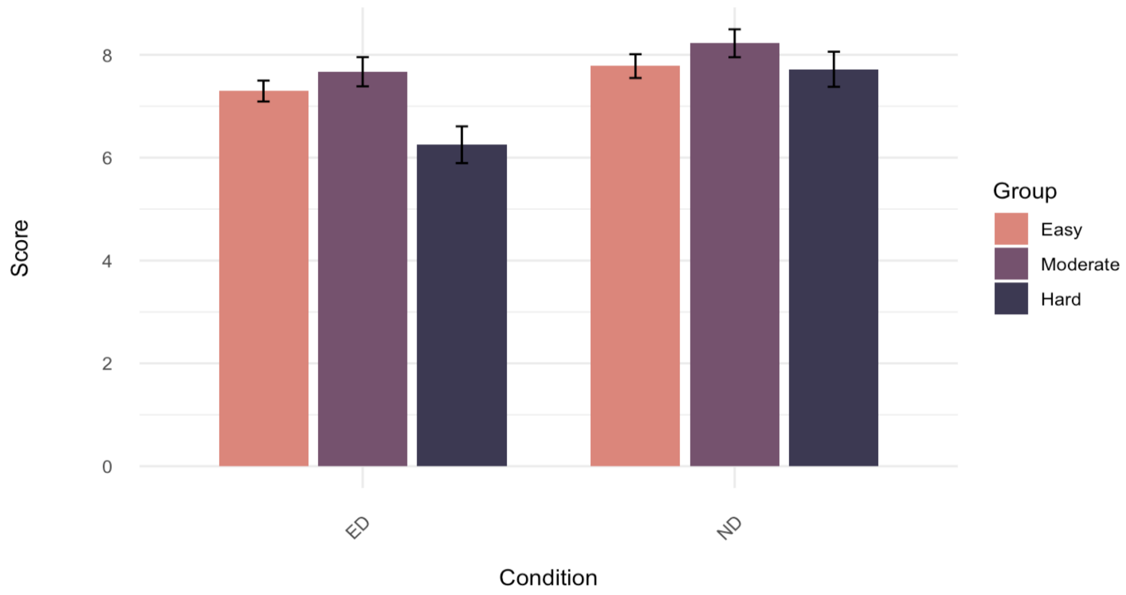

Figure 4.10: Progression score by condition and group. Error bars represent +/- 1 standard error.

Separate analyses were calculated for trials with darker and brighter distractors compared to the target path to determine whether group differences are dependent on the absolute brightness of distractors. Four one-way ANOVAs were performed for each success rate in trials with darker distractors (dark_success), success rate in trials with brighter distractors (bright_success), progression in trials with darker distractors (dark_prog), and progression in trials with brighter distractors (bright_prog). For all outcome variables, a significant group effect was found (dark_success: $F(2, 126) = 12.34$, $p < 0.001$, $\eta^2 = 0.17$; bright_success: $F(2, 126) = 8.75$, $p < 0.001$, $\eta^2 = 0.12$; dark_prog: $F(2, 126) = 5.03$, $p = 0.008$, $\eta^2 = 0.08$; bright_prog: $F(2, 126) = 7.31$, $p < 0.001$, $\eta^2 = 0.11$). Results of post-hoc comparisons are shown in Table A1. For each outcome variable, performance was significantly higher in Group Easy than in Group Hard, and significantly higher in Group Moderate than in Group Hard, mirroring the outcomes obtained in the overall analysis. The effects of target-distractor similarity on performance thus do not appear to be specific to distractors that are brighter or darker than targets, wherefore the subsequent analysis disregards the direction of this difference when looking at target-distractor similarity.

4.4.3.3 Associations Between Difficulty and Player Experience

To determine whether the difficulty of distractor filtering predicts PX irrespective of players' performance, univariate ANOVAs comparing each of the observed PX metrics across groups were calculated. Significant group effects were found for mastery and perceived balance. The main effect for group regarding mastery ($F(2, 116) = 3.57$, $p = 0.031$, $\eta_p^2 = 0.06$) was characterised by higher values in Group Easy ($M = 0.72$) than in Group Hard ($M = -0.07$; $t(116) = 2.65$; $p = 0.027$). The main effect for group regarding perceived balance ($F(2, 114) = 5.39$, $p = 0.006$, $\eta_p^2 = 0.09$), was characterised by significantly higher ratings in Group Easy ($M = 1.07$) than in Group Hard ($M = 0.33$; $t(114) = 2.76$; $p = 0.014$), and significantly higher ratings in Group Moderate ($M = 1.20$) than in Group Hard ($t(114) = 3.02$; $p = 0.009$). No group differences were found for any other observed PX metric.

4.4.3.4 Correlations Between Performance and Player Experience

Figure 4.11 depicts boxplots for each of the scales of the PXI including enjoyment. The lowest ratings obtained autonomy and meaning with negative mean scores, and the highest ratings yielded ease of control and clarity of goals. The means of the remaining scales were all located between 0 and 1.

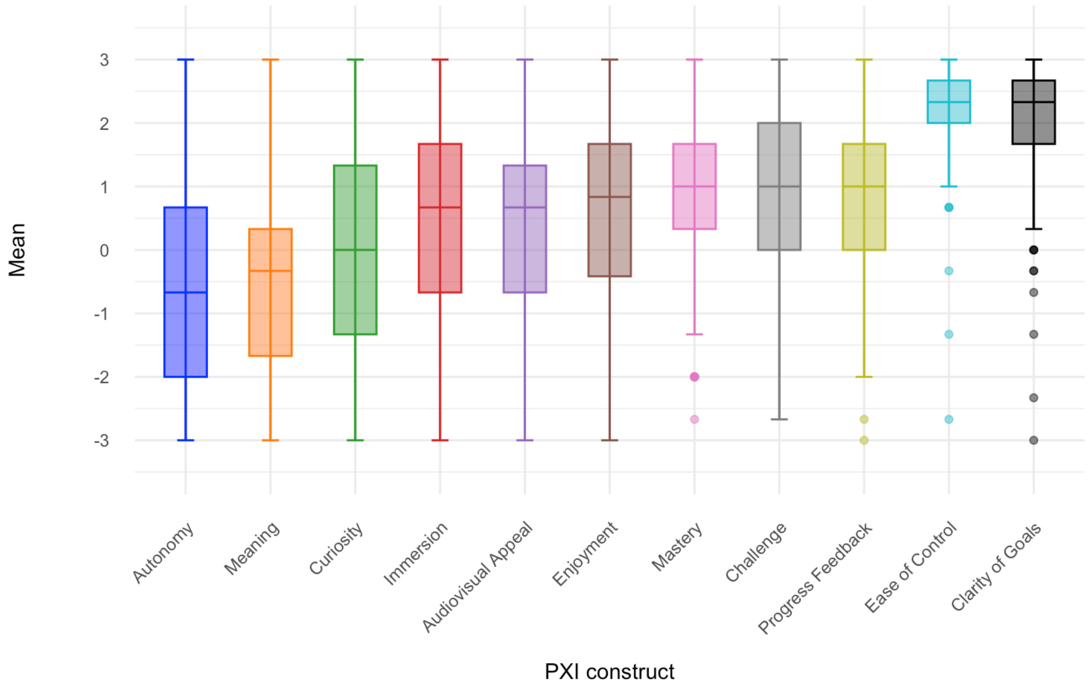

Figure 4.11: Boxplot for each of the scales of the PXI including enjoyment, sorted by mean score. Boxes represent the interquartile range (IQR) between the third and first quartile (IQR = Q3 - Q1). Lower whiskers extend to Q1 - 1.5 * IQR; upper whiskers extend to Q3 + 1.5 * IQR. Horizontal lines within each box represent the median.

The correlations between the performance metrics in each condition, the PXI measures, age, and gaming expertise are shown in Figure 4.12 for all groups combined, in Figure 4.13 for Group Easy, in Figure 4.14 for Group Moderate, and in Figure 4.15 for Group Hard. Correlation matrices with exact values for each group and across groups can be found in Appendix B (Tables B1, B2, B3, and B4).

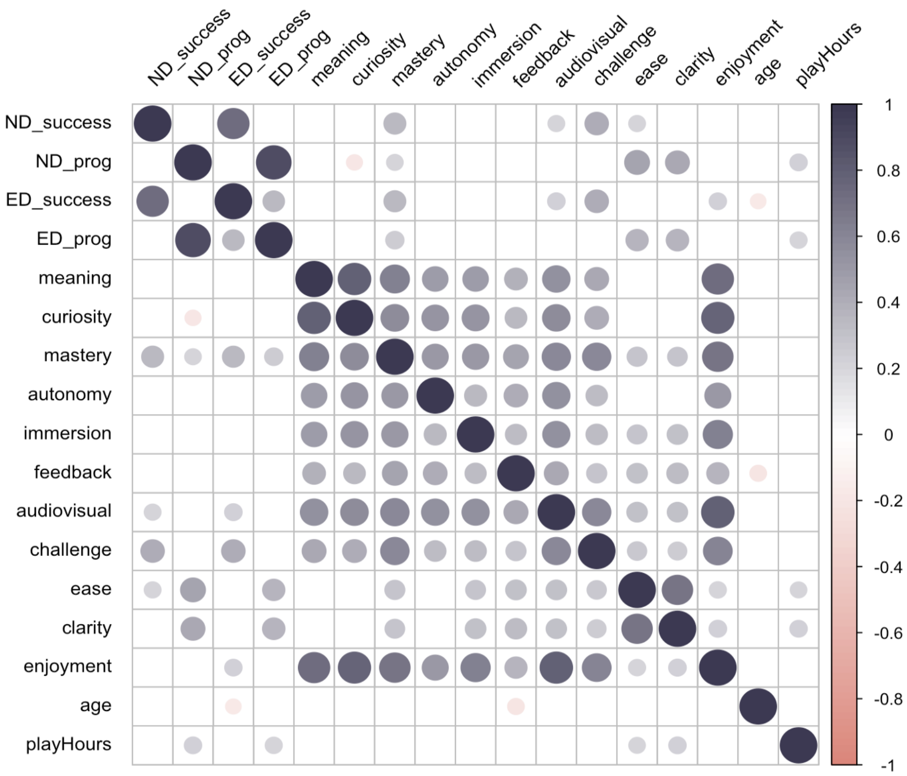

Figure 4.12: Correlation Matrix for performance measures, PXI values, age, and gaming expertise (playHours) across all groups.

Across groups, success rate in the ED condition was correlated with success rate in the ND condition (r = 0.73, $p < 0.001$), and progression in the ED condition was correlated with progression in the ND condition (r = 0.89, $p < 0.001$), as well as success in the ED condition (r = 0.34, $p < 0.001$). Mastery was associated with all performance metrics (ND_success: r = 0.36, $p < 0.001$; ED_success: r = 0.35, $p < 0.001$; ND_progression: r = 0.20, p = 0.028; ED_progression: r = 0.25, p = 0.007). Audiovisual appeal was positively correlated with success in the ND (r = 0.21, p = 0.026) and ED condition (r = 0.23, p = 0.015). Similarly, perceived balance was positively correlated with success in both conditions (ND: r = 0.41, $p < 0.001$; ED: r = 0.41, $p < 0.001$). Enjoyment was positively associated with success in the ED condition (r = 0.22, p = 0.022), whereas age was negatively correlated with the same metric (r = -0.18, p = 0.047). Age was further negatively associated with progress feedback (r = -0.20, p = 0.028). Gaming expertise was positively associated with progression in both conditions (ND: r = 0.22, p = 0.013; ED: r = 0.21, p = 0.018), with ease of control (r = 0.20, p = 0.034), and with clarity of goals (r = 0.22, p = 0.018)

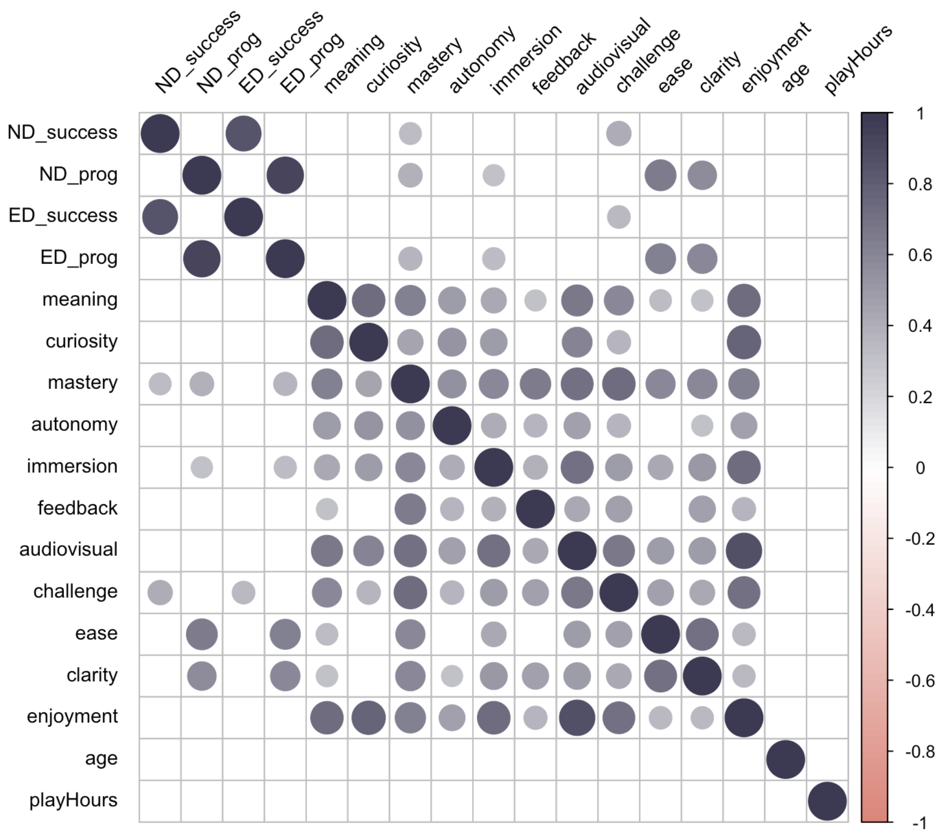

Figure 4.13: Correlation Matrix for performance measures, PXI values, age, and gaming expertise (playHours) in Group Easy.

In Group Easy, success in the ND condition was further correlated with success in the ED condition (r = 0.85, p < 0.001), and progression in the ND condition was highly correlated with progression in the ED condition (r = 0.92, p < 0.001). Mastery correlated with success (r = 0.33, p = 0.023) and progression (r = 0.39, p = 0.007) in the ND condition, and with progression in the ED condition (r = 0.37, p = 0.010). Immersion was associated with progression in both the ND (r = 0.31, p = 0.035) and ED condition (r = 0.34, p = 0.021). Perceived balance correlated with with both success metrics (ND_success: r = 0.41, p = 0.003; ED_success: r = 0.35, p = 0.013). Enjoyment did not correlate with any performance measure. Age and gaming expertise did also not correlate with any other variable.

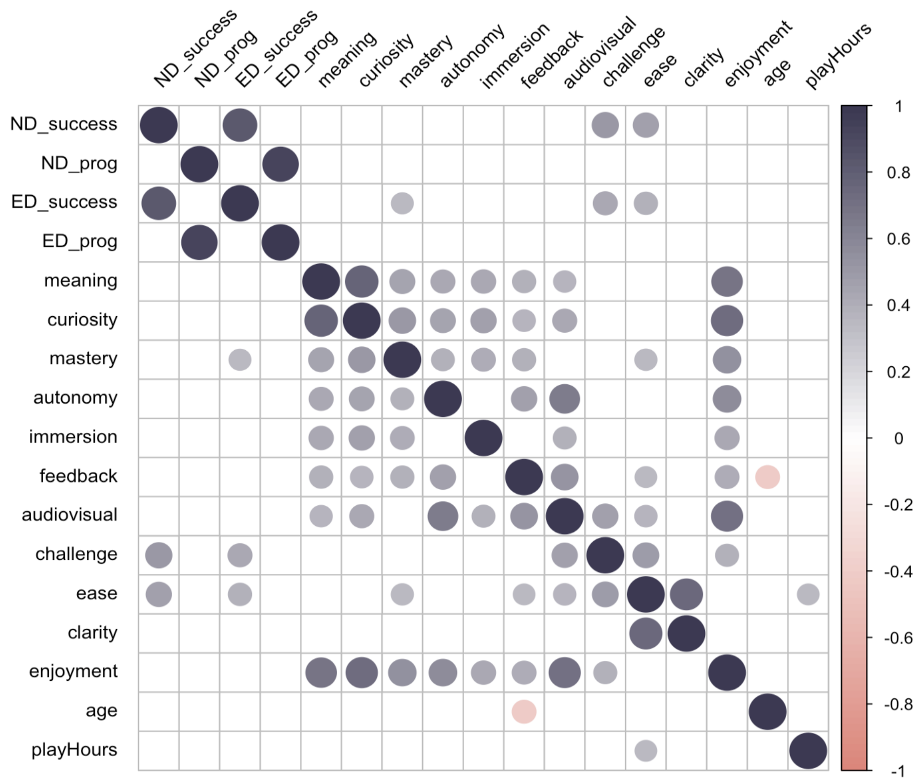

Figure 4.14: Correlation Matrix for performance measures, PXI values, age, and gaming expertise (playHours) in Group Moderate.

In Group Moderate, success in the ND condition was further correlated with success in the ED condition (r = 0.84, p < 0.001), and progression in the ND condition was highly correlated with progression in the ED condition (r = 0.93, p < 0.001). Mastery was associated with success in the ED condition (r = 0.35, p = 0.036). Unlike in Group Easy, immersion was not correlated with any measure in this group. Perceived balance correlated only with one performance measure, which was success in the ND group (r = 0.50, p = 0.002). Enjoyment again did not correlate with any performance measure. Age was not correlated with any performance metric, but was negatively associated with progress feedback (r = -0.41, p = 0.010). Gaming expertise did not correlate with any performance measure but did correlate with ease of control (r = 0.34, p = 0.041).

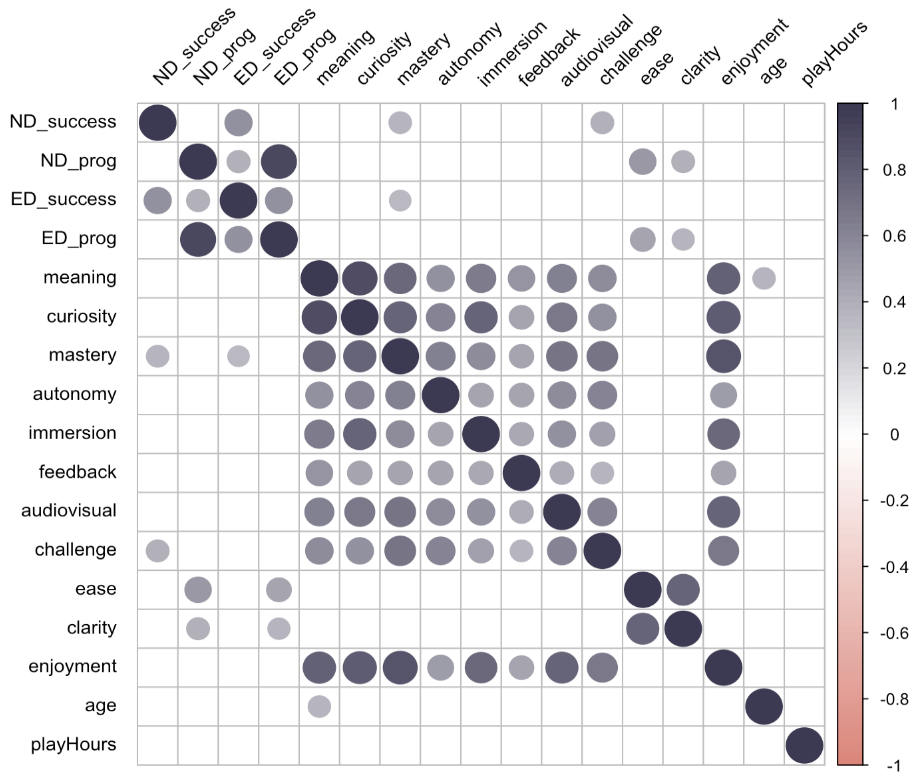

Figure 4.15: Correlation Matrix for performance measures, PXI values, age, and gaming expertise (playHours) in Group Hard.

In Group Hard, success in the ND condition was further correlated with success in the ED condition ($r = 0.55$, $p < 0.001$), and progression in the ND condition was correlated with success in the ED condition ($r = 0.39$, $p = 0.016$), and progression in the ED condition ($r = 0.91$, $p < 0.001$). Progression in the ED condition and success in the ED condition were further correlated ($r = 0.54$, $p < 0.001$). Mastery correlated with success in both the ND ($r = 0.38$, $p = 0.024$) and the ED condition ($r = 0.34$, $p = 0.041$). Similar to Group Moderate but different to Group Easy, immersion was not associated with any other measure in this group. Like in Group Moderate, perceived balance again correlated only with success in the ND group among all performance measures ($r = 0.38$, $p = 0.027$). Enjoyment did again not correlate with any performance measure. Age and gaming expertise were as in Group Easy not associated with any performance measure. Age was however associated with the PXI measure Meaning ($r = 0.37$, $p = 0.034$).

4.4.3.5 Associations Between Difficulty, Performance, and Player Experience

Since Study 4 revealed a unique influence of success rate in the ED condition on enjoyment, I sought to replicate this result in the current study. Similar to Study 4, a hierarchical regression was calculated. At Stage 1, ND success was used to predict enjoyment (Model 1), and then ED success was entered at Stage 2 (Model 2). Neither model was significant (Model 1: adjusted $R^2 = 0.02$, $F(1, 106) = 3.19$, $p = 0.077$; Model 2: adjusted $R^2 = 0.03$, $F(1, 105) = 2.21$, $p = 0.140$), indicating that when taking into account performance in conditions without distractors, success rates in ED trials did not have a separable influence on enjoyment, contrary to what was found in Study 4.

Further analyses were conducted to uncover whether the associations between performance and PX metrics as obtained through the correlation analyses are dependent on the difficulty of distractor filtering. Based on the obtained correlation results and evidence from the literature regarding associations between game difficulty, performance, and PX, a particular focus was placed on how enjoyment and perceived balance were predicted by player performance and game difficulty.

Enjoyment was predicted by overall success (ND and ED success combined) (Model 1a: adjusted $R^2 = 0.04$, $F(1, 106) = 5.00$, $p = 0.027$, standardised $\beta = 0.21$). Looking at ND success and ED success separately uncovered that this association was driven by success rates in ED trials: Enjoyment was predicted by ED success (Model 1b: adjusted $R^2 = 0.04$, $F(1, 106) = 5.44$, $p = 0.021$, standardised $\beta = 0.22$), but not by ND success (Model 1c: adjusted $R^2 = 0.02$, $F(1, 106) = 3.19$, $p = 0.077$, standardised $\beta = 0.17$). When group was added to Model 1a, the model became non-significant (adjusted $R^2 = 0.02$, $F(5, 102) = 1.38$, $p = 0.238$), with no significant predictor. Similar results were obtained when group was added to Model 1b (adjusted $R^2 = 0.01$, $F(5, 102) = 1.28$, $p = 0.278$) and Model 1c (adjusted $R^2 = 0.01$, $F(5, 102) = 1.25$, $p = 0.293$). These results suggest that enjoyment is driven by success in distractor filtering trials, but independent of the difficulty of distractor filtering (see Figure 4.16).

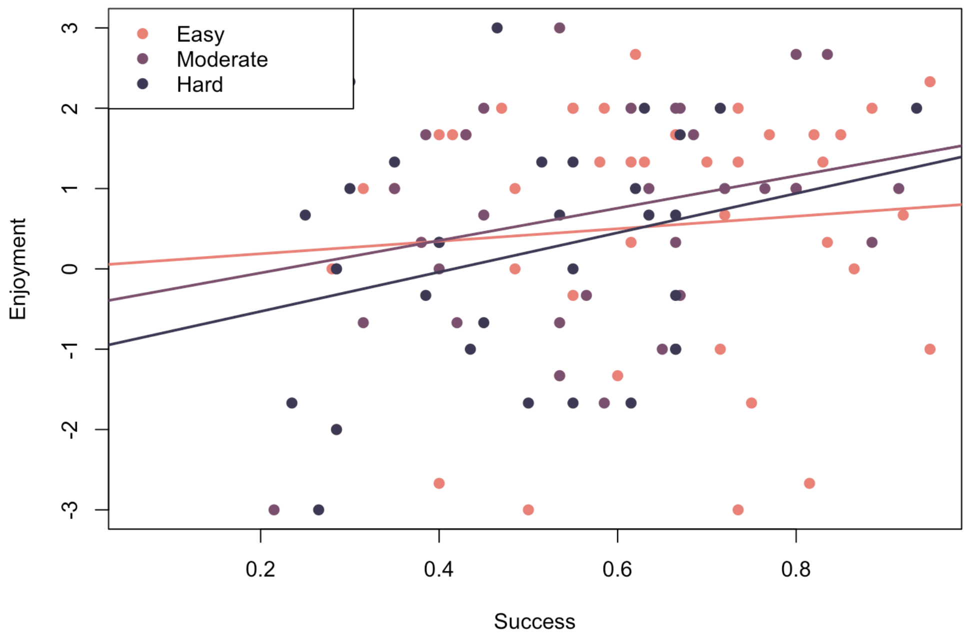

Figure 4.16: Enjoyment predicted by success rates across conditions for each group.

Perceived balance was positively correlated with success in ED and ND trials in Groups Easy and Moderate, and with success in ND trials in Group Hard. Moreover, a group difference was observed in perceived balance. Thus, I was interested in whether perceived balance was predicted by success metrics, and if so, whether this depended on the difficulty of distractor filtering. Perceived balance was predicted by overall success (Model 2a: adjusted $R^2 = 0.19$, $F(1, 115) = 27.59$, $p < 0.001$, standardised $\beta = 0.44$), as well as by ED success (Model 2b: adjusted $R^2 = 0.16$, $F(1, 115) = 22.99$, $p < 0.001$, standardised $\beta = 0.41$), and ND success (Model 2c: adjusted $R^2 = 0.16$, $F(1, 115) = 22.79$, $p < 0.001$, standardised $\beta = 0.41$). When adding group as a predictor to Model 2a, the model remained significant and explained an additional 6% of variance (adjusted $R^2 = 0.22$, $F(5, 111) = 7.42$, $p < 0.001$). However, only the predictor Overall Success was significant ($p = 0.005$, standardised $\beta = 0.36$). When adding group as a predictor to Model 2b, the model also remained significant and explained an additional 3% of variance (adjusted $R^2 = 0.17$, $F(5, 111) = 5.64$, $p < 0.001$). Again, only the predictor ED Success was significant ($p = 0.014$, standardised $\beta = 0.33$). When group was added as a predictor to Model 2c, the model remained significant and explained an additional 9% of variance (adjusted $R^2 = 0.23$, $F(5, 111) = 7.86$, $p < 0.001$). Again, however, only the predictor ND Success was significant ($p = 0.003$, standardised $\beta = 0.38$). These outcomes indicate that while there were overall group differences in perceived balance, the PX metric was mainly driven by success, irrespective of the distractor condition. These outcomes suggest that irrespective of the difficulty of distractor filtering, success predicts perceived balance (see Figure 4.17).

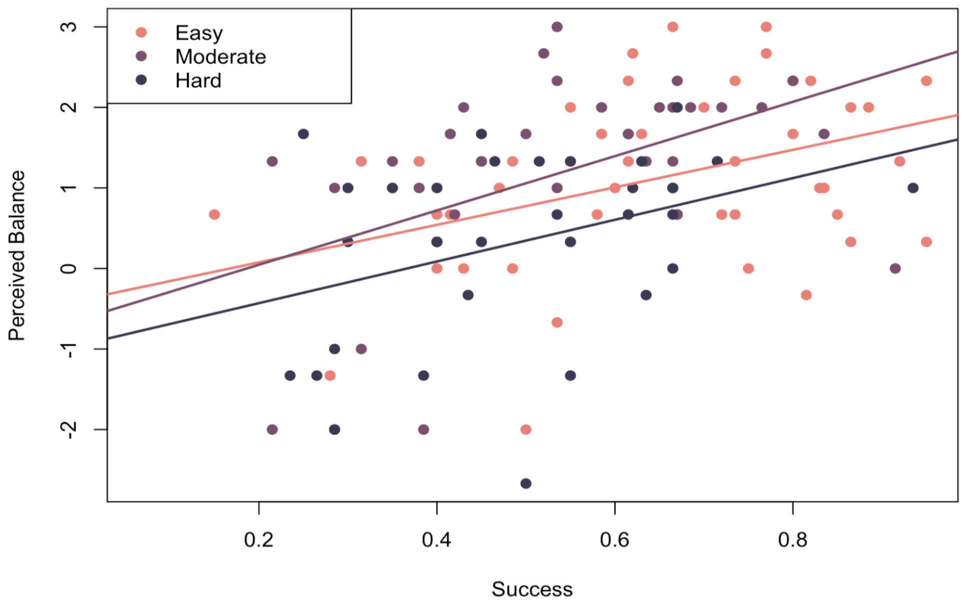

Figure 4.17: Perceived balance predicted by success rates across conditions for each group.

4.4.3.6 Direction of Target-Distractor Difference

In order to rule out potential effects of stimulus brightness per se rather than the relative distance to the target, t-tests across groups and separately for each group were calculated, comparing performance in dark trials (distractors darker than target) with performance in bright trials (distractors brighter than target). This was done for both success and progression as performance outcomes. Overall, the difference between dark and light trials was not significant for either success ($t(126)$ = -1.55, p = 0.124), or progression ($t(126)$ = -1.76, p = 0.081). However, when comparing dark and bright trials within groups, a significant difference in Group Moderate was found for both success ($t(38)$ = -2.40, p = 0.022) and progression ($t(38)$ = -2.30, p = 0.027). Performance was higher in trials where distractors were brighter than the target. In Groups Easy and Hard, no differences were found. Because of this finding, additional analyses were calculated comparing performance in trials with brighter distractors and trials with darker distractors separately to see whether the effects of target-distractor similarity (group) on performance depend on absolute stimulus brightness. The results of these analyses can be found at the end of section 4.4.3.2.

4.5 General Discussion

In two studies, the visual similarity between target items and task-irrelevant distractors and how that affects game difficulty and WM performance at different times of information processing were examined. Associations between game difficulty, performance, and PX metrics including enjoyment and perceived balance were further explored and investigated. While Study 4 served to provide a general idea of how target-distractor similarity may affect game difficulty, Study 5 served to strengthen this notion by replicating the findings in a between-subjects design. Moreover, Study 5 allowed for a more comprehensive account of the relationship between game difficulty, performance, and PX by directly comparing measures of PX across different difficulty modes.

4.5.1 The Influence of Distraction on Game Difficulty

Overall, both studies revealed that all distractors, irrespective of their visual characteristics and presentation period (encoding or delay), had a debilitating effect on performance when compared to trials without any distractors, suggesting that game difficulty can be increased when irrelevant items are present in the game world. This finding is in line with evidence from cognitive research reporting impaired WM performance in the presence of distraction [79], [118], [228]. Performance in DD conditions was overall better than ED performance, which suggests that ignoring distractors during encoding of the target path was more difficult than ignoring distractors that appear after the path has already been encoded. Contrary to these findings, the majority of studies looking at ED and DD resistance report better memory performance in the presence of encoding distractors as opposed to delay distractors [212], [229], [230]. A reason for this may be the nature of the task and stimuli in the present experiment compared to previous studies. In the present experiment, the to-be-remembered stimuli formed a coherent object (the path), which may be more resistant to delayed distraction than individual elements, since it may be represented in memory as one object. In the encoding period, such an object representation might not have been fully formed and could have further been disrupted by the presence of distractors that diverted attention away from the path. Also, since in the current experiment, participants knew that after encoding the path, any additional items are irrelevant, top-down influences could have helped participants retain their memory representation in the delay period.

Nonetheless, these results highlight the importance of visual design considerations during periods of memory encoding. There are many situations in video games where players are asked to retain certain information (e.g., quest targets, pathways, enemy attack patterns) and the current results suggest that stimuli presented during these periods may add (unwanted) difficulty to the task by distracting from the main goal. Acknowledging these potential consequences could be particularly relevant in games where the baseline difficulty of memory retention is high, such as in open-world games, which are prone to have many different moment-to-moment gameplay aims and a variety of visual stimuli competing with player attention [231], [232]. Future studies could research the impact of delayed versus simultaneous distraction in these more complex games to further inform how different types of games could be designed in a way that reduces unwanted challenge during memory encoding. It is also worth considering that individuals show differences in their ability to ignore distractors at encoding versus at maintenance [233] and may therefore be impacted differently by distraction during or immediately after memory encoding, which has implications for providing a consistent PX.

4.5.2 The Influence of Target-Distractor Similarity on Game Difficulty

Both studies further uncovered a gradual pattern of decreased performance as target-distractor similarity increases when distractors were presented during memory encoding, suggesting that the more similar task-relevant and task-irrelevant items are, the more difficult the game becomes. This was particularly pronounced for the smallest target-distractor similarity level (Diff10), for which performance was poorer than for both the medium and larger target-distractor similarity levels. Importantly, this was observed both within participants, who played at all three target-distractor similarity levels, as well as between participants. These results are in line with the stated hypotheses and consistent with findings reported in a recent study by Duan et al. [229], who reported a decreased efficiency in ignoring distractors when targets and distractors could only be distinguished by a pre-cue indicating target locations but were otherwise identical in appearance. However, this pattern was not observed in the delay period, where participants performed similarly well irrespective of the distractors' visual setup, suggesting that maintaining information in memory is more robust to the interference of similar distractors than encoding information.

These results further illustrate the importance of considering potential distraction through visual elements during memory encoding periods in video games. Non-goal-related game elements, and particularly those that are visually similar to goal-related elements could present a source of additional challenge for players. This can cause accessibility problems, not only for players with visual or cognitive impairments but also more generally when games are played in sub-optimal viewing conditions such as in bright sunlight or on small screens. To combat such issues, game accessibility guidelines recommend options to hide potentially distracting background movement or to adjust contrast to highlight essential game elements or information [e.g., 234]. El-Nasr and Yan [195] illustrate such a highlighting effect in an action-adventure game, where players' attention was drawn to a health object only once it changed its appearance from being very similar to the background to a bright red colour. The current results indicate that highlighting methods such as increasing contrast between target elements and distractors can not only aid the initial identification of relevant elements but also further help retain such information in memory. However, since distraction has to be interpreted with player aims in mind, such bottom-up stimulus characteristics are not the only relevant aspects. As El-Nasr and Yan also emphasise, attention is highly dependent on top-down influences such as where players expect certain items to appear [195], wherefore it can further be argued that the current aim of the player influences whether or not a stimulus can be considered relevant or potentially distracting. Given the present results, game design efforts might consider the visual similarity of stimuli unrelated to the current player goal in gameplay situations that demand attention and memory-encoding capabilities.

4.5.3 Effects of Game Difficulty on Player Experience

Due to its between-subjects design, Study 5 allowed for the comparison of PX metrics across different difficulty levels based on target-distractor similarity. Group differences were found for two out of the ten observed PX metrics: mastery and perceived balance. Since average performance was highest in the group with the least similar distractors and poorest in the group with the most similar distractors, it was to be expected that players in the former group naturally felt a higher sense of achievement and mastery.

Mastery was furthermore positively associated with enjoyment, which is in line with research by Ryan, Rigby and Pryzybylski [56], who demonstrated that feelings of competence constitute a major aspect of the motivational appeal of video games. However, although mastery was rated significantly lower by players in the most difficult group, enjoyment was not reduced in this group. This indicates that players may have still deemed their performance acceptable, resulting in similar ratings of enjoyment across groups.

Perceived balance was, similar to mastery, also rated highest in the group with the least similar distractors and poorest in the group with the most similar distractors. This suggests that the subjective balance between game difficulty and player skill is generally lower for harder games. It can be assumed that the difficulty level of the hard version of the utilised game was higher than what would have been the optimal difficulty level for most players in the current sample in relation to their skill. In the easier versions, where players generally performed better, players may have felt that the game was better suited for their abilities. While perceived balance was highly correlated with enjoyment, surprisingly no group differences were found for enjoyment, which indicates that although the game felt less balanced in the hard group, enjoyment did not suffer from this. Vice versa, in the easy group, which felt most balanced, enjoyment was not higher. This stands not only in contradiction to previous reports of higher enjoyment in easy compared to hard games [63] but also to flow theory, which assumes an inverted U-shaped relationship between the difficulty-skill balance of the game and the experience of flow, where too much difficulty in relation to the player's skill leads to anxiety and too little difficulty to boredom [235]. In fact, the predictions of flow theory are not universally corroborated [226], [236], [237], and other aspects such as novelty or curiosity may also be important predictors of game enjoyment [226].

Thus, while performance, mastery, and perceived balance, all of which showed a decline the more difficult the game was, were positively associated with enjoyment, difficulty as such did not seem to exert a significant influence on enjoyment. Instead, other factors may be present that keep enjoyment fairly consistent at different difficulty levels. For instance, in very hard games, the inherent challenges may boost enjoyment, consistent with the common notion of challenge as a major motivational aspect for video game entertainment [238], and repeated reports about the positive relationship between challenge and enjoyment in games [49], [166]. In very easy games instead, players may feel less frustrated since they do not fail that often. Other factors such as performance expectations, difficulty preferences, or player motives may also play a role [237]. For instance, Yee [239] proposed three player motivation categories: achievement, socialisation, and immersion. While socially oriented players are interested in working together in groups and socialising with other players, and immersion-focused players value story-driven aspects such as discovery and customisation, achievement-oriented players strive towards competition and challenge and towards progressing quickly in the game. It can therefore be assumed that achievement-oriented players are more likely to enjoy games that are more challenging than players who are motivated by socialisation or immersion. In sum, the present results suggest that objective difficulty per se is not an indicator of enjoyment. Individual factors including but not limited to the player's skill and difficulty preferences may be more important to consider.

4.5.4 Associations Between Performance, Player Experience, and Gaming Expertise

While difficulty per se seemed to have a limited influence on enjoyment, another important factor to look at is the skill of the player or their performance, which could also influence further aspects of PX. In the current study, this was measured with the ratio of trials in which players succeeded, irrespective of their actual WMC (i.e., success rate), as well as with the amount of information they could remember (i.e., progression). It has to be noted that the subsequent findings were the result of exploratory analyses as there were no specific hypotheses regarding any such associations.

Correlation analyses revealed that the performance metrics for ND, ED, and DD trials were highly intercorrelated, indicating that individuals who were more successful in trials without distraction were also better in trials with distractors. In addition, individuals who were better in trials where distractors were presented together with the target were also better in trials where distractors were presented during memory retention. This was expected since all conditions required shared abilities such as WM or the ability to follow task instructions.

4.5.4.1 The Performance-Enjoyment Relationship

Analysis of the PXI scales and performance measures revealed that enjoyment correlated with success rate in all conditions except the ND condition, indicating that a better performance in conditions with distractors was associated with higher enjoyment ratings, although in Study 5 this relationship was only observed when looking at all groups combined. This is in line with previous findings reporting that better performance leads to higher enjoyment [63], [74]. The absence of a correlation between enjoyment and performance in ND trials in both studies suggests that enjoyment is particularly related to distraction and not WM in general. In the present game, the aim was specifically linked to memory retention, so any additional challenge associated with distractors was related to the player's goal. It could therefore have been the case that distractors made the game more interesting and challenging, and players may have been particularly satisfied when they succeeded in these levels compared to levels without distractors. Consequently, this may have led to the higher ratings of enjoyment that were observed. Additionally, since grid size was calibrated to individual performance in the absence of distraction, ND success rates were similar in all players, while distractor success rates were also based on the individual abilities of the players to handle distraction, which were found to be associated with enjoyment.

Notably, no correlations were found between enjoyment and the number of moves participants were able to progress, indicating that enjoyment is not a result of participants' skill per se, but particularly of the successful completion of levels. A reason for this may be that players do not necessarily assess their own performance very well and rely on feedback given by the game [63], [74], particularly since they do not have a reference as to how well they are doing in comparison to others. Likewise, mastery was mostly found to be associated only with success rate but not progression, which also suggests that (objective) skill in terms of how far players proceeded did not necessarily elicit feelings of achievement when they did not complete the level successfully. The only exception was Group Easy in Study 5, where mastery was also associated with progression, albeit the correlation was weaker.

Thus, more skilful players - irrespective of whether this skill is related to WMC, their ability to follow instructions, or to handle game controls - did not necessarily feel that they did particularly well, especially when they did not successfully complete the level, and consequently may not have enjoyed the game as much as players who were less skilful objectively but had higher success rates. This is in line with previous studies reporting associations between player performance and enjoyment [63], [64], [217], [240], [241]. It has been suggested that such associations are mediated by feelings like self-efficacy [217] or by the satisfaction of intrinsic needs of competence [242], which is closely related to the PXI scale of mastery that was assessed in the current study [243]. Since the present results revealed that both enjoyment and mostly also mastery were associated with success rate but not progression, and further that enjoyment and mastery were correlated, players who actually succeeded and thus were rewarded with positive feedback and points may have attained a higher sense of mastery or competence and consequently enjoyed the game more.

From a game design perspective, this can have important implications regarding the length of levels or when players are rewarded since even though players might do well, positive player experiences may only arise from recognizing the successful completion of a task [63], [74]. Rewards are indeed thought to bear a central role in driving video game motivation [244], and in addition, the timing and frequency of rewards are crucial: breaking down complex tasks into smaller steps that allow for immediate feedback is considered much more effective in eliciting positive player experiences than providing a single reward for accomplishing a long-term goal [245]. In fact, progress feedback is considered crucial for games, regardless of the objective difficulty of the game [63], [74], and players "heavily depend on visible success and positive feedback provided by the game" [63, p. 9].

Regression analyses further revealed that the influence of success rates in the ED condition uniquely predicted enjoyment. Notably, in Study 4, this was similar for progression, with a significant unique contribution of ED performance to enjoyment when added to the regression model. Thus, it seems that when accounting for the shared variance between ND and ED performance, not only the experience of success, but the number of grid positions participants were able to remember in the presence of distractors contributed to enjoyment. The ND and ED condition differed merely in the presence of distractors in the ED condition, wherefore the unique part of ED progression may be specifically related to resisting distractors. DD performance did not significantly explain more variance in enjoyment when added to the model, suggesting that the ability to resist distraction during memory maintenance did not affect enjoyment. In Study 4, the regression analysis for progression also revealed a unique contribution of ND performance to enjoyment, yet only when ED was added to the model and thus the shared variance between ND and ED scores was effectively removed. Notably, the coefficient for ND was negative, whereas ED performance positively predicted enjoyment as mentioned beforehand. This may seem counterintuitive at first, however, it could again indicate that individuals who perform well in the absence of distraction may find the task less engaging or challenging, which could have led to lower ratings of enjoyment. Hence, a high performance per se does not necessarily enhance PX, but may only do so when the task is interesting or challenging, highlighting the importance of providing an adequate challenge level for each player.

Overall, the finding that ED performance explained significant variance in enjoyment for success and in Study 4 also for progression suggests that particularly ED resistance abilities may be an important predecessor of enjoyment in games that require players to retain information in the presence of distracting elements. The conducted follow-up analyses looking at whether this effect was specific to ignoring very similar or dissimilar distractors hint at a contributing unique effect of ignoring encoding distractors with a 20% target-distractor difference (ED20) when accounting for shared variance with performance in ND trials and trials with very similar distractors (ED10). Since it was found that trials with a 30% target-distractor difference were the easiest, and trials with a 10% target-distractor difference were the most difficult, this indicates that a good performance only in trials with medium difficulty leads to enjoyment. In players who performed well in easy or difficult trials, it is possible that feelings of frustration or boredom dampened a sense of achievement and thus limited enjoyment. Yet, it has to be noted that the unique contribution of ED20 became non-significant when performance in ED30 trials was added to the model and was further only observed for progression and not success rate. To yield more conclusive outcomes, future studies are needed that investigate more closely the unique effects of performance in different game difficulty modes on enjoyment.

4.5.4.2 Performance and Other Aspects of PX

A pattern similar to the one observed for enjoyment was found for the relationship between success rate and audiovisual appeal, yet compared to Study 4, in Study 5 not only success rates in ED trials but also in ND trials were associated with the PX metric. There were no correlations between progression and audiovisual appeal in either study, suggesting that high ratings of audiovisual appeal specifically depend on whether players actually succeed, and not how far they proceed within levels. This finding is in line with a study by Wiley et al. [246], who report a relationship between game performance and audiovisual appeal when success was rewarded with points, indicating that the visual feedback in the form of points after succeeding led to higher ratings of audiovisual appeal. The current game also featured a point system to reward successful completion of levels, but also to punish failures (albeit players were awarded twice as many points for succeeding as were deducted for not succeeding). Yet, the correlation results from Study 4 show that higher success rates were associated with experienced progress feedback, suggesting that players were more aware of positive feedback after success than negative feedback after failure, which may have led to the observed higher ratings of audiovisual appeal. Audiovisual appeal further correlated very highly with enjoyment, indicating that games that are perceived as more appealing are enjoyed more, a relationship that has been proposed before [247], [248]. Audiovisual design can thus be a powerful way to increase enjoyment in video games. It has to be noted that the game created for the present study was very minimalist in order to eliminate noise in examining subtle contrast differences and their effects on game performance. There were further no audio effects, thus providing very little opportunity for audiovisual appeal. Further studies are needed that directly manipulate visual and auditory features of games in addition to their difficulty and examine the relationship between players' success rate, progress feedback, perceived audiovisual appeal, and enjoyment in order to make more meaningful conclusions.

In Study 5 in particular, associations were found between perceived balance and success rates, but not progression. This also indicates that it is more the sense of achievement coupled with positive feedback rather than the actual skill of the player that leads to a higher sense of balance. Success rates in ED trials were associated with perceived balance only in Group Easy, indicating that a higher distractor filtering difficulty in terms of visual similarity between targets and distractors may have at least some influence on how balanced the game feels, even if players were still successful in these trials. Moreover, and also specific to Study 5, immersion was related to the progression measure in both conditions, but only in Group Easy. A higher progression value means a longer time spent on each trial. Assuming that with each field moved on the grid, the task becomes somewhat more difficult since a longer time has passed since having seen the path, progressing further may mean higher levels of concentration and in turn immersion.

4.5.4.3 The Relationship Between Performance and PX by Game Difficulty

Although adding the difficulty factor to the regression model predicting perceived balance from success rates explained somewhat more variance overall, PX generally did not seem to be dependent on the game difficulty induced by the visual similarity of distractors and targets. This indicates that while overall the introduction of distractors had positive effects given players were successful in these trials, increasing the visual similarity of these distractors to the target may not lead to higher levels of enjoyment or perceived balance when successful. In other words, whereas solving a more difficult task may lead to positive experiences, this may only be the case when the increase in difficulty is substantial and not when the increase in difficulty is rather subtle, which is supported by the more pronounced performance differences between the different distractor presentation conditions (i.e., ND, ED, and DD in Study 4) than the performance difference between the target-distractor similarity conditions.

4.5.4.4 Video Gaming Expertise and Performance

Finally, both studies revealed positive associations between the number of hours spent playing video games per week and progression in ND, ED, and DD conditions. Since higher grid sizes were generally more difficult since more grid positions need to be remembered, these associations were not observed for success rates (except in condition DD20 in Study 4). These results indicate that more experienced gamers tended to reach higher grid sizes, which is in line with empirical evidence of a relationship between video game expertise and cognitive functions, including perceptual abilities [181]–[183], attentional abilities [172] and WM [173], [174]. While these findings may suggest that video gaming can improve cognitive functions, the present results (as well as much of the existing empirical evidence) are only correlational, thus not allowing us to assume a causal link as to whether video gaming can improve cognitive functions or whether individuals with better cognitive abilities tend to play more.

4.5.5 Limitations and Future Directions

In order to eliminate differences in baseline ability (i.e., performance in the ND condition), an adaptation phase was implemented that should determine the optimal grid size for each individual. This procedure allowed individuals with a high WMC to play at a level where they would be less likely to feel bored and reduce the likelihood of frustration in individuals with a lower WMC. Yet, the adaptation phase might have not eliminated all individual differences in baseline performance. As it was quite short and only two out of three trials needed to be correct for the grid size to increase, chance could have influenced the grid size players reached. Since there was a 50 per cent likelihood of guessing the right grid position for every move (possible moving directions were right and down), there was still a 25 per cent chance to guess the last two moves correctly, and a 12.5 per cent chance to guess the last three moves correctly.

Another limitation related to the design of the game is that the spatial proximity between targets and distractors was not controlled. This was due to the varying grid sizes which made it impossible to ensure a consistent spatial distance between path and distractors. Consequently, on larger grids, the likelihood was higher that distractors were further away from the target since a fixed number of distractors was used for all grid sizes (except for grid size 3x3, where there was space for only 4 distractors, which all were adjacent to the path). This increased spatial distance could have reduced interference with memorizing the target path. There is evidence that spatial proximity between targets and distractors can interfere with visual search speed and accuracy [249]–[251], and also with visual WM [252], so subsequent studies may further investigate how spatial proximity between goal-relevant and irrelevant items affect difficulty in video games.

In Study 5, a significant difference in performance was found between dark and bright distractors in Group Moderate, although target-distractor similarity was identical. Performance was better for bright distractors than for dark ones. Bright distractors were more similar to the white background and could thus have been more easily ignored, although they were still clearly distinguishable against the background. In addition, in the easy group, bright distractors were even more similar to the background, but performance did here not differ between dark and bright trials. The observed effect may thus have just been an artefact, but it is important to note that results could be affected by this, since half of the trials may have been experienced as easier or more balanced than the other half.

In the current studies, only a single visual variable was observed, which was brightness. While this variable can be reliably used to alter the similarity between target and distractor stimuli, other visual variables may have separable effects from the ones observed in the present study. Variables such as size, colour, orientation, or shape may be utilised for further investigations to uncover potential effects on game difficulty and PX. It is important to note that some of these variables may also increase stimulus saliency, which can have separable effects from similarity on cognitive performance [153]. Investigating saliency as a second difficulty factor could yield further insights that can inform the design of goal-relevant and -irrelevant game elements.

Finally, to broaden the applicability of the findings, further studies should look at more complex games such as 3D action games or open-world games in which players are faced with multiple in-game goals in a highly saturated visual environment. The relationship between performance and enjoyment and the influence of distraction may in these contexts be more complex than in the currently examined very simple game.

4.6 Conclusion

The two conducted studies demonstrate that the presence of distractors can impact memory for task-relevant items and hence difficulty in video games that require players to retain information over short periods of time. More precisely, it was found that performance was most impaired when distractors were presented simultaneously with the to-be-remembered stimulus, and in these conditions, performance gradually declined with increasing target-distractor similarity, adding to existing evidence of greater distractor interference on visual search and memory performance with increased target-distractor similarity. These findings emphasise the importance of considering potential influences of both the presence and the visual appearance of goal-unrelated elements during memory encoding periods in video games in order to provide an optimal challenge level for players.

With regards to PX, exploratory analyses revealed positive correlations between performance and enjoyment, specifically during memory encoding, which fits within the extensive body of literature associating enjoyment with game performance. Moreover, rather than the actual memory or distractor filtering skill of the player, it seems to be particularly the successful completion of trials that drive this association, highlighting the importance of providing adequate progress feedback in video games. Notably, game difficulty per se did not influence enjoyment, although other metrics that were highly correlated with enjoyment, such as perceived balance and mastery, did decline with increasing difficulty. This suggests that other factors such as player preferences or motives may be more important than the mere difficulty in explaining game enjoyment. It is important to note that the current study utilised a very simple memory game and only looked at a single visual variable (brightness). Further studies are necessary that investigate such effects with different visual variables, and also within more complex game environments. Nevertheless, the present results highlight the importance of taking into consideration the visual design of both task-relevant and task-irrelevant game elements during cognitively demanding tasks and may be used to inform practices to reduce unwanted challenges or accessibility barriers for different kinds of players.

Chapter 5

Study 6: Adaptation based on Cognitive Abilities and its Effects on Performance and Player Experience

5.1 Motivation and Research Questions

The previous two studies demonstrated that game difficulty can be altered by introducing distractors to the game, and also by manipulating target-distractor similarity. The more similar task-irrelevant distractors were to currently task-relevant target items, the more performance was impaired, i.e., the more difficult the game became. The outcomes of Study 5 in particular have demonstrated that while players felt a higher sense of mastery and also that the game was more balanced to their skill the easier it was, enjoyment was not directly dependent on game difficulty. Rather, enjoyment appeared to depend on players' success rate, particularly in distractor trials, which was also found in Study 4. It was concluded that other factors such as individual preferences, motives, or skills are more important than difficulty in explaining game enjoyment. Naturally, such individual aspects differ from player to player, wherefore there is most likely no universal factor that makes a game enjoyable for all players. Instead, the games industry as well as games research have increasingly focused on providing a personalised gaming experience in the past years. A notable example of such a user-centred approach is the so-called Dynamic

Difficulty Adjustment (DDA). DDA relies on the principal assumption of flow theory, which assumes that optimal experience (i.e., a state of flow) is the result of an optimal balance between game difficulty and player skill, which is also a central aspect of Self-Determination Theory (SDT; see Section 2.1.2.2)). Although there are some difficulties associated with such an approach, like how to reliably determine this custom difficulty level for each player, several studies report positive effects of DDA on PX [24], [67], [69]–[71].

The present study examines whether adapting game difficulty based on players' individual Working Memory Capacity (WMC) as well as their skill to ignore distractors of varying similarity to target items leads to higher enjoyment, contributing to RQ 4: *How does a personalised gaming experience based on the ability to ignore distraction affect PX?*

The same custom-made video game as in the previous two studies was used here. Players were assigned to one of four groups, in which either the number of items to remember (i.e., the length of the path), the similarity between targets and distractors in terms of brightness, both, or neither was adapted to player skill. Thus, two adaptation types based on players' WMC as well as their ability to filter distraction, could be compared. Surmising that the assumptions of flow theory and of SDT hold true, we should observe that adapting the number of items to remember as well as target-distractor similarity to players' individual skills leads to heightened enjoyment compared to when neither is adapted. Since two different types of adaptation are investigated, the outcomes will further give more insights into how adaptation to different skills affects PX, which can inform an adequate selection of the "optimal" difficulty level for each player. Based on the findings of the previous studies as well as on further empirical evidence and theories from cognitive psychology and games research, the study hypotheses are as follows:

1. H1a: Success rate declines with increasing grid size
2. H1b: Performance in distractor trials declines with increasing target-distractor similarity
3. H2a: Perceived difficulty-skill balance will be higher when grid size is adapted than when it is not adapted to player skill
4. H2b: Perceived difficulty-skill balance will be higher when distractor shade is adapted than when it is not adapted to player skill

5. H3a: Enjoyment will be higher when grid size is adapted than when it is not adapted to player skill

6. H3b: Enjoyment will be higher when distractor shade is adapted than when it is not adapted to player skill

Interaction effects between grid size adaptation and distractor shade adaptation on performance and PX are further explored in order to make conclusions about the effects of adapting difficulty only to specific skills. Since this has not been investigated before, I did not have specific hypotheses regarding such associations and the associated calculations are exploratory in nature.

5.2 Methods

The study was approved by the Ethics Committee of the Department of Psychology at the University of York. The design and procedure, study hypotheses, as well as a data analysis plan were preregistered using the Open Science Framework repository (https://osf.io/98zn2). No deviations from the preregistration were made.

5.2.1 Participants

194 participants (114 female, 77 male, 3 other) aged between 18 and 55 years (M = 26, SD = 8.04) took part in the experiment. Participants were recruited online via the participant pool system SONA and the online survey platform Prolific, and they received either course credits or monetary compensation of £2 for their participation. No participants were excluded from the main analysis as specified in the preregistration. All participants gave informed consent ahead of the experiment and were debriefed after the study.

5.2.2 Experimental Design and Task

The experimental procedure was built upon Studies 4 and 5, and the participants' task was very similar: a path consisting of circles was presented on a rectangular grid, which participants were instructed to memorise. After the path had disappeared, players needed to follow the memorised path with their player character. In half of the trials, additional grey circles (distractors) were presented simultaneously with the path, and participants were instructed to ignore these.

The current experiment had three phases. In Phase 1, grid size was adapted to players' ability to remember a path of a certain length. This phase was almost identical to the grid adaptation phase in Studies 4 and 5, with the exception of the shade of the target circles which was changed from grey to black in the current study (see below). Participants started at a grid size of 4x4, and if they remembered at least two out of three paths correctly, grid size increased by 1 field in width and 1 field in height. If they remembered less than two out of three paths correctly, grid size decreased again. The minimum grid size was 4x4 and the maximum grid size was 8x8. Phase 1 therefore allowed for determining a grid size at which players' skill was aligned with their WMC. In Phase 2, the grid size was fixed at 6x6, which previous studies identified as the grid size that the majority of players reached. A pilot study with 5 participants further confirmed that both larger as well as smaller grid sizes were reached, wherefore it can be assumed that a grid size of 6x6 will less likely lead to ceiling or floor effects. Phase 2 served to identify the level of target-distractor similarity that reflects a balance between players' skill to ignore distraction and the difficulty of distractor discriminability. Players were again instructed to memorise a path, this time with distractors present simultaneously with the path. In the first three trials, distractors differed by 50% in brightness from the black target circles (i.e., distractors had a grey value of H=0, S=0, B=50, targets had a value of H=0, S=0, B=0). If participants succeeded in at least two out of these three trials, distractor brightness decreased by 10%, down to a target-distractor similarity of 10%. If players got less than two trials correct at a certain level, target-distractor similarity increased again by 10%, up to 50%. As mentioned above, black circles were used as targets, and circles with gradually brighter shades as distractors. This alteration was made in order to allow for more target-distractor similarity steps. Since the previous studies did not suggest that there are any differences in the effect of target-distractor similarity on difficulty and performance as to whether distractors are brighter or darker than the target, there was no need to include both brighter and darker distractors in the current study. All possible distractor colours were thus 10% (H=0, S=0, B=10), 20% (H=0, S=0, B=20), 30% (H=0, S=0, B=30), 40% (H=0, S=0, B=40), and 50% (H=0, S=0, B=50). Each adaptation phase consisted of 18 trials.

After completing both adaptation phases, the main phase commenced. Like in Studies 4 and 5, participants were instructed to memorise the target path, ignore any distractors that were presented in half of the trials, and afterwards follow the memorised path with their player character. In this study, however, grid size and distractor shade were fixed to one value. Players were allocated to one of four groups, in which either (a) grid size, (b) distractor shade, (c) both grid size and distractor shade, or (d) neither was adapted to players' individual skill, which was determined in Phases 1 and 2 of the experiment. Where grid size was not adapted, the fixed grid size of 6x6 was chosen, similar to the adaptation phase. Since this was the median grid size players reached in both previous studies as well as in a pilot study, choosing this grid size increased the chance that the game was easy for some players and hard for other players in relation to their skill. Similarly, where distractor shade was not adapted, a fixed shade of 30% was chosen. Since no data from previous studies existed concerning the highest distractor shade where players would still succeed in the majority of trials, this value was based on a pilot investigation, which confirmed that participants reached both higher as well as lower target-distractor similarity values than 30%. Again, doing this reduced the risk that all players for whom distractor shade was not adapted played at an easy level or hard level in relation to their skill, and increased the chance that this was evenly distributed with some playing at an easier level and some at a harder level. In total, there were 15 distractor trials and 15 trials without distractors. As in previous studies, trials were randomised to limit expectation effects.

Finally, like in Studies 4 and 5, participants were asked to complete the PXI questionnaire including the three questions for enjoyment [223]. Two questions about participants' expertise in playing video games (years playing digital games, hours per week playing digital games) were further asked. The total duration of the experiment was around 17 minutes.

5.2.3 Data Analysis

The same outcome measures as for the previous two studies were chosen to allow for comparability: success rate, which is the win-to-lose ratio across all trials within the respective condition (1: win, 0: lose), and progression, which is the average numbers of moves participants were able to progress before failing or succeeding across trials within the respective condition. In order to replicate previous results, two paired samples t-tests (one for success rate and one for progression) were calculated to compare performance in trials with and without distractors. To address hypothesis H1a, a two-way mixed ANOVA with the within-factor condition (2 levels: ND, ED), the between-factor grid size (5 levels: 4x4, 5x5, 6x6, 7x7, 8x8), and success rate as the outcome measure was calculated. Similarly, for hypothesis H1b, two one-way ANOVAs with the between-subject factor target-distractor similarity (10, 20, 30, 40, 50) were calculated for both success rate and progression. To investigate hypotheses H2a and H2b, as well as H3a and H3b, 2x2 ANOVAs were conducted with the factors grid adaptation (yes/no) and distractor adaptation (yes/no) for perceived balance and enjoyment as the two outcome measures. Follow-up comparisons were corrected using the Bonferroni-Holm method.

To further explore how PX was related to game difficulty, linear regressions predicting PX measures from grid size and distractor shade were calculated. I further explored how the relative difficulty of grid size or distractor shade (easier, harder, or balanced relative to players' skill) affected PX with a focus on enjoyment and perceived balance by calculating linear regressions predicting the relevant PX metric from the relative grid size or distractor shade difficulty. Finally, in an attempt to replicate previous results regarding the association between performance and PX, further linear regressions were calculated predicting PX measures (enjoyment, perceived balance) from performance.

Research data was prepared for analysis using Microsoft Excel 365 [206] and statistical analyses were performed using IBM SPSS Statistics [207] and R Studio [227].

5.3 Results

5.3.1 Descriptive Statistics

On average, participants spent 8.1 hours per week playing video games ($SD = 11.8$, min: 0, max: 60), and have been playing video games for 16 years (min: 2, max: 35). Participants reached a grid size of 6x6 (reached by 30.4% of people) on average, with the minimum reached grid size being 3x3 (note that this entails participants who failed in at least 2 out of the 3 easiest 4x4 trials, but in the main phase still played at a grid size of 4x4), and the largest being 8x8 (reached by only one person, which represented 1.5% of the total sample; see Figure 5.1). The average target-distractor difference level participants reached was 30% (reached by 19.1% of people), with a minimum of 10% (reached by 6.7%) and a maximum of 50%. 33.5% of participants did not surpass the 50% target-distractor similarity level (see Figure 5.2).

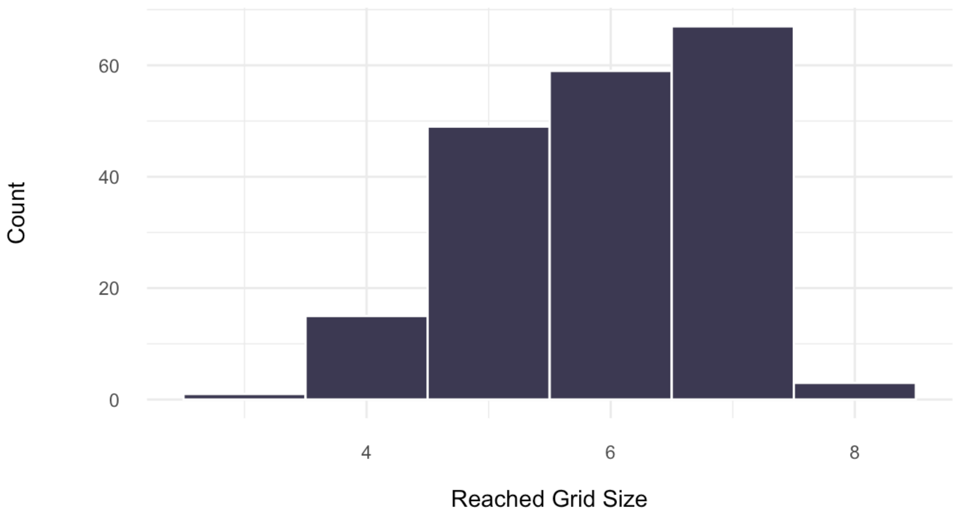

Figure 5.1: Reached grid sizes across all groups. Values on the x-axis refer to the number of fields in width and height (i.e., 4 refers to a 4x4 grid)

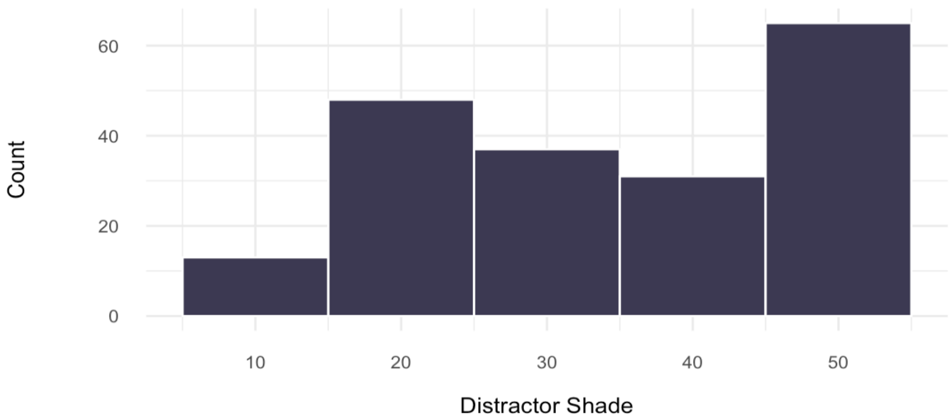

Figure 5.2: Reached distractor shades across all groups. Values on the x-axis refer to the percentage difference in brightness from the black target circles.

When looking at the relative difficulty level at which players in non-adaptive groups played the main phase of the experiment, more participants played at an easier than harder or balanced level regarding grid size (see Figure 5.3), and more players played at a harder level than easier or balanced level with regard to distractor difficulty (see Figure 5.4).

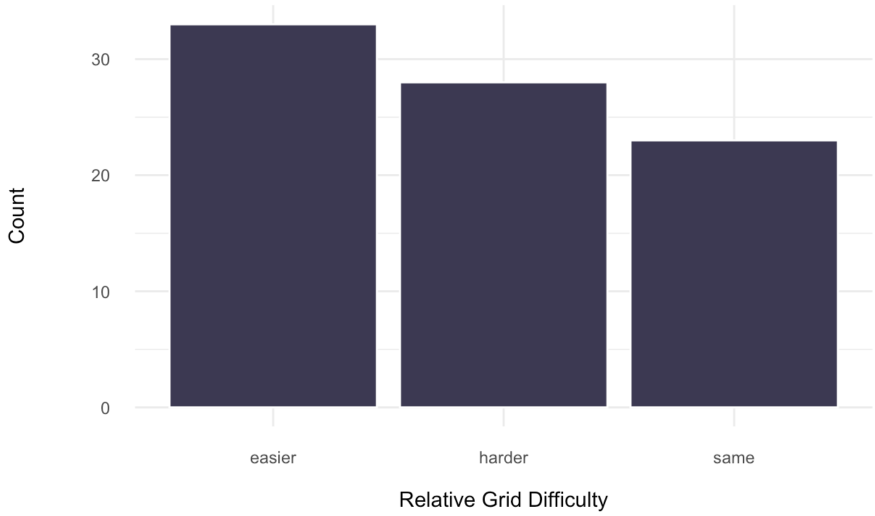

Figure 5.3: Relative grid size difficulty in groups where grid size was not adapted to players' individual skill.

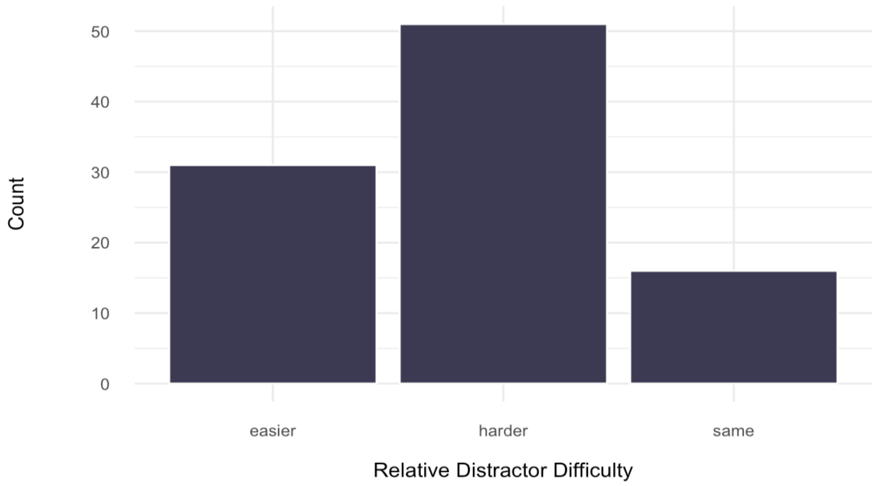

Figure 5.4: Relative target-distractor difficulty in groups where distractor shade was not adapted to players' individual skill.

5.3.2 Performance in Trials With Versus Without Distractors

A one-sided paired-samples t-test revealed a higher success rate in ND trials ($M = 0.68$, $SD = 0.19$) than in ED trials ($M = 0.60$, $SD = 0.20$; $t(193) = 6.52$, $p < 0.001$). Similarly, a further one-sided paired-samples t-test revealed a higher average number of moves in ND trials ($M = 8.49$, $SD = 1.32$) than in ED trials ($M = 8.12$, $SD = 1.28$; $t(193) = 6.03$, $p < 0.001$), replicating the results of the previous studies.

5.3.3 Difficulty and Performance

Success Rate

A repeated-measures ANOVA for success rate as outcome variable, the within-factor condition (ED, ND), and the between-factor grid size (4x4, 5x5, 6x6, 7x7, 8x8) revealed a main effect for grid size ($F(4,\ 189) = 11.61$, $p < 0.001$, $\eta_p^2 = 0.20$), as well as a main effect for condition ($F(1,\ 189) = 11.64$, $p < 0.001$, $\eta_p^2 = 0.06$). No significant interaction was found. Follow-up pairwise comparisons revealed significant differences in success rate between 4x4 and 6x6 ($p = 0.007$), 4x4 and 7x7 ($p < 0.001$), 5x5 and 6x6 ($p < 0.001$), 5x5 and 7x7 ($p < 0.001$), and 6x6 and 7x7 ($p = 0.004$). With the exception of grid size 8x8, which only one person reached, success rate declined with increasing grid size (see Figure 5.5).

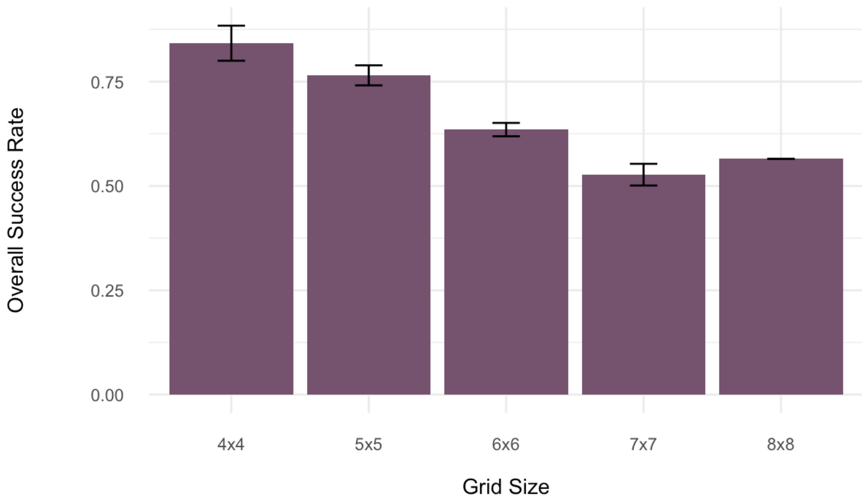

Figure 5.5: Overall success rates by grid size. Error bars represent +/- 1 standard error.

A univariate ANOVA for success rate in the ED condition as outcome variable and target-distractor similarity as independent factor (10, 20, 30, 40, 50) revealed a main effect ($F(4,\ 189) = 2.95$, $p = 0.021$, $\eta_p^2 = 0.06$). Follow-up pairwise comparisons revealed a significant difference only between shades 40 and 50 ($p = 0.020$), with a better performance at shade 40 ($M = 0.71$) than at shade 50 ($M = 0.52$; see Figure 5.6).

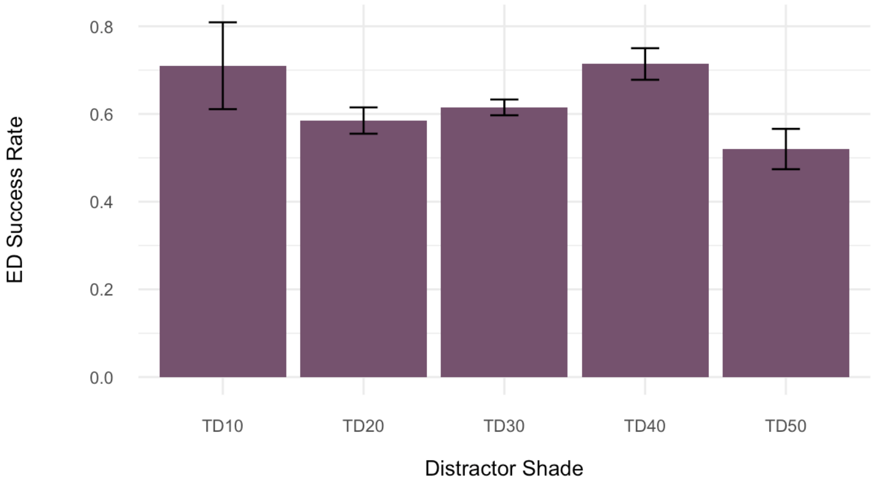

Figure 5.6: ED success rates by distractor shade. Error bars represent +/- 1 standard error.

Progression

Another univariate ANOVA with the independent factor target-distractor similarity was calculated for the outcome variable ED progression. Again, a main effect that was slightly larger than for ED success was found ($F(4, 189) = 5.94$, $p < 0.001$, $\eta_p^2 = 0.11$), with significant differences between shades 20 and 50 ($p < 0.001$), between shades 30 and 50 ($p < 0.001$), and between shades 40 and 50 ($p = 0.007$), as revealed by follow-up pairwise comparisons (see Figure 5.7). Progression was poorest at a distractor shade of 50.

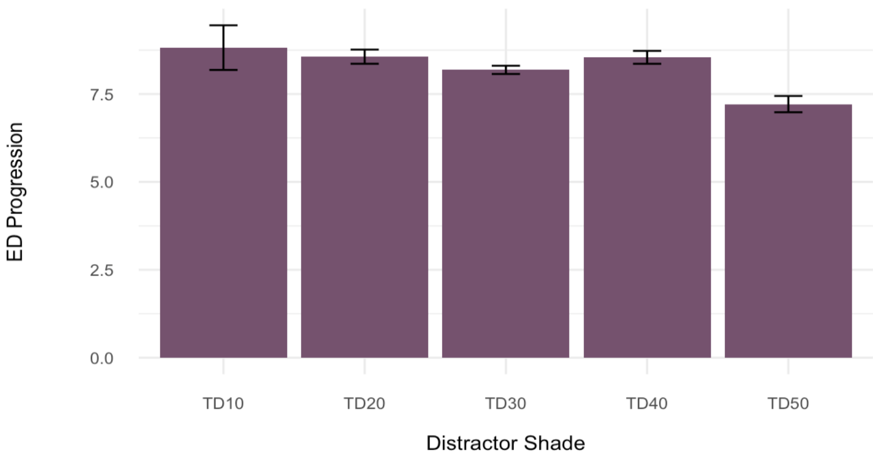

Figure 5.7: ED progression by distractor shade. Error bars represent +/- 1 standard error.

5.3.4 Adaptation and Player Experience

To investigate whether difficulty adaptation of either grid size or distractor shade affects PX, a two-way ANOVA with the outcome measure enjoyment and the factors grid adaptation (yes/no) and distractor shade adaptation (yes/no) was calculated. No significant main effects or interactions were found (grid adaptation: $F(1,\ 180) = 0.24$, $p = 0.626$, $\eta_p^2 = 0.00$; distractor adaptation: $F(1,\ 180) = 0.00$, $p = 0.892$, $\eta_p^2 = 0.00$; interaction: $F(1,\ 180) = 0.04$, $p = 0.839$, $\eta_p^2 = 0.00$). Similarly, the two-way ANOVA for the outcome measure perceived balance didn't yield significant main effects or interactions (grid adaptation: $F(1,\ 185) = 0.11$, $p = 0.740$, $\eta_p^2 = 0.001$; distractor adaptation: $F(1,\ 185) = 0.01$, $p = 0.907$, $\eta_p^2 = 0.00$; interaction: $F(1,\ 185) = 0.23$, $p = 0.630$, $\eta_p^2 = 0.00$).

5.3.5 Difficulty and Player Experience

Similar to Study 5, I further investigated whether game difficulty per se affected measures of PX. Linear regressions were calculated to determine how grid size or distractor difficulty affects these measures. Significant effects were found for perceived balance, which was predicted by distractor shade ($F(1,\ 187) = 3.93$, $p = 0.049$, adj. $R^2 = 0.015$), with a lower perceived balance with decreasing target-distractor similarity. Perceived balance was not affected by grid size ($F(1,\ 187) = 0.15$, $p = 0.700$, adj. $R^2 = 0.00$). Enjoyment was neither predicted by grid size ($F(1,\ 182) = 0.15$, $p = 0.700$, adj. $R^2 = 0.00$) nor by distractor shade ($F(1,\ 182) = 0.25$, $p = 0.616$, adj. $R^2 = 0.00$). Curiosity was predicted by grid size ($F(1,\ 184) = 5.34$, $p = 0.022$, adj. $R^2 = 0.02$). No further significant effects were found.

When taking into account the relative difficulty for each participant (i.e., the game was easier, harder, or aligned with their skill), no significant effects were found for the two-way ANOVA predicting enjoyment or perceived balance from relative grid difficulty and relative distractor difficulty. In other words, there was no difference in enjoyment or in perceived balance in players who played an easy version, a hard version, or a balanced version in relation to their skill, both with regards to grid size difficulty (enjoyment: $F(2,\ 175) = 0.38$, $p = 0.682$; perceived balance: $F(2,\ 181) = 0.90$, $p = 0.411$) and distractor shade (enjoyment: $F(2,\ 175) = 0.14$, $p = 0.866$; perceived balance: $F(2,\ 181) = 0.55$, $p = 0.575$)).

There was the possibility that players played at an easier grid size in relation to their WMC and a harder distractor shade in relation to their distractor filtering skills or vice versa, i.e., the game was not universally easier or harder in relation to their skill, but easier in one respect and harder in the other respect. This could have led to possible effects of adaptation cancelling themselves out. Therefore, four groups were identified that took into account the combined relative difficulty: a Group Easier which entailed players who played at an easier level both with regards to grid size as well as distractor shade, a Group Harder which entailed players who played at a harder level both with regards to grid size and distractor shade, a Group Mixed, where one of either grid size or distractor shade was harder and one was easier than participants' skill level, and one Group Same, which is analogous to the full adaptation group, but could also occur in the no-adaptation groups by chance (and by design, since the average grid size/distractor shade was chosen as no-adaptation default). Enjoyment and perceived balance were compared across these groups using ANOVAs, yet, no differences were found for either PX measure (enjoyment: $F(180) = 0.11$, $p = 0.956$; perceived balance: $F(3, 185) = 0.24$, $p = 0.866$).

5.3.6 Performance and Player Experience

Since the previous studies found that performance, particularly success rate, predicted enjoyment, linear regressions were calculated to predict enjoyment from success rate or progression. Success in ED trials just missed the significance threshold in predicting enjoyment ($F(1, 182) = 3.69$, $p = 0.056$, $R^2 = 0.015$). Neither success rate in the ND condition nor progression in either condition predicted enjoyment. With regards to perceived balance however, overall success (ED and ND success rates combined) significantly predicted the PX measure ($F(1, 187) = 16.44$, $p < 0.001$, adj. $R^2 = 0.08$), as well as ED success ($F(1, 187) = 16.75$, $p < 0.001$, adj. $R^2 = 0.08$) and ND success ($F(1, 187) = 10.49$, $p = 0.001$, adj. $R^2 = 0.05$) separately. Similarly, progression across both conditions ($F(1, 187) = 5.49$, $p = 0.02$, $R^2 = 0.02$), as well as progression in the ED condition ($F(1, 187) = 6.79$, $p = 0.009$, $R^2 = 0.03$) predicted perceived balance.

5.4 Discussion

The main goal of this study was to determine whether adaptation based on WMC and distractor filtering led to improved PX, specifically enjoyment and perceived balance. Further aims were the replication of previous results and to provide additional data explaining the relationship between difficulty, performance, and PX.

5.4.1 Effects of Game Difficulty on Performance

It was again demonstrated that performance scores were higher in trials without distractors compared to trials with distractors, which was consistent with all previous studies presented in this thesis and which aligns with empirical evidence of performance-debilitating effects of distracting items. Such effects have not only been found in cognitive-psychological research [79], [118], [228], but also with regards to video games [14]–[16]. The current study contributes to this evidence and strengthens the notion that video games can indeed place substantial demand on central cognitive functions such as WMC and distractor filtering. In addition, the present study revealed declining success rates with increasing grid sizes, supporting H1a. This result is in line with empirical evidence reporting poorer WM performance with increased set size [101], [253], [254] since higher grid sizes imply a longer path and thus more information to remember.

Yet, with regards to distractor filtering difficulty, which was manipulated with target-distractor similarity, performance differences were less straightforward, undermining the predictions of H1b. For instance, success rates were significantly lower at a 50% difference compared to a 40% difference, and progression was also significantly lower at a 50% difference than each 20%, 30%, and 40% differences. Theories of target-distractor similarity as well as the results of the previous studies indicate that performance declines with increasing target-distractor similarity, yet this time, performance was poorest at the objectively easiest level. It has to be noted though that the design of the current study was tailored to the main goal of investigating the effects of adaptation on PX. The relationship between game difficulty and performance was only of secondary importance since this has been investigated in Studies 4 and 5. As a consequence, the number of participants at each distractor shade level as well as at each grid size level was highly unequal in the current study, which makes comparisons less reliable. Still, the present results indicate that a significant number of participants may have had general difficulties in ignoring distractors, even at the easiest level, wherefore performance in this group was the poorest. This again suggests that the mere presence of distractors can affect performance, even though they may be fairly distinct from target elements. Game designers should take into account that such difficulties in ignoring task-irrelevant game elements may be present in some players, which may have adverse consequences on their PX.

5.4.2 Effects of Game Difficulty and Adaptation on Player Experience

5.4.2.1 Perceived Balance

The current results revealed that perceived balance decreased with decreasing target-distractor similarity. In other words, the game felt less balanced at the distractor shade level that was expected to be the easiest, which stands in contrast to the findings of Study 5, which demonstrated that perceived balance was highest at the biggest target-distractor difference. This outcome indicates that participants who played at objectively easier levels tended to feel that the game matched their skills less. Yet, as already mentioned above, the presumed easiest level was not the actual easiest level in the current study as reflected by performance. Many individuals already had difficulties ignoring distractors even at this level, and consequently, those players would likely feel that the game is not balanced to their skill or too easy, but rather too difficult. Yet, there was still a significant number of participants who reached the levels with a higher target-distractor similarity, which highlights that there are substantial individual differences in the ability to ignore distraction, which is in line with empirical evidence [33], [255], and should be taken into account when designing games.

Regarding difficulty adaptation, no significant effects were observed for either adapting grid size or distractor shade to players' skills. More specifically, perceived balance was not higher in adapted groups, contrary to what was expected for grid size adaptation (H2a) as well as distractor shade adaptation (H2b). By design, all participants in an adaptation group played a game balanced to at least one of the assessed skills (WMC or distractor filtering). Yet, participants in the no-adaptation group could play at either an easier or harder level, or at a level matching one or both assessed skills, which could happen by chance in this group. The adaptation analysis did not take this into account but rather mirrored a real game design testing scenario, where difficulty in the non-adapted group would be set to a predefined level instead of deliberately choosing a level that does not match the player's skill. Yet, in order to get more detailed insights into what effects balanced vs. imbalanced difficulty can have on PX, further calculations were made that considered the relative difficulty level, i.e., whether participants played at an easier, harder, or balanced level in relation to their skill. Results revealed no differences in ratings of perceived balance between those groups, although objectively, balance differed. Taken together, these results indicate that there was a discrepancy between objective difficulty-skill balance and perceived difficulty-skill balance in the present experiment. Empirical evidence indeed suggests that objective and subjective difficulty are somewhat independent, and manipulating objective difficulty does not necessarily impact subjective difficulty [256] and vice versa [257].

While objective difficulty-skill balance or adaptation did not yield any significant effects on perceived balance, it was found that success rate in both distractor and no-distractor conditions, as well as the number of moves in distractor trials, predicted the PX metric. In other words, the better players were, the higher they perceived the game to be aligned with their skill, which is in line with the findings of Study 5. In sum, participants did not necessarily rate perceived balance based on the actual difficulty of the game in relation to their skill, but rather based on their performance.

5.4.2.2 Enjoyment

Contrary to perceived balance, enjoyment was not related to either grid size or distractor shade, underscoring the evidence of no direct effects of game difficulty on enjoyment found in Study 5. While in the previous studies, it seemed that success rates rather than difficulty per se predicted enjoyment, in the current study, success rates in distractor trials just failed to significantly predict enjoyment. Thus, enjoyment seems to also depend on other factors besides game difficulty and performance, one of which could be the balance between game difficulty and player skill. Yet, the analysis concerning difficulty adaptation yielded no significant effects - this was the case for both adapting grid size to players' WMC, as well as adapting distractor shade to players' filtering abilities. More specifically and contrary to the study hypotheses, enjoyment did not rise when players played at a difficulty level that matched their WMC (as predicted by H3a) or their distractor filtering abilities (as predicted by H3b). Even when taking into account the relative difficulty level, no differences were observed in enjoyment in players who played an easier, balanced, or harder game in relation to their own skill, both with regards to WMC and distractor filtering.

These findings are not compatible with the predictions of SDT or flow theory, which assume that a balance between the skill of the player and the difficulty of the game, which is the principal idea of DDA, leads to a state of optimal experience (see Section 2.1.2.2). One reason for this discrepancy could be that objective balance did not translate to perceived balance in the current study. Csikszentmihalyi, who originated the concept of flow, indeed emphasised that it is the balance between *perceived* challenges and *perceived* skills that determines the experience [258]. Yet, there is also increasing evidence of the limited effectiveness of DDA, to which the present results add. Guo et al. [259] for example present a literature review surrounding DDA approaches and argue that the effects of DDA on PX are not well supported. For instance, Smeddinck et al. [72] found no significant impacts of automatic difficulty adjustment on PX in both a custom-designed as well as a commercially available casual game. It has to be noted though that in the current study, difficulty adjustment was not dynamic throughout, but only in the first phase of the experiment, whereas in the second phase, difficulty was fixed. Yet, while many of the studies reporting limited effects on PX may be an artefact of how DDA is applied, Guo et al. also argue that there may be a problem with the idea of a balanced difficulty-skill balance as a predictor of flow, which has been challenged repeatedly [e.g., 236], [260].

Together with other studies that question the idea of an optimal difficulty-skill balance as a precursor of game enjoyment, the present results further emphasise that the relationship between game difficulty, player skill, and enjoyment is not as straightforward as often believed. Game designers need to take into account that the perceived balance between the game's challenges and players' own skills may not always reflect the objective difficulty-skill balance as for instance determined by the win-lose ratio. Moreover, the "optimal" level of challenge can be hard to determine and vary between players or game genres [73]. As Alexander, Sear, and Oikonomou [74] also add, players' experience, play style, or motivation can be better indicators of what difficulty level is best to choose. In addition, other factors, such as player choices, novelty, or suspense should be considered as potentially more important contributors to game enjoyment than difficulty, which has been suggested by Lomas and colleagues [261].

5.4.3 Limitations and Future Directions

It can be argued that the adaptation in the current study did not work as intended since ratings of perceived balance did not differ between objectively not balanced and objectively balanced games. A reason for this could be that the adaptation phase was too short to reliably determine each player's individual skill level. In addition, the individual difficulty level for the adapted modes was set to the highest level where players still solved at least 2 out of 3 trials correctly. While this should ensure that the challenges are sufficiently high so that they provide the opportunity for players to demonstrate their skill, but not so high that players get overwhelmed or frustrated, the actual skill level may still be at a different point. Some players may not have paid much attention and therefore received a lower difficulty level than their actual skill, and others could have reached higher levels just out of luck. Yet, merely guessing the complete path correctly becomes more and more unlikely with increasing grid sizes, since every row and column added to the grid adds another 50% chance of moving in the wrong direction (since two possible moves - down and right - are possible). With regards to distractor shade, however, some players may have had an easier task in cases where distractors were placed further away from the path, which could happen by chance. Future studies might therefore consider controlling the proximity between targets and distractors, which could further influence distractibility, as well as longer adaptation phases in general to increase the likelihood of obtaining a more accurate estimate of the optimal difficulty level for each player. Yet, as mentioned before, it may be that individual experience, play styles, or motivations, as suggested by Alexander et al. [74], play a more important role in determining the optimal difficulty level rather than player skill. Future studies should consider these aspects as well.

While it is possible that the adaptation did not work as intended, the discrepancy between objective and subjective difficulty-skill balance could also indicate that players are just not very good at estimating their own skill in relation to game difficulty. Subsequent studies could take a closer look at the relationship between objective and perceived balance, and how it is related to players' skill and PX.

Another potential limitation is related to the fact that the adaptation in the current game was not dynamic throughout. Game difficulty was adapted to the player only in the first phase, whereas in the second phase, it was fixed to the level determined as the highest level at which players still got at least 2 out of 3 trials correct. Players may have gotten better in the course of the second experimental phase, and their skill may have not necessarily matched the difficulty of the game until the end. However, although DDA has become more frequent, many video games still offer players to select their difficulty mode, which then also stays constant, or alter difficulty only at predefined stages. In these games, the same phenomenon could occur. The present experiment is more reflective of these kinds of difficulty adjustment rather than of games with a true DDA approach. It would therefore be interesting to also examine the same research questions in a fully dynamic game. This would provide more insights about different approaches to difficulty adjustment and their effects on PX.

Future studies could further look at commercial video games to test adaptation effects of distractor filtering difficulty and WM difficulty on performance and PX. The current study served as a starting point to see whether such effects can be observed in a fairly controlled game setting, which may not be fully representative of many commercially available video games. Moreover, it may be that adapting game difficulty to cognitive abilities such as WM and distractor filtering may have different effects in different types of games that place separable demands on the player. All these questions need to be addressed by further studies to make definite conclusions about whether and under which circumstances adaptation can influence PX in video games.

5.5 Conclusion

The current study again demonstrated that the mere presence of distractors can increase game difficulty, reiterating the findings of all previous studies conducted as part of this thesis. However, neither adapting game difficulty to players' WMC nor to their distractor filtering abilities had a significant effect on PX. More specifically, enjoyment was not higher when game difficulty was tailored to players' skills. Likewise, perceived balance did not differ between the different adaptation groups, i.e., participants who played a non-adaptive game rated it as balanced as participants who played game levels adapted to their WMC or distractor filtering abilities. While adaptation may be beneficial in certain circumstances or for certain types of games, the present results suggest that adaptation to WM-related player characteristics does not always lead to improvements in PX. Moreover, objective difficulty-skill balance does not necessarily translate to subjective ratings of difficulty-skill balance. Rather, it seems that perceived balance increases with players' performance.

To conclude, while performance adaptation may make sense in certain situations, this study does not support a universal benefit of such an approach. The decision of whether to adapt should thus be carefully made and informed by playtesting data in order to manage resources in the game development process well. Importantly, both the game material that is subject to adaptation as well as the characteristics of the player to which the game is adapted need to be considered with individual differences and specific game contexts in mind. The relationship between WM capabilities, play performance, and enjoyment appears to be much more complex than sometimes claimed, and may be influenced by multiple factors, including individual differences and specific types of games. Game researchers, designers, and developers may therefore benefit from a thorough understanding of the expectations, motivations, and experiences of their target audience to best fine-tune potentially visually distracting game elements for an optimal PX.

Chapter 6

General Discussion and Conclusion

6.1 Summary of Empirical Studies and Contributions

6.1.1 Chapter 3 - What Makes a Distractor Distracting?

Chapter 3 comprises three separate studies, investigating a range of basic visual characteristics of task-irrelevant stimuli (i.e., distractors) and their potential to distract players. Fundamental research in cognitive psychology has demonstrated that our ability to process information in Working Memory (WM) is limited [9], [78], and can be negatively influenced by distractor stimuli. Such a distraction can have a notable impact on performance depending on the level of cognitive demand imposed by the task [116], [204] and the similarity between distractors and target stimuli [13], [204], and has also been associated with negative emotional reactions, such as frustration [262], [263]. It is in particular visual distraction that is a topic of interest in game design and games research, as video games often involve highly complex and cognitively demanding tasks communicated through rich visual stimuli [42]. However, while many cognitive-psychological studies have examined the influence of distractors on attention and WM [104], there is a knowledge gap in understanding the implications of distraction when applied to real-world tasks such as video gaming. For example, while the visual similarity between distracting stimuli and target stimuli has been identified as a relevant factor that influences the impact of distractors on performance [204], it is yet unclear if this holds true for specific visual characteristics (such as shape, colour, or brightness) - which could inform the visual design process for video games in particular and user interfaces in general. The three studies presented in this chapter therefore examine different visual characteristics of distractors and how these influence information processing (RQ 1).

6.1.1.1 Study 1

29 participants were asked to solve several trials of a WM task in which they had to remember four black circles on a circular grid with 16 potential stimulus positions. In half of the trials, irrelevant stimuli (distractors) were presented either alongside the black target circles (Encoding Distraction (ED)) or in a delay period after the black circles had disappeared (Delay Distraction (DD)). Distractors could be one of two types that differed only in visual characteristics from each other and from the target circles. Visual alterations were made based on Jacque Bertin's classification of primitive visual variables [126], and included the variables shape, value (brightness), colour (this variable was used in Study 3 only), and texture. The first type of distractors, which remained identical across the three studies described in this chapter, consisted of grey circles, therefore differing only in their brightness value from the black target stimuli. The second type consisted of grey triangles with white stripes, therefore differing in brightness, shape, and texture compared to the target stimuli. The experiment included five different conditions in a within-subjects-design: ND (No Distraction), ED_Type1 (grey circle distractors presented in the encoding period), ED_Type2 (striped triangle distractors presented in the encoding period), DD_Type1 (grey circle distractors presented in the delay period), and DD_Type2 (striped triangles presented in the delay period). Trials of the different conditions were presented in a random sequence to avoid order effects. Results revealed poorer performance in trials with Type 1 distractors compared to both Type 2 distractors and no distractors when distractors were presented in the encoding period, and also poorer performance in trials with Type 1 distractors as opposed to trials with Type 2 distractors when distractors were presented in the delay period.

These findings indicate that visual characteristics of task-irrelevant items do have a separable impact on WM performance. Distractors with a more similar shape and texture to targets (in this case, grey circles versus black target circles) led to poorer performance as compared to distractors with different shape, texture, and colour (in this case, striped triangles versus black target circles). The latter type of distractors was not found to influence performance, which did not differ significantly from performance in trials without any distractors, indicating that either altering the shape or adding texture rendered the stimuli sufficiently distinct to eliminate distraction costs on performance.

6.1.1.2 Study 2

The setup for Study 2 was almost identical to Study 1. 51 participants solved the same WM task in a within-subjects design with five conditions. Yet, this time, stimuli in Type 2 conditions were grey triangles, therefore differing only in shape and brightness from the target stimuli (and only differing in shape from Type 1 distractors, which were again grey circles and had the same shade of grey as the triangles). Results revealed differences between trials with Type 1 distractors and trials without distractors, with only the presence of grey circles presented during the encoding period leading to decreased WM performance. Notably, no difference between Type 2 distractors and any other condition was observed, providing further evidence that the visual similarity between targets and distractors, particularly when shape matches, might play an important role in impacting cognitive performance. Shape alterations instead appeared to offer sufficient distinction from the target in the present experiment that effectively eliminated any performance costs.

6.1.1.3 Study 3

Again, the setup of the previous studies was reused to test another set of distractors. 49 participants solved the five within-conditions that were identical to the previous experiments, and while Type 1 distractors again stayed consistent with previous experiments (i.e., grey circles), Type 2 distractors were now changed to red circles, i.e., colour (brightness, hue, and saturation) was altered in relation to both target stimuli and Type 1 distractors. Results again showed a significant difference between Type 1 and no distractors, with a poorer performance in trials with grey circles when presented during the memory encoding period. However, similar to Study 2, no effect was found for Type 2 distractors compared to the other conditions. This time, the different results of red vs. grey distractor circles cannot be explained if colour is seen as a one-dimensional construct (i.e., black, grey, and red as equally distinct colour values). Instead, the results of this experiment suggest that certain visual features of distractors interact with complex cognitive processes in multiple ways. For instance, certain suppression or enhancement mechanisms could favour specific features of task-relevant stimuli [144], [148], which could be shape (as in Studies

1 and 2) or colour hue (and not brightness, as in Study 3). Distraction could therefore be seen not as a characteristic of a certain stimulus, but as a result of a complex interaction between the user and visual features of task-relevant and task-irrelevant stimuli, combining top-down cognitive process with bottom-up stimulus effects. As a consequence, when applying these psychological findings to a game design context, it is important to recognise that potential distractors and their visual features may not be useful to consider in isolation. The relevance of visual features and their effects on performance and potentially also Player Experience (PX) may instead be dependent on the interplay between visual features of task-relevant and task-irrelevant elements as well as potentially individual differences.

6.1.1.4 Conclusions and Implications

Aside from the general finding of debilitating effects of distractors on WM, which is in line with pervasive evidence of impaired cognitive performance under distraction [79], Studies 2 and 3 further revealed unique contributions of ED filtering (i.e., ignoring distractors when information accesses WM) and DD filtering (i.e., ignoring distractors when information is maintained in WM). These outcomes add to the notion of separate mechanisms for filtering distractors at different stages of processing that have been suggested previously [205], thus providing important contributions also to cognitive science. Especially the finding that only one type of distractor actually impaired performance in the current set of experiments indicates that under certain circumstances, individuals may be more or less immune to distraction, a phenomenon that has not been researched in much detail yet but may provide more clarity about potential cognitive mechanisms that may protect against the adverse effects of distraction, particularly given that distractors are almost universally understood to impair attention and WM [79]. Cognitive studies may build upon the obtained results and investigate any potential mechanisms (such as top-down and bottom-up processes) that may attenuate or enhance the effects of distraction on performance, which can in turn provide useful insights for game designers in order to avoid any negative effects on PX that may occur with distraction.

Interestingly, the present results also suggest unique contributions of handling different types of distractors, which might represent separate strategies employed to reliably differentiate target items from distractors. These results again suggest that the basic visual characteristics of stimuli should be considered in the context of visual features of surrounding elements rather than in isolation. Visual considerations are particularly important for the design of video games since they often communicate almost exclusively through the visual channel, and often exhibit a high level of visual complexity. Given this complexity, considering single elements not in isolation (e.g., a health pack should be highlighted with a green border), but rather in relation to surrounding items or contextually related game elements (e.g., a health pack should be highlighted with a coloured border that is sufficiently distinct to the background) may improve visibility of important game elements, which can lead to improved usability and accessibility, and might even lead to more positive player experiences.

6.1.2 Chapter 4: How Perceptual Characteristics Influence Difficulty and Player Experience in a Working Memory Game

As the results of the previous three studies suggest, visual manipulation of distractor stimuli in terms of their similarity to target items may increase cognitive demand and consequently affect WM performance. Yet, the previous experiments do not allow us to make conclusions as to how visual similarity between targets and distractors affect performance in a video game scenario, and thus the game's difficulty, and neither what consequences these distraction effects have on PX. In addition, existing empirical studies that have looked at target-distractor similarity effects in video games mostly concentrated on visual search tasks [e.g., 14]–[16] and not on tasks involving WM, which however is a key cognitive ability required by many video games [171]. Two studies were therefore conducted in order to address the questions of how perceptual distraction affects game difficulty (RQ 2) and what consequences this has on PX (RQ 3).

Following the findings of the previous study, an applied video game was developed to test the effects of visual characteristics of task-irrelevant distractors in a real gameplay scenario. The aim of this study was to provide initial empirical evidence of how visual distraction may impact game performance and PX in a video game designed to make explicit use of players' Working Memory Capacity (WMC). The newly developed video game consisted of multiple levels where players had to memorise a path on a grid (which was visible for 1500 milliseconds and then disappeared) and then navigate their player character towards a target position without leaving the grid positions where the path has appeared previously. In some trials, distractors (i.e., task-irrelevant visual stimuli) could also appear on the grid, either simultaneously with the path or with a 1500 millisecond delay. Visually, the game was kept minimalistic in order to better understand how target-distractor similarity influences play performance and PX without having to consider potential confounds due to the complexity of the game. The path consisted of grey circles, and any one circle could occupy one grid position. In every trial, the beginning of the path was the top left grid position, and the end was the bottom right position. Distractors were also grey circles with only their brightness value manipulated (10%, 20%, 30% brighter and darker than targets, leading to 6 different distractor shades and three different target-distractor similarity levels). Since contrast is widely used to highlight objects against their surroundings in user interfaces, and also because the previous experiments demonstrated distraction effects when only brightness was manipulated, this contrast system was also used here to determine target-distractor similarity as the key distractor characteristic of interest.

6.1.2.1 Study 4

36 participants played the custom-made video game in a within-subjects design. The study followed a 2x3 design: there were 3 ED conditions (small, medium, and large difference between target and distractor brightness), where distractors were presented simultaneously with the path, and 3 DD conditions (small, medium, and large difference between target and distractor brightness), where distractors were displayed only after the to-be-memorised path had disappeared. In addition, the experiment included a ND condition, in which no distractors were presented at any time. The main aim of this study was to identify how and under which presentation period conditions target-distractor similarity affects game performance and PX. Results revealed that game performance was significantly reduced in both distractor presentation conditions compared to the no-distractor condition. Performance was also significantly lower in the ED conditions compared to the DD conditions. When presenting distractors simultaneously with the target path, visual similarity had a significant effect, with high target-distractor similarity negatively influencing performance. Building a regression model to predict game enjoyment, the best prediction was attained when success specifically in the ED conditions was added. These findings demonstrate that (a) distraction (particularly when present at the time of target encoding) can impact gameplay performance in a video game scenario; and that (b) the impact of distraction is dependent on both visual characteristics and presentation period (i.e., a higher impact was found for encoding distractors with high similarity to the target path circles); and that (c) game enjoyment was related to success (i.e., performance) when

distractors were present.

These findings highlight the importance of careful visual design considerations in player-game interactions. When players are confronted with cognitively demanding tasks where they need to focus on a specific goal or target, which is frequently the case in video games, the presence of task-irrelevant distractors that are similar to this goal may negatively impact performance and as a consequence enjoyment.

6.1.2.2 Study 5

In order to fully understand the complex relationship between enjoyment, performance, and visual distraction in video games, Study 5 sought to replicate Study 4 in a mixed design. This approach provided the possibility to validate previous results (by reducing potential spill-over effects between different difficulty conditions and by replicating findings in a slightly different setting) and to analyse differences in PX between conditions. 127 participants were randomly allocated into one of three groups, which were either easy, medium, or hard in difficulty based on target-distractor similarity (reflecting brightness difference levels of 30%, 20%, and 10%, respectively), and played through different trials featuring either no distractors (ND condition) or distractors presented simultaneously with the target path (ED condition), similar to the previous experiment but eliminating the DD condition since no significant target-distractor similarity effects were obtained for this condition in the previous study. Results largely replicated the findings of Study 4: better performance was observed in trials without distractors compared to trials with distractors. For trials with distractors, the easy group outperformed the hard group, reiterating the effect of visual similarity between targets and distractors in the context of a video game setup. Again, enjoyment was predicted by success in trials with distractors, however, this effect was not dependent on group differences. In other words, visual target-distractor similarity did not impact the relationship between game enjoyment and success, and there was also no difference between groups in enjoyment ratings. In a broader context, this could imply that aspects of the player, such as individual gameplay preferences or motivations might be more important than universal distraction difficulty levels when it comes to the aim of increasing game enjoyment. Considering potential individual preferences, gameplay scenarios designed to facilitate effective distractor filtering could enhance enjoyment across various game difficulty levels. With respect to other aspects of PX, group differences were only found for perceived balance and mastery, with higher ratings in the easy group than in the hard group, consistent with performance results. Although both these metrics were positively related to enjoyment, this was not due to the difficulty of the game in terms of target-distractor similarity, suggesting that the relationship between game difficulty and PX is not a simplistic one and may be influenced by aspects such as player motives, difficulty preferences, or performance expectations.

6.1.2.3 Conclusions and Implications

Overall, these findings provide evidence for the importance of visual design considerations in light of possible distraction in video games and underline the complex nature of the relationship between visual distraction, performance, and enjoyment. Again, the specific perceptual characteristics of distractors may not be important when regarded in isolation, but could impact game enjoyment when considered in combination with task-relevant stimuli and individual differences, which may not be limited to player skill, but also involve motivational aspects or player expectations. In addition, the findings of both studies reveal a relationship between performance (and particularly success rates) and enjoyment, but not between game difficulty and enjoyment, which indicates that it might be particularly the positive feedback given by the game after succeeding that boosts enjoyment. This insight can be particularly valuable for video game design: rather than the objective difficulty of the game, it might be the positive feedback players receive from the game that drives enjoyment.

6.1.3 Chapter 5: Adaptation Based on Cognitive Abilities and its Effects on Performance and Player Experience

Given the previous findings, this thesis does not support the notion that the visual characteristics of task-irrelevant in relation to task-relevant game material and the associated difficulty of the game per se can lead to better gameplay experiences. Rather, enjoyment in the WM game seems to be associated with the success rate of individual players, albeit only when distractors were present, i.e., when there is an increased baseline difficulty. In other words, the objective visual similarity of distractors compared to target stimuli may not be as important a design consideration as the ability of a given player to solve a task. To test this theory, the previously used video game was again used for this final study and adapted either to players' general WMC, their distractor filtering abilities, or to both, and compared to a non-adaptive control version. Dynamic Difficulty Adjustment (DDA) has been shown to impact game enjoyment in multiple ways (see for example [69], [264]), but it is unclear if adaptation based on specific capabilities of the player, such as their WMC or distractor-filtering abilities could have a positive impact on PX. This last study therefore examined how a personalised gaming experience, adapted to a player's WMC and their ability to ignore distraction, affects PX.

6.1.3.1 Study 6

194 participants were assigned to one of four groups: (1) an adaptive group in which the length of the path was adapted to player skill (i.e., their WMC); (2) an adaptive group in which the visual similarity between targets and distractors was adapted to player skill (i.e., their distractor filtering abilities); (3) an adaptive group where both adaptations were applied; (4) or a non-adaptive group. The task was very similar to Studies 4 and 5, and players were asked to memorise a path consisting of black circles presented on a rectangular grid, which they would later, after the path had disappeared, need to follow with their player character. Again, distractor stimuli were presented together with the path in half of the trials, which participants were asked to ignore. Participants in all four groups first completed an adaptation procedure, where first grid size was gradually adapted to the player's ability to memorise a path of a given length, and then distractor shade was gradually adapted to the player's ability to ignore distractors. In the grid adaptation phase, participants started playing the game at a grid size of 4x4, and with every at least 2 out of 3 correct trials, grid size increased by 1 field in width and 1 field in height. Analogously, if participants failed at least 2 out of 3 trials of a given grid size, grid size decreased again 1 field in width and 1 field in height. This procedure continued for 18 trials with a maximum reachable grid size of 8x8. No distractors were presented in this phase. In the distractor adaptation phase, grid size was fixed, and distractors were presented together with the to-be-remembered path. Distractors first differed to 50% in brightness from the black target circles, and with every 2 out of 3 correctly memorised paths, distractor shade decreased by 10% in brightness, up to a target-distractor brightness difference of 10%, rendering the distractors gradually more similar to the target circles. Again, if participants failed in at least 2 out of 3 trials of a given distractor shade, target-distractor similarity decreased again by 10%. These two adaptation procedures served to determine an individual grid size and an individual distractor shade at which the game should be challenging, but neither too easy nor too hard for any given player.

Although all participants completed the adaptation phase to keep the experimental procedure and length consistent across players, in the main phase of the experiment, only participants who were assigned to the respective adaptation groups received their individual grid size or distractor shade level. This means that players who were assigned to Group 1 only received their individually determined grid size, while distractor shade remained fixed to a pre-defined value. Players in Group 2 instead only played with their individually determined distractor shade, while grid size was set to a fixed value for every player. In Group 3, participants played levels that both adopted their individual grid size and distractor shade, and in Group 4, grid size as well as distractor shade were set to a pre-defined value for every player, and thus were not adapted to the individual performance of each player. Effects of each type of adaptation on the PX measures *perceived balance* and *enjoyment* were examined in order to address RQ 4: How does a personalised gaming experience based on a player's WMC and ability to ignore distraction affect PX?

While results again revealed a better performance when no distractors at all were present, and a gradually declining success rate with increasing grid size, neither grid size nor distractor shade adaptation had any significant effect on enjoyment or perceived balance. While adaptation should generally optimise skill-difficulty balance, the *perceived* balance was not dependent on whether the game was objectively balanced. Instead, the less similar distractors were to targets (i.e., the easier ignoring distractors should be), the lower participants' perceived balance was. While this might seem counterintuitive, the performance results clarify this finding: performance was also poorest at the objectively easiest level with the largest target-distractor difference. This outcome indicates that the introduction of distractors itself, irrespective of the distractors' similarity to the target stimuli, might present a relatively high baseline difficulty factor that a large part of players may have perceived as exceeding their skills. This is important to consider for game design, particularly in light of the high visual complexity of many modern video games, where many game elements are not currently goal-relevant, but might rather present a distraction from the main goal. A significant proportion of players may be overwhelmed by this visual complexity, which might lead to negative emotions and might even cause them to stop playing.

Enjoyment, which was also not influenced by grid size or distractor shade adaptation, further did not depend on grid size or target-distractor similarity directly. Contrary to

Studies 4 and 5, enjoyment was also not related to success rates in distractor trials, again suggesting that enjoyment may be determined by other factors not investigated in the current study, such as for instance play style, difficulty preferences, or motivations. Individual differences that go beyond players' skills are therefore an important aspect to consider when designing games.

6.1.3.2 Conclusions and Implications

Taken together, the findings of this study suggest that simplistic claims about the effectiveness of DDA may not be supported. Particularly the idea of a U-shaped relationship that predicts the highest state of enjoyment at a difficulty level that is neither too easy nor too hard for a player's individual skills might not be universally true [see 259]. This may be due to several reasons. Firstly, it is not clear how the "optimal" difficulty level can be reliably determined, particularly in light of individual differences in game difficulty preferences [220]. In addition, given the mechanical complexity of many games, the decision of what game elements to adapt is not straightforward, and neither is the decision of what player characteristic the game should adapt to. With emerging evidence of limited effectiveness of DDA in recent years, there has also been a shift from the notion of adapting the game solely based on players' performance towards adapting the game based on players' emotional states - a process known as affective adaptation [265].

6.2 Limitations and Future Directions

The present studies conducted as part of this thesis attempt to illuminate the relationship between basic visual characteristics of goal-relevant and -irrelevant elements, video game difficulty, and PX. Yet, while the outcomes of this project contribute useful insights for cognitive science and game design, there are some limitations that need to be acknowledged and addressed by future research in order to broaden the applicability and relevance of the obtained outcomes.

Video games are highly complex forms of entertainment and researching them is accompanied by some challenges. First and foremost is the consideration of whether to strive for a high ecological validity, which pleads for the use of a fully-fledged, commercially available video game, or whether to eliminate every game element that may be unrelated to the central research question, at the expense of providing only a somewhat game-like experience. Particularly for the first set of experiments conducted as part of this thesis (i.e., Studies 1-3), one may argue that the task used is not necessarily reflective of a real video game and may thus limit the significance of the obtained results. However, any meaningful conclusion can only be made when adopting a more comprehensive approach. Investigating fundamental cognitive processes in a setting with many potential confounds can present its own problems, and any obtained results may even only hold true in the one single game investigated, since the results may be explained by other variables that remain unaccounted for. Thus, the first set of experiments deliberately made use of a traditional cognitive task to eliminate as many confounds as possible. (Of course, there is still the possibility of influences that could not be controlled in the present experimental setup, such as external distractions or varying Internet speeds throughout the experiment.) Subsequent studies gradually altered the experimental setup and procedure to mimic a real video game in order to make conclusions that are more applicable to game design settings. Again to avoid any potential confounds, the game was still very minimalist, however. Given that visual distraction could be particularly a problem in highly complex and visually rich games, such as *Overwatch* or *Fortnite*, there is still the need to investigate the relationship between perceptual distraction, game difficulty, and PX in these more complex games.

In addition, with recent advancements in computer graphics and the advent of Augmented Reality (AR) and Virtual Reality (VR), the borders between virtual worlds and the real world become more and more blurred, and games making use of such technologies can benefit from a more comprehensive understanding of cognitive processes such as distractor filtering and WM in real-life scenarios. While particularly distraction and attention are already researched quite extensively in applied scenarios such as driving cars, AR and VR technologies further open up new avenues to research cognitive processes and emotional reactions in highly realistic, but still controllable settings, and thus may tell us more about the interplay between cognition and gaming that holds equal relevance for both cognitive science and HCI.

Another limitation consists of the fact that the current work only considered visual sources of distraction, and even within this domain, only examined a subset of visual characteristics. Although the majority of video games rely heavily on the visual channel, auditory sources of information should not be disregarded. There is ample evidence in cognitive science that auditory stimuli can be distracting, affecting attention and WM [266]. Considering that auditory stimuli often supplement the visual game environment (e.g., ambient sounds), and may even be a necessity when a game is already very complex in visual terms [267], interaction effects may occur between visual and auditory stimuli. The separate and combined effects of these types of inputs, which may present a source of distraction, on game difficulty and PX remain to be investigated. In addition, modern technologies further allow the integration of haptic feedback, introducing yet another source of sensory input, which may or may not have distracting effects on different types of players, and again potentially impacting PX. More studies are needed that integrate different sources of distraction and examine their effects on cognitive processes and PX.

The most intriguing question of almost any game designer is arguably how to maximise enjoyment. While some of the studies conducted as part of this project suggest that players' success rate (potentially combined with the positive progress feedback the game provides) can explain a significant part of the variance in the enjoyment experience, there may be additional factors that may be even more important. The present studies did not consider factors such as game difficulty preferences or preferences for certain game genres, player motives, play styles, performance expectations, or more general individual skills such as hand-eye coordination. Future studies could integrate these factors in addition to player performance and progress feedback in order to gain a clearer understanding of what predicts the enjoyment experience, which can ultimately help increase the entertainment value of many video games.

6.3 Conclusion

The current thesis investigated how basic visual characteristics of task-relevant and -irrelevant stimuli affect cognitive processes, game difficulty, and user experience in digital games. What can be concluded in unison from all six of the conducted empirical studies is that task-irrelevant elements do affect performance negatively, thus providing a source of distraction that may for some players be overwhelming or frustrating. The finding that task-irrelevant items were more distracting when they were more similar to target items also suggests that visual characteristics should not be seen as isolated components when investigating their effects on information processing but in relation to the surrounding visual context. It is therefore crucial to carefully evaluate every individual game with regards to its difficulty and evoked experiences, and not rely solely on common UX or PX guidelines that cannot take into account the particular visual setup of any one game but can only make generalised recommendations.

What the present studies also demonstrate is that the relationship between game difficulty and enjoyment is not straightforward. Rather, there may be individual differences that are not related to players' cognitive skills, such as different play styles or game difficulty preferences, which may be of relevance in explaining the difficulty-enjoyment relationship. Yet, participants who had a higher success rate tended to enjoy the game more, which implies that adequate progress feedback that is presented at the right time might play an important role in the enjoyment experience. Finally, the results of the last study suggest that the topic of DDA is more complex than often believed. A simplistic view of an optimal skill-difficulty balance leading to maximum enjoyment was not supported by the current findings, which is not a novel claim, but in concordance with emerging evidence from games research. While this may be partly due to methodological challenges such as correctly determining a player's optimal difficulty level, adapting to other aspects than merely the player's skills might be more promising in eliciting positive player experiences.

Taken together, the findings of the studies conducted in this project suggest a complex interplay between the visual design of game elements, game difficulty, performance, and PX. Acknowledging these interactions in the game design process by adequately testing the visual design with different types of players can not only ensure basic usability and accessibility but also increase the chance of eliciting positive player experiences such as enjoyment.

The current thesis not only provides specific insights about distractor filtering, game difficulty, and PX but also aims to emphasise that bridging the gap between psychological science and the games industry can provide valuable insights and benefits for both fields. All interactive experiences, including video games, are created for and consumed by humans, wherefore an understanding of psychological processes, not only limited to cognition but also including knowledge about emotions and personality, is essential. Any endeavour to create an engaging and enjoyable experience for the consumer needs to take into account how the human brain works, including how we process information, how we react emotionally to a given input, and what preconceptions, preferences, or expectations we have. Only then can we create experiences that are truly tailored to the user, and at the same time understand humans better by expanding the scope in which their behaviour is observed.

Appendix A

Study 4

A.1 Correlation Matrices

	ND	ED	DD	ED10	ED20	ED30	DD10	DD20	DD30	Enjoy-ment	Mea-ning	Curio-sity	Mas-tery	Auto-nomy	Immer-sion	Progress Feed-back	Audiovis. Appeal	Chall-enge	Ease of Control	Clarity of Goals	Age	Play Hours
ND	1	.661**	.716**	.459**	.574**	.600**	.627**	.447**	.672**	.262	.278	.142	.426*	.014	.133	.347*	.226	.284	.371*	.322	-.134	.245
ED	.661**	1	.742**	.797**	.916**	.735**	.509**	.656**	.660**	.499**	.436**	.359*	.471**	.174	.254	.485**	.529**	.306	.602**	.435*	-.164	.226
DD	.716**	.742**	1	.525**	.592**	.726**	.839**	.782**	.825**	.357*	.263	.139	.495**	.106	.013	.381*	.382*	.242	.441**	.285	-.086	.215
ED10	.459**	.797**	.525**	1	.642**	.281	.385*	.421*	.479**	.366*	.436*	.345*	.263	.227	.264	.415*	.424*	.182	.513**	.294	-.206	.230
ED20	.574**	.916**	.592**	.642**	1	.578**	.323	.627**	.515**	.486**	.438**	.339*	.491**	.134	.262	.417*	.506**	.347*	.572**	.404*	-.162	.156
ED30	.600**	.735**	.726**	.281	.578**	1	.571**	.560**	.645**	.400*	.176	.197	.400*	.064	.098	.356*	.378*	.216	.394*	.359*	-.027	.178
DD10	.627**	.509**	.839**	.385*	.323	.571**	1	.495**	.549**	.324	.235	.205	.527**	.212	.025	.316	.236	.175	.383*	.190	.099	.167
DD20	.447**	.656**	.782**	.421*	.627**	.560**	.495**	1	.450**	.253	.261	.123	.306	.071	-.050	.274	.325	.335*	.441**	.223	-.082	.336*
DD30	.672**	.660**	.825**	.479**	.515**	.645**	.549**	.450**	1	.273	.165	.022	.368*	-.023	.055	.320	.377*	.098	.261	.296	-.233	.040
Enjoy	.262	.499**	.357*	.366*	.486**	.400*	.324	.253	.273	1	.697**	.721**	.540**	.523**	.716**	.231	.795**	.457**	.332	.371*	-.209	-.114
Mean	.278	.436**	.263	.436*	.438**	.176	.235	.261	.165	.697**	1	.700**	.473**	.631**	.725**	.411*	.548**	.277	.185	.197	-.247	-.107
Curio	.142	.359*	.139	.345*	.339*	.197	.205	.123	.022	.721**	.700**	1	.368*	.610**	.660**	.379*	.645**	.259	.144	.225	-.066	-.004
Mast	.426*	.471**	.495**	.263	.491**	.400*	.527**	.306	.368*	.540**	.473**	.368*	1	.401*	.373*	.411*	.528**	.454**	.332	.520**	-.024	-.143
Auto	.014	.174	.106	.227	.134	.064	.212	.071	-.023	.523**	.631**	.610**	.401*	1	.612**	.369*	.385*	.333	.138	.070	.049	-.037
Imm	.133	.254	.013	.264	.262	.098	.025	-.050	.055	.716**	.725**	.660**	.373*	.612**	1	.364*	.585**	.193	.148	.211	-.218	-.265
Feedb	.347*	.485**	.381*	.415*	.417*	.356*	.316	.274	.320	.231	.411*	.379*	.411*	.369*	.364*	1	.339	.215	.467**	.551**	-.022	.142
Audio	.226	.529**	.382*	.424*	.506**	.378*	.236	.325	.377*	.795**	.548**	.645**	.528**	.385*	.585**	.339	1	.230	.438*	.521**	-.257	-.109
Chall	.284	.306	.242	.182	.347*	.216	.175	.335*	.098	.457**	.277	.259	.454**	.333	.193	.215	.230	1	.279	.297	-.164	.010
Ease	.371*	.602**	.441**	.513**	.572**	.394*	.383*	.441**	.261	.332	.185	.144	.332	.138	.148	.467**	.438*	.279	1	.646**	.024	.150
Clar	.322	.435*	.285	.294	.404*	.359*	.190	.223	.296	.371*	.197	.225	.520**	.070	.211	.551**	.521**	.297	.646**	1	-.193	.037
Age	-.134	-.164	-.086	-.206	-.162	-.027	.099	-.082	-.233	-.209	-.247	-.066	-.024	.049	-.218	-.022	-.257	-.164	.024	-.193	1	.107
PlayHours	.245	.226	.215	.230	.156	.178	.167	.336*	.040	-.114	-.107	-.004	-.143	-.037	-.265	.142	-.109	.010	.150	.037	.107	1

Table A1: Correlation matrix with Pearson values for all performance and PX variables, age, and gaming expertise (PlayHours). The first nine rows and columns (ND to DD30) represent correlations between success rates. *** p < .01; * p < .05*

	ND	ED	DD	ED10	ED20	ED30	DD10	DD20	DD30	Enjoy-ment	Mea-ning	Curio-sity	Mas-tery	Auto-nomy	Immer-sion	Progress Feed-back	Audiovis. Appeal	Chall-enge	Ease of Control	Clarity of Goals	Age	Play Hours
ND	1	.873**	.852**	.829**	.757**	.857**	.801**	.847**	.749**	-.046	-.063	-.144	-.170	.080	-.062	.125	-.149	.005	.280	.437*	.045	.498**
ED	.873**	1	.866**	.939**	.946**	.908**	.782**	.873**	.780**	.175	.140	.064	-.027	.180	.036	.249	.089	.125	.426*	.451**	-.032	.447**
DD	.852**	.866**	1	.767**	.782**	.886**	.958**	.935**	.920**	.103	.036	-.083	-.003	.121	-.122	.182	.035	.080	.355*	.452**	.016	.401*
ED10	.829**	.939**	.767**	1	.836**	.756**	.701**	.778**	.676**	.113	.130	.088	-.118	.146	.051	.220	.060	.073	.383*	.326	-.071	.460**
ED20	.757**	.946**	.782**	.836**	1	.812**	.694**	.796**	.710**	.264	.246	.118	.076	.214	.074	.214	.143	.182	.451**	.416*	-.018	.344*
ED30	.857**	.908**	.886**	.756**	.812**	1	.803**	.879**	.811**	.122	-.005	-.042	-.023	.145	-.034	.261	.046	.102	.342*	.512**	.010	.440**
DD10	.801**	.782**	.958**	.701**	.694**	.803**	1	.862**	.830**	.099	.046	-.060	.095	.144	-.148	.179	.005	.080	.397*	.438*	.076	.414*
DD20	.847**	.873**	.935**	.778**	.796**	.879**	.862**	1	.765**	.096	.070	-.032	-.043	.131	-.091	.130	.058	.124	.314	.422*	.040	.477**
DD30	.749**	.780**	.920**	.676**	.710**	.811**	.830**	.765**	1	.091	-.013	-.146	-.060	.063	-.102	.201	.035	.018	.285	.407*	-.075	.229
Enjoy	-.046	.175	.103	.113	.264	.122	.099	.096	.091	1	.697**	.721**	.540**	.523**	.716**	.231	.795**	.457**	.332	.371*	-.209	-.114
Mean	-.063	.140	.036	.130	.246	-.005	.046	.070	-.013	.697**	1	.700**	.473**	.631**	.725**	.411*	.548**	.277	.185	.197	-.247	-.107
Curio	-.144	.064	-.083	.088	.118	-.042	-.060	-.032	-.146	.721**	.700**	1	.368*	.610**	.660**	.379*	.645**	.259	.144	.225	-.065	-.004
Mast	-.170	-.027	-.003	-.118	.076	-.023	.095	-.043	-.060	.540**	.473**	.368*	1	.401*	.373*	.411*	.528**	.454**	.332	.520**	-.024	-.142
Auto	.080	.180	.121	.146	.214	.145	.144	.131	.063	.523**	.631**	.610**	.401*	1	.612**	.369*	.385*	.333	.138	.070	.049	-.037
Imm	-.062	.036	-.122	.051	.074	-.034	-.148	-.091	-.102	.716**	.725**	.660**	.373*	.612**	1	.364*	.585**	.193	.148	.211	-.218	-.264
Feedb	.125	.249	.182	.220	.214	.261	.179	.130	.201	.231	.411*	.379*	.411*	.369*	.364*	1	.339	.215	.467**	.551**	-.022	.142
Audio	-.149	.089	.035	.060	.143	.046	.005	.058	.035	.795**	.548**	.645**	.528**	.385*	.585**	.339	1	.230	.438*	.521**	-.257	-.108
Chall	.005	.125	.080	.073	.182	.102	.080	.124	.018	.457**	.277	.259	.454**	.333	.193	.215	.230	1	.279	.297	-.164	.011
Ease	.280	.426*	.355*	.383*	.451**	.342*	.397*	.314	.285	.332	.185	.144	.332	.138	.148	.467**	.438*	.279	1	.646**	.025	.150
Clarity	.437*	.451**	.452**	.326	.416*	.512**	.438*	.422*	.407*	.371*	.197	.225	.520**	.070	.211	.551**	.521**	.297	.646**	1	-.192	.037
Age	.045	-.032	.016	-.071	-.018	.010	.076	.040	-.075	-.209	-.247	-.065	-.023	.049	-.218	-.022	-.257	-.164	.025	-.192	1	.107
PlayHours	.498**	.447**	.401*	.460**	.344*	.440**	.414*	.477**	.229	-.114	-.107	-.004	-.142	-.037	-.264	.142	-.108	.011	.150	.037	.107	1

Table A2: Correlation matrix with Pearson values for all performance, and PX variables, age, and gaming expertise (PlayHours). The first nine rows and columns (ND to DD30) represent correlations between progression measures. *** $p < .01$; * $p < .05$*

Appendix B

Study 5

B.1 Comparison between Brighter and Darker Distractors

Dependent Variable	Pair	Mean Difference	t	p-value (Bonf.-Holm-adjusted)
dark_success	Easy - Mod	0.08	1.66	0.098
	Easy - Hard	0.24	4.92	< 0.001***
	Mod - Hard	0.16	3.10	0.005**
bright_success	Easy - Mod	-0.01	-0.24	0.817
	Easy - Hard	0.17	3.70	0.001**
	Mod - Hard	0.18	3.68	0.001**
dark_prog	Easy - Mod	-0.13	-0.33	0.743
	Easy - Hard	1.12	2.71	0.015*
	Mod - Hard	1.26	2.85	0.015*
bright_prog	Easy - Mod	-0.62	-1.60	0.112
	Easy - Hard	0.96	2.46	0.031*
	Mod - Hard	1.58	3.81	< 0.001***

Table A1: Paired t-test results comparing trials with distractors brighter and darker than the target for both outcome measures success rate and progression. **** $p < .001$; ** $p < .01$; * $p < .05$*

B.2 Correlation Matrices

	ND Success	ND Progression	ED Success	ED Progression	Meaning	Curiosity	Mastery	Autonomy	Immersion	Progress Feedback	Audiovisual Appeal	Challenge	Ease of Control	Clarity of Goals	Enjoyment	Age	PlayHours
ND Success	1	.080	.733**	.024	.165	.087	.356**	.124	.046	.171	.206*	.407**	.206*	.111	.171	-.055	.129
ND Progression	.080	1	.122	.894**	.032	-.187*	.202*	.030	.154	.118	.108	.121	.457**	.421**	.080	-.046	.221*
ED Success	.733**	.122	1	.341**	.117	.121	.353**	.153	.034	.103	.225*	.408**	.173	.148	.221*	-.177*	.117
ED Progression	.024	.894**	.341**	1	.030	-.118	.246**	.074	.122	.092	.145	.156	.366**	.373**	.108	-.112	.213*
Meaning	.165	.032	.117	.030	1	.791**	.628**	.482**	.481**	.382**	.559**	.420**	.134	.104	.733**	.166	.023
Curiosity	.087	-.187*	.121	-.118	.791**	1	.571**	.526**	.537**	.348**	.563**	.416**	.072	.066	.775**	.092	.034
Mastery	.356**	.202*	.353**	.246**	.628**	.571**	1	.503**	.513**	.457**	.595**	.596**	.293**	.284**	.692**	-.015	.119
Autonomy	.124	.030	.153	.074	.482**	.526**	.503**	1	.360**	.415**	.555**	.339**	.053	.147	.501**	-.044	-.001
Immersion	.046	.154	.034	.122	.481**	.537**	.513**	.360**	1	.330**	.548**	.339**	.289**	.313**	.635**	.111	-.018
Progress Feedback	.171	.118	.103	.092	.382**	.348**	.457**	.415**	.330**	1	.426**	.298**	.313**	.335**	.362**	-.203*	.126
Audiovisual Appeal	.206*	.108	.225*	.145	.559**	.563**	.595**	.555**	.548**	.426**	1	.596**	.310**	.306**	.784**	-.096	-.173
Challenge	.407**	.121	.408**	.156	.420**	.416**	.596**	.339**	.339**	.298**	.596**	1	.274**	.257**	.613**	-.059	-.043
Ease of Control	.206*	.457**	.173	.366**	.134	.072	.293**	.053	.289**	.313**	.310**	.274**	1	.689**	.213*	-.069	.201*
Clarity of Goals	.111	.421**	.148	.373**	.104	.066	.284**	.147	.313**	.335**	.306**	.257**	.689**	1	.228*	-.065	.223*
Enjoyment	.171	.080	.221*	.108	.733**	.775**	.692**	.501**	.635**	.362**	.784**	.613**	.213*	.228*	1	.006	-.018
Age	-.055	-.046	-.177*	-.112	.166	.092	-.015	-.044	.111	-.203*	-.096	-.059	-.069	-.065	.006	1	.010
PlayHours	.129	.221*	.117	.213*	.023	.034	.119	-.001	-.018	.126	-.173	-.043	.201*	.223*	-.018	.010	1

Table B1: Correlation matrix with Pearson values for all performance and PX variables, age, and gaming expertise (PlayHours) across groups. ** $p < .01$; * $p < .05$

	ND Success	ND Progression	ED Success	ED Progression	Meaning	Curiosity	Mastery	Autonomy	Immersion	Progress Feedback	Audiovisual Appeal	Challenge	Ease of Control	Clarity of Goals	Enjoyment	Age	PlayHours
ND Success	1	.170	.847**	.130	.140	-.097	.331*	.030	-.022	.229	.141	.410**	.256	.226	.037	-.002	.124
ND Progression	.170	1	-.002	.922**	.205	-.182	.389**	.054	.312*	.204	.268	.248	.659**	.562**	.110	-.072	.236
ED Success	.847**	-.002	1	.136	.097	.039	.241	.068	.014	.149	.113	.354*	.134	.189	.141	.005	.135
ED Progression	.130	.922**	.136	1	.233	-.075	.370*	.139	.340*	.217	.268	.233	.622**	.598**	.171	-.073	.276
Meaning	.140	.205	.097	.233	1	.736**	.625**	.500**	.435**	.308*	.667**	.584**	.325*	.319*	.730**	.157	-.020
Curiosity	-.097	-.182	.039	-.075	.736**	1	.443**	.539**	.490**	.295	.614**	.379*	.163	.218	.772**	.098	.080
Mastery	.331*	.389**	.241	.370*	.625**	.443**	1	.541**	.588**	.643**	.707**	.733**	.588**	.600**	.637**	-.024	.131
Autonomy	.030	.054	.068	.139	.500**	.539**	.541**	1	.415**	.364*	.477**	.380**	.139	.308*	.461**	-.051	.270
Immersion	-.022	.312*	.014	.340*	.435**	.490**	.588**	.415**	1	.392**	.715**	.487**	.421**	.501**	.737**	.037	.236
Progress Feedback	.229	.204	.149	.217	.308*	.295	.643**	.364*	.392**	1	.425**	.466**	.283	.477**	.370*	-.126	.099
Audiovisual Appeal	.141	.268	.113	.268	.667**	.614**	.707**	.477**	.715**	.425**	1	.670**	.484**	.490**	.871**	-.052	.077
Challenge	.410**	.248	.354*	.233	.584**	.379*	.733**	.380**	.487**	.466**	.670**	1	.462**	.424**	.703**	-.106	-.133
Ease of Control	.256	.659**	.134	.622**	.325*	.163	.588**	.139	.421**	.283	.484**	.462**	1	.707**	.352*	-.056	.293
Clarity of Goals	.226	.562**	.189	.598**	.319*	.218	.600**	.308*	.501**	.477**	.490**	.424**	.707**	1	.343*	-.101	.219
Enjoyment	.037	.110	.141	.171	.730**	.772**	.637**	.461**	.737**	.370*	.871**	.703**	.352*	.343*	1	-.028	.014
Age	-.002	-.072	.005	-.073	.157	.098	-.024	-.051	.037	-.126	-.052	-.106	-.056	-.101	-.028	1	-.040
PlayHours	.124	.236	.135	.276	-.020	.080	.131	.270	.236	.099	.077	-.133	.293	.219	.014	-.040	1

Table B2: Correlation matrix with Pearson values for all performance and PX variables, age, and gaming expertise (PlayHours) in group Easy. *** $p < .01$; * $p < .05$*

	ND Success	ND Progression	ED Success	ED Progression	Meaning	Curiosity	Mastery	Autonomy	Immersion	Progress Feedback	Audiovisual Appeal	Challenge	Ease of Control	Clarity of Goals	Enjoyment	Age	PlayHours
ND Success	1	.009	.836**	.003	.174	.198	.323	.153	.024	.148	.204	.503**	.467**	.284	.225	-.129	.297
ND Progression	.009	1	.014	.929**	-.169	-.263	-.075	-.078	.109	.055	.001	-.019	.176	.172	-.149	.020	.302
ED Success	.836**	.014	1	.173	.168	.224	.350*	.186	.125	.211	.304	.422*	.395*	.313	.309	-.281	.186
ED Progression	.003	.929**	.173	1	-.158	-.227	.020	-.054	.129	.131	.059	-.039	.138	.119	-.103	-.084	.271
Meaning	.174	-.169	.168	-.158	1	.778**	.457**	.421*	.433**	.395*	.362*	.073	.180	-.130	.686**	-.056	.122
Curiosity	.198	-.263	.224	-.227	.778**	1	.515**	.452**	.470**	.371*	.422*	.266	.280	-.008	.723**	.017	.032
Mastery	.323	-.075	.350*	.020	.457**	.515*	1	.381*	.413*	.391*	.312	.257	.358*	.042	.555**	-.100	.295
Autonomy	.153	-.078	.186	-.054	.421*	.452**	.381*	1	.280	.470**	.649**	.111	.039	-.026	.561**	-.006	.231
Immersion	.024	.109	.125	.129	.433**	.470**	.413*	.280	1	.192	.382*	.148	.306	.231	.430*	.128	-.176
Progress Feedback	.148	.055	.211	.131	.395*	.371*	.391*	.470**	.192	1	.522**	.174	.343*	.030	.416*	-.414**	.084
Audiovisual Appeal	.204	.001	.304	.059	.362*	.422*	.312	.649**	.382*	.522**	1	.468**	.365*	.272	0.714**	-.279	-.316
Challenge	.503**	-.019	.422*	-.039	.073	.266	.257	.111	.148	.174	.468**	1	.487**	.258	.387*	-.154	.001
Ease of Control	.467**	.176	.395*	.138	.180	.280	.358*	.039	.306	.343*	.365*	.487**	1	.759**	.317	.079	.343*
Clarity of Goals	.284	.172	.313	.119	-.130	-.008	.042	-.026	.231	.030	.272	.258	.759**	1	.248	.236	.189
Enjoyment	.225	-.149	.309	-.103	.686**	.723**	.555**	.561**	.430*	.416*	.714**	.387*	.317	.248	1	-.077	-.045
Age	-.129	.020	-.281	-.084	-.056	.017	-.100	-.006	.128	-.414**	-.279	-.154	.079	.236	-.077	1	.110
PlayHours	.297	.302	.186	.271	.122	.032	.295	-.231	-.176	.084	-.316	.001	.343*	.189	-.045	.110	1

Table B3: Correlation matrix with Pearson values for all performance and PX variables, age, and gaming expertise (PlayHours) in group Moderate. *** p < .01; * p < .05*

	ND Success	ND Progression	ED Success	ED Progression	Meaning	Curiosity	Mastery	Autonomy	Immersion	Progress Feedback	Audiovisual Appeal	Challenge	Ease of Control	Clarity of Goals	Enjoyment	Age	PlayHours
ND Success	1	.062	.548**	-.090	.188	.256	.375*	.270	.177	.209	.239	.385*	-.104	-.233	.311	-.048	-.078
ND Progression	.062	1	.393*	.913**	-.003	-.209	.228	.104	.012	.051	.061	.100	.518**	.386*	.218	-.041	.055
ED Success	.548**	.393*	1	.540**	.087	-.041	.342*	.265	-.001	.111	.121	.255	.134	.049	.172	-.243	-.009
ED Progression	-.090	.913**	.540**	1	-.019	-.268	.218	.105	-.058	-.024	.050	.060	.454**	.363*	.136	-.090	.044
Meaning	.188	-.003	.087	-.019	1	.884**	.746**	.551**	.640**	.522**	.624**	.562**	-.097	-.104	.781**	.370*	-.078
Curiosity	.256	-.209	-.041	-.268	.884**	1	.777**	.604**	.778**	.449*	.666**	.557**	-.202	-.211	.817**	.201	-.101
Mastery	.375*	.228	.342*	.218	.746**	.777**	1	.622**	.572**	.440*	.696**	.699**	-.031	-.007	.855**	.088	-.086
Autonomy	.270	.104	.265	.105	.551**	.604**	.622**	1	.451*	.452*	.570**	.613**	-.063	-.060	.498**	-.069	-.030
Immersion	.177	.012	-.001	-.058	.640**	.778**	.572**	.451*	1	.434*	.553**	.465**	-.038	-.050	.740**	.185	-.122
Progress Feedback	.209	.051	.111	-.024	.522**	.449*	.440*	.452*	.434*	1	.413*	.378*	.325	.314	.444*	-.088	.195
Audiovisual Appeal	.239	.061	.121	.050	.624**	.666**	.696**	.570**	.553**	.413*	1	.618**	.062	.127	.764**	.057	-.299
Challenge	.385*	.100	.255	.060	.562**	.557**	.699**	.613**	.465**	.378*	.618**	1	-.081	.050	.673**	.149	-.082
Ease of Control	-.104	.518**	.134	.454**	-.097	-.202	-.031	-.063	-.038	.325	.062	-.081	1	.764**	-.045	-.235	-.106
Clarity of Goals	-.233	.386*	.049	.363*	-.104	-.211	-.007	-.060	-.050	.314	.127	.050	.764**	1	.006	-.242	.324
Enjoyment	.311	.218	.172	.136	.781**	.817**	.855**	.498**	.740**	.444*	.764**	.673**	-.045	.006	1	.166	-.102
Age	-.048	-.041	-.243	-.090	.370*	.201	.088	-.069	.185	-.088	.057	.149	-.235	-.242	.166	1	-.026
PlayHours	-.078	.055	-.009	.044	-.078	-.101	-.086	-.030	-.122	.195	-.299	-.082	-.106	.324	-.102	-.026	1

Table B4: Correlation matrix with Pearson values for all performance and PX variables, age, and gaming expertise (PlayHours) in group Hard. *** $p < .01$; * $p < .05$*

Abbreviations

ANOVA Analysis of Variance

AR Augmented Reality

CCT Contingent Capture Theory

DD Delay Distraction

DDA Dynamic Difficulty Adjustment

DW Dimension-Weighting

ED Encoding Distraction

ERP Event-Related Potential

FBA Feature-Based Attention

FPS First-Person-Shooter

HCI Human-Computer Interaction

IQR Interquartile Range

M Mean

Mdn Median

ND No Distraction

PENS Player Experience of Need Satisfaction

PX Player Experience

PXI Player Experience Inventory

RQ Research Question

SD Standard Deviation

SDT Self-Determination Theory

UX User Experience

VR Virtual Reality

WM Working Memory

WMC Working Memory Capacity

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