Individualizing Learning Games:

Incorporating the Theory of Multiple Intelligences in Player-Centered Game Design

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Dedicated

To

The memory of my grandfather who inspired me

And my family who continue to support and inspire me

Abstract

Over the past decades, computer-based learning systems have been implemented in a wide variety of domains, ranging from industry and military, to healthcare and education. They allow us to reach a large population, while being able to provide individualized experiences. Computer-based learning systems are especially useful in education where media such as games can be utilized to emerge students in rich, motivating and playful environments to acquire new insights and skills.

The concept of individualization is complex, and if examined systematically, composed of different facets. One of the facets essential to the realization of individualization is the “aspects of the player used to drive the individualization”. This facet includes aspects such as performance, affective states and physiological parameters. While some aspects have been fairly well researched, others, such as the *Multiple Intelligence (MI) dimensions* based on the “Theory of Multiple Intelligence” (MI) have been largely neglected. This is peculiar, since MI is in particular recognizing differences between people in term of their abilities to solve problems or create products.

In this dissertation, we explored by means of a survey study, possible relationships between MI intelligences and games, as well as its relation with the fundamental building block of games, known as game mechanics. The results of this study show that correlations exist between the MI *intelligences* of players and preferences for games. The study also indicates that these correlations can be further refined into mappings between the MI dimensions and preference for game mechanics. We argue that the findings can be used in the design of player-centered games that target players with specific MI intelligences. Therefore, we also evaluated the effectiveness of some of the proposed mappings for the individualization of learning games by means of experiments. In order to do so, we designed and developed two games targeting players with certain MI intelligences. The design was based on the insights gained from our research, i.e. the mappings. The results show that for these two games, individualization based on the MI intelligences of the players contributes positively to both game experience and learning outcome.

To support such a player-centered design approach, a tool that supports the use of the aforementioned mappings has been developed. As such, this dissertation offers game designers, developers and researchers a stepping-stone towards

designing individualized games that successfully enhance players' game experience and learning outcomes.

Dutch Abstract

Computer-gebaseerde leersystemen worden, sinds verschillende decennia, gebruikt in een breed scala van domeinen, zowel in industrie als in het leger, de gezondheidszorg en het onderwijs. Ze laten toe om een grote groep te bedienen, terwijl er nog steeds ruimte is voor een individuele benadering. Computer-gebaseerde leersystemen zijn heel nuttig in het onderwijs en voor opleidingen in het algemeen omdat geavanceerde media zoals games (spelletjes) kan worden gebruikt om leerlingen beter te motiveren voor het verwerven van nieuwe inzichten en vaardigheden en hun een leuke leeromgeving aan te bieden.

Het begrip individualisering is complex en samengesteld uit verschillende facetten. Eén van de facetten, essentieel voor het realiseren van individualisering, betreft "de aspecten van de speler waarop de individualisering kan gebaseerd zijn". Deze aspecten kunnen zaken omvatten betreffende de leerprestaties, of gebaseerd zijn op fysiologische parameters of gemoedstoestanden. Terwijl sommige aspecten redelijk goed onderzocht zijn, zijn anderen, zoals het gebruik van de meervoudige intelligentie (MI) dimensies uit de Theorie van meervoudige intelligentie, grotendeels genegeerd. Dit is merkwaardig, omdat deze theorie toe laat mensen te onderscheiden op basis van hun verschil in natuurlijke gaven om problemen op te lossen of producten te creëren.

In dit proefwerk onderzochten we, door middel van een verkennende studie, wat de mogelijke relaties zijn tussen MI intelligenties en games, evenals de relatie met de “game mechanics” (die de fundamentele bouwstenen zijn van games). De resultaten laten zien dat er correlaties bestaan tussen de intelligenties (volgens MI) van de spelers en hun voorkeur voor games. De studie geeft ook aan dat deze correlaties verder kunnen worden verfijnd tot relaties tussen de verschillende MI intelligenties en game mechanics. In het licht van deze resultaten, betogen we dat de resultaten kunnen worden gebruikt bij het ontwerp van (leer)spellen die speciaal bedoeld zijn voor spelers met specifieke MI intelligenties. Daarom werd de effectiviteit van het gebruik van aan MI intelligenties aangepaste game mechanics geëvalueerd door middel van experimenten. Om dat te kunnen doen, hebben we twee spelletjes ontwikkeld, gebruik makend van onze aanbevelingen. De resultaten van de experimenten geven aan dat individualisering op basis van de MI intelligenties van de spelers positief bijdraagt aan zowel spelervaring als aan leerresultaten.

Om dit soort van speler-gericht ontwerp van games te ondersteunen, werd een software tool gebouwd. Als zodanig biedt dit proefschrift aan ontwerpers, ontwikkelaars en onderzoekers in het domein van games, een opstap voor het ontwerpen van geïndividualiseerde leerspellen die de spelervaring en de leerresultaten verbeteren.

Acknowledgment

I would like to express my sincere gratitude to my promoter Prof. Dr. Olga De Troyer, co-director of the WISE Laboratory of the Vrije Universiteit Brussel. Without her continuous support, guidance, and vision, accomplishing this research would not have been possible. Her brilliance is only overwhelmed by her patience and generosity to her students, and I am forever grateful to her for believing in me, giving me the opportunity to join her team, and teaching me how to think like a researcher.

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Chapter One:
Introduction

"A journey of a thousand miles begins with a single step."

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1.1 Context

Since the advent of modern computers, digital technology has become an increasingly important part of learning environments (Amory, Naicker, Vincent, & Adams, 1999; Garrison, 2011; Koehler & Mishra, 2009; Rosenberg, 2001). In fact, over the past decades, we have witnessed the creation of prevalent computer-supported learning systems in a wide variety of domains: from industry and military, to healthcare and education. According to (Koehler & Mishra, 2009), technology enhance education can be effectual only when three main bodies of knowledge, i.e. content, pedagogy, and technology, are considered and successfully interact and integrate (i.e. the TPACK model). This model is a testament to the fact that a wide range of expertise is required to realize such systems, and research in this context is inherently interdisciplinary. These systems appeal to educators because they support rich content and have the potential to reach a large population while being able to maintain a personalized approach. In education, offering a personalized approach is argued to be an effective way to positively affect the learning outcomes of individuals (see e.g. (Tseng, Chu, Hwang, & Tsai, 2008; Yasir & Sharif, 2011)). A personal approach is the opposite of the "one-size-fits-all" approach often used in traditional classroom learning environments. To be able to offer a personalized approach, one must first understand the users' needs, abilities and preferences. This is a principle also used in software engineering in the user-centered design, introduced in early usability work (Norman, 1986) and now well accepted in the domain of HCI (Human Computer Interaction). In the context of computer-supported learning systems or so-called e-learning systems, the users are the learners. The personalized approach used in e-learning systems aligns with the increased focus on learner-centered design (LCD) in education (Quintana, Krajcik, & Soloway, 2000). Both approaches are based on the same principles. For instance, according to (Quintana et al., 2000), there are three components of LCD: the *audience* targeted, the *central problem* addressed, and the *approach* taken to address the problem. These components are also recognized in the process of personalization and adaptation used in e-learning systems (Brusilovsky, 1996; Kareal & Klema, 2006; Tavangarian, Leypold, Nölting, Röser, & Voigt, 2004). They are used to tailor the learning process based on the needs and preferences of the learners (Beldagli & Adiguzel, 2010; Brusilovsky, 2001; Kickmeier-Rust & Albert, 2010; Vandewaetere, Desmet, & Clarebout, 2011). Since different terms are used for referring to the principle of using a personal or learner adapted approach in the context of learning and e-learning, e.g. *Learner-centered design*, *personalization*, *adaptivity*, *adaptation,* we will use the general term *individualization* to refer to this principle. This term is discussed in detail in chapter 2.

E-learning corroborates individualization in different ways. For instance, in (Schiaffino, Garcia, & Amandi, 2008) a differentiation between individualized educational and intelligent tutoring systems is made. Individualized educational systems generally provide different types of presentation and navigation of content based on the profile of the learner (e.g. Henze & Nejdl, 2001; Yasir & Sharif, 2011). Intelligent tutoring systems on the other hand, recommend different educational activities while providing individualized feedback based on the profile of the learner (e.g. Forbes-Riley, Litman, & Rotaru, 2008; Schiaffino et al., 2008).

In recent years, we also see a growing interest in the use of rich and sophisticated media, such as games for learning. Games have the potential to provide an environment that is motivating and fun, and at the same time powerful enough to support players in learning new concepts or to help them acquire new skills or behaviors (Dondlinger, 2007; Paras & Bizzocchi, 2005; Wouters, van der Spek, & van Oostendorp, 2009). Indeed, many scholars have argued that games are inherently motivating, both *intrinsically* and *extrinsically* (e.g. (Dondlinger, 2007; Gee, 2004)). "***Intrinsic*** *motivation pushes us to act freely, on our own, for the sake of it;* ***extrinsic*** *motivation pulls us to act due to factors that are external to the activity itself, like reward or threat*" (Denis & Jouvelot, 2005) (Page 1). Given that motivation is an important condition for learning and the fact that games play an important role in the lives of youngsters and adults today (Kirriemuir &

McFarlane, 2004), it is reasonable to try and take advantage of this rich medium to enhance education and learning. In the literature, a variety of terms are used to refer to games for learning. This includes concepts like *educational games*, *edutainment games*, *serious games* and *learning games*. The term *learning games* will be used throughout this dissertation to refer to this principle.

Researchers in the domain of learning games have applied and combined knowledge and contributions from the domains of e-learning and games. Strategies such as learner-centered design (called player-centered design in the context of games), and individualization were already given due attention (Chanel, Rebetez, Bétrancourt, & Pun, 2008; Hwang, Sung, Hung, Huang, & Tsai, 2012; Lopes & Bidarra, 2011; Magerko, 2009; Moreno-Ger, Burgos, Martínez-Ortiz, Sierra, & Fernández-Manjón, 2008; Muir & Conati, 2012; Georgios N Yannakakis et al., 2010). Individualization has particularly been of interest and importance in the context of learning games. Research has shown that good game experience (which includes metrics such as the flow state and immersion) is positively correlated with better learning. It is argued (Millis et al, 2011; Poels et al, 2007) that good game experience could lead to a state of absolute absorption into a task to a point of losing self-consciousness. In this “flow state”, the activity itself becomes rewarding in its own and enables individuals to function at their fullest capacity (Csikszentmihalyi & Csikszentmihalyi, 1992) including the capacity to learn (Kiili, 2005; Webster, Trevino, & Ryan, 1993). So, by considering the needs, abilities and preferences of players (i.e. individualization), one could create games that can positively influence the game experience of the players, which, in turn, will positively affect their learning outcomes.

Various conceptual frameworks on individualized learning through games have proposed different factors that could contribute to the process of individualization (see e.g. (Charles, Kerr, & McNeill, 2005; Kickmeier-Rust, Mattheiss, Steiner, & Albert, 2012; Lopes & Bidarra, 2011; Peirce, Conlan, & Wade, 2008; Sajjadi, Van Broeckhoven, & De Troyer, 2014; Vandewaetere, Cornillie, Clarebout, & Desmet, 2013)). These range from factors used to drive the individualization, such as different aspects of the player and how they are measured, to aspects of the game that can be subject to individualization, over strategies for when and how to apply individualization. The research presented in this dissertation and its contributions to the state of the art in the domain of learning games are directly related to one of the least explored aspects of the players. More precisely, in this dissertation, we consider the intelligence levels of players with respect to the “Theory of Multiple Intelligences” (Gardner, 2011) as a factor that can be used to drive individualization. Furthermore, based on our findings, we focus on game mechanics as the aspect of the game that can be subject to individualization. The motivation for this focus is given in section 1.2. The research presented in this dissertation shows that individualization of games based on the intelligences of the players (henceforth referred to as MI intelligences) and of relevant game mechanics could result in better game experiences as well as higher learning outcomes.

1.2 Goal and Motivation

A large body of work on player-centered game design, personalization and adaptation in learning games can be found in the literature. Nonetheless, there are still vast opportunities for exploration and adoption of a variety of contributing factors to the process of individualization.

With respect to the aspects of the player that can drive the individualization, the most well researched aspects are *knowledge level*, *skill level*, and *player style*. In contrast, more novel aspects such as *engagement*, *anxiety*, and *attention* have been studied to a much lesser extent, mainly because it is not (yet) easy to measure those aspects in a non-intrusive way. More pedagogical aspects of players such as *learning styles* and *intelligence levels* on the other hand, have even been largely neglected. This is rather peculiar given the inherent potential for individualization expressed in the descriptions of these theories. For instance, Kolb & Kolb describe *learning styles* as "*individual differences in learning based on the learner's preference for employing different phases of the learning cycle*" (Page 4) (Kolb & Kolb, 2005), where learning is defined as "*the process whereby knowledge is created through the transformation of experience. Knowledge results from the combination of grasping and transforming experience*" (page 41) (D. A. Kolb, 1984), and the different phase of the learning cycle are defined as: concrete experience, observation and reflection, formation of abstract concepts and generalization, and testing implications of concepts in new situations (Kolb & Kolb, 2005).

Quite similarly, the "Theory of Multiple Intelligences" (MI for short) draws a framework for defining individual differences between people. According to Howard Gardner, the author of MI (Gardner, 2011), the intelligence of a human being is multi-dimensional, as opposed to the one dimensional understanding of intelligence represented by popular measures such as the Intelligence Quotient (IQ). According to Gardner, an intelligence is "*the ability to solve problems, or to* *create products, that are valued within one or more cultural settings*" (Gardner, 2011) (page 28). Based on this definition, eight distinct *intelligence dimensions* have been proposed. These dimensions are *visual-spatial*, *bodily-kinesthetic*, *musical-rhythmic*, *linguistic*, *logical-mathematical*, *interpersonal*, *intrapersonal*, and *naturalistic*. Moran and Gardner (2006) argue that everyone possesses all dimension of intelligence, be it, however, to different degrees. Furthermore, they state that these different dimensions of intelligence work together in an orchestrated way. In this way, MI dimensions can be used to explicate the differences between abilities of individuals and has been used in the context of learning (e.g. (Armstrong, 2009; Christison, 1998; Fogarty, 1997)). Furthermore, Chan (Chan, 2005) suggests that people with different "intelligences" or intellectual abilities (*MI intelligences*) often exhibit clear preferences toward specific modalities and types of interaction in relation to learning and self-expression. This makes the concept of MI dimensions an appropriate candidate to support individualization of games for learning. In light of this, the focus of this dissertation will be on the use of MI intelligences, i.e. the degrees to which a player possesses the different dimensions of intelligence defined by MI, as a driving factor for individualization. Honesty obliges us to mention that the "Theory of Multiple Intelligences" has also been criticized in the literature for lack of empirical evidence for the existence of multiple intelligences. For instance, in (Waterhouse, 2006b) an overview of the discussions about the existence of multiple intelligences over the years (1994-2004) is given. The objective of this dissertation is not to contribute to this discussion or to investigate the validity of MI as such, but to investigate its applicability, and specifically the definitions of the different MI dimensions, in the context of the individualization of learning games. More in particular, we want to investigate whether we can use the differences between people reported by the instruments developed for measuring these MI intelligences, as input for the process of individualization and whether this will result in improved game experience and learning outcome. MI is explained in more detail in section 4.2

With respect to the aspects that can be subject to individualization, the majority of researches focus on *(dynamic) difficulty adjustments* and *learning content adjustments.* These two strategies may be sufficient in the e-learning context, but games possess much richer environments and may require or offer more opportunities for individualization. In the context of learning games, aspects such as narratives, music, game mechanics etc. play an equally important role. These aspects have been hardly studied in relation to the individualization of learning games. Furthermore, our findings while investigating the possibility of using MI dimensions in the individualization of games pointed to the direction of the fundamental building blocks of games (i.e. game mechanics). In light of this, with respect to aspects of the game that can be subject to individualization, the focus of this dissertation will be on game mechanics as defined by Sicart: "*methods invoked by agents, designed for interaction with the game state*" (Sicart, 2008) (paragraph 25).

The lack of incorporating pedagogical characteristics of the players in the process of individualization, as well as the observation that individualization strategies are mostly limited to dynamic difficulty and learning content adjustments, have informed and motivated the research presented in this dissertation. We believe that using more pedagogical-oriented characteristics of players (e.g. MI intelligences, learning styles) for driving the individualization process can be beneficial for the learning outcome.

In summary, the goal of this dissertation is to investigate the different attitudes that people with specific pedagogical-oriented characteristics (i.e. different MI intelligences) might have towards specific game mechanics and how these findings can be used for advancing the state of the art in individualization of learning games. More in particular, and after an empirical investigation of the relation between the MI intelligences and game preferences, we propose a mapping between the MI dimensions and the fundamental building blocks of games, i.e. game mechanics. These mappings express what game mechanics could suit (or not) the different MI dimensions, and thus can be used to inform the design of games targeting people having one or more specific MI intelligences.

Of course, it is also important to evaluate the effectiveness of the proposed individualization strategy on the game experience and learning outcome of the players. Although this looks as an important and obvious issue, it seems that in practice empirical evidence on the success of learning games in general, and individualization of these games in particular is often lacking. A study performed in 2012 aggregated publications that present empirical evidence about the effect of computer games on learning and engagement (Connolly, Boyle, Macarthur, Hainey, & Boyle, 2012). From a large pool of 7392 papers, only 129 met the criteria of the authors to be considered as studies that provide empirical evidence. Therefore, empirical validation of the results obtained, i.e. our mappings, is an explicit goal of our research. However, because of the large amount of mappings proposed, we were only able to perform a partial evaluation. This is simply due to the fact that a complete evaluation would require an extensive amount of time and is thus unfeasible to be carried out in the context of one PhD.

In addition, easy dissemination of our findings was another objective. For this reason, we developed a software tool that makes the proposed mappings easily assessable by means of visualizations, search and filtering mechanisms.

To conclude, we want to clearly state what was not among the objectives of this dissertation. Firstly, although the Theory of MI will be used extensively throughout this dissertation, it is not the aim of this dissertation to empirically validate this theory. Rather, the MI dimensions defined by this theory are used to profile learners and to investigate what game characteristics (i.e. game mechanics) would suit those profiles. Secondly, it was not our objective to come up with truly empirically based mappings between the different dimensions of MI and game mechanics. The proposed mappings are based on our subjective interpretation of the results of our survey study that investigated the relationship between MI intelligences and game preferences. Establishing the mentioned mappings in a truly empirical manner would be rather infeasible in the context of one PhD. We rather adhere to the research methodology commonly used in Computer Science. In computer science, design science (Hevner, March, Park, & Ram, 2004) is commonly used as research method. In design science, a solution is proposed for a problem and afterwards the solution is evaluated in order to ensure its utility for the specific problem. This is the approach we have taken: the proposed mappings are our solution to the problem of how to take profiling based on MI dimensions into consideration for individualization. As explained, the validation could only be done partially. Validation has been done for two MI dimensions and in the context of two games.

1.3 Research Questions and Methodology

Through a comprehensive study of the literature (see chapter 2), we have identified the current limitations of the individualization of learning games. The different aspects of a player that can drive the individualization process were identified. Moreover, the different methods for assessing these aspects were analyzed. The individualizations that are made to a game as a result of using these aspects were also explored. Based on the results of the literature study, the main objective of the dissertation was formulated as:

To investigate whether individualization based on player's intelligences (according to MI) and the game's mechanics has a positive influence on the game experience and learning outcome of the players.

Furthermore, based on the results of the literature study, a comprehensive conceptual framework for the individualization of learning games was developed in order to identify the different relevant components for individualization and to clarify their role in this process. This conceptual framework is also used to position the research work and contribution of the dissertation. The conceptual framework is described in chapter 3.

To reach the objective of the dissertation, several underlying research questions (RQ) need to be answered. In order to be able to successfully incorporate concepts such as MI dimensions and game mechanics in the process of individualization of a game, one needs to investigate whether there are any relationships between the two and if so, of what nature those relationships would be. These relationships could then facilitate the investigation of the main objective of this dissertation through evaluating individualized games. This resulted into the following research question:

RQ1: Are there any correlations between player's intelligences (with respect to MI) and their preferences for games?

RQ2: If there are correlations between players' MI intelligences and their preferences for specific games, can they be attributed to the game mechanics and if so how?

RQ3: Can player-centered game design based on the findings of RQ2 contribute to better game experience?

RQ4: Can player-centered game design based on the findings of RQ2 contribute to higher learning outcome?

RQ5: How can our findings of RQ2 be provided to game designers and developers in a more accessible way?

With respect to answering **RQ1**, first a learning game called "Maze Commander" was created to investigate possible correlations between MI intelligences and enjoyment and attitudes towards games that utilize different types of interaction modalities. The results of the evaluation failed to find any significant correlations. In retrospective, we discovered that the influence of the collaborative aspect of the game was too large to reveal the correlations we aimed for. Therefore we will not discuss this experiment in the dissertation and we abandoned the use of the game for the rest of the research work. However, the description and a discussion on the possible explanations for the outcome of the experiment, as well as lessons learned can be found in Appendix A. This experience informed the creation of a survey study to investigate whether there are correlations between MI intelligences and games in general or not. The survey provided empirical evidence for the viability of using MI dimensions as part of individualization.

In order to investigate **RQ2**, the results of the survey study were further analyzed. It was revealed that characteristics of games such as genres could not justify entirely why certain MI intelligences were correlated with preferences for certain games. This called for investigating the relationships with more fundamental components of games, i.e. game mechanics. This meant that the games that showed to be correlated to specific MI intelligences had to be decomposed into their game mechanics. Moreover, an analysis of the games used in the survey based on their game mechanics had to be performed to identify relations between MI dimensions and game mechanics. Furthermore, the nature of those relations had to be identified. We identified three possible relations: positive, negative and dubious (uncertain). Based on this, mappings between MI dimensions and game mechanics were proposed that could be used in individualization.

To answer **RQ3**, a game called LeapBalancer was designed and developed. As a case study, LeapBalancer was designed and developed specifically for people who exhibit a high bodily-kinesthetic intelligence of MI. Based on the proposed mapping, the design process included the selection and incorporation of game mechanics that were identified to be positively related with the bodily-kinesthetic dimension of MI. An evaluation was performed to confirm our hypothesis with respect to the effect of our proposed individualization on game experience of the players. This case study provided a first answer to **RQ3**.

To answer **RQ4**, a game called TrueBiters was designed and developed. TrueBiters was inspired by a board game called b00le0 aimed at teaching Boolean logic. TrueBiters was slightly changed during the digitization process, and its topic was shifted from Boolean logic to Proposition logic. According to our mappings, the core gameplay mechanics of TrueBiters should suit and affect players who are logically-mathematically intelligent. The game was evaluated to confirm our hypothesis with respect to the effect of our proposed individualization on both game experience and learning outcome of the players. This case study provided a first answer to **RQ4**.

Finally, to answer **RQ5**, a software tool was designed and developed to visualize the mappings between MI dimensions and (classes) of game mechanics, which will allow game designers to easily access and filter the information contained in the mappings. Game designers and/or developers can use this tool to inspect and select the game mechanics they want to include in their game, depending on which MI dimension(s) they are targeting. The tool also has a reporting facility that highlights possible conflicts when targeting different MI intelligences.

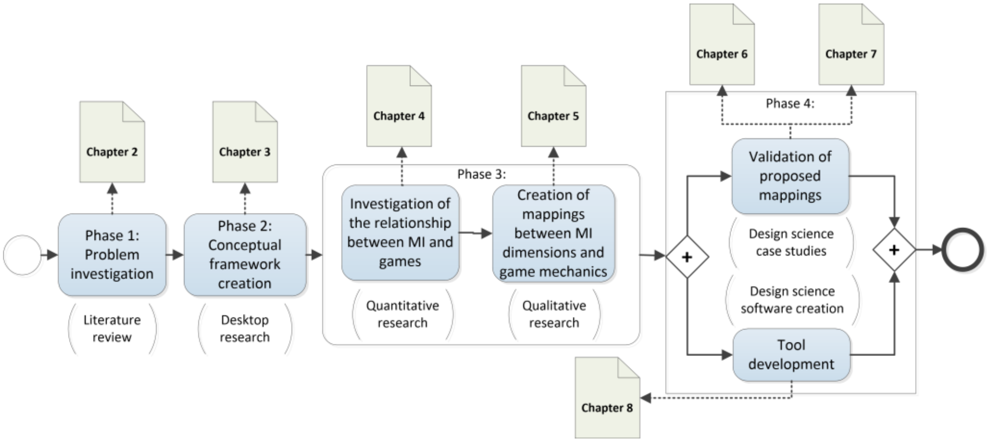

Figure 1 – Research steps – notation based on BPMN[1]

The different steps taken for the research are visualized in Figure 1. Four phases can be distinguished. In the first phase, **Problem investigation**, the underlying problem has been investigated by means of a literature review to narrow down the scope of the thesis. The outcome is provided in **chapter 2**. In the second phase, **Conceptual framework creation**, a generic conceptual framework for individualization of games has been designed by means of desktop research based on results of the literature review, and the dissertation is positioned in this framework. The outcome is presented in **chapter 3**. In the third phase, **Elaboration of the solution,** a solution to the formulated problem has been proposed and elaborated. This was performed in two sub-phases. In the first sub-phase a quantitative study by means of a survey has **investigated the existence of possible correlations between MI intelligences and games**. This sub-phase is described in **chapter 4.** In the next sub-phase a qualitative analysis over the results of the previous sub-phase lead to the **establishment of mappings between MI dimensions and game mechanics**. This is described in **chapter 5**. In the last phase, two sub-phases were performed in parallel. On the one hand, the (partial) **validation of the proposed mappings** has been considered by means of two case studies. Each case study focuses on one MI dimension and a number of game mechanics. These validations are described in **chapters 6** and **chapter 7**. On the other hand, a **support tool** has been developed that visualizes the mappings and provides search and filtering facilities for better accessibility. The tool is described in **chapter 8**.

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[1] http://www.bpmn.org/

The outcome of this dissertation has been communicated to peers in different conferences including CHI play, VS Games, ECGBL, GALA and Gamedays (see next section for an overview).

1.4 Research Contributions

The research presented in this dissertation contributes to the state of the art in individualizing learning games in the following ways:

1) It provides a comprehensive overview of the state of the art in individualization (player-centered, personalization, and adaptation) of learning games. (chapter 2)
2) It provides a review of the different aspects of a player used to drive the individualization process, and highlights the most frequently used ones and the neglected ones. (chapter 2)
3) It provides a conceptual framework for dealing with individualization of learning games that can be used for personalization and/or adaptation, as well as for designing player-centred games targeting a specific audience. (chapter 3)
4) It provides empirical evidence for the existence of correlations between MI intelligences and preferences for certain games. (chapter 4)
5) It provides mappings between MI dimensions and game mechanics, which can be used to tailor the game mechanics to the MI intelligences of the target players. (chapter 5)
6) It provides a partial validation of the proposed mappings by means of their use in two games, specifically developed for this purpose. In particular, we have seen a positive effect on game experience of bodily-kinesthetically intelligent players in the game LeapBalancer (chapter 6) and a positive effect on learning outcome and game experience of logically-mathematically intelligent players in the game TrueBiters (chapter 7).
7) It provides a support tool for researchers, game designer and game developers to search, browse, and inspect the mappings in a visual way, and for selecting appropriate game mechanics targeting specific MI dimension(s). (chapter 8)

Parts of this dissertation has been presented and published in the proceedings of peer reviewed conferences:

- **Dynamically Adaptive Educational Games: A New Perspective** (Sajjadi, Broeckhoven, et al., 2014) – Earlier version of chapter 3
- **Maze commander: a collaborative asynchronous game using the oculus rift & the sifteo cubes** (Sajjadi, Cebolledo Gutierrez, Trullemans, & De Troyer, 2014) – Partly covers the motivation behind chapter 4.
- **Relation Between Multiple Intelligences and Game Preferences: an Evidence-Based Approach** (Sajjadi, Vlieghe, & De Troyer, 2016b) – Partly covers chapter 4.
- **Evidence-Based Mapping Between the Theory of Multiple Intelligences and Game Mechanics for the Purpose of Player-Centered Serious Game Design** (Sajjadi, Vlieghe, & De Troyer, 2016a) – Partly covers chapter 5.
- **Exploring the Relation Between Game Experience and Game Mechanics for Bodily-Kinesthetic Players** (Sajjadi, Lo-A-Njoe, Vlieghe, & De Troyer, 2016) – Partly covers chapter 6.
- **On the Impact of the Dominant Intelligences of Players on Learning Outcome and Game Experience in Educational Games: The TrueBiters Case** (Sajjadi, El Sayed, & De Troyer, 2016) – Partly covers chapter 7.

1.5 Structure of the Dissertation

This dissertation is organized as follows:

Chapter 2 presents the literature review. Through this literature review, we identified the current limitations of individualization of learning games, and formulated the main objective of this dissertation. It also provides the necessary background for understanding some of the general terms and concepts used throughout this dissertation. This chapter also sets up the necessary grounds for understanding the current approaches, techniques, and variables involved in the process of individualization.

Chapter 3 delineates a conceptual framework for the individualization of learning games. This chapter first reviews related similar conceptual frameworks. It then presents a conceptual framework that caters for the different contributing factors of the individualization, and the different ways individualization can take place.

Chapter 4 starts by providing background information on the "Theory of Multiple Intelligences" (MI). It then presents the related work on MI and games.

Next, we describe the study performed to find empirical correlations between MI intelligences and games through an online survey. In light of this, the methodology used, results, discussion, and limitations of this survey study are explained.

Chapter 5 describes the further investigation of how the results of chapter 4 can be used in favor of individualization. It describes how the games, used in the survey study, were decomposed based on their game mechanics, and how we arrived at a mapping between the MI dimensions and game mechanics. This chapter also defines the term game mechanic, and possible categorizations for game mechanics. Furthermore, the related work in this context is discussed.

Chapter 6 deals with the validation of the proposed mappings for the specific case of one MI dimension, i.e. bodily-kinesthetic intelligence and in the context of one game. It discusses the design and development of a game, called "LeapBalancer", as well as the methodology used for the experiment to investigate **RQ3**, and the results of the experiment and conclusions.

Chapter 7 deals with the validation of the proposed mappings for the case of the logical-mathematical intelligence and in the context of one game, the TrueBiters. It discusses the design and development of this learning game. Furthermore, the methodology used for the experiments to investigate **RQ3** and **RQ4** is explained, and the results are reported and discussed.

Chapter 8 presents the tool created for the practical use of the mappings between MI dimensions and game mechanics. We also explain how this tool can be used by game designers and developers for creating player-centered games with respect to MI dimension(s).

Chapter 9 provides a summary, and the overall conclusions of the dissertation. It highlights the contributions made to the state of the art in this domain and points out the limitations, opportunities for improvement and the future direction for this research.

Chapter Two:
Background & Literature Review on Individualization

"If I have seen further than others, it is by standing upon the shoulders of giants."

Isaac Newton

2.1 Introduction

The objective of this chapter is to provide the necessary background for understanding the fundamental terms and concepts used throughout this dissertation. This includes concepts such as e-learning, learning games, adaptation, personalization, individualization and more. These will be explained and defined in section 2.2. This chapter also identifies in section 2.3 the different facets of individualization, which will be used as a framework for the literature review on individualization. Next, a literature review on individualization, focusing on the scope of the dissertation, is given. Since many individualization methods, strategies, and approaches in learning games are borrowed from e-learning, we start by providing a brief literature review of individualization in the domain of e-learning (section 2.4). In section 2.5, we present an extensive review of the literature on the individualization of learning games, focused specifically on *the aspects of the user that can be used for individualization*, as this is the focus of this dissertation. A summary of the reviewed researches is provided, grouped based on the aspects of the user that can be used for individualization. Finally, conclusions are drawn, which further motivate the focus of our research on the "Theory of Multiple Intelligences".

2.2 Terminology and Concepts

Computer-based learning is a broad domain with many different terms and concepts used in its literature. To delimit the context of the dissertation and to avoid any misunderstanding, we start by clarifying the concepts fundamental for comprehending its core topics, i.e. *learning games* and *individualization*. As we do so, we also position these concepts with respect to other related terms in the domain.

2.2.1 Digital Game-Based Learning (DGBL)

The concept of Digital Game-Based Learning (DGBL) covers a variety of terms, including learning games, educational games, edutainment games, and serious games. Often these terms, with the exception of edutainment games, are used interchangeably in the literature. The term serious game is defined by Michael and Chen as "*games that do not have entertainment, enjoyment or fun as their primary purpose*" (Michael & Chen, 2005) (page 21). This definition is quite similar to the common understanding of the terms educational and learning games. As an example, according to (Dondlinger, 2007) games that require their players to strategize, test hypotheses or solve problems which usually require some form of higher order thinking can be considered as educational games. On similar grounds, in (Van Eck, 2007) the term learning games is used to refer to the same concept. These three types of game-based learning take advantage of the inherently rich features of games and use them for teaching a concept, a skill, an attitude, a behavior, etc.

The term "serious game" specifically refers to games used to teach something to their players, as well as creating/changing a value for them. Besides classical learning context (i.e. classrooms) and with conventional learning topics (i.e. topics studied in schools and universities), serious games are also used in domains such as emergency management, city planning, engineering, politics, military and more. According to (Wouters et al., 2009), a serious game can focus on the following learning outcomes: *cognitive*, *motor skills*, *affective*, and *communicative*. In addition to that, one can also mention *players' beliefs*, *knowledge*, *attitudes*, *emotions*, *physical and mental health*, and *behavior*. Although the primary objective of these types of games is not entertainment, they do employ motivating and fun features of games to create effective and engaging experiences for their users. Edutainment games on the other hand are mostly used for making the "drill and practice" instructional methods a bit more fun. We do not consider them explicitly in our research, as the type of individualization possible for them is often limited to adjusting the learning content and difficulty. Nonetheless, some of our findings may also apply to edutainment games.

Note that we focus on games that have an *explicit pedagogical goal*. Each game can be considered to be useful for learning, as players need to learn how to play the game before they can actually play it. Most games offer a relatively simple and easy challenge in the beginning and get more difficult as the game progresses. The players need to acquire the necessary skills and learn how to deal with the progression of the challenges inside the game. Some entertainment games can also be used to learn or improve general skills, like reasoning (e.g. by playing chess). Therefore "learning" and games go hand in hand. In fact, "learning" inside the game environment is actually necessary (Harteveld, 2011). However, in learning games, educational games, and certain serious games, a pedagogical goal is explicitly targeted.

In this dissertation, we use the term "learning game" to refer to the range of learning-oriented serious games and educational games.

2.2.2 Individualization

Individualization is opposed to the "one-size-fits-all" approach in general, used in traditional (class-based) teaching. For the classical learning settings, the term is defined as: "*Individualization means that teachers instruct each student by drawing upon the knowledge and experience that that particular student already possesses.*" (Wenglinsky, 2002) (Page 5). In light of this, its objective in the more contemporary educational settings is defined as tailoring the learning environment to the individual's needs, abilities and preferences (Beldagli & Adiguzel, 2010; Brusilovsky, 2001; Kickmeier-Rust & Albert, 2010; Vandewaetere et al., 2011). Realizing individualization in the context of a classroom is often difficult. In the context of computer-based learning, however, tailoring the learning environment to the individuals can be achieved in different ways and at different stages. Tailoring can be done in advance (during design), at the start of using the environment (often called static adaptation), or completely dynamically while using the environment (often called dynamic adaptation or adaptivity). Tailoring can range from adapting the learning environment to a specific target group, to true personalization.

In the literature, the term adaptation and adaptivity are often used synonymously. The two terms have been used in different research areas including e-learning and games. In (Linssen, 2011) the term adaptivity is defined as: "*the* *autonomous alteration of certain properties*" (page 6). Linssen further explains this term, indicating that "*by itself, adaptivity is a non-specific term: it simply denotes the possibility of change in accordance with other factors. It is an automated process in which something is able to alter itself in order to 'fit' into its surroundings*" (page 15). Moreover, in (Beldagli & Adiguzel, 2010) adaptation is defined as having a less complex and highly flexible environment where the differences of individuals are taken into account. Similarly in (Lopes & Bidarra, 2011), player-centered game adaptivity is introduced as dynamically adjusting game elements, according to the individual performance of the player to make the game experience more unique and personal (Lopes & Bidarra, 2011). Similarly, (Ismailović, Haladjian, Köhler, Pagano, & Brügge, 2012), define the term adaptivity as "*adaptivity in serious games is an approach that enables a serious game to learn from learner's behaviour by intelligently monitoring and interpreting learner's actions in the game's world and to intervene in the game by automatically adjusting the learning content and the game elements according to the player's characteristics*" (page 3).

A slightly different definition for the term adaptation is given by Glahn (2010). According to Glahn, adaptation is changes in a system's look and behavior, based on external factors. Furthermore, adaptation is differentiated from personalization, by defining the latter as changes to a system's look and behavior based on the personal profile of a system user (preferences, user behavior). Glahn concludes that personalization is a special form of adaptation. Göbel and colleagues (Göbel, Hardy, & Wendel, 2010) have also considered changes made to a system based on *static* information obtained from the user as personalization, while dynamically created information and changes during the gameplay fall into adaptation.

Additionally, in (Oppermann, 1997), the terms *adaptable* and *adaptive* have been differentiated as follows: "*Systems that allow the user to change certain system parameters and adapt their behaviour accordingly are called adaptable, and systems that adapt to the users automatically based on the system's assumptions about user needs are called adaptive*" (page 1). Oppermann represent the entire spectrum of adaptation in computer systems by means of the diagram given in Figure 2.

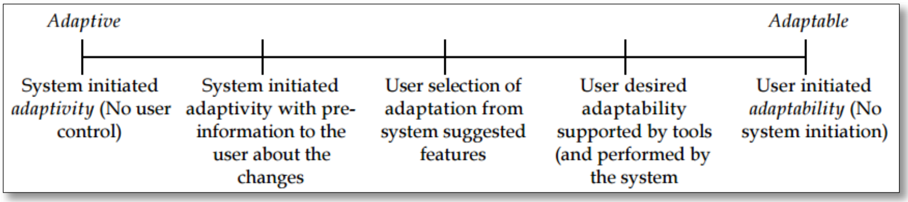

Figure 2 - Spectrum of adaptation in computer systems (Oppermann, 1997)

For the sake of consistency within the dissertation and to avoid misunderstanding, we will use the following interpretation for the concepts adaptation and personalization. Note that our interpretation of the two concepts is close to the ones given by Göbel and colleagues in (Göbel et al., 2010).

Definition of personalization: *The changes made to a game prior to the gameplay based on more stable and static aspects of the player (e.g. personality, learning style, intelligence) that are measured beforehand.*

Definition of adaptation: *The changes made to a game during the gameplay based on more dynamic aspects of the player (e.g. attention, stress, performance) measured in real-time.*

Player-centered game design on the other hand is different from these two concepts. In the case of adaptation and personalization, a rather generic version of the game (learning system) is available, which will be either tailored based on static information about the player, or will dynamically change during the gameplay based on the player's performance or other dynamic factors. In player-centered game design however, the game is designed for a specific group of people (called audience). This means that (in principle) no generic version of the game is created but the game is directly tailored to the target audience. Note that the term player-centered game design has also been used in the literature with a different semantic. In (Charles & Black, 2004) for instance, player-centered game design is about catering adaptation for individual players. This may be a source of confusion. Our definition for the concept player-centered game design is as follow:

Definition of player-centered game design: *A game design paradigm by which different aspects of the game (e.g. game mechanics, game narrative) are tailored to suit one or more groups of players that can be clustered based on a certain characteristic (e.g. playing style, personality, intelligence).*

Each of the concepts discussed thus far addresses customization in a different way. The customization in terms of player-centered game design is completely static because it focuses on designing a game for a specific group of players. It targets a group of users that have common characteristics (such as common playing style, learning style, personality, or intelligence) rather than individuals. Furthermore, the assessment of these characteristics and customization choices are made prior to the design of the game.

Customization in terms of personalization is semi-static because it is concerned with having a generic version of a game that can be personalized for different (groups of) users. Since the game is generic, it can be used and personalized for multiple and different users. For this, characteristics such as prior knowledge, experience, performance history, etc. can be used. The assessment of these characteristics and the corresponding personalization choices are also made prior to playing and can be therefore considered as a testament to the static nature of this concept.

Customization in terms of adaptation is fully dynamic because here, a generic version of a game is adapted dynamically to the player whilst she or he is playing. Since the game is generic, it can be used and adapted to a variety of players. For this, it uses characteristics such as performance, affective states, real-time playing style, etc. Furthermore, the assessment of these characteristics and the corresponding adaptations are performed in real-time during play. As the characteristics of the players are reassessed during play, the "model" of the players (i.e., profile) that is used for adaptation is frequently updated throughout the gameplay session. This is, of course, an indication of the dynamic nature of this concept.

Note that a combination of one or more of these concepts at the same time inside a single game is possible. This means that for example, a game can be designed for visually-spatially intelligent players (using the player-centered design concept), and then, for instance, incorporate adaptation (changing the difficulty of the game dynamically) on top based on the performance of the player.

It is important to mention that although the presented concepts of individualization differ in purpose, they all have to deal with the same issues, like deciding which aspects of the user should be used for individualization, as well as which aspects of the system should be individualized. We call these issues “facets” and discuss them in the next section.

2.3 Facets of Individualization

Individualization, and hence the different concepts it entails, with respect to computer-based learning was first investigated in the context of e-learning systems. Many researchers in that domain have explored motivations, requirements, and approaches for implementing effective individualization. When the concept of individualization was applied in learning games, a good amount of the motivations, requirements and approaches could be reused. Therefore, we first briefly explore individualization in e-learning, focusing on the most influential works.

Brusilovsky (1996) for example, has raised a series of pivotal questions in the context of adaptive hypermedia, that are relevant and applicable to any system that aims for individualization. Although these questions were defined in the context of adaptivity, one can immediately see that they easily transfer to issues related to player-centered game design and personalization. The questions proposed by Brusilovsky are:

Where and why adaptive can hypermedia be helpful? This question addresses the proper application area in which adaptivity could be useful. Brusilovsky (1996) argues that adaptivity could be beneficial regardless of whether it is in the context of educational hypermedia or online help systems. In the context of educational hypermedia specifically, Brusilovskya argues that users are quite different when it comes to their knowledge level and learning pace. That is why some learning material might seem unclear for some while trivial for others. Moreover, novice users have no familiarity with the learning material and may need navigational help to guide them through the material. This question is represented by the “Where” and “Why” blocks in Figure 3.

Adapting to what? This question addresses the different user aspects that can be taken into account as inputs for adaptation. These aspects may include knowledge, goals, background, expertise and preferences. This question is represented by the “To what” block in Figure 3.

What can be adapted in adaptive hypermedia? This question addresses the different parts of the system that can differ between individual users. In other words, the different aspects of the system that can be affected as the result of adaptivity (e.g. presentation and navigation). This question is represented by the "What" block in Figure 3.

How can adaptation be done? This question addresses the methods (conceptual level) and the techniques (implementation level) by which adaptive hypermedia can be realized to solve a problem. This question is represented by the two "How" blocks in Figure 3.

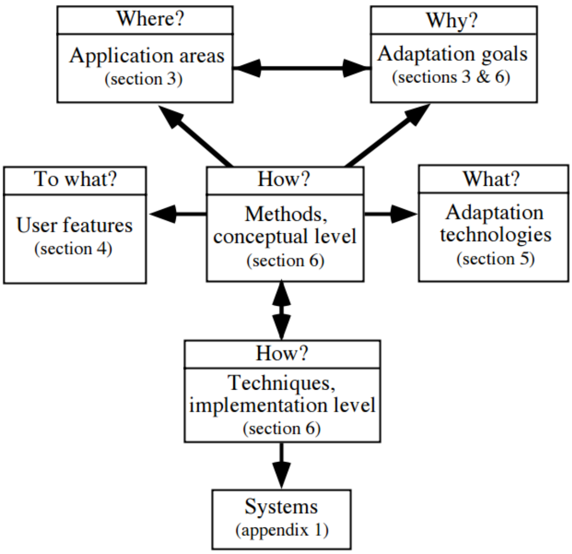

Figure 3 - Possible classifications for adaptive hypermedia methods and techniques (Brusilovsky, 1996)

Much like Brusilovsk, Karagiannidis and Sampson (2004) argue that any adaptive personalized learning environment must have the three main components of **determinants**, **constituents** and **rules**. These three components were first identified and introduced in (Stephanidis, Karagiannidis, & Koumpis, 1997) in the context of intelligent user interfaces. In short, **determinants** are the inputs for the adaptation. They are the aspects that *derive* the adaptation. The **constituents** are the aspects of the system that are *subjected to adaptation*. And the **rules** are the adaptation rules which *define* what determinants are selected for which constituents.

Based on the work of (Karagiannidis & Sampson, 2004) and (Brusilovsky, 1996) we propose four fundamental questions (called facets) to be used for the purpose of analyzing and understanding individualization in the context of e-learning and learning games:

1. What is the motivation for individualization?
2. What aspects of the user are used for individualization?
3. What aspects of the system are individualized?
4. How is the individualization realized?

Each of these facets are briefly explained in the following sub-sections and related to the work of Karagiannidis and Sampson, and Brusilovsky.

2.3.1 Facet "What is the motivation for individualization?"

This facet maps to the "*Where and why adaptive hypermedia can be helpful?*" question of Brusilovsky and addresses the reason for employing individualization in a system. In the literature review, the motivations for employing individualization in e-learning and learning games are given in sub-section 2.4.1 and sub-section 2.5.1 respectively. The general motivation for incorporating individualization in e-learning and learning games could be summarized as *creating better learning/gaming experience(s)*, and *achieving the objective(s) of the learning system more effectively*.

2.3.2 Facet "What aspects of the user are used for individualization?"

This facet maps to the "*Adapting to what?*" question of Brusilovsky and the "*determinants*" component of Karagiannidis and Sampson. Numerous aspects of a user can be taken into account as inputs for individualization. To mention a few examples, one could refer to *performance, background*, *expertise*, *prior knowledge*, *skill requirements*, *preferences*, *learning style*, *intelligence levels*, *affective states* and etc. These different aspects of the user can be measured either prior to using the learning system, or while the user is using it. The factors taken into consideration are usually grouped in what is often called in the literature a "*user profile*". This facet is reviewed for e-learning in sub-section 2.4.2 and for learning games in sub-section 2.5.2.

2.3.3 Facet "What aspects of the system are individualized?"

This facet maps to the "*What can be adapted in adaptive hypermedia?*" question of Brusilovsky and the "*constituents*" component of Karagiannidis & Sampson. An example of an aspect of a system that can be adapted is the learning content (Tavangarian et al., 2004). This facet of individualization basically targets the question of how individualization can enhance the user experience (from the point of view of both learning and using).

In the context of e-learning, these aspects are generally divided into two main categories: presentation and navigation. Games are inherently richer mediums than traditional e-learning systems, and thus the number of possible aspects of a game that can be subjected to individualization is greater. In addition to the individualization of the learning content and navigation, a wide variety of game aspects including *difficulty level* (challenges), *game objects & game world*, *narrative, NPC behavior*, *game AI*, *music*, *interaction modality*, *game mechanics* and etc. can be subject to individualization.

As this facet is outside the scope of the dissertation, we only briefly review it for e-learning (sub-section 2.4.3).

2.3.4 Facet "How is the individualization realized?"

This facet maps to the "*rules*" component of Karagiannidis and Sampson and the "*How can adaptation be done?*" question of Brusilovsky. This facet is concerned with how the different aspects of a user (profile) can be used to individualize the different aspects of the learning system. This is often dealt with by means of so-called "*adaptation rules*". For instance, in the case of player-centered design, the "how" is about following rules (guidelines) that suggest certain aspects of the system based on aspects of the user. In the case of a dynamic adaptation on the other hand, adaptation rules are defined which are deployed in real-time based on the real-time measurements of the aspects of the user and the objectives of the learning system.

As this facet is outside the scope of the dissertation, we only briefly review it for e-learning (sub-section 2.4.4).

2.4 Individualization in E-learning

This section provides a brief review of the literature of individualized e-learning systems on all the different facets. We start with the motivations given for individualization in the domain of e-learning.

2.4.1 Motivation for Individualization

Most motivations given to justify individualization for e-learning were given in the earlier years and can be summarized by the fact that individuals are different and that this should be taken into consideration to have an optimal learning process. The followings are examples of the motivations given:

In (Tavangarian et al., 2004), the authors criticize e-learning tools that are focused too much on technical gadgets and organizational aspects of teaching, resulting in “de-individualized” and demoted systems. Instead, they argue that e-learning tools should focus more on supporting learning. They suggest that one way out of this problem is the creation of individualized learning material.

Hauger and Köck (2007) argue that there are two main reasons for why adaptivity is important in e-learning. The first reason is that individuals are different. This difference could be in terms of goals, learning style, preferences, knowledge, background and more. Additionally, the knowledge of the learner (as part of their profile) changes over time (as they learn through interacting with the e-learning system). A second reason is that user specific navigation paths would provide personalized access to the content that fits the learner’s profile most appropriately.

Similarly, in (Kareal & Klema, 2006) the authors points out that since individuals are different in the way they learn and in their preference for the format and presentation of the content, adaptation plays an important role in the learning process.

2.4.2 Aspects of the User Used for Individualization

The aspects of the user found in the literature in the context of e-learning systems range from performance, to learning styles, competency, history with the learning platform, intelligences, concentration, excitement and tiredness. Below, we provide an overview of work done in this context:

The work presented in (Schiaffino et al., 2008) demonstrates an intelligent agent called "eTeacher" that observes (unobtrusively) the behavior of the students while they are taking online courses. This agent then automatically builds a profile of the learner containing information about their *learning style*, *performance*, *exercises done*, *topics studied* and *exam results*. The learning styles of the students are based on the model of Felder Silverman (1988) and is measured based on observation. For example, if the learner tends to use chat rooms and forums, eTeacher will infer that the student prefers to process information *actively* and not *reflectively*, with respect to the information processing dimension of the Felder Silverman learning style.

Similarly, in (C. M. Chen, Lee, & Chen, 2005) *learner ability* is used as the main "aspect of the user" for providing individualized learning paths based on Item Response Theory (IRT). IRT is an education measurement theory and is usually applied in the Computerized Adaptive Test (CAT) domain to select the most appropriate items for the examinee based on individual ability (Baker, 2001). The aspect of the user used for individualization in this work is *the knowledge or the competency* (that is presented as learner ability) of the learner.

In addition, a large body of works point to *learning styles* as the main aspect of the learner for individualization. One of the most popular learning style theories is the one of Kolb (D. A. Kolb, 1984). Kolb defines the term as "*the process whereby knowledge is created through the transformation of experience. Knowledge results from the combination of grasping and transforming experience*" (page 41) (D. A. Kolb, 1984) (page 41). Some studies have shown that the individualization based on learning style can have a positive impact on learning effectiveness (Graff, 2003). To mention a few works on individualization based on learning styles, the work presented in (Papanikolaou, Grigoriadou, Kornilakis, & Magoulas, 2003) demonstrates individualization of a learning tool based on *Honey and Mumford's learning style theory*. In a very similar direction, the work presented in (Franzoni, Assar, Defude, & Rojas, 2008) states that many researchers agree that the learning content and material needs to be adapted based on different learning styles of students. Furthermore, it tackles the problem of matching the teaching content to the learning styles of students based on an adaptive taxonomy (which is about the selection of appropriate teaching strategy and electronic media) based on the *Felder Silverman's learning style* (Felder & Silverman, 1988). This work is based on the dual coding theory, stating that information is processed through one of two usually independent channels; one channel processes verbal info such as audio and text and the other one visual info such as diagrams, pictures and animations (Beacham, Elliott, Alty, & Al-Sharrah, 2002).

The authors of (Yasir & Sharif, 2011) have integrated learning styles as part of adaptation in e-learning platforms. Based on an experiment conducted with their system, the results show that students who used the adaptive system based on learning style, have significantly better academic achievement than those who used the same material but without adaptation. According to the authors, these findings support the use of learning styles as a valid and important aspect of a user for individualizing e-learning systems.

The EDUCE system, introduced in (Kelly & Tangney, 2004), is an intelligent system that identifies and predicts learning characteristics, including the intelligence dimensions according to the *"Theory of Multiple Intelligence" (MI)* (Gardner, 2011) in real time, in order to provide a customized learning path. Gardner's MI defines eight intelligences that are defined as "*the ability to solve problems, or to create products, that are valued within one or more cultural settings*" (Gardner, 2011) (page 28). As the students proceed with the content, the system automatically builds a model of their learning characteristics and strengths.

More novel aspects have also been subject of research. In (Barrios et al., 2004) *eye tracking* (of real time behavior) in used to provide real time data *about the user's reading and learning behavior*. In the proposed AdELE framework, the goal is to observe the learning behavior of learners in real-time through monitoring characteristics such as objects and areas of focus, time spent on objects, frequency of visits and sequences in which content is consumed. The employed Eye Tracking Module gives the system "hints" about *concentration*, *excitement* and *tiredness* of the learner.

2.4.3 Aspects of the System That Are Individualized

Aspects of an e-learning system subject to individualization, found in the literature range from difficulty, to presentation and navigation. Below, we provide an overview of work done in this context:

The authors of (Hauger & Köck, 2007) have examined different aspects by reviewing a relatively large number of individualized e-learning frameworks. Two forms of individualization, namely *adaptive presentation support* on the content level, and *adaptive navigation support* on the link level were identified. Adaptive presentation support considers the content as an assembly of fragments. Depending on how these fragments are grouped together, the individualized presentation can be categorized into: conditional presentation, stretch-text and frame based. Hauger and Köck (2007) provide a list of methods for individualized presentation extracted from (Brusilovsky, 1996). Adaptive navigation support is concerned with the different possibilities of how the learner can navigate through the learning content (e.g. by direct guidance, reordering, hiding, or link annotation). Also for adaptive navigation support, Hauger and Köck provide a list of methods for individualized navigation support extracted from (Brusilovsky, 1996).

Chen and colleagues (2005) have used the learners' ability to determine how the course material difficulty should be changed. Their approach is based on Item Response Theory (IRT), and can provide learning paths that are individualized to various levels of difficulty of the course materials, and different abilities of the learners. The system is not just individualized on the difficulty level it provides to its learner, but also on filtering out the unsuitable course material to reduce the cognitive load of the learner. The results of the experiment conducted on this system have yielded that the system can accelerate learners' efficiency and effectiveness in learning. In this work, the *difficulty level*, *the content of the course* and the *learners' navigation path* are the aspects of the system that are subjected to individualization. To some extent, their concept of individualized difficulty corresponds to adaptive presentation, unless learning content is generated in real-time. Indeed, individualizing the difficulty level can be realized by presenting a different sequence of fragments.

Other works that adapt the presentation of the learning material are: (Papanikolaou et al., 2003; Wolf, 2002; Yasir & Sharif, 2011). Also in EDUCE (Kelly & Tangney, 2004) which considers the intelligences of the learners with respect to MI, the aspects of the system that are altered are on the presentation level. The system forces the learners to make a choice in terms of what presentation they prefer, and to follow it. However, they have the possibility to go back and try a different presentation style. Smap (Yang, Liu, & Huang, 2010) is an example of the use of adaptive navigation by creating different learning paths depending on the learning style of the learner.

2.4.4 The Way Individualization is Realized

The different aspects of a user (profile) can be used in a variety of ways to individualize the different aspects of the e-learning system. As the actual way to realize the individualization is outside the scope of the dissertation, we only provide some examples. In general, adaptation rules that are used are either specified explicitly (e.g. by means of an adaptation model), or integrated into some intelligent "agent".

To give an example, one can refer to the agent of the “eTeacher” platform (Schiaffino et al., 2008) explained earlier. The agent of the “eTeacher” uses the (measured) profile of the students to proactively assist them by suggesting individualized courses of action that would help them during the learning process. Based on the profile of the learner, eTeacher will make suggestions or recommendations to the learner. As an example, if it was determined by the system that the learner is “sequential” (meaning that the learner tend to learn better when the learning material is presented in the proper sequence as opposed to having a general picture of the whole topic at once), the agent will suggest to the learner to study the topic A first, before studying topic B based on the fact that A is a prerequisite for B. Results of an experiment with this system have indicated that with 83% of precision, eTeacher manages to provide proper assistance to the learners. This example demonstrates an “adaptation rule”, which maps the knowledge level of the player (prerequisite knowledge) to the navigation. Note that this work provides suggestions (changing the content and/or navigation of the content) rather than automatic individualization.

Another example is the work of (Yasir & Sharif, 2011) that proposes an *adaptation model* to implement the adaptation rules (content selection, navigation and presentation). The adaptation model specifies the way in which the knowledge and learning style of the learner modifies the presentation of the content. This is done using a series of adaptation rules. The rules are of classic condition-action type.

The individualization process used in the AdELE framework (Barrios et al., 2004) is coordinated by the Interactive Dialog Module (IDM). The User Information Module (UIM) of the framework, that contains all the information about the user, is used by the Interactive Dialog Module (IDM) to adjust or automatically infer information about the user as well as forcing the user’s interaction. For example if the system, based on the UIM infers that the learner is tired, this module will force the interaction to a relaxing exercise as a break.

2.5 Individualization in Learning Games

Individualization in learning games has its roots in hypermedia and e-learning. However, games are inherently richer compared to e-learning platforms; they may employ stories, virtual worlds, music, different game mechanics, etc. This characteristic makes room for more opportunities, especially in terms of the *motivations for using individualization*, the *aspects of the user that can be used for individualization* (e.g. playing style, gamer type), *the aspects of the system that can be individualized* (e.g. game objects and game world, narrative, music, game mechanics), and *how individualization can be realized*. In this section, we will present the results of our literature review on individualization in learning games. Since the focus of this dissertation is on the aspects of the user used for individualization, we will only focus on this facet in addition to the motivations for individualization.

Although individualization has been part of commercial video games for a long time, we will not discuss or review individualization in commercial games, as our main focus is individualization for enhancing both the game experience and the learning outcome of the players of learning games, while individualization of entertainment games is used as a mechanism solely for enhancing the game experience of the players and sustaining their engagement to the game. Just as an example, techniques such as dynamic difficulty adjustment (discussed in sub-section 2.5.2.1) were first used in commercial entertainment games. For example, this technique is used in the game *Max Payne*[2], and known as auto-dynamic difficulty (Charles, Kerr, &, cNeill, 2005). The difficulty level of shooting the enemies is automatically altered based on the number of enemies present at the time, the difficulty of killing them, or the competence of the player in doing so. A similar technique has been used for games like *Rocksmith*[3], where the player assumes the role of a musician and plays a musical instrument. If the player performs well, the game will become more difficult by presenting more musical notes and emphasizing on timing. On the other hand, the game becomes easier if the player does not perform well. In (Togelius, De Nardi, & Lucas, 2007), personalized racing tracks are generated based on certain in-game characteristics of the player for the purpose of increasing the entertainment value of the game experience. There are many more sophisticated individualization strategies and approaches for entertainment games, e.g. dynamic scripting (Spronck, Ponsen, Sprinkhuizen-Kuyper, & Postma, 2006), NPC interactions (Geogios N. Yannakakis, 2012) and structured unpredictability[4].

The section is organized as follows: we first review the different motivations given for individualization of learning games (sub-section 2.5.1), next we provide the literature review about the different aspects of the players used as input for

[2] http://www.rockstargames.com/maxpayne/
[3] http://rocksmith.ubi.com/rocksmith/en-GB/home/index.aspx
[4] http://www.valvesoftware.com/publications/2009/ai_systems_of_l4d_mike_booth.pdf

individualization (sub-section 2.5.2), and sub-section 2.5.3 provides a summary and conclusions.

2.5.1 Motivation for Individualization

Considering individual differences among players is considered to be an important factor for the success of learning games by different scholars, e.g. as mentioned by Van Eck: "*If we continue to preach only that games can be effective, we run the risk of creating the impression that all games are good for all learners and for all learning outcomes, which is categorically not the case*" (Van Eck, 2006) (Page 2). Therefore, one of the most engaging question in the domain of learning games can be simply put as: beyond the obvious benefits of individualization in games (i.e. boosting game experience as done in entertainment games), what other benefits individualization can bring to learning games? It has been argued by many that taking individual differences into account can contribute to the improvement of the learning outcome as much as it can to game experience. Researchers have identified a variety of reasons for taking individual differences among players into consideration. On this point, Peirce and Wade (2010) point out as benefits of individualization: reduction of the development cost, separation of game and individualization logic, and the possibility of increased instances of individualized games.

Moreno and Mayer (2007) argue that a massive amount of information imposed by a game may overload the working memory capacity of the player leading to weak or incorrect learning. Therefore some players may benefit from a slower pace in the presentation of the information and instructions inside the game. On the other hand, if the pace is too slow, it may lead to cognitive underload, which can lead to boredom and disengagement and consequently detrition of performance (Paas, Renkl, & Sweller, 2004; Saxby, Matthews, Hitchcock, & Warm, 2007). This notion basically points to the "Flow state", introduced in the "Flow theory" (Csikszentmihalyi & Csikszentmihalyi, 1992). The flow state is defined as a state of absolute absorption to a task to a point of losing self-consciousness where the activity itself becomes rewarding in its own, and this enables an individual to function at his fullest capacity (Shernoff et al., 2003). According to several authors, this means that a game must provide a balance between challenge and the competence of the players (Cowley, Charles, Black, & Hickey, 2008; Sweetser & Wyeth, 2005) (see Figure 4). Furthermore, it has been stated that when experiencing the flow state, individuals work at their fullest capacity, including the capacity to learn (Kiili, 2005; Webster et al., 1993), and thus, flow is an important factor for effective learning in games. The notion of flow state itself can be looked at as an argument in favor of incorporating individualization in learning games as it addresses individual differences in terms of competence and challenge.

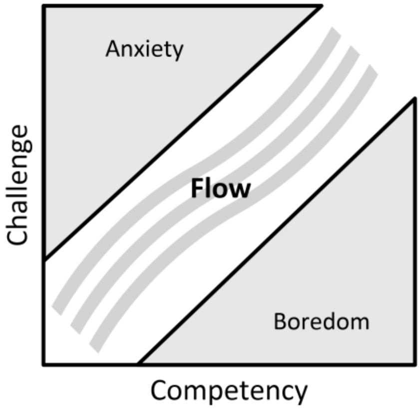

Figure 4 – The flow state diagram

Good game experience also often involves a high level of immersion. While having a strong entertainment value, immersion has also been claimed to positively affect learning. One of the most frequently used definitions for the term immersion is given by Murray (1997) as "*the experience of being transported to an elaborately simulated place is pleasurable in itself, regardless of the fantasy content. We refer to this experience as immersion. Immersion is a metaphorical term derived from the physical experience of being submerged in water*" (Page 98). Similarly, the term has been defined by (Witmer & Singer, 1998) as "*a psychological state characterized by perceiving oneself to be enveloped by, included in, and interacting with an environment that provides a continuous stream of stimuli and experiences*" (Page 3). Dede (2009) has argued that there are three ways in which immersion can enhance learning. First of all, immersive experiences give people the "*ability to change one's perspective or frame of reference [which] is a powerful means of understanding complex phenomenon*" (ibid, Page 2). Secondly, immersion into authentic contexts and activities can foster forms of situated learning as the learner can gain and apply knowledge in an environment that closely resembles a real world situation. This goes hand in hand with the third way in which immersion can enhance learning, namely by improving the transfer of the knowledge to a real-world situation based on accurate simulations of those situations. As such, these arguments appear to provide further support for the claim that good game experiences can positively influence learning outcomes and thus a primary motivation for individualization.

On similar grounds, the necessity for incorporating individualization in learning games is motivated in (Charles et al., 2005) based on the fact that people learn in different ways, at different paces, and based on different learning styles. Additionally, people have different playing strategies and styles. Moreover the range of gaming skills and capabilities among the players may vary. This justifies the need for principles that can individualize the challenge, difficulty level, or other aspects of the game based on the profile and preferences of the players.

Incorporation of individualization in games has been further motivated in (Lopes & Bidarra, 2011). Lopes and Bidarra argue that the content of the game, the rules, the narrative, the environment, and etc. are mostly static, while the player that interacts with them is dynamic. Having static content throughout the game constantly could lead to problems such as losing the motivation to continue playing, predictability, no-replayability, and repeatedly using a previously successful strategy. As Lopes and Bidarra point out, this problem is more severe in the case of learning games, due to the fact that not everyone learns in the same way.

We can conclude that the motivations for individualizing learning games are the same as those from the domain of e-learning (i.e. better learning outcome) but complemented with motivations from the domain of entertainment games (better game experience). It is important to note, as we will see throughout the rest of the section that different factors, such as performance, affective states, playing style and learning style, may contribute to both a better gaming experience and a better learning outcome. Therefore, achieving good game experience and better learning outcome is a primary motivation for individualization.

2.5.2 Aspects of the Players Used for Individualization

In this sub-section, the different aspects of the players measured and used as input for individualization are reviewed. To structure the literature review, we will discuss the works grouped based on the aspects of the players considered. For this purpose, we have grouped the reviewed user aspects into three main categories: *performance of the player* (sub-section 2.5.2.1), *physiological parameters and affective states of the player* (sub-section 2.5.2.2), and *personal traits of the player* (sub-section 2.5.2.3). Furthermore, for the reviewed researches we discuss *how the user aspects were measured*, *which aspects of the game were adapted* (and if relevant how), and *if the work included an empirical validation* for the effectiveness of the approach. The objective is to obtain a clear overview of what aspects of players have already been used for a successful individualization, i.e. an individualization that enhances the game experience and/or the learning outcome. This overview together with the conclusions are provided in sub-section 2.5.3.

2.5.2.1 Performance

The performance of the player is one of the main and most frequently used aspects of the player in the process of individualization. However, although most of the games that employ individualization share performance as a common denominator, the aspects of the games that are affected as the result of individualization are different. Basically, we identified three main aspects of the game that are individualized based on the performance of the player: *difficulty*, *level/story*, and *feedback and intervention*. To further group the different researches using performance for individualization, we discuss them based on this grouping.

For dynamic difficulty adjustment (DDA)

Dynamically adjusting the difficulty level of a game based on the performance of the player has been widely researched. It is usually done to keep the players in the flow state (see sub-section 2.5.1). The goal is to provide the perfect balance between the player's level of competency and the challenge level imposed by the game. Following this principle, the work presented in (Berger & Wolfgang, 2012) introduces a game called *Project Manager* that adapts in real-time to the over and under performers. The learning objectives of this game are to develop project managerial skills such as parallelizing tasks and managing resources. The progress of the project which managed by the player in the game, is monitored by the game and is compared with a reference progress (authored by an expert). If the player's progress deviates from the reference progress, the game deploys an in-game tutor to assist the player. Furthermore, this game also adapts to over-performers. Meaning that if the progress of the player exceeds the reference progress, the game will become more challenging. No empirical evaluation for the effectiveness of the proposed individualization in this work is provided. However, it was mentioned as part of the future work.

Other examples of using the DDA technique based on performance are found in rehabilitation games. The work of (Burke et al., 2009) is an example of using individualized serious games for physical rehabilitation of stroke patients. A series of mini-games that use a webcam to track the movements of the arms of the players while manipulating game objects are used. The games include a user profile that stores information about the player and keeps track of the player's progress. The initial difficulty level of the game is set to an appropriate level based on the impairment of the patient by a therapist. Moreover, the games employ an individualized difficulty mechanism to adjust the difficulty to the in-game performance of the player. A study with two phases (one with participants with able-bodied and one with participants with disability caused by stroke) was conducted. Both phases show positive results with respect to the playability and usability of the mini-games. A more recent work, (Hocine et al., 2015), shows that a game following the same principle, positively affects the training outcome of stroke patients.

Similarly, in (Davies, Vinumon, Taylor, & Parsons, 2014) a DDA mechanism based on the competency of the players was also used for a Microsoft Kinect[5] based game to increase the balance and coordination of older people. A usability study was conducted, and the results indicated that the participants enjoyed the experience and considered it to be a good substitute for the traditional methods.

The work of van Oostendorp and colleagues (van Oostendorp, van der Spek, & Linssen, 2013) is among the few that uses DDA and in addition investigated the effect on learning outcome. The focus of the work is on dynamically changing the difficulty level of the game with respect to the proficiency of the player by varying attributes of the NPCs. The game, called *Code Red Triage*, is designed to teach the triage procedure (a procedure for medical responders to prioritize the victims of a mass casualty event based on how urgently they need medical attention). The game environment is a subway where a bomb has gone off, and the player will have 17 minutes to examine the victims and give them a priority. Once a priority is assigned to a victim, the victim changes colour to indicate the triage category assigned by the player. Furthermore, the players will receive a score reflecting their proficiency level. The difficulty of the game is then adapted based on this level of proficiency. There are six paths (with multiple victims in each path) with an increasing number of steps in the triage procedure, and there are 6 levels of complexity tires (in terms of the attributes of the victims) for the triage procedure in total. If a player scores above the threshold, he or she can proceed to a more complex victim tier. This is done by deleting all remaining victim cases within the same tier. Similarly a player, who scores below the threshold, will receive one or more of the remaining cases of that tier before he can proceeding to the next level of complexity. The threshold is established based on the data from a pilot experiment. The researchers also performed an experiment to test their hypotheses:

[5] https://developer.microsoft.com/en-us/windows/kinect

"*players feel more engaged by the dynamic adaptive version, because the game always remains challenging* (compared to a control version), and secondly *it is expected in the dynamic adaptive version of the game that players are able to learn more efficiently, because redundant learning experiences (triage cases) can be skipped*". 28 participants (14 in adaptive and another 14 in control condition) were used for the experiment. Three types of instruments were used to measure the learning of players: the in-game score, pen and paper knowledge test (in the form of 8 verbal and 8 pictorial questions about the triage procedure), and a structural knowledge assessment (indicating how well the participants organized the information about the triage procedure structurally). Furthermore, the engagements of the players were measured using the subscale of ITC sense of presence inventory (Lessiter, Freeman, Keogh, & Davidoff, 2001). First, the participants performed the structural knowledge assessment and then the knowledge test. Next, the participants played the game and directly after that, they answered the engagement questionnaire, performed the structural knowledge assessment and the knowledge test (with different order of the questions compared to the pre-game tests). The results indicated that the adaptation had no effect on the engagement of the players, but had an effect on the learning outcome. Participants in the adaptive group did learn significantly more than those in the control group.

For personalized level/story generation

Dynamic level/story generation based on the performance aspect of the player, unlike DDA, is less researched. In (Hodhod & Kudenko, 2007), an architecture for a system utilizing dynamic story generation in real-time based on the user's features, and with the objective of improving engagement and increasing immersion to have a potentially better educational outcome was introduced. Based on the proposed architecture, the story of a game is composed of levels, where each level is composed of a one or more "StoryBits". Each StoryBit has characters, properties and different functions. A function is defined as a single event in the story. Each StoryBit can be connected to many different bits in different levels. Based on the interactions of the player with the game, the model of player is updated. This update results in the individualization of the order of the StoryBits that contain the learning content. No evaluations on the effectiveness of the proposed approach have been reported.

On similar grounds, in (Grappiolo, Cheong, Togelius, Khaled, & Yannakakis, 2011) a serious game about conflict resolution utilizing this individualization strategy was presented. The underlying architecture of the introduced game generates level content automatically. The content is adapted based on the *player* *experience* and *behavior* as claimed by the authors of this work. The game introduced in this research simulates a resource management (RM) conflict scenario. The objective of the game is for the player to distribute a series of scarce resources among the NPCs, while keeping all of the NPCs happy. The NPCs have a happiness value, which decreases over time. The only way to become happier is to obtain resources (fireballs). However, the NPCs cannot actively collect fireballs and it is the job of the player to collect and distribute them among the NPCs. The NPCs are divided into two groups of blue and red. There are 10 levels in total with variable durations, starting from 30 to 180 seconds. The game monitors and assesses the playing style of the player, in particular focusing on the player's strategy for the distribution of resources fairly and cooperatively. Upon finishing each level, the game will generate a new level automatically, based on the game's prediction of the playing style as well as the experience of the player, with the objective of guiding the player to maximum fairness and cooperation. For this, a fitness function based on the profile of the player is used; the game will search for levels that will minimize the fitness function. A pilot study indicates that the average level of player cooperation had increased as the game progressed, i.e. the cooperation value of the last level played, was significantly higher than the first level. Hence the individualization used in this work has positively affected the learning outcome of the players.

In (Berger, Liapis, & Yannakakis, 2012; Karpouzis et al., 2013; Georgios N Yannakakis et al., 2010) the *Siren* project is introduced and discussed. The Siren project is about a series of learning games aimed at educating people how to resolve conflicts in a peaceful and constructive way. There will be a conflict generator that will need as input information about the conflict domain and a library of conflict components (resources, desires, taboos, etc.), as well as a model of the skill and experience of the players involved and desired learning outcomes of the game. Moreover, as part of the proposed plan, a global optimization algorithm (e.g. evolutionary computation and particle swarm optimization) for configuring a conflict scenario that would be optimized for the abilities of the player and the desired learning outcome of the game will be used. Additionally, the researchers plan to monitor the effect of the generated personalized game scenario in real-time and if the learning outcomes are not satisfied, dynamic changes to the game during the gameplay should be made. These changes could range from introducing new constraints, to hint or guide for the player. In terms of game scenarios, the objectives could be translated into collaborative puzzle solving games, a game about scarce resource management in a village, and so on. These serious games are "adaptive" in the sense that the scenarios of the games are tailored to the player's profile by means of procedural content generation.

For feedback and intervention

Individualizing the feedback and/or the intervention strategies in a game based on the performance of players is a common approach. An example of such a strategy can be found in the well-known *80Days project* (Göbel, Mehm, Radke, & Steinmetz, 2009; Kickmeier-Rust, Gbel, & Albert, 2008; Zaharias, Mehlenbacher, Law, & Sun, 2012). The project had the objective of bringing together "*adaptive learning, storytelling and gaming in order to build intelligent adaptive and exciting learning environments in the form of Storytelling-based digital educational games (DEGs)*" (Göbel et al., 2009) (Page 1). The learning topic in this project is geography, and the story of the game is about an alien that has kidnapped a boy and is hovering over the earth collecting geographical information. Two different approaches of individualization are implemented in this game: *macro* and *micro adaptivity*. The micro approach is in the form of motivational interventions and cognitive hints given to the player by the alien, and the macro approach is about the adjustment of the story pace and story construction. The process of individualization in this project goes beyond adaptive hints and interventions, but it is among the first researches on providing adaptive feedback and interventions in the context of learning games. Furthermore, this game is evaluated in (Zaharias et al., 2012). The effectiveness of the micro (cognitive hints and motivational encouragements) and macro (pace of the game) approaches, were evaluated and the results indicated that the players could benefit from the individualized game. The knowledge level of the players was measured using pre and post-game questionnaires, and the results showed a significant difference between their values. This was interpreted as substantial knowledge gain through the game. Moreover, the results showed that a high game experience and a better learning experience compared to classroom were achieved.

The micro adaptation approach was developed in the context of the ELEKTRA project, the predecessor of the 80 Days project, one of most famous projects on individualized learning games. In (Kickmeier-Rust & Albert, 2010), this notion is defined as "*an approach to non-invasive assessment of knowledge and learning progress in the open virtual worlds of computer games and a corresponding adaptation by personalized psycho-pedagogical interventions*" (Page 3). According to the authors of this work, one way to guide and support the learners in the process of acquiring knowledge is intervening when misconceptions happen, or providing hints and feedback when the learning progress is unsatisfactory. As the first necessary step in fulfilling the mentioned, one should be able to measure the knowledge of the players, monitor the cognitive states they go through (motivation, attention, etc.), understand possible misconceptions or unsuccessful problem solving strategies they used and more. In games, such assessment needs to be done in a non-invasive manner so the immersion and motivation of the player is not impaired (Kickmeier-Rust et al., 2007). Five adaptation strategies that could provide feedback interventions are identified in the context of the mentioned research:

- *Competence activation interventions:* are applied if a learner gets stuck in some part of the problem space and has not yet used some of his competencies, although the system assumes he possess them.
- *Competence acquisition interventions*: is applied in situations when the system concludes that the player lacks certain competencies.
- *Motivational interventions*: is applied when the player stays idle for a certain long period of time.
- *Feedback*: is applied in situations when it is needed to provide the player with information about the learning progress or the game.
- *Assessment clarification interventions*: is applied, in the form of a query, if the learner's actions contradict the assumption of a certain competence possession.

The results of the experiment with the ELEKTRA game, a 3D adventure game with the objective of teaching physics of optics to the students of the age 13 to 15, showed that the tailored interventions caused higher learning performance, and a higher level of immersion compared to inappropriate or no interventions.

The ELEKTRA game has been used in other researches focusing on providing adaptive hints and feedback. In (Peirce et al., 2008) the ALIGN system (Adaptive Learning In Games through Non-invasion) is introduced. The proposed approach, as claimed by its authors, promotes augmentation rather than intervention in individualizing existing educational game content. This means a separation of the "adaptation" logic from the game logic. Although this is the aim of ALIGN, the authors admit that there exist an overlap between the game and adaptation logic. This overlap is in the preservation of the flow experience. According to the authors, the flow experience is part of both worlds. This means that the balancing between challenge and skill is important in both worlds. The ALIGN system provides adaptation in two phases. First, through a process of *inference,* which translates game specificities into abstract educational concepts. And secondly, through *realizations*, which translates abstract adaptations into changes in the game. An example of inference would be the mapping of failure during a task to the decrease in the skill related to that task (Albert, Hockemeyer, Kickmeier-Rust, Peirce, & Conlan, 2007). An example for realization would be translating the abstract desire to help the player acquiring a skill into a NPC offering verbal guidance. This separation of concern is the core of the ALIGN system.

The ELEKTRA game in the context of the ALIGN system, was evaluated with 49 players, a pre-game test was used to assess the knowledge level of the students on the learning topic of the game. After the gameplay session, a post-game test was used to assess the learning impact, as well as questionnaires for qualitative player experiences such as game difficulty, flow experience, and the perceived invasiveness of the adaptation. The results of the tests were complemented by game logs of the players. The results indicated that the flow experience of the game was preserved, which was a reason for the authors to conclude that the ALIGN approach is not invasive. It was shown that adaptive hints following a failure improved the players' approach to a correct solution. Furthermore, a comparison between low adaptivity and high adaptivity was performed, indicating that the group receiving higher adaptivity invested more effort and time and had a higher degree of absorbedness, higher relatedness to the NPC, higher confidence in their learning achievement and better use of the game mechanics than the group with low adaptivity

The ALIGN system was demonstrated with different games. The *Language Trap game,* an online causal educational game, developed for the Irish secondary school students who are studying German and are preparing for the certificate exam, was made adaptive using the ALIGN system (Peirce & Wade, 2010). Four types of adaptation are supported: *adaptive dialogue difficulty, performance feedback, motivational support* (used when for instance the system notices a pattern of a series of inappropriate dialogues chosen by the player), and *meta-cognitive hints* (hints based on identified trends in the dialogues used). The *Language Trap* game was evaluated with 83 students. Pre and post-game questionnaires that measured the proficiency of the German language were used to observe the effect of the game on the learning. During the user experiments, the students were randomly allocated to a basic adaptation or an advanced adaptation group. The basic adaptation group played the game with a naive and simple adaptation, and the advanced adaptation group played the game with a more sophisticated inference and assessment method for adaptation. Both versions had the exact same story and learning content. From the point of game experience, the results indicate that most students liked the game and found it to be useful for learning German. In terms of educational impact, it was observed that the mean score from the pre-test 7.22 increased to 8.87 in the post-test, and the advanced adaptation group showed greater average improvement (1.91) than the basic group (1.35).

The work presented in (Conati & Manske, 2009) evaluates the impact of *adaptive feedback* in a game on the learning of the students. The evaluation was done with a game called *Prime Climb*, which is an adaptive educational game that teaches number factorization and designed for the students in the 6th and 7th grade. While playing the game, the players have a pedagogical agent that provides individualized support, both on demand and automatically (when it is determined that the student does not seem to be learning). Three variations of a game were used for this experiment, one with no agent and two with an agent but different in the accuracy of the player model that guides the agent's intervention. 13 students played the version with no agents, 14 students with an agent based on a less accurate player model, and 17 students played the version with an agent with a more accurate player model. All the students performed a pre-test exam that assessed their knowledge about factorization. Next, students played with one of the three versions of the game and then a post-game test was administered. The results indicate that no difference in learning was observed across all three versions. Note that this result is in contradiction with the results of the previously explained researches.

2.5.2.2 Physiological Parameters and Affective States

The different affective states players experience while playing a game are considered by some researchers as aspects of a player that can be used in the process of individualization. These states, including *anxiety and stress*, *attention*, *engagement*, and *emotions* can be derived from different physiological parameters, such as *heart rate*, *breathing*, *head motions*, *facial expressions*. Physiological parameters and affective states are among the more recently considered user aspects for individualization, and are hence less researched in the context of individualization of learning games. However, different researchers have addressed their potential as effective contributing factors to better game experience and higher learning outcome in recent years. In the following sub-sections we review work done in this context. We consider work that targets the use of affective states: anxiety and stress, attention, engagement, and emotions, as well as work that use the physiological parameters heart rate and breathing.

Anxiety and stress

Players experience different levels of anxiety and stress while playing games. Depending on the goal of the game and the value it attempts to create in the players, these states can be measured and used as inputs for individualization. As an example, in (Liu, Agrawal, Sarkar, & Chen, 2009), an individualization based on these factors is showcased. To the best of our knowledge, this work is the first that measures anxiety using a sensor and uses it as a factor to dynamically change the difficulty level of a game. How the anxiety of the players was exactly measured, quantified and classified is outside the scope of this dissertation, however we will describe the game and how individualization takes place with respect to anxiety, as well as the setup of the experiment.

Two version of a *Pong Game* both with dynamic difficulty adjustment mechanism (one based on performance, and the other based on the anxiety level of the player) were played in two sessions by nine participants. In the first session, the difficulty level of the game was simply adjusted based on the in-game performance of the player, without considering their anxiety level. In the second session, the anxiety levels of the player were detected through psychological sensors using a *Biopac system* and synchronized with game events. The difficulty of the game was changed in real-time based on the detected anxiety levels, without considering the in-game performance of the players. The results of the experiments show that, dynamic difficulty adjustment based on the anxiety level has led to a more challenging game with a better game experience, and at the same time improved the in-game performance of the players compared to the dynamic difficulty adjustment version based on performance.

On similar grounds, the work presented in (Yun, Shastri, Pavlidis, & Deng, 2009) used a novel approach to individualization by using the facial physiology of the players to dynamically adapt the difficulty level of the game. The approach used in this work monitors in a non-intrusive way, the stress levels of the players using a thermal imaging-based stress monitoring and analysis system called *StressCam.* StressCam continuously monitors the facial physiological changes of the player and quantifies them into psychological states (different stress levels). Based on this information the game adjusts its difficulty level. The result of an experiment conducted with 14 participants, show that this individualization approach led to a better gaming experience.

Heart rate and breathing

The heart rate variability and the breathing pattern of the players are also aspects of the player that can be used for individualization. Several researches have used these factors. As an example, in (Göbel et al., 2010), the authors introduce a series of exergames (games with the objective of performing health related exercises). The individualizations in this work are carried out in two forms. One form is the use of static information about the player (e.g. training plans and player model, authored by doctors or fitness coaches) that will be used for *personalization*. In the second form, vital parameters of the player (*speed, revolutions per minute, watt and heart rate, and activities and movements*) that are measured in real-time using sensors will be used for dynamic *adaptation*, with the objective of changing the behavior of the player. An adaptive engine acts as the control unit, in which it is decided on how a story-based exergame will continue at specific moments during gameplay. The different training and exercise modules are considered as game levels in the authoring environment and are annotated based on the characteristics of the player (i.e. the vital parameters). During the gameplay, the vital parameters of the player are then measured using sensors and compared with the training plan. Based on the results of this comparison, adaptations will take place. As an example, based on the information (heart rate of the player) assessed from a warm up session, the system will decide on a high or low intensity core exercise to be played. According to the authors, the preliminary results of an evaluation show the benefits of this approach.

On similar grounds, in (Hardy, Göbel, Gutjahr, Wiemeyer, & Steinmetz, 2012), the authors propose an approach towards adaptive, long term motivating and physically demanding exergames for indoor training. This approach has three components: application-specific hardware, software, and the human psychology and physiology. With respect to individualization, the software (that includes gaming and training modules) and the psychology (that includes effectiveness and attractiveness modules) have the possibility of being changed during the gaming. On the other hand, the hardware component as well as the physiological characteristics of the players cannot be changed during the game. An example of the use of a physiological aspect for adaptation in an exergame in this case would be the use of an ergometer bike with adjustable resistance, so that the game can be played at a predefined heart rate. In order to evaluate the effectiveness of the proposed components, a prototype called *ErgoActive* was used that included three mini-games. One of the mini games will be explained here as an example:

Ergo Balance (Figure 5) is a combination of *Shoot 'Em Up* and *Skill Game*. The objective of the game is to keep a clown balanced on a ball. This is done my maintaining a fixed level of heart rate, speed and cadence by the player. If the player cycles too slow or too fast, the clown will fall. At the same time, the player needs to click on the balloons with a mouse in order to gain points.

Figure 5 – Ergo Balance (Hardy et al., 2012)

48 participants were used to evaluate the mini-games. Prior to the start of the gameplay session the participants filled out a questionnaire about gender, age, sportiness, frequency of watching TV and computer use, and their estimated personal fitness level. Afterwards, the participants played the mini-games (all three) and filled out questionnaires about their opinion on the game. The results of the experiment indicate that the motivation of the players were different for each of the mini games. This result was "*dependent on the gender of the participants and their estimated fitness*" (Page 12). The general results show that "*people with a higher personal fitness rating find the applications more motivating than people with lower fitness rating*" (Page 10).

Depending on the topic and goal of the game, the breathing patterns of the players can also be used in the process of individualization. As an example, the game, called *Chill-Out* (Figure 6), presented in (Parnandi & Ahmed, 2014) uses breathing as physiological parameter for individualization. It is an adaptive biofeedback game that teaches its players relaxation by monitoring their breathing rate. The hypotheses of this work are that "*Chill-Out would lead to (1) better transfer of DB (Deep or diaphragmatic breathing) skills, (2) a reduction in physiological arousal, and (3) improved performance, all measured during a* *subsequent stress-inducing task*" (page 2). The frozen bubble game (in the Figure 6, parts (a) and (b)) was adapted and used for this research.

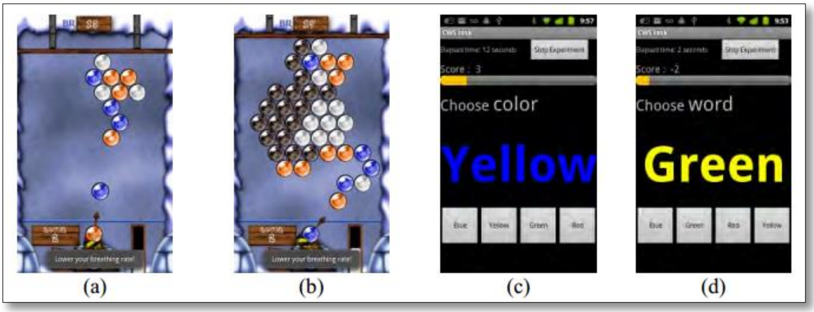

Figure 6 – Chill-Out (Parnandi & Ahmed, 2014)

In frozen bubble the user shoots bubbles with different colors into the playing area. The objective is to eliminate all the hanging bubbles, by grouping three or more of the same color, before the ceiling collapses. This is done by shooting colored bubbles with a cannon. Among the parameters of this game that could be subjected to individualization the auto shooting frequency was chosen. The individualization follows the following principle: if the breathing rate crosses the threshold, the auto shooting frequency increases, making the game more difficult. Therefore, to be able to play the game, the player must maintain a slow and sustained breathing pattern. The experiment performed using this game was composed of three phases with nine participants. During the first phase (the pre-test), participants performed a modified Stroop color word test (i.e. a stress inducing task), as shown in Figure 6 (c) and (d), for 4 minutes. During the second phase (treatment), the participants were randomly assigned into one of three groups: a group that played the biofeedback game (respiratory sensor was used to measure breathing rate) (GBF), a baseline group that performed deep breathing (DB), and a control group that played the original Frozen Bubble game without adaptation or respiratory feedback (game only). Once the game was over, the participants performed the Stroop color word test again for an additional 4 minutes. To compare the effectiveness of the adaptive game on stress management, two physiological measures were extracted: heart rate variability (HRV) and electro dermal activity (EDA). The combination of the two measures, provide a robust index of arousal. The results show that the adaptive version of the game with bio-feedback (GBF) has led to the most effective results in terms of both performance and transferring of deep breathing skills to another stress inducing task (the Stroop color word tests). Also it has led to a significantly lower arousal level. These results indicate that, as opposed to the old belief that a quiet and peaceful environment is a necessity for controlling and reducing stress, games can be used as an effective tool to achieve the mentioned. It also demonstrates that the breathing patterns of the players can be effectively used as one of their aspects for individualization.

Attention, engagement, and emotions

There are a variety of information that can be extracted from the facial expressions, eye gazing, head movements and other behaviors of the players while they are playing a game. This information can be used to measure attention, engagement and emotions such as frustration. There exist a large body of research on the usage of this kind of aspects of players for individualization.

One of the objectives of the *Siren* project (Berger et al., 2012; Karpouzis et al., 2013; Georgios N Yannakakis et al., 2010) (previously explained in 2.6.2.1.) is creating models of the in-game affective states (e.g. *emotion*, *mood*, *attitude*, *preference*, *stress*, and *attention*) of the players. The authors mention that there is a need to define the relevant metrics of playing style and other indicators of affective states and cognitive processes, so they can be assessed from the gameplay data of the player. In (Karpouzis et al., 2013) the authors elaborate more on the concept of individualization based on affective states. In order to assess *emotions and attention* of the players, they use video feed from a web camera mounted on top of the player's screen (Asteriadis, Tzouveli, Karpouzis, & Kollias, 2009). The combination of the detected states and the in-game behavior and performance of the players are mapped to the flow diagram (Csikszentmihalyi & Csikszentmihalyi, 1992). The assumption here is that when the player is experiencing the flow state the game becomes interesting and the learning objectives intuitive. If the game determines that the player is bored (inattentive), it will produce a more difficult instance of the game to create a balance between the skill level of the player and the challenge(s) in the game. Definitions and interpretations of different facial expressions and head poses, as levels of attention the player has, were based on the analysis of the Siren gameplay database (Asteriadis, Shaker, & Karpouzis, 2012). Once the game is over, the user model that constitutes the affective and behavioral indicators, will be used to generate a relevant and interesting instance of the next game (the games are procedurally generated (Georgios N. Yannakakis & Togelius, 2015)) based on the predicted levels of challenge and frustration.

On similar grounds, the work presented in (Asteriadis et al., 2012) uses the *head movement* of the player as an indicator of the *player's frustration and engagement*, as well as the degree of *challenge* imposed by the game. The goal is to use this information in the individualization. Based on the methodology introduced in (Asteriadis et al., 2009), the head movements of the players that are recorded during their gameplay sessions (while playing infinite Mario Bros) were extracted, analyzed using the following metrics, and were classified as challenged-not challenged, engaged-not engaged, and frustrated-not frustrated:

- Average head motion per game: was reported to be an indicator that distinguished between challenging and non-challenging games.
- Head motion when player loses: high expressivity was reported as frustration caused by loss.
- Head motion at stomping on an enemy to kill him: high expressivity was reported when stomping to kill an enemy that seems positively correlated with high levels of challenge and frustration, although for engaging games the contrary was the case.
- Head motion when player is about to make a critical move: low expressivity was reported when a critical move is about to be taken, when players felt challenged by the game. According to the authors this is probably because the players were trying to concentrate on the critical move. On the contrary, it was reported that frustrating games caused high expressivity at the start of critical moves.

The preliminary results of this work indicate that head motions can be used during gameplay with the objective of assessing hidden information regarding the different states of the users. It was observed that different players pose different expressions, and according to the authors, this triggers the idea of building profiles for individualization purposes.

In (Chanel et al., 2008) the authors maintain the player's *engagement* to the game through changing the difficulty level. This research aims at investigating the following hypotheses:

1. *Playing at different levels of difficulty will give rise to different emotional states.*
2. *Those emotional states (and the underlying conditions) can be assessed using central and peripheral signaling.*
3. *As the skill (competency) increases, the player will switch from the engagement state to the boredom state.*

In order to test the mentioned hypotheses, the game *Tetris* was used with 20 participants. Before commencing the experiment, each participant played the game several times in order to determine the game level they reported to be engaging. This was used as the point of reference for the participants' skill level. Then depending on the skill level of the players, three experimental conditions were determined: medium condition (game difficulty equal to the skill level), easy condition (lower difficulty in relation to the player's skill level), and hard condition (higher difficulty in relation to the player's skill level). During the experiment session participants were equipped with several sensors: GSR (Galvanic Skin Response) to measure skin resistance, plethysmograph to measure relative blood pleasure, respiration belt to estimate abdomen extension, and a temperature sensor to measure palmar temperature changes. Furthermore, EEG was used to measure the task engagement, but its analysis was not part of this experiment. During the experiment session, participants played 6 sessions (5 minutes each, 2 sessions for each of the three experimental conditions) of Tetris. The objective of participants was to obtain the highest score. After each session, a questionnaire about the emotions felt and the level of involvement in the game was administered. The result of the experiment indicated that playing a Tetris game with the mentioned three different levels of difficulty evoked different emotional states in the players that could be identified as boredom, engagement and anxiety. Furthermore, it was observed that at least two of these states could be with a reasonable accuracy, detected from physiological signals. Moreover, it was established that players' level of engagement could decrease if the game difficulty did not change effectively with respect to their skill. These results show that affective states of the players could be used as a factor for game difficulty adaptation. Moreover, in (Chanel, Rebetez, Bétrancourt, & Pun, 2011) the researchers have complemented this result with EEG. They denote that the use of EEG for measuring emotion is a more robust approach.

Apart from engagement, *attention* of the players while playing a game is another aspects that has been deemed important by many researchers. However, to the best of our knowledge, there is little work on actually using attention for the process of individualization. In (Muir & Conati, 2012), the authors present a user study that investigates what factors affect the attention of students to user-adaptive hints while interacting with an educational game. The game used for the experiment in this research is *Prime Climb*. The objective of the game is to teach number factorization skills, and is played with a partner. As part of the adaptation, individualized hints are given to the players based on their model. In order to capture and analyze player's attention to the adaptive-hints, *eye-tracking* was used that capture the attention patterns of the players. The results of the study indicated that the eye movement patterns are affected by factors including existing user knowledge, hint timing and attitude toward getting help. This result could be used to make the hint delivery individualized based on these factors. 12 participants were used for the experiment conducted in this research. A pre-test was used to measure the participant's level of knowledge about number factorization. Then the calibration phase of the eye-tracker for the Tobii[6] device was performed. Next, each participant played the game with an experimenter as a partner. Once the game session was over, the participants took a post-test equivalent to the pre-test and completed a game experience questionnaire. In order to analyze the attention of the participants to the adaptive hints, an area of interest (AOI) was defined that covered the text of the hint message. Furthermore, two eye gazing metrics were used to measure attention: *total fixation time* and *ratio of fixation per word*. The total fixation time is "the total time a student's gaze rested on the Hint AOI of each displayed hint", which is a measure of overall attention. The ratio of fixations per word "gives a sense of how carefully a student scans a hint's text". The results of the experiment show that there was no improvement from pre to post-test performance. Each factors (Time of Hint, Hint Type, Attitude, Move Correctness and Pre-test Scores) to some extent affected the attention to the hints in the game. Furthermore, it was observed that attention to hints decreased as the game proceeded and the highest level of attention drop was for definition hints (definition of rules, theorems, principles, etc.), suggesting that these kinds of hints are not perceived well. In terms of attitude, it was observed that low attention for those with the attitude of not wanting help, and higher attention for those with the attitude of wanting help was the case. This indicates that attitude plays a bold role in adaptive hints. In terms of game performance, it appears that when students paid attention to the hints they made fewer errors on subsequent moves. This result may suggest that future investigation on how to increase player's attention to the hints might be useful because it can improve their performance and possibly their learning outcome.

2.5.2.3 Personal Traits

Similar to performance and affective states, characteristics such as *personality*, *preferences*, *play style*, *learning style*, *intelligences* are also aspects of the player that can be utilized in an individualization process. The objective of this sub-section is to delve deeper into researches that have used such aspects of the player. Some of the more prominent works that utilize these aspects of the player either

[6] http://www.tobii.com/

directly in the process of individualization, or demonstrate their potential to do so, will be reviewed.

In (Kickmeier-Rust et al., 2012), it is claimed that the motivation of the player stems from various factors, including their specific goals, preferences, abilities, strength and weaknesses, personality and experience with gaming. As pointed out by the authors, the design of the game can have a huge influence on the level of motivation players have, but sheer design cannot solve individual difference; thus a mechanism for assessing what the learner needs and adjusting the game accordingly is needed. Although this work is rather conceptual, it clearly points out the necessity for considering individual differences as part of individualization to sustain the motivation of the players.

Player types/*Learning styles* are considered in (Magerko, Heeter, Fitzgerald, & Medler, 2008), which presents an approach for "*methodically identifying the possible adaptations a game can take and mapping those adaptations to learner needs*" (Page 2). In order to demonstrate this principle, a game called S.C.R.U.B was explained that *intelligently* adapts its gameplay based on the learning style of the players. Super Covert Removal of Unwanted Bacteria, or in short S.C.R.U.B is a game with the objective of teaching principals about the ways of preventing the spread of microbial pathogens. It teaches its player how to effectively remove microbes from their hands to avoid MRSA (methicillin resistant staphylococcus aureus) infection. In order to adapt the game based on the different types of players, the authors have made a mapping between the different motivations for playing games (extrinsic and intrinsic), and the different player types (achiever, explorer and winner). According to Magerko and colleagues achiever player type can be mapped to extrinsically motivated gameplay since they are constantly looking for rewards, high scores and benefits. On the other hand, explorer player type can be mapped to intrinsically motivated game play since their play is not derived by achievement but rather exploration. Thus, they provide the following three player-learner types: *Intrinsically motivated Explorers*, *Extrinsically motivated performance-approach Achievers*, and *Extrinsically motivated performance-avoidance Winners* (players who are motivated to win to avoid losing). Furthermore, the authors perform a mapping between game features and the player-learner types. This mapping has resulted in 6 adaptive features that are suitable for each of the player-learner types. These mappings and hence the adaptive features can be found in the Figure 7.

	Intrinsic	Extrinsic	
	EXPLORER	ACHIEVER	WINNER
		Performance-Approach	Performance-Avoidance
Explore Mode	Yes	No	No
Bonus (extra) Trivia	Yes	No	No
Timer (speed bonus points)	No	Yes	No
Leader Board	No	Yes	Yes
Trivia Qs (show me option)	No	No	Yes
Tutorial	No	No	Yes

Figure 7 – Player-learner types in S.C.R.U.B (Magerko et al., 2008)

To explain the rationale for this mapping, an example for the explorer player-learner type is given here. Explorers need to have enough time to explore the game freely, therefore any temporal constraint or bonus speed points should be omitted for them. Explorers should also be able to enter an "explore mode", where the normal flow of the game is actually paused and the players would have the chance to closely examine aspects of interest in the game. On the point of how the player profiling needs to be done in the game, and based on what the different adaptation strategies should be deployed, the authors suggest three ways. One would be giving the option of choosing what type of player the players-learners are and thus deploying an instantiation of the game based on the relevant adaptation principles. Two would be to give the players a questionnaire prior to the game to assess what type of players they are. And three would be to infer this information from their gameplay. The automatic or implicit detection of the player types however, is planned as part of the future work in this research. Moreover, the authors mention that more work needs to be done on conflicting motivations (cases where a play has more than one motivation), and finer grained adaptation rules.

	extrinsic (achiever)	*intrinsic (explorer)*
Reflective	**Use tutorial** (player would like to see what is coming and have time to prepare) **Unlimited Resources** (though this player is fuelled by extrinsic values, the need to acquire resources may hinder their ability to reflect on how and why resources work in different situations.) **Static UI** (the player is mainly fuelled by	**Use tutorial** (player would like to see what is coming and have time to prepare) **Unlimited resources** (the need to acquire resources will hinder their ability to reflect on how and why resources work in different situations.) **Modifiable UI** (to view score) (does not need to see score or time to enjoy the game, but may

	achievements, which score and time are key, and so would have no need to get rid of them.) **Score** (part of Static UI) **Timer** (part of Static UI) **Pause button** (to allow the player to pause and reflect on the situation) **Buffs (Score based)** (part of achieving, while they have unlimited resources, getting extra points or abilities are still achievements) **Information stops game play** (for reflection, they want to have time to see the content) **Receive points for information gathering** (while they may want to reflect on the content they would also like to receive some achievement for how much content they have experienced) **Levels - provide content and points** (levels in the game give an educational value, how different layers of the skin react to washing)	choose to, for exploring purposes) **Pause button** (to allow the player to pause and reflect on the situation) **Buffs (Unique abilities)** (part of exploring, they want to find new abilities that they can use to find and make sense of content) **Information stops game play** (for reflection, they want to have time to see the content) **Ability to watch game instead** (they are not fuelled by achieving, or actively participating in the game, and wish to learn the information and have time to figure problems out on their own. **Levels provide content** (levels in the game give an educational value, how different layers of the skin react to washing)
Active	**No tutorial** (players wish to jump right in, they want to learn by doing not by being told) **Limited resources** (they need to achieve and be active in their performance, so they need to be challenged on how they manage their resources) **Static UI** (the player is mainly fuelled by achievements, which score and time are key, and so would have no need to get rid of them.) **Score** (part of Static UI) **Timer** (part of Static UI) **Buffs (Score based)** (part of achieving, while they have unlimited resources, getting extra points or abilities are still achievements) **Information separate from game play** (they do not necessarily care too much about finding learning content and just wish to experience the game. The content is placed elsewhere for them to access.) **Levels provide points** (levels are seen as achievements, higher level means the player feels they are doing better)	**No tutorial** (players wish to jump right in, they want to learn by doing not by being told) **Unlimited resources** (the need to acquire resources will hinder their ability to explore how and why resources work in different situations.) **Modifiable UI (to view score)** (does not need to see score or time to enjoy the game, but may choose too, for exploring purposes) **Buffs (Unique abilities)** (part of exploring, they want to find new abilities that they can use to find and make sense of content) **Information available during game play (play continues)** (they are interested in learning the content but want to experience on their own terms and not have it pushed on them) **Levels provide content** (levels in the game give an educational value, how different layers of the skin react to washing)

Table 1 - Mappings between player-learner profiles and game mechanics (Magerko, 2009)

In more recent work (Magerko, 2009), the author has dropped one of the player-learner types and have actually added the *learning styles dimension* to their work. Two types of player-type motivations were kept: Extrinsic (achiever) and Intrinsic (explorer). The *learning style model of Kolb*[7] (A. Y. Kolb & Kolb, 2005) was used on its dimension of Processing that categorizes people into active and reflective. Therefore, four types of player–learner are defined: *Reflective-extrinsic* (achiever), *Reflective-intrinsic* (explorer), *Active-extrinsic* (achiever), and *Active-intrinsic* (explorer). A mapping between each of the player-learner profiles and game mechanics was then suggested (see Table 1).

On similar grounds, the work in (Hwang et al., 2012) proposes a personalized game-based learning approach based on the *sequential/global dimension of the Felder Silverman learning style theory*[8] (Felder & Silverman, 1988). The individualization takes place based on the way the game is presented to the player as well as the way the player navigates the game. This work, which was published in 2012, claimed to have evidence for the existence of a positive correlation between personalized computer games based on learning style and learning achievement of students, as well as their learning motivation. The authors of this paper introduce the individualization in their work as one that affects the presentation as well as the interaction with the game content.

The *"Theory of Multiple Intelligence" (MI)*[9] (Gardner, 2011) has also received attention in learning games. However, we are not aware of researches that actually use MI for individualization of learning games. Most work concentrate on the impact on or use of games for the improvement of (one or more) intelligence dimension(s) (Chuang & Sheng-Hsiung, 2012; de Boer, du Toit, & Bothma, 2015; Li, Zhang, Wang, & Wang, 2013). For example, Li and colleagues (Li et al., 2013) have investigated the effect of RPG (Role Playing Game) games on interpersonal intelligence dimension, and claimed that RPG games have a positive effect on development of the interpersonal intelligence. On similar grounds, the work in (Chuang & Sheng-Hsiung, 2012) claims that games can be used as a tool to enhance the intelligences of the players.

[7] According to Kolb, learning style represents "*the process whereby knowledge is created through the transformation of experience*" (Page 38) (D. A. Kolb, 1984). This process is composed of the four stages of: concrete experience, reflective observation, abstract conceptualization and active experimentation.

[8] According to Felder and Silverman "*a learning-style model classifies students according to where they fit on a number of scales pertaining to the ways they receive and process information*" (Page 3) (Felder & Silverman, 1988). The style of a person can be then defined on four dimensions of: active-reflective, sensing-intuitive, visual-verbal, and sequential-global.

[9] The term intelligence is defined by Garner as "*the ability to solve problems, or to create products, that are valued within one or more cultural settings*" (Page 28) (Gardner, 2011). In light of this, he has proposed eight dimensions of intelligences possessed by everyone, but to different degrees. These dimensions are: visual-spatial, bodily-kinesthetic, musical-rhythmic, linguistic, logical-mathematical, interpersonal, intrapersonal and naturalistic.

Prior knowledge is considered an important aspect for individualization in e-learning but also in learning games. For instance, in (Moreno-Ger, Burgos, Sierra, & Fernández Manjón, 2007), an “adaptive” mechanism based on the knowledge level of the player is utilized. The knowledge level of the player is assessed in an in-game questionnaire prior to the start of the actual game, and the player is then assigned a grade in his/her profile. Based on the grade, it is then decided if the player is eligible to skip some levels or not.

2.5.3 Summary and Conclusions

Based on the literature review we can draw the following conclusions. First, extensive arguments were found as to why taking individual differences among players into account is important for the success of a learning game. Secondly, either empirical evidence or extensive arguments were found for different aspects of the player that, if used in the process of individualization, can cause an improvement in the game experience and/or learning outcome of the player. Thirdly, a wide range of different aspects of players was already investigated for the purpose of individualization.

Table 2 provides a summary of the reviewed researches grouped according to the user aspects that they consider (first column). Furthermore, the variety of instrument(s) used for measuring the aspect is indicated (second column). The column “Empirical evidence for effect on” indicates whether the work includes empirical evidence, and if so for which effect. The last column provides the references to the research work.

Table 2 shows that quite a large number of the reviewed researches focus on the effect(s) individualization may have on the game experience of the players. This insinuates a general belief among researchers in this domain that a good game experience is an important requirement for achieving a high learning outcome, and thus should also be studied in the context of individualized learning games.

From Table 2, we can conclude that many different aspects of users have already been investigated, but more pedagogical oriented traits of players such as learning style and MI dimension are far less explored. This seems peculiar, as these aspects are based on pedagogical approaches that are well researched and adopted in education. One would expect such findings to be incorporated in researches focusing on individualized learning games more frequently. As pointed out by Van Eck, the design of learning games should be based on research-based theories of how people learn (Van Eck, 2006). This is particularly the case for MI where the ability of people to solve a problem or to create a product is defined in terms of eight different dimensions, which can be exploited during learning. Furthermore, researchers such as Chan (Chan, 2005) suggest that people with different MI profiles exhibit clear preferences toward specific modalities and types of interaction in relation to learning and self-expression. This provides a rather appropriate ground for individualizing games targeting players with specific MI profiles. For this reason, we decided *to focus our research on the use of the MI dimensions for addressing individualization*.

Furthermore, we also see that there is still much room for *empirical evidence on what pedagogical aspects of players can be used in individualizations and on their contribution to both better game experiences and improvement of learning outcomes*. Therefore, this will be also a major concern in this dissertation.

Aspect	**Measurement Instruments**	**Empirical evidence for effect on**	**Sources**
Player style	Strategy & in-game performance	Learning outcome	(Grappiolo et al., 2011)
		-	(Hodhod & Kudenko, 2007; Karpouzis et al., 2013; Georgios N Yannakakis et al., 2010)
Task skill	In-game performance	-	(Berger & Wolfgang, 2012; Burke et al., 2009)
		Game experience	(Davies et al., 2014)
		Learning outcome	(Grappiolo et al., 2011; Hocine et al., 2015)
		Learning outcome, game experience	(Kickmeier-Rust & Albert, 2010)
Knowledge level	In-game performance	-	(Göbel et al., 2009; Kickmeier-Rust et al., 2008)
		Learning outcome	(Grappiolo et al., 2011; Peirce & Wade, 2010)

		Learning outcome, game experience	(Kickmeier-Rust & Albert, 2010; Peirce et al., 2008; van Oostendorp et al., 2013; Zaharias et al., 2012)
Attention & emotion	Video feed from webcam	-	(Asteriadis et al., 2012; Karpouzis et al., 2013)
Engagement	Head movement	-	(Asteriadis et al., 2012)
Engagement	Galvanic skin response, plethysmography, respiration belt, EEG	Game experience (engagement)	(Chanel et al., 2008, 2011)
Attention	Eye tracker	Learning outcome, game experience	(Muir & Conati, 2012)
Anxiety	Physiological sensor	Game experience, in-game performance	(Liu et al., 2009)
Stress	Thermal imaging camera	Game experience	(Yun et al., 2009)
Heart rate & activity	Different sensors	-	(Göbel et al., 2010)
Heart rate	Ergometer	Game experience (motivation)	(Hardy et al., 2012)
Heart rate & breathing	Respiratory sensors	Learning outcome, performance	(Parnandi & Ahmed, 2014)
Multiple Intelligences	Self-assessment questionnaire	Enhancement of intelligence	(Li et al., 2013)
Multiple Intelligences	N.A		(Chuang & Sheng-Hsiung, 2012)
Learning style	Self-assessment questionnaire	Learning outcome, motivation	(Hwang et al., 2012)
Learning style	N.A	-	(Magerko, 2009)
Prior knowledge	In-game questionnaire	-	(Moreno-Ger et al., 2007)

Table 2 – Summary of the literature review

2.6 Summary

This chapter has defined and explained the terminology and concepts that will be used in the rest of the dissertation. In particular, we defined the term *learning game* and the term *individualization*. Next, we identified the different *facets of individualization*. These facets were then used to explore the state of the art on individualization. We started with a brief review of the literature on individualization in e-learning because a lot of individualization methods, strategies, and approaches in learning games are borrowed from e-learning. We structured the review based on the different identified facets of individualization. For the domain of learning games, we did an extensive literature review with a focus on the aspects of the user that can be used for individualization, as this is the focus of the dissertation. Next, conclusions were drawn, which motivated the focus of our research on MI dimensions. We do so, because we believe it is important to focus on pedagogical aspects of players that are explicitly distinguish between people based on their abilities.

Chapter Three:
Conceptual Framework for Individualization

"The reasonable man adapts himself to the world; the unreasonable one persists in trying to adapt the world to himself. Therefore all progress depends on the unreasonable man."

George Bernard Shaw

3.1 Introduction

As already indicated, individualization in learning games can be used to positively affect the game experience and the learning outcome of the players. Furthermore, in sub-section 2.2.2, we have identified three different types of individualization: adaptation, personalization and player-centered game design. We also identified the different facets of individualization (section 2.3). Naturally, if one decides to successfully implement individualization in a learning game, one should analyze and incorporate these facets in a methodological way. To support this, in this chapter we propose a conceptual framework for individualization. In this framework the different facets of individualization that were discussed in section 2.3 are represented and their interrelations are conceptualized. Furthermore, this framework accommodates all three types of individualization.

Given the focus of the dissertation, the proposed conceptual framework is on a level of granularity that presents game designers with concrete examples of aspects mostly for the facet *aspects of the player*, and to a lesser extent the facets *aspects of the game*, and *the way individualization is realized*. The example aspects included are extracted from the literature reviewed in chapter 2, and selected for inclusion based on the criteria 'frequency of use' and 'empirical evidence for effectiveness'. Of course, more aspects can be added later if it is deemed necessary.

A variety of researches have also proposed frameworks that portrait the process of individualization in learning games. These frameworks differ on their level of granularity, with respect to the different facets that they consider, and the concrete examples they provide for each facet. First, we start by discussing the related work (section 3.2). Next, we provide a detailed discussion of our own conceptual framework and point out the differences with existing frameworks (section 3.3). Subsequently, we position our research with respect to our framework (section 3.4). We conclude the chapter with a summary (section 3.5).

3.2 Related Work

In light of the focus and scope of our research, this section briefly discusses a number of interesting frameworks that focus on individualization in the context of learning games.

The individualization framework proposed by Charles and colleagues (Charles et al., 2005) heavily relies on *player modeling* using aspects of the player such as *in-game behavior* and *performance*. In addition to stressing the importance of differentiating between players (i.e. by means of player types and preferences), Charles and colleagues point out that the player model is never completely accurate and flawless, or fixed over time. The model needs to be updated regularly to correspond to the player's progress in the game. In some cases it is even preferable to remodel the player based on the newly available data. The conceptual framework proposed by Charles and colleagues is depicted in Figure 8.

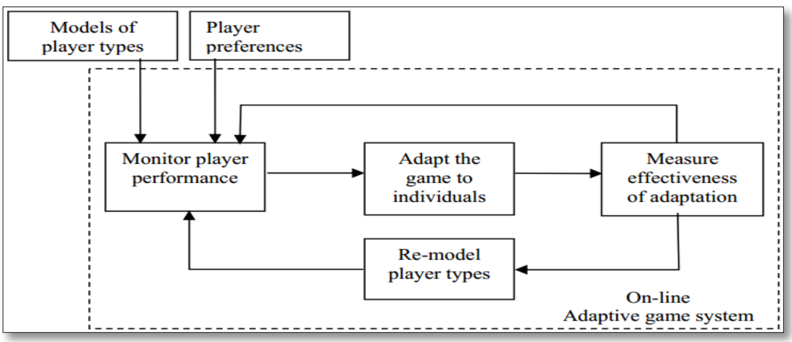

Figure 8 – Proposed conceptual framework on individualization by (Charles et al., 2005)

This framework is at a rather high level and does not take into accounts facets such as *aspects of the game that can be adapted* and *how the individualization can be realized*. With respect to the *aspects of the player* facet, only *player types* and *preferences* are considered, and no factors such as *knowledge level*, *performance*, *affective states*, etc.

Lopes & Bidarra (2011) focus on *player-centric dynamic game adaptation*. Based on an analysis of different individualization frameworks for learning games, they identified different *aspects of the player* and *aspects of the game* and determine how adaptivity can be implemented and effectuated. According to Lopes and Bidarra, the purpose of adaptivity is "*to better suit the game to a dynamic element, for example, the skills of a player, the size of a team or the physical environment in which the game is played*" (Page 3). In light of this, the authors argue that adaptivity must be steered by factors that game developers can identify, measure and influence. If for example, the difficulty level of a game needs to be adjusted, the game must first be able to recognize what constitutes high difficulty. Furthermore, the game also needs to know exactly which in-game factors can be used to affect the difficulty level, and what effect each adjustment would have on the game as whole. This knowledge informs the construction of *rules for adaptation*.

In light of their findings, Lopes and Bidarra propose the use of game logs and recordings of player performance as input for the player modeling process. They argue that this process should result in a *player model* expressed in terms of *actions*, *preferences* and *personality*. This player model will drive the game adaptation. In order to do so, the model is assessed in relation to the current game state to predict the next game state desired by the player. In combination with this performance-based player model, the experience model will steer the adaptation and generation engine. This engine will adjust the necessary game components. Lopes and Bidarra claim that all components considered during the development of the game can be used for adaptation. These include: *the game world and the objects in it*, the *gameplay mechanics*, the *non-playable characters* (NPC), the *Artificial Intelligence* (AI), the game *narratives* and the game *scenarios* and *quests*. Figure 9 outlines the architectural principle of this framework.

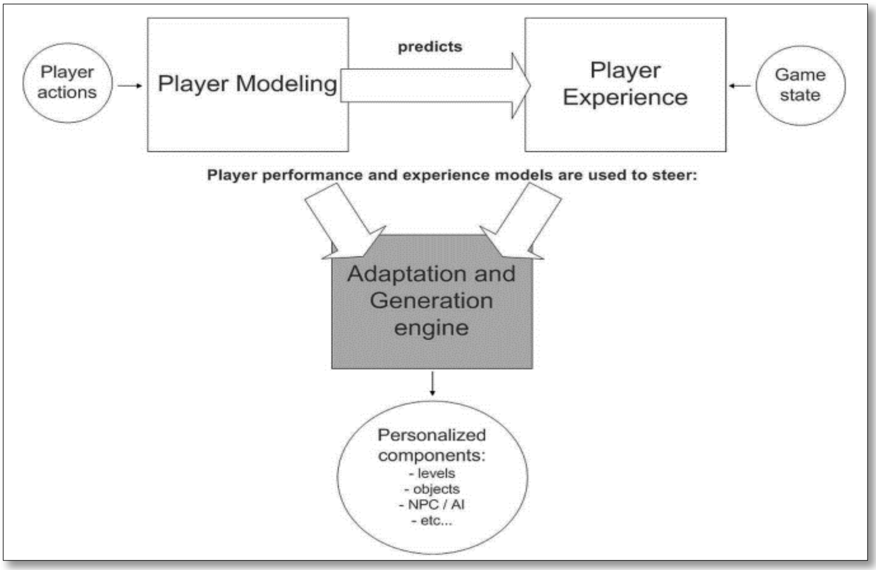

Figure 9 – Proposed conceptual framework on individualization by (Lopes & Bidarra, 2011)

Lopes and Bidarra use the term adaptivity on two levels: *offline* and *online*. Offline adaptivity means that the adjustments made to the game are based on some *player-dependent* data, and are applied prior to the start of the game, whereas online adaptivity is referred to the ability of the game to adjust based on certain factors in real-time. Customized and procedural content generation belong to offline adaptivity. An example of online adaptivity can be found in (Bakkes, Spronck, & van den Herik, 2009) where the NPC opponents inside the game actually learn from their mistakes and manage to act more effectively over time, based on the performance of the player. Dynamic difficulty adjustment is also an example of adaptivity belonging to this category.

Kickmeier-Rust and colleagues (2012) argue that the design of a game can have a huge influence on aspects such as player motivation. They argue that learning games need a mechanism for assessing the learners' needs in order to adjust the game accordingly. This can be particularly challenging due to the fact that multifaceted aspects like motivation often stem from a combination of macro and micro factors. In order to sustain and support such aspects, the balance between the different factors needs to be continuously monitored within the game. This process of monitoring enables swift and proper adaptation of the game in order to preserve a positive balance. Kickmeier-Rust and colleagues propose a psycho-pedagogical approach for this kind of embedded but non-invasive assessment. This implies feeding the assessed information into a dynamic and ontology driven learner model.

On simialr grounds, Sottilare & Gilbert (2011) propose an adaptation framework that is based on “macro” and “micro” approaches (see Figure 10). The idea is to have an adaptive and personalized training where the scenario and challenge level of the game is based on a flexible template that relies on a series of predefined parameters. In this context, the micro approach refers to the use of physiological and behavioral data used to classify learner states such as *engagement* or *frustration*. This data is obtained by monitoring the behavior of the players while they are performing a task (e.g. performance, attention, stress) and use to adapt in real-time some aspects of the game (e.g. difficulty, narrative, hints and feedback) (Mödritscher, Garcia-Barrios, & Gütl, 2004). The macro approach refers to the use of relevant learner characteristics (e.g. learning goals, intellectual abilities, and prior knowledge), that influence learning and which are part of the learner profile (Mödritscher et al., 2004).

In (Vandewaetere et al., 2013), the authors propose a conceptual framework that considers various player and gameplay characteristics that can be used for adaptivity in learning games. The focus of this framework is mostly on the facet: *aspects of the player*. Vandewaetere and colleagues have identified two main categories within this facet of individualization: “*player characteristics*” and “*gameplay characteristics*”. The player characteristics category itself is composed of two sub categories: “*Prior player characteristics*” and “*Runtime player characteristics*”.

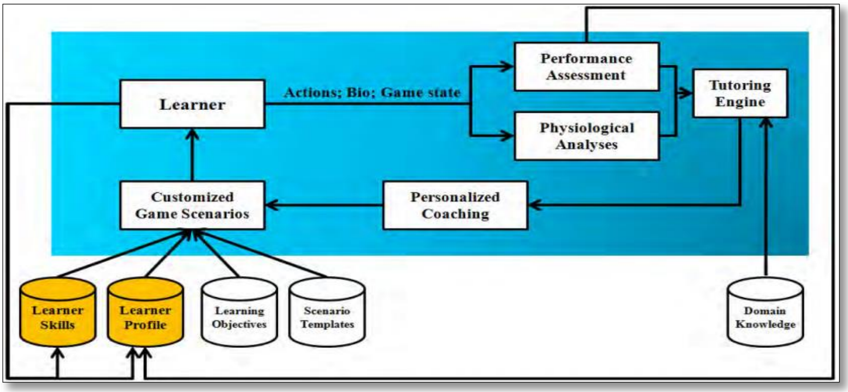

Figure 10 - Proposed conceptual framework on individualization by (Sottilare & Gilbert, 2011)

The first category comprises *prior knowledge*, *learning style/cognitive style/cognitions*, *gaming skills*, *personality*, *goal settings* and *motivation*. According to the authors, these factors can be measured before the player enters the game and have the potential to be used as inputs for adaptation in learning games. The category Runtime player characteristics comprises motivation, gameplay skills and knowledge, and goal settings. According to the authors, these characteristics can change during and because of the gameplay. The gameplay characteristics on the other hand, include learning process characteristics and learner behavior such as reaction times, tool use, need for help, etc. The overview of the propose framework can be seen in the Figure 11.

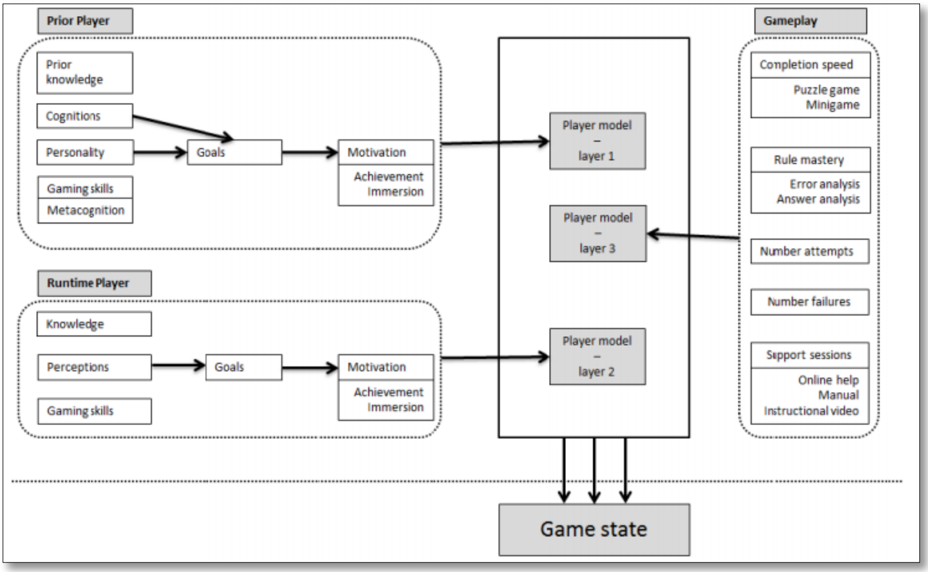

Figure 11 - Proposed conceptual framework on individualization by (Vandewaetere et al., 2013)

As depicted in Figure 11, each group of characteristics (prior player, runtime player, and gameplay) forms a separate layer within the player model. The combination of the different layers in the player model is then used to infer a *game state*. As an example, a player can be attributed with a game state of “gaming behavior”, indicating that a player is misusing the system’s features in order to finish the game easily. This misuse could be in the form of continuously asking for hints or taking the easiest way to complete quests. Therefore, “gaming behavior” could be identified by looking up whether a player has a low motivation, shows performance goals, has specific perceptions about the gameplay (e.g. obligatory learning rather than experiencing fun), and shows a high finishing speed but with a high number of failures. The authors suggest using a probability model for inferring the game states. Such a model would include several characteristics (nodes) and links between those characteristics. Each link will then be given a weight that depends on the initial game state, goals of the game, prior player characteristics and etc. Once a game state is identified, a series of factors that comprise *aspects of the game* (i.e. gameplay mechanics, game scenario and quests, game worlds and objects, and (action) feedback) could be changed. The focus of this work is quite similar to ours with respect to the facets: aspects of the player and aspects of the game.

The reviewed frameworks suggest different possibilities for the individualization facets: "*aspects of the player*", "*aspects of the game",* and "*how is the individualization realized?"*. We observed that the main focus of most of these researches was on the first two facets and less on the facet "*how is the individualization realized?"*.

Furthermore, none of the reviewed researches provides a framework that accommodates all three types of individualization. The notions of *offline* and *online* adaptations, and to some extent *Macro* and *Micro* adaptations, can be argued to be close to our interpretations of the terms personalization and adaptation, however player-centered game design as a type of individualization is usually not covered. We tackle this issue in the following section where we propose a conceptual framework for individualization in learning games that accommodates all three types of individualization.

3.3 Conceptual Framework for Individualization

This section introduces and explains a conceptual framework for dealing with individualization of learning games. From our point of view, a framework for individualization of learning games should be based on the different facets of individualization identified in chapter 2, as well as their interrelations. In particular, the framework presented in this section covers the facets "what aspects of the user are used for individualization", "what aspects of the game are individualized", and "how individualization is realized". The facet "motivation for individualization" is not in the scope of the framework, as this facet should be clarified before deciding to individualize a learning game. The aspects included are extracted from the literature reviewed in chapter 2, and selected for inclusion based on the criteria: their frequency of use and availability of empirical evidence for their effectiveness. Obviously, this is not exclusive. Other aspects can be added if they seem relevant and meet the criteria. Furthermore, we aimed for a framework that is usable for all three types of individualization, i.e. adaptation, personalization, and player-centered game design.

Our framework proposes the use of three main components to drive the individualization process: *aspects of the player, aspects of the system, and rules*. Each of these components is first discussed individually (sub-section 3.3.1 to sub-section 3.3.3). Next we explain the components' relationships and how each component can contribute to the different forms (i.e. types) of individualization (sub-section 3.3.4).

3.3.1 Aspects of the Player

In a similar way to Lopes & Bidarra (2011) and Vandewaetere and colleagues (Vandewaetere et al., 2013), we make a difference between *offline* and *online* aspects, i.e. aspects which can be determined before the player starts the game and which remain rather stable during the gameplay, versus aspects which may change during gameplay and should therefore be measured while the player is playing the game.

The online aspects are further decomposed into *Affective states* and *Performance*. The offline aspects are captured in the so-called *Player model* (and commonly used in works on individualization but sometimes under different names, like user profile or user model).

These three sub-components of the aspects of the player component can be further described as follows:

- **Player model:** represents player characteristics like *preferences*, *learning styles*, *personality*, and *intelligence levels,* which can be measured independently from the game.

- **Physiological parameters and affective states:** represents a variety of player characteristics that may change while the player is playing the game, like *heart rate, blood pressure, anxiety*, *stress, attention*, *engagement*, and other *emotions,* which should be measure in real-time while the player is playing a game.

- **Performance:** because the performance of the player is often used as a key contributor to individualization, we have added it as an explicit aspect in our framework. The performance of the player, depending on the game, could be in form of *task performance,* but it may also be useful to keep track of *task skill*, *knowledge level*, *playing style* as all these may influence performance and can change while playing the game.

The examples given for the sub-components are taken from the literature review given in chapter 2.

3.3.2 Aspects of the Game

The “aspects of the game” component deals with the aspects of the game that can be subject to individualization. Various aspects of a game can be subject to individualization. However, some aspects are more difficult to individualize than others. It is also dependent on whether the individualization should be done dynamically (at runtime), at the start of game, or could be done in advance (e.g. at design time), in other words whether we are dealing with adaptation, personalization or player-centered design. Based on the literature review given in chapter 2, complemented with our own insights, we have organized these aspects into the followings categories:

- **Game state:** A game can be in different states. Some states may be more desirable for certain players and in certain situations. In the case of adaptation, the prior states of the game can be combined with one or more of the aspects of the player to determine the next state. In the context of personalization, possible game states could be selected based on the offline aspects of the player and, if available, on information about game states reached in previous gameplay sessions by this player. However, in the case of player-centered game design, previous states of the game cannot be used. This is because we are still in the phase of designing the game. The best that can be done in this case is to take into account the playing history of the target players with similar games, as well as their preferences for certain types of game states.

- **Game difficulty:** the difficulty level of a game can be subject to change based on different aspects of a player, as explained in chapter 2. The adjustments made to the difficulty level of a game can be in different forms. One is dynamic difficulty adjustment (DDA), whereby the difficulty level of the game is dynamically changed in real-time and thus suitable for adaptation. Another form would be having different difficulty levels of a game that are predefined and selected upon the start of the game. This strategy is suitable for personalization and is used in numerous games where the players are categorized into different groups of for example novice, intermediate or expert, and a different difficulty level of a game is employed depending on the category the player belongs to. From a large body of works reviewed for chapter 2, the works of (Burke et al., 2009; Davies et al., 2014) are clear examples of game difficulty adjustment.

- **Learning content:** apart from the difficulty level of the game, the learning content can also be subject to individualization. Depending on the knowledge level of the player, the learning content that is given to the player either in the form of a challenge, hints, feedback, or intervention can be individualized to match his/her current knowledge level. This form of individualization can for instance be observed in works that employ the Competence-based Knowledge Space Theory (Kickmeier-Rust et al., 2007).

- **Game content:** in addition to learning content, game content is also considered as another aspect of a game that can be subject to individualization. Examples that could be changed for the game content are: game mechanics, narrative, level, NPC, game objects' positions, color, texture and etc. For a few examples of these aspects see (Lopes & Bidarra, 2011).

- **Level/Story:** In some situations it can also be useful to completely individualize the story and levels of the game. Apart from static individualization, this could also be realized by generating the story/level dynamically. In general the individualizations to the story are rather limited as completely changing the story may have a huge impact on all aspects of the game and the learning. Examples of works that target this aspect of a game for individualization are (Berger et al., 2012; Grappiolo et al., 2011).

- **NPC behavior:** the behavior of the NPCs inside a game can also be subject to individualization. The way the NPCs interact with the player or with each other can be based on various aspects of a player (e.g. personality, intelligence). For instance, the explanation given by an NPC to the player can be based on the player's characteristics or behavior, or based on the choices made by the player, the NPC can vary from a kindly and sympathetic character to an angry or abusive one. Other examples of individualized NPC behavior can be observed in games such as *Façade* (Mateas, Stern, & Tech, 2003) and *Prom week* (Mccoy et al., 2014).

- **Hints, feedback and intervention:** other aspects of a game that can be subject to individualization are the hints, feedback and interventions. These can be provided by the NPCs or by another means inside a game. Individualization of these aspects can be done in order to foster more effective learning and/or to sustain the motivation of the players. Examples of works on individualization that do this are (Conati & Manske, 2009; Kickmeier-Rust & Albert, 2010; Kickmeier-Rust et al., 2008; Peirce & Wade, 2010).

- **Interaction modality:** research has shown that the choice of interaction modality can have an effect on the game experience of the players. Therefore, the interaction modality can be considered as an aspect of the game that could be subject to individualization. As an example, the research presented in (Limperos, Schmierbach, Kegerise, & Dardis, 2011) reports that greater feelings of control and enjoyment were experienced by the players when playing with the PlayStation 2 (traditional controller) compared to Nintendo Wii (technologically advanced controller). (McEwan, Johnson, Wyeth, & Blackler, 2012) have also shown that the more natural an interaction modality for a game, the higher the involvement of the players. McEwan and colleagues also report that the game experience seems to be related to the degree of natural mapping of the interaction modality, and not to the players' performance or capability with the interaction modality. Aspects of a player such as personality, learning style and intelligences could be used for individualizing the interaction modality of a game.

3.3.3 Rules

The "rules" component of our framework is responsible for expressing how the individualization should be done in relationship to the "aspects of the player" and the "aspects of the game". This component basically deals with the facet *how the individualization should be realized*. This could be in the form of using a series of pre-defined individualization rules, or inferring and generating them in real-time. Examples of rules for individualization have, for instance, been discussed in the ALIGN system (Peirce et al., 2008), and for serious games such as the *Code Red Triage*. As an example, the latter employs adaptation rules by establishing a threshold for performance, stating that if the player scores above the threshold, the game becomes more complex and if they score less than the threshold, the game will give them extra exercises (van Oostendorp et al., 2013). A similar strategy is used in the game of *frozen bubble* where the auto-shooting mechanic of the game will increase its frequency if the breathing rate of the player crosses a predefined threshold (Parnandi & Ahmed, 2014).

Individualization rules with respect to personalization work slightly different. As an example, in *S.C.R.U.B* (Magerko et al., 2008) different versions of the same game were created based on different learning style profiles. The players are then given the option to select to what type they belong, and will then be given the instance of the game tailored for them. Hwang and colleagues (Hwang et al., 2012) did the same but for the sequential/global dimension of the Felder Silverman learning style (Felder & Silverman, 1988). Two versions (one personalized for the sequential, and one for the global learners) of the same game were developed and based on their learning style, the players would receive one of the two versions. Rules can also use the gameplay data of the player (e.g. performance) for generating a personalized next level of a game (Berger et al., 2012; Karpouzis et al., 2013; Georgios N Yannakakis et al., 2010). This could be by adding or removing obstacles in a level based on how well the player has performed in the previous level.

Individualization rules with respect to player-centered game design are fundamentally different. Rules in this case should be interpreted as *recommendations*. These recommendations can be in the form of mappings between different aspects of the players and aspects of the game, to be used during the design process. Based on these mappings, aspects of the game, such as game mechanics, interaction modality, narrative, etc. can be tailored during the game design to target (a) particular audience(s). Therefore, in the case of player-centered game design, rules are rather design rules or guidelines. Examples of such guidelines and recommendations are given in chapter 8, as the focus of this dissertation is on individualization with respect to player-centered game design.

3.3.4 Overall Architecture

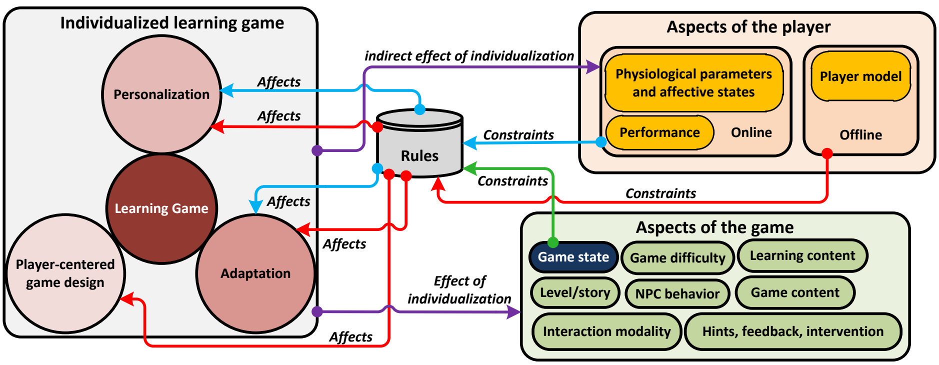

Figure 12 – Overall Architecture of our Conceptual Framework for Individualization

Figure 11 provides the overall architecture of our conceptual framework. The components as well as the interrelations (indicated by arrows) are explained in the flowing paragraphs.

During individualization, the values of the different “aspects of the player” used, and possibly also the current game state, will constraint the applicability of the “rules”, i.e. based on these values and thresholds used in the rules and the game state, the applicable individualization rule(s) are selected and applied. The methods for selecting the “appropriate” rules can be different and may be dependent on the targeted type of individualization. As an example, in the case of adaptation, a weighting mechanism can be used to aid the selection of the most appropriate rule for that particular moment (e.g. (Spronck, Sprinkhuizen-Kuyper, & Postma, 2003)). Also note that not all aspects of the player are applicable to all types of individualization. *Online* aspects that are measured during the gameplay are applicable for adaptation and some also for personalization, but not for player-centered game design, because the exact values of these aspects are not available during the design process. Sometimes average values for the target audience could be used but it should be taken into consideration that the data is dependent on the type of game and can vary significantly across different games and contexts. On the other hand, *offline* aspects are most suited for personalization and player-centered game design, since they represents aspects of the player that are more stable, and do not change rapidly and/or frequently. In fact, the offline aspects, in our opinion, are applicable to all three types of individualization (adaptation, personalization, and player-centered game design). The difference in applicability is denoted with different arrow colors. A blue arrow is used for the online aspects and may affect adaptation as well as personalization (indicated by the blue "Affects" arrows). A red arrow is used for the offline aspects and may affect adaptation as well as personalization and player-centered game design (indicated by the red "Affects" arrows). The green "Constraints" arrow indicates the fact that also the game state may be used to constraint the application of the rules.

The consequences of individualization in terms of the changes made to the "aspects of the game", is denoted with the purple arrow labeled "Effect of individualization". Note that this process may also update the game state. Moreover, in the case of personalization and adaptation, it can also calculate the next desired game state. Furthermore, the goal of the individualization process is to affect the player. This is indicated by the purple arrow labeled "Indirect effect of individualization". For instance, when, based on the value of an affective state of the player it is determined that the player is stressed and the rules component decides to change the difficulty level of the game, the individualization made to the game is with the objective of lowering the stress level of the player. If this is successful, this will be reflected in a change of the relevant online aspects of the player. The online aspects are among the ones that change more rapidly and frequently, and are dependent on the game and context. Therefore the individualization of the game can directly affect them.

Note that individualization is a highly iterative process: at specific moments (determined by the game or by the developer of the game), the game state in combination with the online and offline player aspects are taken as inputs to trigger one or more rules, which will affect different aspects of a game and result in a new game state. This in turn, may affect the player's aspects and result in a new iteration. In case of player-centered design, the individualization process is only done once, at design time. In that case, the purpose is to provide the most suitable environment for the player to have the best game experience and the best learning outcome.

3.4 Positioning the Research

The focus of the research presented in this dissertation is with respect to the aspects of the player on the "Theory of MI", and with respect to the aspects of the game on game mechanics. The choice for the latter is further justified in chapter 4, where we investigate the relationship between the MI intelligences and games. Furthermore, with respect to how the individualization can be realized, the focus is on player-centred game design. These foci are highlighted in our conceptual framework in Figure 13. The MI intelligences are part of the offline aspects of the player, and the game mechanics are part of the aspects of the game, more in particular "Game content". As it was stated earlier in this chapter, for player-centred game design, the rules serve as recommendations or guidelines. They suggest specific design choices with respect to certain aspects of the game, based on particular aspects of the player.

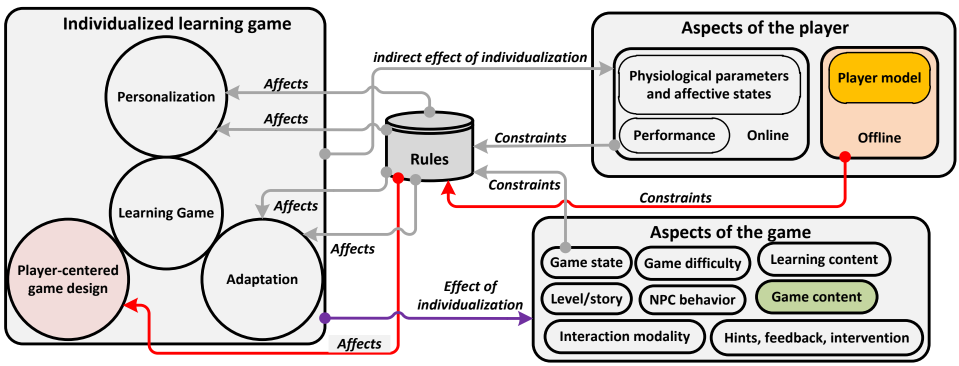

Figure 13 - The foci of the dissertation

3.5 Summary

This chapter presented a conceptual framework for the individualization process. The three main facets of individualization were mapped to the different components of the framework, and their interrelations were specified. The aspects included in the framework are extracted from the literature reviewed in chapter 2, and selected for inclusion based on the criteria 'frequency of use' and 'empirical evidence on their effectiveness'. Given that no existing conceptual framework seems to accommodate all three types of individualization, we have proposed a framework that can be used for personalization and/or adaptation, as well as for designing player-centred games targeting a specific audience.

Although the proposed framework is meant to be used within the context of learning games, we don't see any argument why its applicability should not extend beyond this, and be used for individualizing entertainment games as well.

Chapter Four:
Relationship Between MI Intelligences and Preferences for Games

"Whenever a theory appears to you as the only possible one, take this as a sign that you have neither understood the theory nor the problem which it was intended to solve."

Karl Popper

4.1 Introduction

One of the least explored opportunities for individualization is the "Theory of Multiple Intelligences" (MI), developed by Howard Gardner (2011). MI states that humans have eight different intellectual capabilities (referred to as *intelligence dimensions*). Furthermore, this theory suggests that individual differences between people are the result of the differences in strength of these intellectual capabilities and how they work together and affect each other. MI explicitly stresses individual differences in terms of the various abilities to solve problems and create products. Gardner suggests that people with different intelligences or intellectual strengths often exhibit clear preferences, abilities and competencies with respect to specific tasks (Gardner, 2011). In this dissertation, we explore whether this knowledge could be transferred to learning games and employed in their design. If people with different intelligences or intellectual strengths (further named *MI intelligences*) exhibit clear preferences for certain game constructs, and if game designers are aware of the MI intelligences of their intended audience, they would be able to design their game accordingly. In order to do so, they could incorporate constructs such as interaction modalities and game mechanics that have been proven to support and improve game experience as well as learning outcome among their targeted audience.

At the time of writing, few researchers have studied MI's merits in relation to games in general, and as an "aspect of the player" that informs individualization of learning games in particular. In fact, evidence-based research that explores the relationship between games and players' or learners' intellectual capabilities with respect to MI seems to be nonexistent.

In this chapter we explore possible correlations between MI and games. In light of this, we performed a survey study to investigate possible correlations between the different MI intelligences and preferences for games. This study is described in section 4.4. Before elaborating on this survey study we discuss MI in more detail in section 4.2. An overview of the related work with respect to MI and (learning) games is also given in section 4.3.

4.2 The Theory of Multiple Intelligences (MI)

MI provides an interesting framework for dealing with individual differences. Gardner (2011), the intellectual father of MI, defines intelligence as a multi-dimensional entity. As such he oppose the classical one-dimensional understanding represented by popular measurements such as the Intelligence Quotient (IQ). According to Gardner, intelligence is "*the ability to solve problems, or to create products, that are valued within one or more cultural settings*" (Gardner, 2011) (Page 28). In light of this definition, Gardner identified eight unique dimensions of intelligence. Each of these intelligence dimensions represents a different way of thinking, problem solving and learning. The intelligence dimensions are defined as follows (taken from (Gardner, 2015), for an elaborate overview and discussion, also see (Gardner, 2011)).

- *Visual-spatial intelligence* is the ability to conceptualize and manipulate large-scale spatial arrays (e.g. like a pilot does), or more local forms of spaces (e.g. as done by an architect).
- *Bodily-kinesthetic intelligence* is the ability to use one's whole body, or parts of the body, to solve problems or create products (e.g. like a dancer).
- *Musical-rhythmic intelligence* implies having sensitivity to rhythm, pitch, meter, tone, melody and timbre. May entail the ability to sing, play musical instruments, and/or compose music (e.g. like a musical conductor).

- *Linguistic intelligence* implies sensitivity to the meaning of words, the order among words, and the sound, rhythms, inflections, and meter of words (e.g. like a poet).
- *Logical-mathematical intelligence* is the capacity to conceptualize the logical relations among actions or symbols (e.g. like a mathematicians or scientists).
- *Interpersonal intelligence* is the ability to interact effectively with others and being sensitive to others' moods, feelings, temperaments and motivations (e.g. like a negotiator).
- *Intrapersonal intelligence* implies being sensitive to one's own feelings, goals, and anxieties, and the capacity to plan and act in the light of one's own traits. Intrapersonal intelligence is not particular to specific careers; rather, it is a goal for every individual in a complex modern society, where one has to make consequential decisions for oneself.
- *Naturalistic intelligence* is the ability to make consequential distinctions in the world of nature as, for example, between one plant and another, or one cloud formation and another (e.g. like a taxonomist).

Moran and Gardner (2006) argue that everyone possesses all dimension of intelligence, be it, however, to different degrees. Furthermore, they state that these different dimensions of intelligence work together in an orchestrated way. This suggests that there is a certain level of interaction and dependency between these different dimensions, which collectively determine a person's overall "intelligence". Indeed, the Confirmatory Factor Analysis of the different theoretical models of the structure of intelligences performed by Castejon and colleagues (2010) has shown that the MI dimensions influence each other. According to Moran and Gardner (2006), there are three different ways in which MI dimensions can influence each other, namely through *interference*, *compensation* and *catalysis*.

- Through *inferences*, a weak intelligence can negatively influence the actualization of the full potential of another intelligence. For example, a highly musically intelligent student with weak self-regulatory abilities (intrapersonal) may have difficulties learning to play a musical instrument due to a lack of motivation.
- Through *compensation*, a weaker intelligence dimension may be supported by the stronger ones. For example, a person with high musical-rhythmic intelligence and lower linguistic intelligence might be weak in writing lyrics, but nonetheless, manages to write a good sounding song.

- Through *catalysis*, one of the intelligences may amplify the expression of another intelligence. As an example, a drummer who uses his or her bodily-kinesthetic intelligence to play the drums catalyzes his or her musical intelligence.

We recognize that controversies exist concerning MI. Most of the discussions are regarding whether the "Theory of MI" could indeed a considered a "theory"[10]. Concerns were raised about the evidence for the *existence* of multiple intelligences. Neuroscience findings have shown that the neural circuits for processing different contents are shared which would be in contradiction with the multiple intelligences (Waterhouse, 2006a). However, differences can be measured between people based on instruments developed for MI (see e.g. (Akbari & Hosseini, 2008; Castejon et al., 2010; Marefat, 2007; Naeini & Pandian, 2010)) and these differences could be useful to consider for individualization. Whether these differences should be called "intelligences" or not, is not important for our purpose. This is in line with Chen's opinion about the value of a theory, stating that: "*rather its value depends on the contribution it makes to understanding and to practice in the field*" (J. Chen, 2004) (page 22). We see potential in applying the MI dimensions for profiling players and use this for the individualization of learning games in practice and therefore we believe that it is worthwhile to investigate this objective.

If we want to use MI dimensions for profiling, we should be able to measure a person's MI levels. However, Gardner never created such an instrument, but instead suggested that researchers should create and test out instruments themselves. Such attempts have led mostly to measuring tools that use a self-reporting questionnaire (see e.g. (McKenzie, 1999; B. Shearer, 1996; Tirri, Kirsi & Nokelainen, 2008; Tirri & Nokelainen, 2011)). Upon inquiring about proper approaches for measuring MI, through private email, Gardner suggested to rely on triangulation for measuring the intelligence levels, thus considering a combination of data sources, like self-assessment, peer assessments, and observations during task execution. This approach is generally considered to arrive at a more reliable and objective assessment. However, using triangulation may not always be feasible in experiments, especially when one wants to involve a large number of participations in an experiment who are located in different parts of the world.

[10] For this reason we have put the term Theory of Multiple Intelligence between quotes or we use the shorthand MI.

4.3 Related Work

The potential relationship between MI and games has been pointed out by other researchers as well. Two of the most important works that suggest the existence of such relationship are the ones of Becker (Becker, 2007) and Starks (Starks, 2014). These two researchers have suggested theoretical mappings between each dimension of MI and certain characteristics of games. These suggestions are briefly explained in the next paragraphs.

Becker (2007) argues that there is a link between the written and spoken elements and instructions in games and the development of the linguistic intelligence. According to Becker, "*this is one reason why children often experience success in learning to read through games like Pokémon*" (Page 371). Similarly, she maps musical intelligence to a game's soundtrack and auditory feedback, referring to games such as *Karaoke Revolution*; logical-mathematical intelligence to in-game strategizing, arithmetic, management style and puzzle games such as *Pikmin*; visual-spatial intelligence to the graphical environment, visual elements of games and how they are perceived through the screen; bodily-kinesthetic intelligence to games that promote physical movement as well as the different physical states a player experiences while playing a game such as *Dance Dance Revolution*; intrapersonal intelligence to games that involve ethical dilemmas and moral decision making such as *Black & White*; interpersonal intelligence to multiplayer collaboration, communication and competition; and naturalistic intelligence to realistic portrayal of natural environments in games such as *Zoo Tycoon*.

Starks (2014) provides similar arguments, stating that in-game graphics engage a person's visual intelligence, while the way a player moves in the game environment engages their spatial intelligence. She also states that relationships inside and surrounding a game refers to the use of the interpersonal intelligence, like in MMO games; that empathy provoking situations inside a game, such as in *Darfur is Dying,* engage a person's intrapersonal intelligence; that music and sounds engage a player's musical intelligence; that narrative and language used inside the game engage the linguistic intelligence; that components like arithmetic, calculations and geometry, as well as pattern detection and logical deduction activate logical-mathematical intelligence; that in-game actions requiring actual physical movement engage bodily-kinesthetic intelligence; and that realistic representations and simulations of natural environments in a game engage a player's naturalistic intelligence.

It is important to note that the observations of both researchers, Becker (Becker, 2007) and Starks (Starks, 2014), are solely based on their theoretical analyses, and they do not provide empirical evidence that sustains their claims.

Apart from application of MI in more conventional contexts (i.e. classrooms), this theory has also been actually used in games as well. Some of these works have been reviewed in chapter 2. In short, in (Crescenzi-Lanna & Grané-Oró, 2016) the importance of developing the MI intelligences of children at an early age is stressed. The study analyses 100 educational apps (including games) for children under the age of eight. The results indicate that the majority of the current apps focus on the visual-spatial and logical-mathematical dimensions. The results also show that other dimensions such as kinesthetic, interpersonal, intrapersonal or musical are neglected, even though they are developmentally essential for children at that age. Jing and colleagues (Jing, Sujuan, & Linqing, 2012), provide an overview of several educational games that can aid in the development of a player's logical-mathematical intelligence. Similarly, Chuang and Sheng-Hsiung (2012) claim that games can be used as a tool to enhance players' MI intelligences and learning outcomes. Li et al (2013) have investigated the effect of Role Playing Games on intrapersonal intelligence.

4.4 MI Intelligences and Preferences for Games: An Empirical Mapping

Despite the potential of applying MI in learning games, empirical correlations between MI intelligences and games are non-existent. However, such empirical evidence is crucial for the continuation of this dissertation, as it will act as the foundation for individualization based on MI dimensions.

To study the relation between MI intelligences and games, we investigated possible relations that may exist between *MI profiles and preferences for certain games* by means of a survey. This investigation is the first step towards unveiling any possible relationships between MI and games.

In this section we present the empirical study performed to investigate whether individual differences in terms of MI dimensions correlate with differences in terms of game preferences. Based on the results of an online survey study conducted among 308 avid gamers in July 2015, we have found that the players can be grouped based on different MI profiles, and that individual differences in terms of MI dimensions and game preferences show significant correlations. The study also showed that these relationships could not be explained by only considering games genres. This indicates that it will be necessary to look into more detail to the components or characteristics of the games to be able to explain the correlations and identify what game characteristics are preferred by players exhibiting dominance for certain MI dimensions. Moreover, our results indicate that the theoretical mappings suggested in the literature (i.e. the ones of Becker and Starks) can be refined and completed based on the evidences we provide. The methodology used for obtaining the mentioned results as well as the details of our findings are discussed in this section.

4.4.1 Methodology

In this study, we performed an online survey to determine (1) if there are correlations between players' MI intelligences and their preferences for certain games, and (2) to what these correlations can be attributed. Before we discuss the findings of our study, we elaborate on the process of data-collection and the instrument used, the population and the sampling methods, as well as the analyses and how they were performed.

4.4.1.1 Data Collection & Instrument

An online survey[11] targeting frequent gamers was created and used to collect the data. We opted for an online survey because it enables us to reach a wide variety of people easily, in this way preserving the heterogeneity of the sample. This allowed us to obtain a sample that is representative of the whole population of gamers.

We launched the survey on July 17th 2015. After 8 days the response rate to the survey had dropped significantly. At that time, 308 participants had responded. We were confident that this amount of participants would suffice for our study and therefor decided to proceed with the available data.

The survey was composed of three sections. The first section of the survey was designed to obtain demographic information (gender, age range, and level of education), as well as game-related background information (frequency of gaming, experience with different game platforms or devices, preferred game genres, and hands-on experience with game design or development) from the participants. It is composed of 7 questions. The information obtained from this first section would allow us to determine the heterogeneity of the sample. It would also enable us to

[11] http://goo.gl/5v6wOR

accurately measure the effect of personal and contextual factors such as age, education and prior experiences.

The second section of the survey was designed to measure the strength of the intelligence dimensions of the participants. For this we used the Multiple Intelligences Profiling Questionnaire (MIPQ) developed by Tirri and Nokelainen (see Tirri & Nokelainen, 2008; Tirri & Nokelainen, 2011). Using MIPQ, the participants were prompted to rate 31 statements (see Appendix B) on a scale of 1 to 5 to measure the eight intelligence dimensions. Each dimension is measured using four questions, except for the naturalist intelligence dimension that is measured by only three questions. Based on the information from this second section, we were able to identify patterns in the compositions and levels of the participants' intelligences.

The third section of the survey contained a list of 47 game titles (see Table 3) that the participants were invited to rate on a scale of 1 to 5 stars to reflect their *enjoyment of and preference towards the game* (i.e. 1 star represents lowest and 5 stars highest enjoyment of and preferences towards a game). The participants were instructed to only rate the games that they had played before. The list of games is composed in such a way that each MI intelligence is targeted by at least five game titles (i.e. 40 in total). The list of games was compiled in collaboration with a team of avid gamers and academic experts on games, and based on suggestions found in academic literature on the mapping between games and MI, i.e. in (Becker, 2007; Starks, 2014). Seven games (highlighted in Table 3) that could be related to more than one MI dimension were also added to the list because of their unique design and popularity. The research team decided to limit the size of the list to reduce the time required to complete the survey in order to maximize participation.

Although the primary objective of this dissertation is in the domain of learning games, the selected 47 game titles are all commercially available entertainment games. The rationale behind this choice stems from the fact that, in general, learning games are not widely spread. Most of the learning games are developed for a special purpose targeting a special group of users, and are thus released only to a very limited population. Therefore, learning games are not as widely played as commercially available entertainment games. Thus, a compilation of learning games instead of entertainment games would introduce the risk of reducing the familiarity of participants with these games, and would consequently significantly reduce participation. In order to attract enough participation and obtain enough data to be able to make sound conclusions, we opted for a compilation of commercially available entertainment games. It remains to be investigated whether the same findings would hold for learning games. We discuss this issue in more detail in the Limitations (section 9.4.1).

Intelligence dimension	***Selected games***
Visual-spatial	World of Warcraft, Minecraft, Dirt^S, Portal^S, Angry Birds, Tetris
Bodily-kinaesthetic	Xbox Fitness, Street Fighter^S, Boom Blox, Kinect Sports, Wii Sports Resort, Just Dance^S, Dance Central Spotlight^S, Dance Dance Revolution^S, Fantasia: Music Evolved
Musical	Guitar Hero^S, Audiosurf, Rock Band, SingStar^S, Bit. Trip Runner, Just Dance^S , Dance Central Spotlight^S, Dance Dance Revolution^S, Fantasia: Music Evolved
Linguistics	The Typing of The Dead^S, Wordament, Scribblenauts^S, Wordfeud, Ace Attorney^S
Logical-mathematical	The Room^S, 2048, Braid, Where's My Water?, L.A Noir, Heavy Rain
Interpersonal	The Sims^S, DayZ, Life is Strange, Second Life, Farmville^S, Word of Warcraft, The Walking Dead, Heavy Rain
Intrapersonal	Fable^S, Black & White^S, Infamous^S, Mass Effect^S, Fallout^S, Heavy Rain, The Walking Dead
Naturalist	Endless Ocean, Spore, Plan It Green, Flower, Afrika

Table 3 - 47 game titles selected for the study. (S represents a game series)

4.4.1.2 Sampling & Population

In order to be able to generalize the results of our study and to avoid cultural bias, it was necessary to target an international population of frequent gamers. We targeted frequent gamers to maximize the number of games familiar to the participants. By targeting frequent gamers and well-known games, the chances of our participants having a history playing them would be relatively high. In order to reach our target population, we spread calls for participation through social media targeting online communities of avid gamers and game designers, developers and researchers (Facebook, Linkedin, Google+, Reddit and Twitter). In addition, we also reached out through email to academic communities focusing on game research (DIGRA, IGDA, DIGRA Australia, IFIP and CHI-WEB) (detailed lists are provided in Appendix C).

In the period from 17-July-2015 to 24-July-2015, 465 people responded to our call for participation, of which 308 participants completed the survey and were included in our study. Our sample of 308 participants contained 97 females and 211 males. We asked our participants to specify their age based on the nine age range categories. The distribution of the age range can be observed in Figure 14. The majority of the participants (210 participants out of 308) were between 18 and 34.

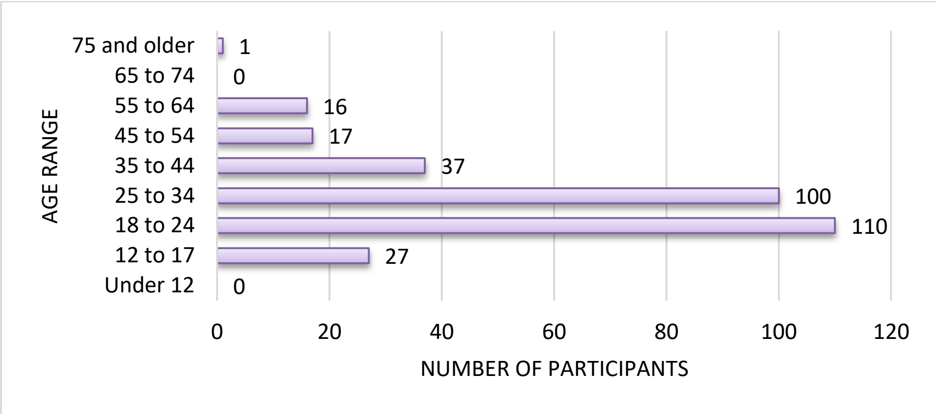

Figure 14 – Age range distribution

Based on the self-reported frequency of gaming activity, 82.79% of our sample can be considered avid gamers: 141 participants reported to play games every day, and 114 participants reported to be playing games 3-6 times a week.

Based on the MIPQ section of the survey, the intelligence dimensions that were the strongest and most frequent were as follows: out of 308, we have 171 participants with a high score for logical-mathematical, 120 participants with a high score for visual-spatial, 101 participants with a high score for bodily-kinesthetic, 119 participants with a high score for musical, 88 participants with a high score for interpersonal, 170 participants with a high score for intrapersonal and 107 participants with a high score for naturalistic dimensions. For each of the dimensions, the strength of the intelligence was considered to be high if the value was above 15 (out of 20 and 12 out of 15 in the case of naturalistic). Because each intelligence dimension is measured using 4 questions (3 in the case of naturalistic) on a scale of 1 to 5 we made the sum of the individual scores to generate a single value for each dimension. The value of each intelligence dimension for a single participant is therefore represented by a number within the interval of 4 to 20 (3 to 15 for the naturalistic dimension). The distribution of the dominant intelligences can be seen in Figure 15.

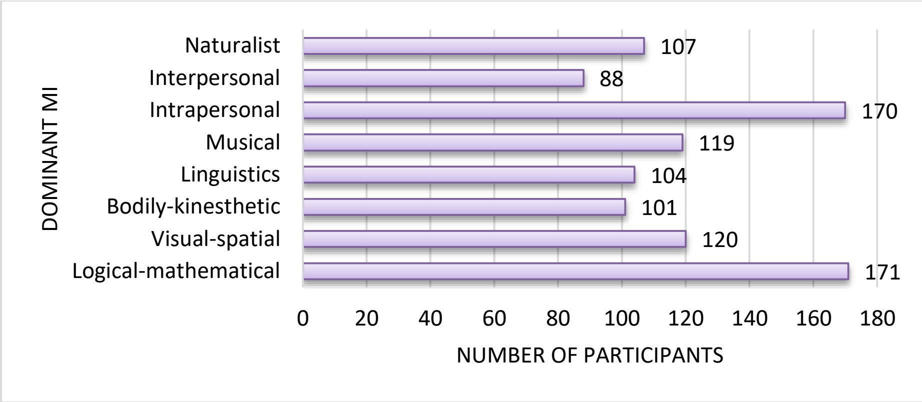

Figure 15 - Distribution of Participants' dominant MI

4.4.1.3 Data Analysis

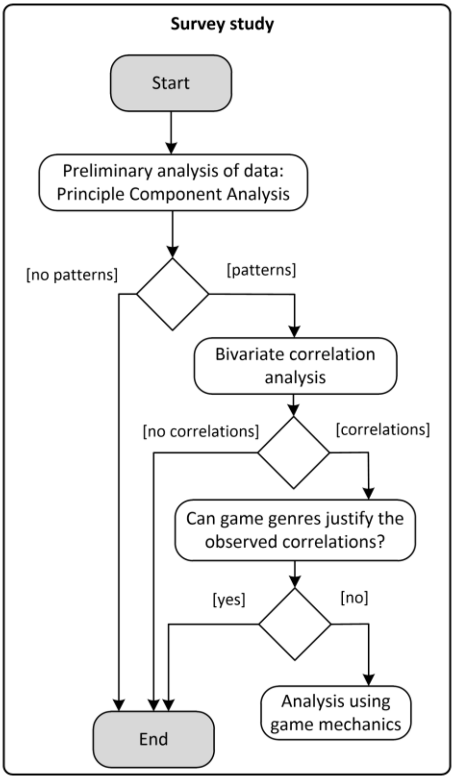

Figure 16 - Methodology for investigation the relation between MI and games presented as a flow chart

The methodology used for analyzing the data consisted of three consecutive steps, depicted in Figure 16. As a first step, we analyzed the data by means of a multivariate analysis, more precisely Principal Component Analysis (PCA). This analytic technique enabled us to investigate whether there were underlying constructs or patterns among the variables in our data set (Jolliffe, 1986). The "Extraction Method Principal Component Analysis" and the "Promax" rotation method provided evidence for the presence of patterns within our data. Next, we were interested in investigating all possible correlations that may exist between each dimension of MI and all 47 game titles. Therefore, we proceeded to test for every possible correlation by means of Bivariate Correlation Analysis We did so by using Spearman's rho. We performed this analysis for each of the MI dimensions in relation to the 47 game titles to measure the existence and strength of correlations between them. The outcome of this analysis confirmed the hypothesis that *correlations exist between participants' MI intelligences and their game preferences*. An elaborated overview and discussion of these findings is given in sub-section 4.4.2 and section 4.5.

The third step of our analysis dealt with finding an explanation for the identified correlations between the participants' intelligences and game preferences. In order to do so, we performed bivariate correlation analysis using Spearman's rho on two levels. On the first level, we analyzed the data by relating the 47 games to their official genres in order to identify relationships between MI dimensions and game genres. On the second level, we included background information (i.e. the preferences for game genres reported by the participants) from the first section of the survey into the analytic process to identify potential relationships between participants' intelligences and participants' preferred game genres. This allowed us to investigate whether the observed correlations between MI dimensions and game preferences could be attributed to the genres of the games. As we will see in section 4.5 this is not the case.

All of the analyses mentioned in this section, were performed using IBM **SPSS** Statistics 22.

4.4.2 Results

4.4.2.1 Principal Component Analysis

Using the technique of PCA, we could identify patterns between each dimension of MI and preferences for games, as well as patterns among the different intelligence dimensions. The results of the PCA (pattern matrix) of the eight intelligence dimension values indicate the presence of three factors (see Table 4). Each factor represents a set of MI intelligences that frequently coincide, henceforth referred to as "*intelligence profile*". More precisely, the coefficients given for each MI dimension represent the regression weights that capture the relationship between an intelligence dimension and an intelligence profile. This confirms, as MI suggest, that MI dimensions coexist.

	Intelligence profile 1	Intelligence profile 2	Intelligence profile 3
Linguistics	.845		
Logical-Mathematical			.705
Visual-Spatial		.508	.401
Bodily-Kinesthetic		.903	
Musical			.730
Interpersonal	.517	.323	
Intrapersonal	.762		
Naturalistic	.465	.436	

Table 4 - PCA of intelligences dimensions - Pattern matrix with KMO of .650 and Sig. of .000

The PCA between each MI dimension and the 47 games was repeated 8 times (once for each MI dimension) to identify patterns. Not all game titles showed associations. However those that did (20 in total) could be grouped into factors. We labeled these factors as *Intelligence-game factor*. Each factor represents a pattern between the MI dimension it embodies and the game titles, as shown in Table 5 (combination of 8 pattern matrices). The coefficients in Table 5 represent regression weights that capture the relationship between an intelligence dimension/game title and an intelligence-game factor.

In the context of this research, PCA is only used for the purpose of identifying the underlying structure in our data and its results are not elaborated any further, i.e. the correlations between factors are not examined, and different types of factor analysis to confirm the existence of these patterns have not been performed. However, instead of investigating correlations between factors (that represent a specific group of preferences for games and/or MI dimensions), we were interested in investigating all possible correlations that may exist between each dimension of MI and all 47 game titles. Of course, the different variables in each factor are associated to one another, but this does not tell us if they are correlated and if so, what the significance level of this correlation is. Therefore, once the underlying structure of our data was identified, we proceeded to test for every possible correlation by means of Bivariate Correlation Analysis.

Games	*Factors*							
	intelligence-game factor 1	***intelligence-game factor 2***	***intelligence-game factor 3***	***intelligence-game factor 4***	***intelligence-game factor 5***	***intelligence-game factor 6***	***intelligence-game factor 7***	***intelligence-game factor 8***
Linguistics	.409							
Logical-Mathematical		.881						
Visual-Spatial			.317					
Bodily-Kinaesthetic				.917				
Musical					.821			
Interpersonal						-.738		
Intrapersonal							.334	
Naturalistic								-.536
Boom Blox						.357		.432
Wii sports resort								.561
Dirt^{S}			.338					
Angry Birds			.544					
Tetris					-.460			
Street Fighter^{S}	.344				-.329			
Just Dance^{S}							.461	
Dance Central Spotlight^{S}							.395	
Dance Dance Revolution^{S}	.469						.622	
Guitar Hero^{S}	.530						.569	
Rock Band	.599						.643	
Wordfeud			.402					
SingStar^{S}			.432		.339			
2048		.308	.574					

Where's My Water?			.345					
Heavy Rain	.543		-.315				.432	
The Sims^{S}		-.398		-.371				
Endless Ocean		-.302				.487		.450
Spore			.358					
Flower	.531						.408	

Table 5 - Summary of the 8 PCA tests. KMO for linguistics .767, logical-mathematical .765, visual-spatial .766, bodily-kinesthetic .763, musical .766, interpersonal .765, intrapersonal .767, naturalistic .765; Sig. levels for KMO and Bartlett's tests .000 (S represents a game series)

4.4.2.2 Bivariate Correlation Analysis Between MI Intelligences & Game Preferences

To test the hypothesis "*correlations exist between participants' MI intelligences and their game preferences*", we performed Spearman bivariate correlation tests between each of the MI dimensions and all of the game preferences.

First, we investigated the correlations between MI intelligences and game preferences, whereby each MI intelligence was represented by a single value (as explained in sub-section 4.4.1.2). The results show significant correlations for each of the eight MI dimensions and multiple game preferences (see Table 6). **The value of each correlation specifies that the variations in the values of the two variables are significantly correlated.** In particular, we observe the following correlations: linguistic intelligence correlates with participants' preferences for the games *Fallout*, *Black & White*, *Angry Birds*, *Heavy Rain*, *The Walking Dead*, *Flower*, *Fable* and *L.A. Noire*. Logical-mathematical intelligence correlates negatively with *The Sims*, and positively with *Braid*. Visual-spatial intelligence correlates with *Spore*, *Second Life*, *Dirt*, *Dance Central Spotlight*, *Minecraft*, *DayZ*, *Black & White*, *SingStar* and *Fable*. Bodily-kinesthetic intelligence correlates with *Where's My Water?*, *Angry Birds*, *Just Dance*, *Tetris*, *Dance Central Spotlight* and negatively with *Ace Attorney* and *Fallout*. Musical intelligence correlates with *Guitar Hero*, *Singstar*, *Dance Dance Revolution*, *Bit.Trip Runner*, *L.A. Noire* and *Rock Band*. Interpersonal intelligence correlates with *Just Dance*, *Farmville*, *Fallout*, *SingStar* and *Where's My Water?*. Intrapersonal intelligence correlates with *Second Life*, *Heavy Rain*, *Rock Band*, *World of Warcraft*, *The Walking Dead*, *Portal*, *Flower*, *Audiosurf*, *Farmville* and

L.A. Noire. And the naturalistic intelligence correlates with *Just Dance*, *Rock Band*, *Dance Central Spotlight*, *Braid* and *Street Fighter*.

Games	**Intelligences**							
	Linguistics	***Logical-Mathematical***	***Visual-Spatial***	***Bodily-Kinaesthetic***	***Musical***	***Interpersonal***	***Intrapersonal***	***Naturalistic***
World of Warcraft							.165**	
Minecraft			.134*					
Dirt [S]			.154**					
Portal [S]							.156**	
Angry Birds	.145*			.171**				
Tetris				.127*				
Street Fighter [S]								.112*
Just Dance [S]				.161**		.163**		.131*
Dance Central Spotlight [S]			.139*	.113*				.117*
Dance Dance Revolution [S]					.134*			
Guitar Hero [S]					.157**			
Audiosurf							.142*	
Rock Band					.117*		.170**	.122*
SingStar [S]			.115*		.135*	.132*		
Bit.Trip Runner					.132*			
Ace Attorney [S]				-.132*				
Braid		.141*						.113*
Where's My Water?				.198**		.113*		
L.A. Noire	.117*				.122*		.120*	

Heavy Rain	.144*						.173**	
The Sims ^{S}		- .166**						
Dayz			.116*					
Second Life			.157**				.187**	
Farmville ^{S}						.137*	.141*	
The Walking Dead	.143*						.161**	
Fable ^{S}	.129*		.113*					
Black & White ^{S}	.156**		.115*					
Mass Effect ^{S}				-.124*				
Fallout ^{S}	.163**					.133*		
Spore			.199**					
Flower	.135*						.151**	

Table 6 - Bivariate correlation analysis level one. ($p < .05$) (** $p < .01$) (S represents a game series)*

To gain a deeper understanding of these correlations, we repeated the bivariate test focusing on the individual questions of the MIPQ, rather than on the single value of each MI dimension. The results highlight which questions correlate to specific game preferences. The overview of these findings can be found in Appendix D. In general we observe that for the linguistics intelligence, the first determining question: “Writing is a natural way for me to express myself” correlates with *Fallout*, *Braid*, *Angry Birds*, *Heavy Rain* and *Street Fighter*; whereas the second question: “At school, studies in native language were easy for me” correlates with *Heavy Rain*, *The Walking Dead*, *The Sims* and negatively with *2048*; and the third question: “I have recently written something that I am especially proud of, or for which I have received recognition” correlates with *Black & White*, *The Room*, *Flower*, *SingStar*, *Fallout* and *Just Dance*; and the forth question: “Metaphors and vivid verbal expressions help me learn efficiently” correlates positively with *Angry Birds*, *Fallout*, *Rock Band*, *Portal*, *The Walking Dead* and negatively with *Endless Ocean*.

For the logical-mathematical intelligence, we observed that the first determining question: “At school, I was good at mathematics, physics or chemistry" correlates positively with *2048* and negatively with *World of Warcraft*, *Heavy Rain*, *The Sims* and *Endless Ocean*; while the second question: "I can work with and solve complex problems" correlates positively with *Fallout*, *Portal*, *Braid* and negatively with *The Sims*, *Wordament* and *Endless Ocean*; and the third question: "Mental arithmetic is easy for me" correlates positively with *Braid*, *Fantasia: Music Evolved*, *Afrika*, *Xbox Fitness* and negatively with *The Sims*; and the fourth: "I am good at solving logical problems and games that require logical thinking" correlates positively with *Portal*, *Fallout*, *Braid*, *Fable* and negatively with *Wordament*.

With respect to the visual-spatial dimension, we observed that the first determining question: "At school, geometry and various kinds of assignments involving spatial perception were easier for me than solving equations" correlates positively with *SingStar*, *Second Life* and negatively with *Ace Attorney*; while the second question: "It is easy for me to imagine and analyse complex and multidimensional patterns" correlates with *Spore*, *Dirt*, *Black & White*, *Second Life*, *The Room*, *Afrika*, *World of Warcraft*, *Dance Central Spotlight* , *Fantasia: Music Evolved* and *2048*; and the third question: "I can easily imagine how a landscape looks from a bird's eye view" correlates with *DayZ*, *Spore*, *Minecraft*, *Dirt* and *Fable*; and the fourth question: "When I read, I form illustrative pictures or designs in my mind" correlates with *The Sims*, *L.A. Noire*, *Dance Central Spotlight* , *Just Dance* and *Fallout*.

For the bodily-kinesthetic dimension, we observed that the first determining question: "I am handy" correlates positively with *Where's My Water?*, *Tetris*, *Just Dance*, *Angry Birds*, *Dance Central Spotlight* and negatively with *Ace Attorney*; while the second question: "I can easily do something concrete with my hands (e.g. knitting and woodwork)" correlates positively with *Just Dance*, *Where's My Water?*, *Tetris*, *Dance Dance Revolution* and negatively with *Ace Attorney*; and the third question: "I am good at showing how to do something in practice" correlates positively with *Angry Birds*, *DayZ* and negatively with *Endless Ocean*; and the fourth question: "I was good at handicrafts at school" correlates positively with *Where's My Water?*, *Angry Birds*, *Just Dance*, *Minecraft*, and negatively with *Infamous*, *The Typing of the Dead*, *Mass Effect* and *Ace Attorney*.

For the musical intelligence, we observed that the first determining question: "After hearing a tune once or twice I am able to sing or whistle it quite accurately" correlates with *Guitar Hero*, *Where's My Water?*, *Dance Dance Revolution*, *SingStar*, *L.A. Noire*, *Dirt* and *Fantasia: Music Evolved*; while the second question: "When listening to music, I am able to discern instruments or recognize melodies" correlates with *L.A. Noire*; and the third question: "I can easily keep the rhythm when drumming a melody” with *Guitar Hero*, *Rock Band*, *Bit.Trip Runner*, *L.A. Noire* and *Spore*; and the fourth question: “I notice immediately if a melody is out of tune” correlates positively with *The Typing of the Dead*, *SingStar*, *Dance Dance Revolution* and negatively with *Street Fighter*.

For the interpersonal intelligence, we observed that the first determining question: “Even in strange company, I easily find someone to talk to” correlates with *SingStar*, *Just Dance*, *Fallout* and *Black & White*; while the second question: “I get alone easily with different types of people” correlates with *Farmville* and *Just Dance*; and the third question: “I make contact easily with other people” with *Just Dance*, *Where’s My Water?* and *Tetris*; and the fourth question: “In negotiations and group work, I am able to support the group to find a consensus” with *Just Dance*, *Dance Dance Revolution*, *SingStar*, *Where’s My Water?*, *Braid*, *Angry Birds*, *DayZ* and negatively with *Endless Ocean*.

For the intrapersonal intelligence, we observed that the first determining question: “I am able to analyze my own motives and ways of action” correlates with *Xbox Fitness*, *Rock Band*, *Portal* and *Second Life*; while the second question: “I often think about my own feelings and sentiments and seek reasons for them” with *Portal*, *Audiosurf*, *Rock Band*, *Heavy Rain*, *Flower*, *Scribblenauts*, *Second Life*, *Farmville*, *Fable* and *The Walking Dead*; and the third question: “I spend time regularly reflecting on the important issues in life” correlates positively with *Second Life*, *The Walking Dead*, *Rock Band*, *Portal*, *Audiosurf*, *Mass Effect* and negatively with *Wordament*; and the fourth question: “I like to read psychological or philosophical literature to increase my self-knowledge” correlates positively with *Farmville*, *Heavy Rain*, *The Walking Dead*, *Just Dance*, *World of Warcraft*, *Rock Band*, *Flower*, *Spore* and negatively with *2048*.

For the naturalistic intelligence, we observed that the first determining question: “I enjoy the beauty and experiences related to nature” correlates positively with *Just Dance*, *Braid* and negatively with *Dirt*; while the second question: “Protecting the nature is important to me” correlates positively with *Street Fighter* and negatively with *Wordfeud*. The third question “I pay attention to my consumption habits in order to protect environment” for this intelligence dimension did not show any correlations with any of the 47 game titles.

To ease the application of our results, we have combined the results of both levels into a single table that shows positive (‘+’) or negative (‘-’) correlations and their significance levels (indicated by * for $P < 0.05$ and ** for $P < 0.01$). The results of the multi-level approach are summarized in Table 7. The results indicate that 42 game titles from the 47 that were pre-selected to be part of this survey, showed to be correlated with one or more MI intelligences on different significant levels, either positively or negatively.

Game Genre	**Game Title**	*Linguistics*	*Logical-Mathematical*	*Visual-Spatial*	*Bodily-Kinesthetic*	*Musical*	*Interpersonal*	*Intrapersonal*	*Naturalist*
Puzzle	***Portal*[S]**	+ *	+ **					+ **	
	Angry Birds	+ *			+ **		+ *		
	***The Room*[S]**	+ *		+ **					
	2048	- *	+ **	+ *				- *	
	Tetris				+ **		+ *		
	Where's My Water?				+ **	+ **	+ *		
	Scribblenauts							+ *	
Word puzzle	***Wordfeud***								- *
	Wordament		- *					- *	
Puzzle/action	***Braid***	+ **	+ **				+ *		+ *
Action	***Street Fighter***	+ *				- *			+ *
Action/sandbox	***Minecraft***			+ *	+ *				
Action/adventure	***L.A. Noire***	+ *		+ *		+ *		+ *	
	Heavy Rain	+ **	- *					+ **	
	***Infamous*[S]**				- *				
Action/shooter	***DayZ***			+ *	+ *		+ *		
Action/RPG/shooter	***Mass Effect*[S]**				- *			+ *	
Music/dance/rhythm/ action/platformer	***Bit.Trip Runner***					+ *			
Action/educational	***The Typing of the Dead***				- *	+ **			
Music/dance	***Rock Band***	+ *				+ *		+ **	+ *

	SingStar^S	+ *		+ *		+ *	+ **		
	Just Dance^S	+ *		+ *	+ **		+ **	+ **	+ **
	Fantasia: Music Evolved		+ *	+ *		+ *			
	Dance Central Spotlight^S			+ *	+ *				+ *
	Dance Dance Revolution^S				+ *	+ *	+ *		
	Guitar Hero^S					+ **			
	Audiosurf							+ **	
Simulation	***The Sims^S***	+ *	- **	+ **					
	Afrika		+ *	+ **					
Simulation/adventure	***Endless Ocean***	- *	- *		- *		- *		
	Spore			+ **		+ *		+ *	
Simulation/RPG	***Second Life***			+ **				+ **	
	Farmville^S						+ **	+ **	
Adventure	***Flower***	+ *						+ **	
	Ace Attorney^S			- **	- *				
	The Walking Dead	+ **						+ **	
RPG	***Fable***	+ *	+ **	+ *				+ *	
	Fallout^S	+ **	+ **	+ *			+ *		
	World of Warcraft		- *	+ *				+ **	
Sports	***Xbox Fitness***		+ *					+ *	
Racing	***Dirt^S***			+ **		+ *			- **
Strategy	***Black & White^S***	+ **		+ **			+ *		

*Table 7 - Summary of the bivariate correlation analyses. + (positive), - (negative), P < 0.01 ** or P < 0.05* (S represents a game series)*

4.4.2.3 Bivariate Correlation Analysis Between MI Intelligences & Game Genres

As a final step, we performed a bivariate correlation analysis to investigate if the correlations could be explained in terms of a preference for particular game genre(s). We first identified the genres for the game titles using the official website of Pan European Game Information (PEGI[12]) (see Table 7).

Game genre	*Linguistics*	*Logical-Mathematical*	*Visual-Spatial*	*Bodily-Kinaesthetic*	*Musical*	*Interpersonal*	*Intrapersonal*	*Naturalistic*
Action/adventure		-.095*			+.115*			
Adventure								+.112*
MMO								
Platform/ platformer					+.145**			
Puzzle				+.146**				
RPG		-.119*						
Racer								
Rhythm/dance					+.198**		+.126*	
Shoot'em up							-.135**	
Sims		-.118*		-.100*	-.105*			
Sports		+.114*						
Strategy		+.141**				+.150**		

*Table 8 - Bivariate correlation analysis between MI and explicit game genre preferences. + (positive), - (negative), the correlation coefficients are at $P < 0.01$ ** or $P < 0.05$**

This categorization is commonly used through the gaming industry. The results suggest that the correlation between MI intelligences and game preferences cannot be explained in terms of unique preferences for one or multiple game genres. We see for example, that the game genre "puzzle" coincides with almost all MI dimensions. We repeated the bivariate test using the participants' *explicit preferences* for game genres obtained from the first section of the survey. This

[12] http://www.pegi.info/en/index/

allowed us to verify if the correlation between MI intelligences and game preferences indeed cannot be explained in terms of unique preferences for one or multiple game genres (see Table 8). For instance, we see that the "action/adventure" genre is correlated with the logical-mathematical and musical dimensions, whereas MI dimensions such as visual-spatial are not correlated with any genre. This is partially in contradiction with the implicit preferences for genres extracted from the preferences for the games correlated to each dimension of MI.

4.5 Discussion & Limitations

The results of our study provide empirical evidence that correlations exist between MI intelligences and game preferences. Out of the pre-selected 47, 42 game titles showed to be either positively or negatively correlated to one or more dimensions of MI on different levels of significance. This means that the strength for certain MI dimensions coincides with having a stronger or weaker preference towards and enjoyment of particular games. As such, the results of our study provide empirical evidence that supports theoretical suggestions made by (Becker, 2007) and (Starks, 2014). Moreover, based on our results, these theoretical suggestions can be refined. For instance, Becker (2007) states that there is a link between logical-mathematical intelligence and in-game strategizing, arithmetic, management style and puzzle games. However, the logically-mathematically intelligent participants in our population also exhibit a significant preference for games that require extensive physical movement such as *Fantasia: Music Evolved* and *Xbox Fitness* (see Table 7). These games do not employ characteristics listed by Becker. Similarly, Starks (2014) states that in-game actions that require actual physical movement by the players engage their bodily-kinesthetic intelligence. In addition, our population of kinesthetic gamers has also shown preferences for games that do not really promote physical movement, such as *Angry Birds* and *Tetris*.

In order to refine these relationships, we need to further investigate this. Such investigation is essential for crafting learning games that properly support and foster learners' individual capabilities, i.e. MI intelligences. Furthermore, these insights could also be used to predict game preferences based on gamers' MI intelligence profiles.

As we have shown, the observed correlations cannot be attributed to specific game genres. The tests point to overlaps and internal conflicts that suggest that no unique combinations of game genres could independently explain the relationship between MI intelligences and game preferences. In light of this, we believe that there must be one or multiple lower-level factors that are shared among games that are correlated to a specific MI dimension, but are not necessarily restricted to particular genres. We believe that these lower-level factors could be the game mechanics employed in the games. This is further explored in chapter 5.

Although our study was designed with the utmost care, inevitably, there are some limitations. Firstly, we recognize that our selection of game titles represents a snapshot of the current landscape of popular video games, and that any selection unavoidably influences the outcome of the study. However, to minimize any effect, we carefully selected a broad range of games. Naturally the list should be updated for future studies aiming at redoing this research.

Secondly, we acknowledge the risk of bias associated with self-evaluation. Although the recommended approach for measuring MI intelligences is a combination of methods (triangulation), as was discussed in section 4.2, given the sample size and the available resources, the use of the MIPQ was the best approach. As MIPQ is validated, it can be considered reliable to a good extent.

4.6 Conclusions

The research presented in this chapter has resulted in answering the first research question ***RQ1:*** *Are there any correlations between player's intelligences (with respect to MI) and their preferences for games?*

To achieve this, we executed a study to investigate relationships between MI intelligences and preferences for games. The set-up and instruments used in our study have enabled us to gather empirical evidence to confirm the existence of correlations between MI intelligences and game preferences. Based on the results, we can conclude (1) that gamers' MI intelligences and their preferences for games have multiple significant relationships; and (2) that the relationships between MI intelligences and game preferences cannot be explained sufficiently based on game genres. To understand the underlying relationships, more research was needed. Chapter 5 addresses this topic.

Chapter Five:
Mapping Between MI Dimensions and Game Mechanics

"The knowledge of anything, since all things have causes, is not acquired or complete unless it is known by its causes."

Avicenna

5.1 Introduction

In the previous chapter, we have elaborated on MI and have empirically shown the existence of correlations between MI intelligences and preferences for games. However, this does not allow us to answer the question: which aspects of a game should or could be individualized based on the players' MI intelligences and how? The answer to this question is needed for individualization based on MI dimensions, as this question is directly related to the third and to a certain extent also to the fourth facet of individualization, i.e. "what aspects of the system can be individualized?" and "How is the individualization realized" as elaborated in sub-section 2.3.3 and sub-section 2.3.4.

It was shown in chapter 4 that the genre of games could not independently explain why certain games are preferred (or not) by players exhibiting certain MI intelligences. In this chapter, we build on the findings presented in chapter 4 and explore whether *game mechanics* can help us explain why people with specific MI intelligences prefer certain games, in other words what game mechanics are preferred by people with specific MI intelligences. Game mechanics can be broadly defined as methods designed for game interaction (see sub-section 5.2.1 for more details). They are the backbone of any game and therefore a candidate for an "aspect of the system" that could be individualized. Identifying and mapping correlations between game mechanics and MI intelligences would thus represent a first big step towards creating design guidelines for individualizing learning games based on the MI dimensions.

We start by defining the term game mechanic and discuss popular schemes used for classifying them (section 5.2). Furthermore, we discuss related work (section 5.3). Next, to be able to explore whether game mechanics can explain why people with specific MI intelligences prefer certain games, we first had to compile a repository of game mechanics (sub-section 5.4.1). We then analyze the games that showed to be correlated to the different MI intelligences in our survey study with respect to their game mechanics (sub-section 5.4.2). Then, we construct lists of game mechanics that seem to be associated with specific MI dimensions (sub-section 5.4.3). We conclude by discussing the results (section 5.5), limitations and by giving conclusions (section 5.6).

5.2 Game Mechanics

Various definitions of the term game mechanic have been proposed. In this section, we provide a brief overview of the different definitions of the term game mechanic. In addition, we also touch upon different ways to classify game mechanics and the classification adopted in this dissertation.

5.2.1 Definitions

Sicart (2008) has provided a rather comprehensive literature study about game mechanics. In this sub-section, we provide a brief overview of different definitions of game mechanics identified by Sicart.

Some definitions focus on the relationship between game mechanics and the rule system of a game. For instance, Lundgren and Björk (2003) define game mechanics as "*any part of the rule system of a game that covers one, and only one, possible kind of interaction that takes place during the game, be it general or specific*" (Page 4). Furthermore, they state that "*mechanics can be regarded as a way to summarize game rules*" (Lundgren & Bjork, 2003) (Page 9). According to Sicart, the definition of Lundgren and Björk consider game mechanics to be the same as low-level game rules that are applied when a player interacts with the game. However, most researchers distinguish between game mechanics and game rules. For example, Adams and Dormans (2012) state that the two concepts are definitely related, however, mechanics are more detailed and concrete. This is an inevitable characteristic of game mechanics since they need to be transformed into code by programmers. On the other hand, Adams and Dormans state that in the game community, rules are often considered as "*printed instructions that the players are aware of*" (Page 3) (Adams & Dormans, 2012), while the mechanics are hidden pieces of software inside the game. As an example, they mention the rules of the *Monopoly* game, which are a few pages, but the mechanics of this game are more than a dozen.

Other definitions see game mechanics as parts of an integrated system. According to Richard Rouse (2010), game mechanics are "*what the players are able to do in the game-world, how they do it, and how that leads to a compelling game experience*" (Page 310). On similar grounds, Cook[13] defines the term as: "*Game mechanics are rule based systems / simulations that facilitate and encourage a user to explore and learn the properties of their possibility space through the use of feedback mechanisms*" (Paragraph 3). According to Cook a game is a series of game mechanics linked together.

Yet other definitions of the term game mechanics are more focusing on the interaction possibilities offered to the player. For example, the definition given by Hunicke, Zubek and LeBlanc (2004): "*mechanics are the various actions, behaviors, and control mechanisms afforded to the player within a game context*" (Page 3); or by Järvinen (2008): "*game mechanic is a functional game feature that describes one possible or preferred or encouraged means with which the player can interact with game elements as she is trying to influence the game state at hand towards attainment of a goal.*" (Page 254-255).

Sicart, himself, provides a more abstract definition of the concept of game mechanics. According to him, game mechanics are "*methods invoked by agents, designed for interaction with the game state*" (Sicart, 2008) (paragraph 25). He argues that this definition can encapsulate a much broader set of mechanics without losing sight of the essential characteristics and functions that bind them. He has explained the main components of his definition as follows:

The first component of the definition, "*methods*", builds on terminology from the object-oriented paradigm in software development. In the context of object-oriented programming, methods refer to the actions or behaviors available to an object. They are the mechanisms used by the object to communicate with another object. In light of this, a game mechanic is defined as "*the action invoked by an*

[13] http://www.lostgarden.com/2006/10/what-are-game-mechanics.html

agent to interact with the game world, as constrained by the game rules" (Paragraph 29). Sicart illustrates the latter with an example from the game *Gears of War*. In this game it is possible for the player to take cover behind the closest possible game object that allows such action. This means that the governing rules of the game world limit the mechanic of "covering", since not every game object would allow the covering action.

The second component, "*invoked by agents*", refers to both players and NPCs (or the different AI agent of the game). These can interact with the game world using different methods.

The third part of the definition, "*designed for interaction",* indicates that game mechanics are to be used by agents to interact with the game. Game mechanics are often, but not necessarily, designed to aid in overcoming a challenge in the game, or to produce one. Based on this definition, game mechanics entail input devices and interaction modalities as well.

The fourth component, "*with the game state*", refers to making a transition between two game states. Game mechanics are thus intended as methods to modify the game states.

In our work, we have adopted the definition of Sicart because the definition is broad and actually covers the other definitions given. Furthermore, other game constructs such as interaction modalities are also covered by his definition.

5.2.2 Classifications

A number of different classification schemes for game mechanics have been proposed. The classifications are done based on the role that the game mechanic plays in a game. In a way, the classifications are game dependent. The proposed classification schemes include classes such as core versus satellite mechanics; primary versus secondary mechanics; sub mechanics and modifiers; global versus local mechanics; and enhancement, alternate, or opposition mechanics. In this sub-section, we provide a brief description of each of these (sub) classes, followed by a presentation of the classification scheme selected for our research.

Core Mechanics

The class *core mechanics* is used to denote the game mechanics that carry out the core gameplay activities. Whether a game mechanic is core or not depends on the game in which it is used.

Salen and Zimmerman (2004) have defined the term *core mechanic* as "*the essential play activity players perform again and again in a game*" (Page 316). They further elaborate that a core mechanic is actually a compound activity which is composed of more than one action.

In this work, we will use the definition of (Fabricatore, 2007), where *core gameplay* is defined as "*the set of activities that the player will undertake more frequently during the game experience, and which are indispensable to win the game*" (Page 12). Also Adams and Dormans (2012) use the term core mechanics in a similar way. According them, this term refers to "*mechanics that are the most influential, affecting many aspects of a game*" (Page 4).

Järvinen (2008) on the other hand, gives a rather specialized definition for the term core mechanic. According to him "*the core mechanic of the game often consists of a set of game mechanics that are available globally but only once at a turn, i.e. use of one rules the other one out for that particular state*" (Page 264). In continuation to this statement, he states that: "*this is the set of primary mechanics. It is primary because it is related to the highest order goal that the game presents to its players at that time*" (Page 264) (note that the highest order goal does not necessarily mean the ultimate goal of the game). As interesting as this classification may be, in our opinion it is too complicated and difficult to apply.

According to Sicart (2008) a single concept of "core mechanic" is not always useful. Therefore, he introduces two specializations of a core mechanic called *primary*, and *secondary* mechanics, explained in the next sub-section.

Primary Mechanics, global mechanics

Sicart (2008) considers the concept of "desired end state" for a game and defines the idea of *primary mechanics* is term of this concept: *primary mechanics* are *core mechanics that can be directly applied to solving challenges that lead to the desired end state. Primary mechanics are readily available, explained in the early stages of the game, and consistent throughout the game experience*" (Paragraph 53). As an example, Sicart identifies some of the primary mechanics of *Grand Theft Auto IV*, being "shooting", "melee fighting", and "driving". These mechanics are available to the player from the beginning of the game and remain available throughout the gameplay.

According to (Järvinen, 2008), "*primary game mechanics are the mechanics related to the highest order goal that the game presents to its players*" (Page 264). He then further states that "*what the player does in relation to a game state during* *a standard turn or sequence*" is a primary mechanic (Page 270). The concept of a primary mechanic (based on the definition of Sicart) is quite close to what is introduced in (Järvinen, 2008) as a "global mechanic". A mechanic is considered to be global if it is available in relation to any game state.

Secondary, Sub, Modifier, & Satellite Mechanics

Opposite to primary mechanics, Sicart (2008) distinguishes *secondary mechanics* as "*core mechanics that ease the player's interaction with the game towards reaching the end state. Secondary mechanics are either available occasionally or require their combination with a primary mechanic in order to be functional*" (Paragraph 55). As an example, he gives the "take cover" mechanic in *Grand Theft Auto IV*, which cannot be used purely on its own to overcome the challenges posed by the game. However, if used properly, it is a powerful mechanism that can help overcoming the challenges and reach the desired end-state of the game.

A very similar concept called *sub-mechanic* is used in the literature as well. Järvinen (2008) states that primary game mechanics often have other mechanic(s) in a supporting role. This means that by using a primary mechanic for instance, one or more sub-mechanics would become available to the player. These mechanics are related to lower order goals. However these goals are imperative for completing the highest order goal(s). Sub-mechanics introduce variety and unpredictability into the game. Järvinen gives the following definition and examples for sub-mechanics: "*what action(s) the player has available to her as a consequence of the primary mechanic, or as instrumental means to perform the primary game mechanic*" (Page 270). An example of a sub-mechanic in the game *Mario Kart* would be "accelerating/braking", in *Black Jack* "choosing additional cards", and in *Tetris* "rotating the blocks".

The concept of *modifier mechanics* is similar to the aforementioned. According to (Järvinen, 2008), modifier mechanics are the kind of mechanics that are locally available either for a short duration or in a particular context. As an example, the power-ups in the game *Mario Kart* modify the speed of the player, but they are only available for a few seconds. In a Tennis game for instance, the power with which the ball is hit is adjustable. This can be considered as a mechanic for applying the appropriate level of force at a moment. Järvinen explains the concept of a modifier mechanic as follows: "*what the player does in a specific game state which occurs on some condition (related to location, player role, time, etc.) specified in the rules*" (Page 270) (Järvinen, 2008).

Furthermore, Fabricatore (2007) defined the concept *satellite mechanic* as "*there is the possibility of extending and enriching the core gameplay by introducing special kinds of mechanics, aimed at enhancing already existing activities. These are called satellite game mechanics since their design is functional to already existing core mechanics*" (Page 13). Moreover, Fabricatore has introduced three different types of satellite mechanics. These types are: enhancement, alternate, and opposition. The primary purpose of an *enhancement mechanic* is enhancing an already-existing core mechanics. *Alternate mechanics* are about providing the same features in different ways. *Opposition mechanics* are specifically designed to enhance the challenges posed by the game, and/or hinder the progress of the player.

Lastly, there is the concept of a *local mechanic* introduced by (Järvinen, 2008). According to Järvinen, if a mechanic is only available conditionally (based on location, time, duration, specific game states, for players with specific roles), it is called a local mechanic.

These classes serve the purpose to indicate that the game mechanic plays a subordinate role compared to some other game mechanics in the game. To represent this group of game mechanics, we selected the term satellite mechanic.

Game Mechanics Categorization Scheme

The categorization scheme used in this research is the one of Fabricatore (2007): *Core* and *Satellite*. We used this distinction because considering whether a game mechanic plays a dominant role in the game or not is an important factor to consider when deciding whether that game mechanic has a relationship with a specific dimensions of MI or not; i.e. a core mechanic is more decisive than a satellite mechanic. Fabricatore decomposed the satellite category into enhancement, alternate, and opposition mechanics. For our purpose, this refinement is not needed. Therefore, we only consider the classes: *core* and *satellite*.

5.3 Related Work

Academic works that provide a mapping between MI and game mechanics are to the best of our knowledge non-existent. However, work that relates other types of personal differences with game mechanics could offer an interesting frame of reference. In this context, we can mention the work of Jason VandenBerghe, called

"Engines of Play". VandenBerghe (2012, 2013) focus on personality traits rather than intelligence, and defined a mapping between the Big Five (Goldberg, 1990) and game mechanics. The purpose of this mapping is to know which game mechanics to incorporate in the design of games to boosts the motivation of target users of the game, based on the personality they have (expressed in terms of the Big Five). An example of such mapping for the "openness to experience" dimension of Big Five is depicted in Figure 17. In this example, the "openness to experience" dimension of the big five model is mapped to the "Novelty" aspect of the domain of play, proposed by VandenBerghe. This mapping results in four quarters, each of which representing a particular type of player based on the mechanics that suits them. For instance, the "Imagineer" represents a player who enjoys the *fantasy* and *building* mechanics. An example of this kind of player would be Tony Stark[14]. VandenBerghe promotes this "Engines of Play" as a method to understand the target audience of a game and tailor the game towards this target audience. He argues that it is necessary to first choose which player motivations (i.e. personality traits of the players according to the Big Five) the game will attempt to engage across the player's entire experience with the game.

Figure 17 - Example of the mappings between the "openness to experience" dimension of big five and game mechanics

Other relevant work, but not related to individualization, is presented in (Arnab et al., 2014; Lim et al., 2015), which proposes the *Learning mechanic-Game mechanic* model. This model links game mechanics to different pedagogical and learning theories. It includes a series of game mechanics extracted from the literature (i.e. from game studies and learning theories) that were used in serious

[14] https://en.wikipedia.org/wiki/Iron_Man

games following different pedagogical or learning theories. It can be used for drawing mappings between the pedagogical and entertainment features of games. Research on this topic has led to the creation of a new concept referred to as “serious game mechanics”.

Game Mechanics	Thinking Skills	Learning Mechanics	
Design/Editing Infinite Game play Ownership Protégé Effect Status Strategy/Planning Tiles/Grids	CREATING	Accountability Ownership Planning Responsibility	LOTS to HOTS
Action Points Assessment Collaboration Communal Discovery Resource Management Game Turns Pareto Optimal Rewards/Penalties Urgent Optimism	EVALUATING	Assessment Collaboration Hypothesis Incentive Motivation Reflect/Discuss	
Feedback Mega-game Realism	ANALYSING	Analyze Experimentation Feedback Identify Observation Shadowing	
Capture/Elimination Competition Cooperation Movement Progression Selecting/collecting Simulate/Response Time Pressure	APPLYING	Action/Task Competition Cooperation Demonstration Imitation Simulation	
Appointment Cascading information Questions And Answers Role-Play Tutorial	UNDERSTANDING	Objectify Participation Questions And Answers Tutorials	
Cut scenes/Story Tokens Virality Behavioral Momentum Pavlovian Interaction Goods/information	RETENTION	Discover Explore Generalization Guidance Instruction repetition	

Table 9 - Mappings between learning and game mechanics with respect to the ordered thinking skills of Bloom

This concept is defined as: "*the design decision that concretely realizes the transition of a learning practice/goal into a mechanical element of game-play for the sole purpose of play and fun*" (Page 1) (Lim et al., 2015) For an example, with respect to the ordered thinking skills of Bloom, see Table 9. The proposed model can be used by designers and developers of learning games, as well as by those who are interested in studying the underlying mechanisms joining pedagogical and game features.

5.4 Methodology

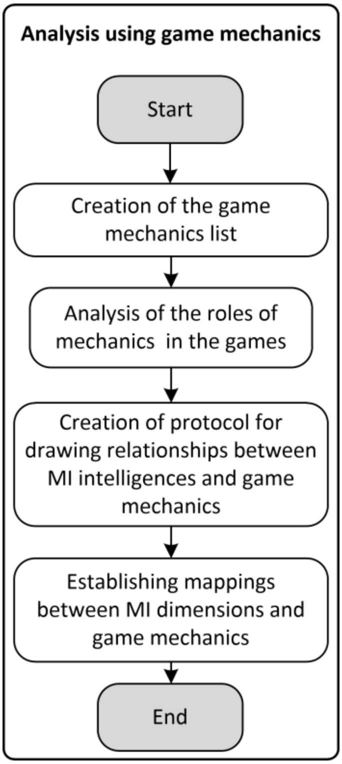

Figure 18 - Methodology for establishing mappings between MI dimensions and game mechanics represented as flow chart

This section explains the methodology used for establishing a mapping between the MI dimensions and game mechanics (see Figure 18 for an illustration). The purpose of this mapping is to indicate which game mechanics suits which MI intelligences. First, we created a comprehensive list of game mechanics that covers different aspects of games belonging to different types and genres. Sub-section 5.4.1 explains how this list was composed. Next, the games that showed to be correlated to MI intelligences (see chapter 4) were analyzed based on their game mechanics. Sub-section 5.4.2 discusses this analysis. Next, we established a protocol for drawing relationships between MI intelligences and game mechanics. Lastly, the protocol was used to establish a mapping between the different MI dimensions and game mechanics. These mapping are important, since the objective of this work is to be able to advise game designers on which game mechanics to use for certain MI dimensions, and which ones to avoid. Sub-section 5.4.3 explains the protocol and shows how this protocol was used to derive the final mappings.

5.4.1 Repository of Game Mechanics

Numerous repositories of game mechanics have been created in order to facilitate the design and development process of games (Arnab et al., 2014; "Game

Mechanic Mixer; Gamification Wiki; SCVNGR's Secret Game Mechanics Playdeck; Social game mechanics; Hamari & Järvinen, 2011; Järvinen, 2008; Lim et al., 2015; Louchart & Lim, 2011; Oberdörfer & Latoschik, 2013). Many of these repositories are quite elaborate and show significant overlaps. Despite the overlaps, the different repositories do show discrepancies in terms of the number of mechanics and their labels and definitions. Thus, for the purpose of this research, we have compiled a comprehensive list of game mechanics based on the existing repositories and complemented it with game mechanics that we have identified in the analysis of the games used in our study. This process led to the creation of a repository of 236 distinct game mechanics, which can be found online[15].

5.4.2 Analyzing Games Based on Mechanics

All 42 game titles that showed to be either negatively or positively correlated to one or more MI intelligences on different levels of significance were analyzed in detail to discover which game mechanics they were using.

It was also important to consider the role a game mechanic was playing in a game in terms of core or satellite mechanics. Core mechanics are used more frequently, and are often indispensable for successfully finishing the game, as opposed to the satellite mechanics. Therefore, the core mechanics is assigned a higher weight than the satellite ones in our protocol that determines whether a game mechanic is related to an MI intelligence. Furthermore, if such relation exists, the protocol considers the roles of the mechanics to decide about the nature of that relationship. We further explain this protocol in sub-section 5.4.3.

For each MI dimension, the games having a correlation with that intelligence were clustered into two groups. The *positive* group contains the games that have a positive correlation with the MI intelligence, and the *negative* group contains the games that have a negative correlation with that MI intelligence. Subsequently, the mechanics for all the games in both clusters were marked as either core (c) or satellite (s) depending on their role in that game. For example, the cells in Table 10 and Table 11 indicate whether the game mechanic is used in a game (column) as core mechanics (indicated by "c") or as a satellite mechanics (indicated by "s") or not used at all (no value). The games colored in green are in the positive group and the ones colored in red are in the negative group. The decision on the role of a game mechanic in a game was made based on our experience in playing the game,

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[15] Available at:
https://dl.dropboxusercontent.com/u/27597047/Complete%20list%20of%20game%20mechanics.xlsx

studying the design of the game based on the information available on the official website, forums and in some cases Wiki pages of the game, as well as by analyzing hours of gameplay videos. Table 10 shows results of the analysis for the logical-mathematical intelligence dimension, and Table 11 for the intrapersonal intelligence dimension. For example, for the logical-mathematical intelligence dimension the game “2048” is in the positive group, while the game “Heavy Rain” is in the negative group (Table 10). For the Intrapersonal intelligence dimension, these two games are respectively in the negative and positive groups (Table 11). Table 10 and Table 11 only provide a small subset of the complete analysis on all 42 games. Each game was analyzed with respect to the 243 collected game mechanics. This process resulted in 8 tables, i.e. one table per MI dimension.

Mechanics	*Portal*	*2048*	*Braid*	*Fable*	*Fallout*	*Xbox Fitness*	*Wordament*	*Heavy Rain*	*The Sims*	*World Of Warcraft*
Discovery	*c*		*s*	*c*	*c*			*c*		*c*
Epic meaning			*s*	*s*		*c*		*c*	*s*	
Infinite gameplay		*c*				*s*	*c*		*c*	*s*
Motion				*s*		*c*				

Table 10 - Example analysis of game mechanics for the Logical-mathematical intelligence dimension

Mechanics	*Heavy Rain*	*Mass Effect*	*Rockband*	*Spore*	*L.A Noir*	*Just Dance [series]*	*Wordament*	*2048*
Protégé effect			*c*	*c*	*c*	*s*	*c*	
Strategizing	*c*	*c*	*c*	*c*	*c*	*c*		*c*
Information overload	*c*				*c*			*c*

Table 11 - Example analysis of game mechanics for the Intrapersonal intelligence dimension

Our objective was to establish relationships between game mechanics and all MI dimensions. We would, for example, like to be able to state whether a game mechanic like “discovery” is preferred by and thus suitable for the logically-mathematically intelligent people or not. Arriving at such relationships requires complementing the analysis with a protocol that determines this relationship. This is explained in the next sub-section.

5.4.3 Mapping MI Dimensions to Game Mechanics

To analyze the relationship between specific MI dimensions and game mechanics, we used a protocol to determine if there is any relation at all and what the nature of that relation is.

We established the following rule to determine if a mechanic is related to an MI dimension: *the game mechanic should be utilized by at least half of the games correlated to that MI dimension in either the negative or the positive clusters.* This rule considers the fact that if more than half of the games correlated to a MI dimension in each cluster are not using a particular game mechanic, there is not sufficient evidence that this game mechanic plays an important role in the preference (or lack thereof) for these games. However, if the majority of the games in either of the clusters utilize the game mechanic, then it is reasonable to conclude that the game mechanic has an influence on the game preference (or lack thereof) of the players. For example, the results for the game mechanics from Table 10 can be seen in Table 12.

Mechanics	***Portal***	***2048***	***Braid***	***Fable***	***Fallout***	***Xbox Fitness***	***Total weight***	***Wordament***	***Heavy Rain***	***The Sims***	***World Of Warcraft***	***Total weight***
Discovery	***c*** (+2)		***s*** (+1)	***c*** (+2)	***c*** (+2)		*7*		***c*** (+2)		***c*** (+2)	*4*
Epic meaning			***s*** (+1)	***s*** (+1)		***c*** (+2)	*4*		***c*** (+2)	***s*** (+1)		*3*
Infinite gameplay		***c*** (+2)				***s*** (+1)	*3*	***c*** (+2)		***c*** (+2)	***s*** (+1)	*5*
Motion				***s*** (+1)		***c*** (+2)	*3*					*0*

Table 12 – Example of the decision protocol for a relationship between the "discovery" mechanic and the logical-mathematical dimension of MI

The "Discovery" game mechanic for the logical-mathematical MI dimension is used in 4 out of 6 games in the positive cluster, and in 2 out of 4 games in the negative cluster. This means that at least half of the games in each cluster have utilized the game mechanic "Discovery", and therefore the mechanic is related to the dimension. For example, the mechanic "Motion" (the players' bodily stances (postures, gestures, etc.) produce input to the game system or benefit in dealing with its challenges) turns out to be not related to the logical-mathematical dimension. Because, only two out of six game utilize this mechanic in the positive cluster, whereas no game utilizes this mechanic in the negative cluster.

The decision for the nature of a relationship, if there is one according to the previous rule, is based on the comparison of the weights of the game mechanic for the positive and for the negative cluster (see Table 12). The weight for a cluster is calculated as follows: each time the game mechanic is used as a core mechanic in the cluster, a weight of +2 is added and when it is used as a satellite mechanic a weight of +1 is added.

We established three types of possible relationships: "positive", "dubious" (uncertain), and "negative" (see Table 13). If the total weight in the positive cluster is larger than the one for the negative cluster by at least 2, that game mechanic is declared to have a "positive" relation with that dimension of MI. On the contrary, if the total weight for the negative cluster is larger than the one for the positive cluster by at least 2, the game mechanic is declared to have a "negative" relation with that dimension of MI. In the other case (i.e. the weights are equal or the difference between the weights is at most one) the relationship is "dubious".

Mechanics	***Decision***
Discovery	***Positive***
Epic meaning	***Dubious***
Infinite gameplay	***Negative***

Table 13 - Results of the decision from table 12

For example, we have seen that the "Discovery" game mechanic is related to the logical-mathematical MI dimension. This game mechanic plays three times the role of "core" and once the role of "satellite" in the positive cluster, giving it a total weight of 7 in this cluster, and two times the role of "core" in the negative cluster, giving it a total weight of 4 in this cluster. Therefore, this game mechanic is declared to have a positive relation with the logical-mathematical dimension of MI. The game mechanic "Infinite gameplay" is used in 2 out of 6 games in the positive cluster while playing once the role of core, and once satellite, giving it a weight of 3, and in 3 out of 4 games in the negative cluster while playing twice the role of core and once in the role of satellite, resulting in a weight of 5. Therefore this mechanic is declared to have a negative relation with this dimension of MI. Lastly, the game mechanic “Epic meaning” is used in 3 out of 6 games in the positive cluster, while playing twice the role of satellite and once the role of core, resulting in a total weight of 4. On the other hand, this mechanic is used by 2 out of 4 games in the negative cluster while playing once the role core and once the role satellite, giving a total weight of 3. In this case, we see that in both clusters at least half of the games have utilized this mechanic, and the different between the total weights is not greater than one. Therefore this mechanic is declared to have a dubious relation with this dimension of MI, meaning that it cannot be decided whether the relationship is positive or negative. The decisions for the mechanics given in Table 12 are given in Table 13.

Following this procedure, we arrived for each MI dimension at a list of relationships with game mechanics including their type (positive, negative or dubious). These relationships are visualized and made available through a tool explained in chapter 8.

5.5 Results & Discussion

Our analysis showed that within our sample, the 8 different MI dimensions have relationships with 116 different game mechanics.

These relationships can be used to help game designers in creating games for a specific audience (i.e. player-centered game design) by providing a tailored gameplay experience that enhances the players’ overall game experience. Positive relationships indicate that players with a particular MI intelligence will generally respond positively to the game mechanic. As a consequence, we *recommend* the use of this game mechanic if designers aim to enhance the game experience of players with this particular MI intelligence. Game mechanics with a negative relationship to a particular MI dimension evoke mostly negative responses and therefore it is *recommended not to use them* if designers aim to enhance the game experience of players with this particular MI intelligence. Dubious relationships point towards a fairly equal mix of positive and negative responses. In our opinion, game mechanics with a dubious relationship can be used but require extra caution as they might results in both positive and negative responses among people within the targeted MI dimension.

As an example the “quick feedback” mechanic has a positive relationship with most of the MI dimensions, indicating that it can be recommended for most MI dimensions. On the other hand, the “infinite gameplay” mechanic has a negative relationship with logical-mathematical, linguistics and intrapersonal intelligence dimensions, indicating that it is recommended not to incorporate this mechanic in games designed for players with those intelligences. The “helping” mechanic has a dubious relationship with two MI dimensions. This means that its incorporation in games designed for those dimensions is neither encouraged nor discouraged. If more than one MI dimension is targeted, the choice for using a dubious mechanic can be based on the type of relationship that this mechanic has with the other MI dimension(s). If there is a positive relationship for those dimensions it will be safer to use it than when there are negative relationship. For example, the game mechanic “reaction time” has a positive relationship with the logical-mathematical, and a dubious relationship with the bodily-kinesthetic intelligence dimensions. If a game is to be designed targeting both these dimensions, this mechanic could be used.

Furthermore, there are game mechanics that have a positive relationship with almost all MI dimensions, such as “quick feedback”. These particular mechanics represent constructs that seem to be appealing to almost all gamers, regardless of the different MI intelligences they exhibit. Thus, they can be assumed to provide a good game experience for all players.

So far, we obtained 8 large tables (on average 58 rows for each), each dedicated to a dimension of MI and containing a list of mechanics and their type of relationship to that MI dimension. A snapshot of one of these tables can be seen in Table 14. Such tables are large and cumbersome to use. Therefore, a tool is developed to visualize the relationships and allow for easy filtering of the information. This tool is described in chapter 8.

Logical-mathematical dimension	
Achievements	Dubious
Bonuses	Positive
Discovery	Positive
Infinite Gameplay	Negative

Epic Meaning	Dubious
Levels	Positive
Loss aversion	Positive
Points	Dubious
Reward Schedules	Positive

Table 14 - Snapshot of the relationships between some of the mechanics and the logical-mathematical intelligence dimension

To ease the process of locating a mechanic, as well as to give more structure to our results, we have introduced classes of mechanics. These classes refer to groups of mechanics that could be placed under the same umbrella. We have grouped our game mechanics into 10 classes: "Involvement", "Challenge", "Motivation", "Competition", "Assistance", "Player movements", "Object manipulation", "Dialogue", "Game environment", and "Relatedness". The names of those 10 classes represent important aspects of a game. A game mechanic belongs to a class when it can be used to realize that aspect of the game. For example, the game mechanic "reaction time" can be used to challenge the player.

The introduction of these classes should ease the use of our MI tables in the design process of games. As an example, if a game designer is interested in designing a learning game targeting the logically-mathematically intelligent players, and wants to include a mechanic related to motivation, he can simply refer to that section of the table for the logical-mathematical intelligence. An example can be seen in Table 15.

Logical-mathematical dimension	
Involvement category	
Achievements	Dubious
Discovery	Positive
Motivation category	
Bonuses	Positive
Infinite Gameplay	Negative
Epic Meaning	Dubious

Levels	Positive
Loss aversion	Positive
Points	Dubious
Reward Schedules	Positive

Table 15 – Logical-mathematical dimension table with game mechanics grouped into the classes

Considering the original endeavor of this dissertation, the pertinent question at this stage is: *Will these mappings work in practice?* In other words, *can they be used in player-centered design to come up with games that positively affect the game experience for their intended audience and/or improve their learning outcome?* (Reformulated as research questions RQ3 and RQ4). The only possible way to objectively answer this question is tying them out. This means using these mappings in practice to design games targeting players with certain dominant MI intelligences, and then evaluate those games on game experience and/or learning outcome. This will be investigated in chapter 6 and chapter 7, by evaluating two games that are designed specifically for people who exhibit dominance for certain MI intelligences, and are based on our proposed mappings.

5.6 Limitations & Conclusions

In this chapter, we have provided an answer to the second research question ***RQ2:*** *If there are correlations between players' MI intelligences and their preferences for specific games, can they be attributed to the game mechanics and if so how?* We found that we indeed can attribute the correlations between players' MI intelligences and their preferences for specific games to the game mechanics. In addition, we have established a comprehensive mapping between game mechanics and the MI dimensions to support our answer. For each MI dimension we have obtained a list of game mechanics that are positively, negatively or dubiously related to that dimension. These findings will help game designers to create games that are better tailored to particular MI intelligences, potentially resulting in better game experience, and possibly better learning outcome. Our results could also enable designers to take advantage of games' inherent opportunities for stealth assessment of the player's MI intelligences and for implicit player profiling. This means that the preference of a player towards the game mechanics used in a game could be measured implicitly (e.g. based on the frequency of use or explicit choice by the players), and their MI intelligences would be inferred from this information.

It should be note that the “preferences” of the players for the game mechanics of the games considered in the survey were derived indirectly and were not explicitly verified with the participants. Moreover, the decisions made throughout the process of establishing the mappings, both in terms of the role a game mechanic plays in a game, as well as the choice for the protocol used for determining the nature of the relationships, were subjective and should thus be considered as suggestions and not as hard and general rules. An approach to make these mappings more objective would be to ask a large group of game-experts to perform step 2, i.e. the analysis of the roles of the game mechanics in the games. However, such an approach would be very impractical. It would require a lot of time and great effort on the part of the experts, which may result in very few completed participations. Limiting the rating of the game mechanics as core or satellite outside the context of a game is also not possible because the role of a game mechanic is dependent on the context (game) in which it is used. In addition, the same game mechanic can be implemented differently in various contexts. For example, a game mechanic such as “Discovery’ might be slightly different in a game like “Portal” where the player needs to discover the correct strategy for overcoming the individual obstacles, compared to a game like “Heavy Rain” where discovery is more related to completing the overall story of the game. Also other protocols could be designed to establish the nature of the relationships. To see the influence of the used protocol, mappings resulting from different protocols could be compared. Although complete objectivity is not possible, it would be good if other researchers could perform similar analyses over our data in order to converge to a single result. Such collective subjectivism would strengthen the value of the proposed mappings, however this is a rather long-time endeavor and could be part of future work.

Chapter Six:
Validation: The LeapBalancer Case Study

"You can discover more about a person in an hour of play than in a year of conversation."

Plato

6.1 Introduction

This chapter focuses on a first application of our mappings for improving game experience and performance of players. In particular, we concentrate on the case of players who exhibit a high bodily-kinesthetic intelligence. We designed and developed a game, called LeapBalancer, in which the game mechanics are highly kinesthetic oriented and selected from the game mechanics recommended by our mapping for the body-kinesthetic dimension. Next, we evaluated the game to investigate whether people exhibiting a high level for the bodily-kinesthetic intelligence have a better game experience than people not having a high bodily-kinesthetic intelligence. As such, this chapter provides a first answer to the third research ***RQ3:*** *Can player-centered game design based on the findings of RQ2 contribute to better game experience?*

We decided to develop a new game rather than using an already existing one, as we wanted to be in full control on what game mechanics should be included in the game to be sure that they were in accordance with our mapping for the bodily-kinesthetic dimension. Furthermore, we chose to design and implement a simple game to minimize the effects that the learning content or complicated stories, challenges and other aspects could impose on our objective. Although LeapBalancer is not a learning game itself, the findings are important for learning games because research has shown that a good game experience is positively correlated with higher learning.

In section 6.2, we offer a detailed description of the design of LeapBalancer. In section 6.3, we discuss the evaluation of LeapBalancer with respect to game experience and performance of the players. In section 6.4, we address our findings, as well as the limitations and opportunities for improvements.

6.2 LeapBalancer

Based on our proposed mappings, we designed a game, called LeapBalancer, specifically for players with a high level of bodily-kinesthetic intelligence. In other words, we have mainly selected game mechanics that were marked as appropriate (i.e. positive relation) for the bodily-kinesthetic dimension, but also some game mechanics marked as uncertain (i.e. dubious) or with no relation. The game mechanics used in LeapBalancer are listed in Table 16 together with the category that indicates the objective the mechanic fulfills in the game. For instance, we selected the mechanics "Motion" and "Timing" to create challenge.

Category	***Game mechanic***
Challenge	Motion (positive)
	Timing (positive)
Motivation	Pavlovian interaction (positive)
Assistance	Tutorial / first run scenarios (dubious)
Game environment	Gravity (dubious)
Movement action	Directed exploration (no relation)
Object manipulation	Controlling (no relation)

Table 16 - Employed game mechanics in LeapBalancer

The definitions of the mechanics employed in LeapBalancer are as follows:

- **Motion**: The players' bodily stances (postures, gestures, etc.) produce input to the game system or benefit in dealing with its challenges.
- **Timing**: The player has to observe, analyze and wait for the right moment to do something.

- **Pavlovian interaction**: this game mechanics follows the principle: “Easy to learn, hard to master”. This means the game is simple to pick up and play, however it increases in difficulty as the user advances through the game.
- **Tutorial / first run scenarios**: Guided sequence of steps in the beginning for new users.
- **Gravity**: Objects are pulled either in a certain direction or are pulled towards certain objects.
- **Directed exploration**: The player has the capability to explore the environment (browse the area, try different paths and etc.), however, this exploration is constrained by the game and the player is directed by the game through the path in which the exploration can take place.
- **Controlling**: Keeping possession of a component and/or handling/controlling it.

The goal of LeapBalancer is to navigate a (blue) ball through a maze towards a (green) target by tilting the maze (see Figure 19). To support the *motion* mechanic, we chose the Leap Motion[16] for the interaction. Tilting the maze is done by moving both hands. The Leap Motion detects the hand movements and transforms them into a movement of the maze which makes the ball roll. In this way, the player moves the ball towards the target. The player can observe the movement of his/her hands in real-time on the screen (see Figure 19). If one or both hands leave the detection zone of the Leap Motion, the game will pause and will notify the player of the problem (see e.g. top left corner in Figure 20).

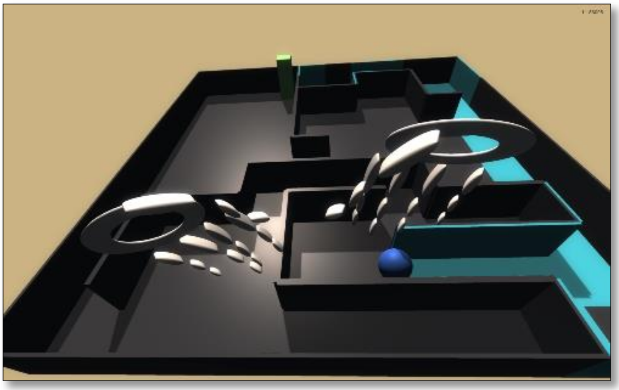

Figure 19 - LeapBalancer - medium difficulty level

[16] https://www.leapmotion.com/

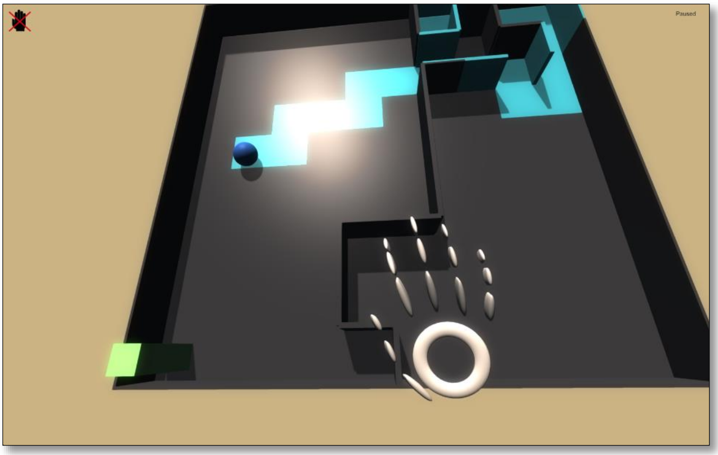

Figure 20 - Absence of one hand is noticed by the game

The surface of the maze is composed of tiles. As the player traverses the maze (i.e. rolls the ball over the tiles), the visited tiles are highlighted to form a colored path that shows how the ball traveled the maze (see e.g. Figure 19 and Figure 20). This helps the players to observe and remember her/his exploratory steps, as well as how they are controlling the ball. This functionality is partially related to the *directed exploration* mechanic, as the players can observed the path they have already explored, and *controlling* mechanics as it enables them to observe how they are handling the objects.

The game is composed of nine levels with increasing difficulty. The first three levels are training levels. The next three levels have a medium difficulty. And the final three levels have a high difficulty. The difficulty is increased by making the mazes bigger and more complex, and by including obstacles in the form of red balls (see Figure 19, Figure 20 and Figure 21). The obstacles move in a fashion similar to the main ball and can block the paths inside the maze. This functionality is directly related to the *pavlovian interaction* game mechanic.

By having 9 levels we assured that the playtime would be at least 15 minutes. This was necessary for properly measuring the game experience afterwards. Note that we did not incorporate any losing condition or time constraint because our goal was to create an experimental environment rather than a full-fledged game. Of course, the game does inherently impose a certain level of challenge (see challenge mechanics in Table 16).

Figure 21 - LeapBalancer - high difficulty level (with obstacles)

It is important to note that in LeapBalancer, the *motion* and *controlling* mechanics are the core mechanics and the rest of the utilized mechanics satellite. Without the use of these mechanics the game is essentially not playable.

Although, LeapBalancer was created specifically for players with a high level of bodily-kinesthetic intelligence, we also investigated how well the game would be suited, based on our mappings, to other dimensions of MI. If the game would also fit well to some of the other MI dimensions, it could also be interesting to look to the game experience of those players. Therefore, Table 17 shows the relationship between the mechanics utilized by LeapBalance and all the dimensions of MI. These relationships indicate that with respect to the core mechanics of LeapBalance, the targeted MI dimension of this game (i.e. bodily-kinesthetic) has one positive relation (for Motion), and the linguistics and intrapersonal dimensions each also have one positive relation (for Controlling). The visual-spatial dimension has one positive and one negative relation, and the naturalistic dimension has one negative relation. So, the bodily-kinesthetic, linguistics and intrapersonal dimensions are similar in the number of positive relations to the core mechanics of this game. Given that linguistics and intrapersonal dimensions also show positive relation with a core mechanic of LeapBalancer, we might expect that this game would also suit these dimensions apart from its intended audience. This is investigated in sub-section 6.3.3.1.

Game mechanics	*Bodily-Kinesthetic*	*Visual-Spatial*	*Logical-Mathematical*	*Musical*	*Linguistics*	*Interpersonal*	*Intrapersonal*	*Naturalistic*
Motion	Positive	Negative	-	-	-	-	-	-
Timing	Positive	Positive	Positive	Positive	-	-	-	Positive
Pavlovian interaction	Positive	Negative	-	Positive	Positive	Positive	-	Positive
Tutorial / first run scenarios	Dubious	Positive	Positive	Positive	Positive	Positive	Positive	Positive
Gravity	Dubious	Positive	Dubious	Positive	Positive	Positive	Positive	-
Directed exploration	-	-	-	-	-	-	-	Negative
Controlling	-	Positive	-	-	Positive	-	Positive	Negative
Summary	3 Positive 2 Dubious	4 Positive 2 Negative	2 Positive 1 Dubious	4 Positive	4 Positive	3 Positive	3 Positive	3 Positive 2 Negative
Core mechanic	1 Positive	1 Negative 1 Positive	-	-	1 Positive	-	1 Positive	1 Negative

Table 17 - Relationships between the game mechanics of LeapBalance and all the dimensions of MI

6.3 Evaluation

The evaluation of LeapBalancer aimed at investigating the question: "*Will people with a high bodily-kinesthetic intelligence have a better game experience compared to non-bodily-kinesthetic players?*".

6.3.1 Methodology

Two groups of players, one group with people who exhibited a high bodily-kinesthetic intelligence score, and another group that did not show high scores for the bodily-kinesthetic dimension, played all 9 levels of the game. They were informed that the first 3 levels were for training.

6.3.1.1 Data Collection

Two instruments were used to obtain the necessary data. First, to measure the MI intelligences of the players we used the Multiple Intelligence Profiling Questionnaire (MIPQ) (Tirri & Nokelainen, 2011). This is the same instrument as used in the survey study presented in chapter 4. Secondly, to measure the game experience of the players we used the Game Experience Questionnaire (GEQ) developed by IJsselsteijn and colleagues (IJsselsteijn et al., 2008; IJsselsteijn, De Kort, Poels, Jurgelionis, & Bellotti, 2007). GEQ has four modules: core, in-game, social presence, and post-game (see Appendix E). Each module is designed to measure the game experience either at a specific moment of gameplay (in-game and post-game) or focused on certain aspects (core and social presence). We used the core module that contains 33 statements, the in-game module that contains 14 statements, and the post-game module that contains 17 statements). All statements are rated on a scale from 0 to 4. The social presence module was not applicable to this experiment, since its purpose is to investigate the psychological and behavioral involvement of the player with other social entities such as in-game characters and other players, which are not present in LeapBalancer.

The core and the in-game modules both measure the game experience based on the following metrics: competence, immersion, flow, tension/annoyance, challenge, negative affect and positive affect. Competence includes, among others, skillfulness and successfulness. Flow is about how much the player forgot the world around him/her and was focused on the game, where immersion includes for example how imaginative, impressed and interested a user felt and how rich his/her experience with the game was. Tension is partly constructed by the degree of annoyance, irritation and frustration. Challenge is about the level of effort, difficulty and pleasure. Negative affect is partially measured by how much a player thought about other things, felt tired and bored. Positive affect is measured by the degree of fun, happiness and enjoyment. The post-game uses the metrics: positive experience, negative experience, tiredness and returning to reality. Positive experience is determined, among other factors, by how revived, victorious, and satisfied the player felt. Negative experience by how bad, regretful, and a feeling of wasting time a player experienced. Tiredness is partially measured by the feeling of exhaustion. Disorientation and a sense of returning from a journey contributed to the return to reality metric.

Although the performance of the player is not directly related to the hypothesis, it was measured using logs of participants' gameplay behavior. From this logs, two measures were derived, i.e. the *percentage of extra movement made by a player*, and the *average time spent on a tile*. For a player, on each level, the *percentage of extra movements* was calculated using formula (1) where the *number of tiles visited* represents the number of tiles in the maze touched by the main ball, and *distance to target* represents the minimum number of tiles required to reach the target. The *average time spent on a tile* for each player on each level is calculated using formula (2) where the *level time* represents the total time it took the player to finish the level. We calculated the two measures for every player over all 9 levels. Then we calculated two averages: one using all 9 levels, and one excluding the training levels.

$$\%\ of\ extra\ movement = \frac{Number\ of\ tiles\ visited - Distance\ to\ target}{Distance\ to\ target} \times 100 \quad \textbf{(1)}$$

$$Average\ time\ on\ a\ tile = \frac{Level\ time}{Number\ of\ tiles\ visited} \quad \textbf{(2)}$$

6.3.1.2 Participants

To select participants with appropriated intelligence profiles, we offered the MIPQ to 200 students of whom 110 responded. Based on the received results, we invited two groups of people: one group with people who exhibited a high bodily-kinesthetic intelligence score, and another group that did not show high scores for the bodily-kinesthetic dimension. An MI dimension score was considered high if its value was above 15 out of 20[17]. The score for a particular MI dimension was calculated by adding up the scores of all the individual questions relating to that dimension.

Despite having a high number of responses from the MIPQ, we only managed to find 11 participants with high bodily-kinesthetic intelligence who were prepared to participate in the experiment. In order to have a balanced design, we opted for 11 non-bodily-kinesthetic players in the other group. From the 11 players in the bodily-kinesthetic group, 3 were female and 8 were male. From the 11 players in the non-bodily-kinesthetic group 2 were female and 9 were male.

6.3.2 Analysis

We compared the results in terms of game experience from the bodily-kinesthetic players and non-bodily-kinesthetic players using a two-tailed T-test. We performed

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[17] Or 12 out of 15 in the case of naturalistic intelligence.

this test between the metrics of game experience (from the GEQ modules) of the two groups in order to identify statistically significant ones. Furthermore, to investigate the relation between game experience and performance of the players, for each group we performed a series of two-tailed bivariate correlation analyses using the Pearson method between the gameplay behavior measures (excluding the training levels) and the game experience modules. These analyses were performed using IBM **SPSS** Statistics 22.

6.3.3 Results & Discussion

6.3.3.1 Game Experience

The differences between the game experience of the kinesthetic and non-kinesthetic players with respect to the different metrics of the GEQ for the core, in-game and post modules are depicted in Figure 22, Figure 23 and Figure 24. The results are given in Table 18, Table 19 and Table 20; the significant differences are highlighted in grey ($P < 0.05$).

The results of the game experience analysis indicates that the bodily-kinesthetically intelligent players are experiencing significantly more competent, and significantly less negative affect compared to the non-bodily-kinesthetically intelligent players with respect to the core module of GEQ. Furthermore, we can see that the bodily-kinesthetically intelligent players are significantly more immersed, and are feeling significantly less tension compared to the non-bodily-kinesthetically intelligent players with respect to the in-game module of GEQ. For a possible explanation of the results, we first investigated the performance.

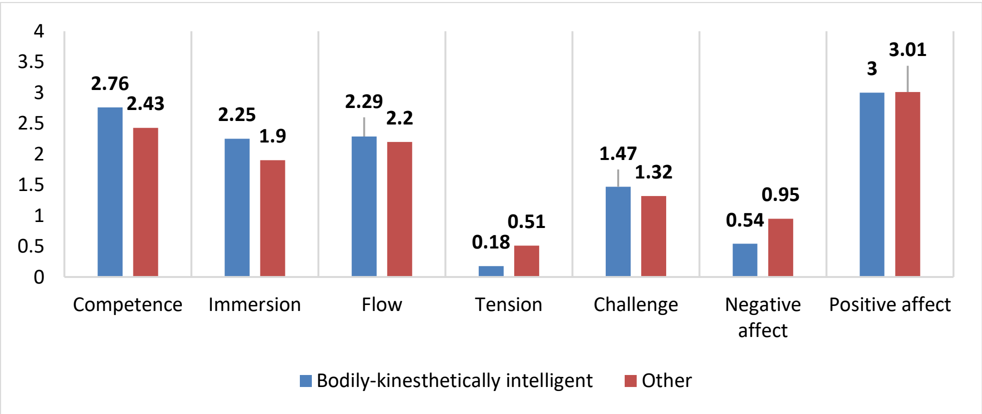


Figure 22 - Difference in game experience (core module)

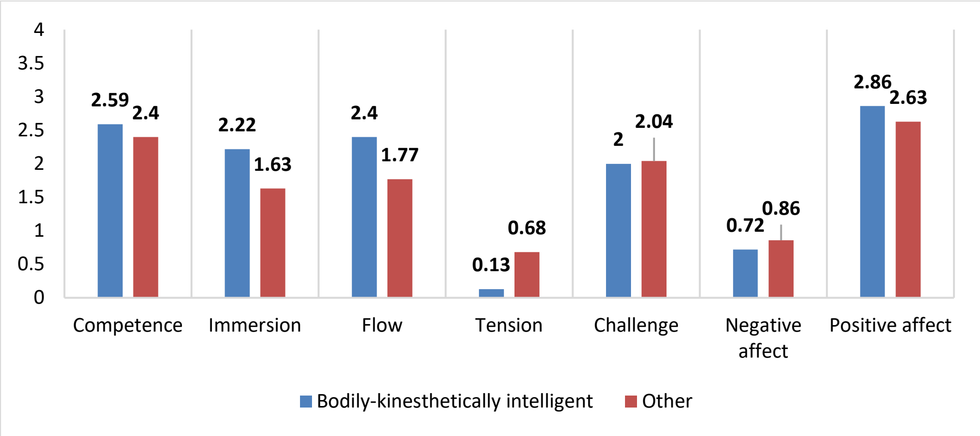


Figure 23 - Difference in game experience (in-game module)

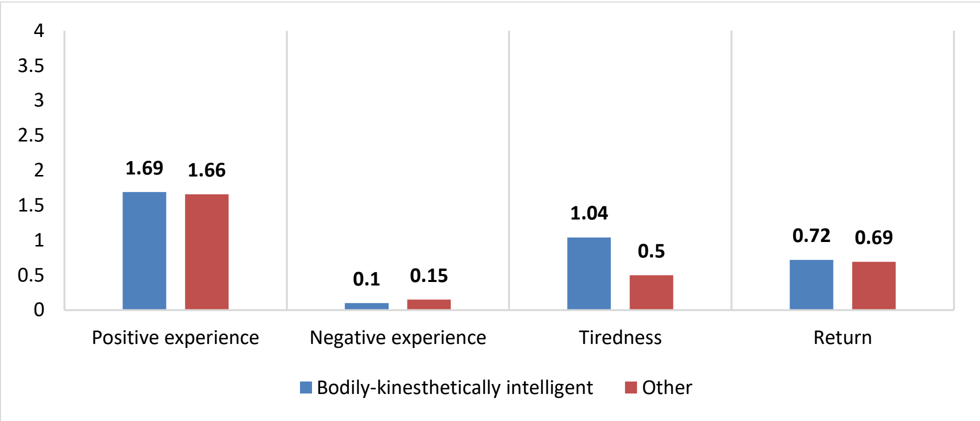


Figure 24 - Difference in game experience (post-game module)

	Bodily-kinesthetically intelligent		**Other**		**T-test**
	Mean	*Standard Deviation*	*Mean*	*Standard Deviation*	*Sig. 2-tailed*
Competence	2.76	0.25	2.43	0.35	**0.021**
Immersion	2.25	0.95	1.9	0.86	0.38
Flow	2.29	0.81	2.2	0.7	0.78
Tension	0.18	0.27	0.51	0.63	0.12
Challenge	1.47	0.84	1.32	0.42	0.61
Negative affect	0.54	0.4	0.95	0.33	**0.017**
Positive affect	3	0.54	3.01	0.54	0.93

Table 18 - Significant difference between the two groups with respect to the core module

	Bodily-kinesthetically intelligent		Other		T-test
	Mean	*Standard Deviation*	*Mean*	*Standard Deviation*	*Sig. 2-tailed*
Competence	2.59	0.43	2.4	0.43	0.34
Immersion	2.22	0.71	1.63	0.59	**0.049**
Flow	2.4	1.26	1.77	0.75	0.16
Tension	0.13	0.23	0.68	0.56	**0.01**
Challenge	2	0.92	2.04	0.52	0.88
Negative affect	0.72	0.81	0.86	0.74	0.68
Positive affect	2.86	0.71	2.63	0.32	0.34

Table 19 - Significant difference between the two groups with respect to the in-game module

	Bodily-kinesthetically intelligent		Other		T-test
	Mean	*Standard Deviation*	*Mean*	*Standard Deviation*	*Sig. 2-tailed*
Positive experience	1.69	0.86	1.66	0.45	0.92
Negative experience	0.1	0.25	0.15	0.13	0.6
Tiredness	1.04	1.25	0.5	0.83	0.24
Return	0.72	0.97	0.69	0.64	0.93

Table 20 - Significant difference between the two groups with respect to the post-game module

Since the analysis of relationships between the mechanics of LeapBalancer and all the dimensions of MI (section 6.2) has revealed that this game might be also a good fit for linguistically or intrapersonally intelligence players, the game experience of those players was also compared with the rest of our population.

The results of a T-test comparing the game experience of linguistically intelligent (11 players) and the rest of our population (11 players) has shown that the difference between the two groups was significant with respect to the immersion metric of the core module of GEQ (P = 0.02, Mean for linguistic group: 2.63, and SD: 0.60 - Mean for the rest of the population: 1.53, and SD: 0.84).

The comparison between intrapersonally intelligent (10 players) and the rest of our population (12 players) however, failed to show any significant differences.

These results show that the bodily-kinesthetically intelligent group are having the highest number of significant differences (with respect to the different metrics of GEQ) compared to the rest of our population. Therefore, we can conclude that LeapBalancer creates the best game experience for its intended target audience: bodily-kinesthetically intelligent players.

6.3.3.2 Performance

On average all bodily-kinesthetically intelligent players made 42.9% extra movements across all 9 levels, whereas the non-bodily-kinesthetically intelligent players made 35.6% extra movements on average. However, if we exclude the training levels, the difference is smaller and reversed: on average, the bodily-kinesthetically intelligent players made 32.4% extra movements, while the non-bodily-kinesthetically intelligent players made 33.2% extra movements (see Table 21). We see two possible explanations for this. One explanation would be that bodily-kinesthetically intelligent players required more practice to get acquainted to the motion modality, but showed more skill once they were sufficiently familiar with the modality. Another explanation could be that the bodily-kinesthetically intelligent players had the tendency to explore the different possibilities of the Leap Motion and the different movements they could make to roll the ball during the training. Once they fulfilled this desire and started the other six levels, they focused more on their performance and made less extra movements compared to the non-bodily-kinesthetically intelligent players. These two explanations are not mutually exclusive, but rather complementary.

With regards to the average time spend per tile, all bodily-kinesthetically intelligent players spent *0.7* seconds on average on a tile across all 9 levels, whereas the non-bodily-kinesthetically intelligent players spent *0.66* seconds. If we exclude the training levels, we see that the bodily-kinesthetically intelligent players spent *0.77* seconds on average on a tile, and the non-bodily-kinesthetically intelligent players *0.73* seconds (see Table 21).

By drawing a connection between game-experience and performance, we might be able explain this result. The bodily-kinesthetically intelligent players were experiencing more challenge, and were feeling more competent during their gameplay compared to the non-bodily-kinesthetically intelligent players, and therefore (and because there was no time limit) were not in a rush to finish the game. The higher in-game flow and immersion experienced by the bodily-kinesthetically intelligent players could be testament to this. On the other hand, we see that the non-bodily-kinesthetically intelligent players are experiencing more tension and more negative affect. Clearly these players are not having a game experience as good as the bodily-kinesthetically intelligent players, and may therefore be in a rush to finish the game. Their low scores for in-game flow and immersion could be a testament to this.

The bivariate correlation-analysis helps us uncover and interpret patterns between gameplay behavior and game experience. This is particularly interesting, given that the gameplay behavior measures seem to differ only slightly between the two groups. The correlation test indicates that when the percentage of extra movements increases, bodily-kinesthetically intelligent players experience more challenge and more tension while having a higher positive experience. They also report feeling more tired. The latter could be explained by the fact that these players might invest more effort in properly performing the movements needed to finish the levels. In comparison, non-bodily-kinesthetically intelligent players have a higher negative experience as the percentage of extra movements increase. In addition, the more time non-bodily-kinesthetically intelligent players spend on a tile, the more tension, and the less challenge and positive affect they experience. These might be signs of unwanted frustration.

	Bodily-kinesthetically intelligent players		**Non-bodily-kinesthetically intelligent players**	
% of extra movement	32.4%	.786** challenge (core) .672* tension (in-game) .603* challenge (in-game) .741** positive experience (post-game) .654* tiredness (post-game)	33.2%	.661* negative experience (post-game)
Average time on a tile	0.77s	-	0.73s	.904** tension (core) -.630* positive affect (core) -.658* challenge (in-game)

*Table 21 - Correlations between game behaviour measures and game experience modules. P < 0.01 ** and P < 0.05 **

6.4 Conclusions

We can see that the LeapBalancer game that targets bodily-kinesthetically intelligent players has a positive effect on the target audience's feeling of challenge and competence. Thus having a good balance between challenge and competence as recommended in (Csikszentmihalyi & Csikszentmihalyi, 1992) for inducing the flow state. At the same time, the game does not provide a good balance between competence and challenge for the non-bodily-kinesthetically intelligent players. The correlations between their gameplay behavior and GEQ indicate that the more time they spend on a tile the less challenged they feel. Therefore, we can conclude that this highly bodily-kinesthetically oriented game provides a better medium for bodily-kinesthetically intelligent players in terms of game experience.

The research presented in this chapter has demonstrated the advantage of considering the MI intelligences of the players during game design. For this particular case study, we can state that using our mappings between MI dimensions and game mechanics led to a game design that contributes to a better game experience for players who exhibit the targeted MI intelligence. This is of course just a partial validation of the proposed mappings. Our results are evidently limited to the MI dimension under study, the used game (LeapBalancer) and the population used. Interesting to note is that our results also show that not all game mechanics and interaction modalities, as novel as they may be, would cause a good game experience for everyone.

The findings of the research presented in this chapter are a first answer to the third research question of this dissertation: ***RQ3:*** *Can player-centered game design based on the findings of RQ2 contribute to better game experience?*

Our results are also important for learning games, since research has shown that good game experience can be positively correlated with improvements in learning. However, in order to generalize our findings, experiments on a larger scale are needed. Moreover, these studies should also further explore and evaluate the relationship between good game experiences and the effectiveness of learning. In chapter 7, we present such a study. This study investigates whether a learning game adapted to the MI intelligence of the players will also result in a better learning outcome.

Chapter Seven:
Validation: The TrueBiters Case Study

"For the things we have to learn before we can do them, we learn by doing them."

Aristotle

7.1 Introduction

In the previous chapter, we have demonstrated that player-centered design based on the mappings between MI dimensions and game mechanics can contribute to a better game experience for players. An important question that is yet to be investigated is whether the use of our mappings can also positively affect the learning outcome of players. This is directly related to the fourth research question of this dissertation: ***RQ4:*** *Can player-centered game design based on the findings of RQ2 contribute to higher learning outcome?* In order to provide a first answer to this question, we present the case of TrueBiters.

TrueBiters is a two-player learning game inspired by a card game called "b00le0[18]". We created this learning game in the context of the logic course in the 1st year Bachelor of Computer Science at our university, the Vrije Universiteit Brussel. This course has been a stumbling stone for the students since years. On average less than 30% succeed in the exam on the first try. Dealing with the formal and abstract language of logic is hard for most students. They easily lose interest and exhibit procrastination, and after a while they are completely lost. The teachers of the course tried to remedy this behavior in different ways but didn't succeed.

[18] https://boardgamegeek.com/boardgame/40943/booleo

Therefore, we decided to try out a learning game using our player-centered design approach. The focus of the game is on practicing of truth tables of proposition logic. This goal was selected because a good knowledge of the truth tables is essential for understanding the rest of the course.

We decided to focus on logically-mathematically intelligent people, as this is the main target audience for the Bachelor of Computer Science. Therefore, TrueBiters utilizes game mechanics that mostly suit logically-mathematically intelligence (according to our mappings), but we also included game mechanics for bodily-kinesthetically intelligent players. The focus on the latter MI dimension resulted from an observation of the teachers of the course. They mentioned that many students in this program seem to have problems sitting still, which could be an indication of bodily-kinesthetically intelligence.

The experiment with TrueBiters allows us to explore the differences emerging among students with different dominant MI intelligences in terms of learning outcome and game experience. Due to practical constraints, related to the schedule of the course in the academic year, the experiment must be regarded as a pilot study. This also means that the number of participants in this pilot study is rather small, thereby limiting our abilities to draw definitive conclusions that can be safely generalized to a broader population. Nonetheless, we will show that the results provide strong indications that the dominant types of MI intelligence affect the effectiveness of a learning game.

The chapter is organized as follows. In section 7.2, we describe the board game b00le0 that partially inspire the design of TrueBiters. In section 7.3, we provide a description of TrueBiters itself. In section 7.4, we discuss the experiment performed. In section 7.5, we present our conclusions.

7.2 b00le0

b00le0 is a card-based strategy game that employs the principles of Boolean Logic. The description of the game is as follows.

The game of b00le0 is a two-player competitive game, and the goal of each player is to reduce a list of bits by building a pyramid using the logical gates of Boolean Logic. Once the game commences, six initial binary cards are placed in a row between the players (see Figure 25). Each initial binary card has a 0 on one side and a 1 on the other. In this way, each player has a row of six bits. To win the game, the players need to complete the pyramid with a card that has a value equal to the right-most bit of his or her initial bit cards. The players each have 4 logic gate cards in their hands, which they can use to reduce two bits into to one. Of course, they should only use the correct logic gates to do so. As soon as they have used a card, they can take another card the card stack. The stack of logical gates is faced down, so the players do not know what card they pick. The reduction process continues until one player finishes the pyramid correctly (see Figure 26). An example gameplay session of this game is depicted in Figure 25 and Figure 26.

Figure 25 - b00le0[19]

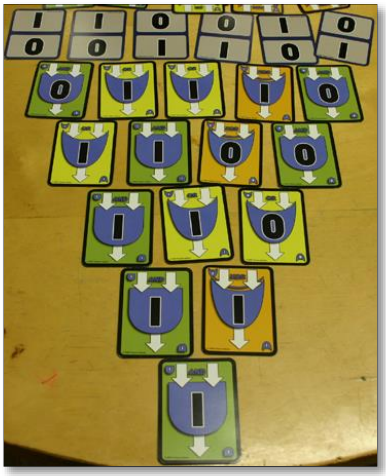


Figure 26 - b00le0

An analysis of the game based on our mappings shows that b00le0 incorporates mechanics that are mostly appropriate for the logical-mathematical dimension of MI. This, in combination with the concept of the game, a game to practice the truth tables, made it a suitable game to be used as basis for our learning game. We digitalized the game to make it easily available and to ensure that the truth tables are used correctly during the game. The analysis of this game with respect to its mechanics can be found in the next section.

7.3 TrueBiters

We applied the principles of the card game b00le0 to create TrueBiters, a digital two-player game for practicing the basic logical operators of propositional logic. It is played over two smartphones and a tablet that are all connected and synched using Bluetooth technology. The tablet is the master and the two smartphones are

[19] https://goo.gl/0w89S1

the slaves. The game has a common area composed of tiles (i.e. the board – see Figure 27), which is rendered on the tablet. Furthermore, every player operates a smart phone that contains a stack of cards representing the logical operators that can be used to perform an action on the common area. As in b00le0, a list of bits needs to be reduced to its rightmost bit, but in our case the different propositional operators should be used to do the reduction.

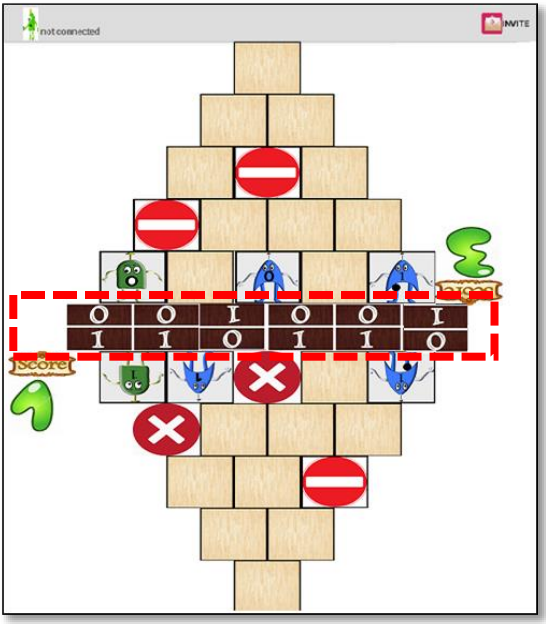


Figure 27 – TrueBiter's board (tablet)

The game is using five logical operators (i.e. conjunction ("AND"), disjunction ("OR"), implication ("IMPLY"), equivalence (EQUIVALENT"), and negation "NOT")) represented by symbols that look like fictive animals that can eat bits (Table 22). As is common in logic, the bit 1 represents TRUE and the bit 0 represents FALSE. Each binary operator (AND, OR, IMPLY, and EQUIVALENT) comes in two versions: one that results in a 1-bit and one that results in a 0-bit. For instance, the OR operator takes two bits as input and can either result in 0 or in 1 (depending on the input values). Next to these symbols, there are two error symbols, the invalid-symbol to indicate that an action cannot be applied to a tile because one or both inputs are not yet defined, and the wrong-symbol to indicate an incorrect action, e.g. the 1-version of the AND operator used on two 0-bits (which is incorrect according to the truth table of the AND operator).

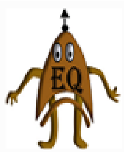
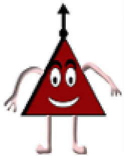
Logical Operators		
 OR	 AND	 IMPLY
 EQUIVALENT	 NOT	
Error Symbols		
 Wrong	 Invalid	

Table 22 – TrueBiter's symbols

Once the game commences each player receives a list of six bits. This list of six bits is generated randomly. One player receives this list and the other player receives the inverted version of the list (Figure 27). Each player has to reduce his list of bits to a single bit, equal to the right most bit of his list. The first player that achieves this is the winner. To do so, the player should use the correct logical operator cards that he has available on his mobile phone. For instance, he can reduce a 0-bit and a 1-bit into a 0-bit by using the 0-version of the AND operator. Example of a card stack shown on a smart phone is depicted in Figure 28.

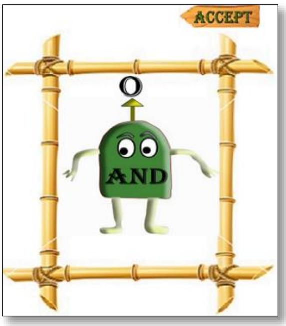


Figure 28 - Example of a card shown on the smart phone

This reduction process is performed by filling a pyramid of tiles. Each player has his own pyramid (Figure 27). The player selects the tile he or she wants to fill on the tablet by tapping on that tile, and swiping the desired card from his or her smartphone to that tile. If the action was allowed and correct the corresponding symbol will show up on the tile, otherwise the appropriate error symbol is displayed. By making a correct move, the player will earn a point; by making a mistake, he or she will lose one. The version of the operator used determines the value of the tile, i.e. a 1-card version results in a 1-bit tile and a 0-card version results in a 0-bit tile. In this way, the tiles can be used as input for future operators. For example, in Figure 27 the player using the topside of the board has chosen the AND operator with output value 0, to reduce the two rightmost bits (0 and 0) into a 0-bit. The players play alternately. At each turn, a player can only make one move. If a player doesn't have a suitable operator at his disposal he has to skip his turn.

Moreover, each player has the possibility to switch one of the initial bits with the corresponding bit of the other player. To do this, the player should have a NOT operator card available on his smartphone. To switch the bits, he or she selects the bit to be switched by tapping on it and swipes the NOT card to the board. This action will invalidate the results of that branch for both players, potentially resulting in extra work for the opponent. The opponent can directly cancel this action by also using a NOT card. An example of using the NOT card is shown in Figure 29.

Each player starts with four randomly chosen operators in their card stack and can browse through them by swiping left or right. Selecting a card (i.e. use the card for the selected tile) is done by swiping up. When a card is used, it is removed from the card stack and replaced by a new card. A player can skip his turn by discarding a card. This is done by not selecting a tile on the board and swiping the desired card up, upon which a new card will be added to his stack.

Beside the competitive game mode, the game also features a self-training mode. This allows the players to become familiar with the game and to learn the different operators. In the self-training mode, only one player is playing the game, thus only one pyramid is shown (see Figure 30) and only one smartphone is needed.

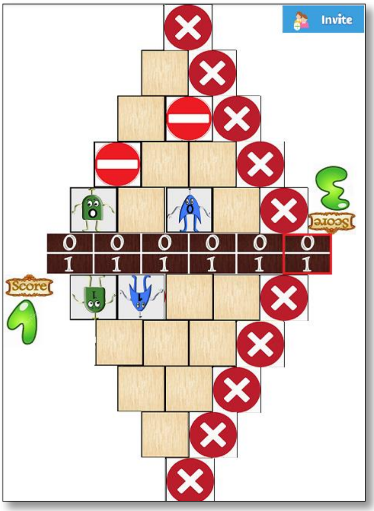


Figure 29 - Example of using the NOT operator

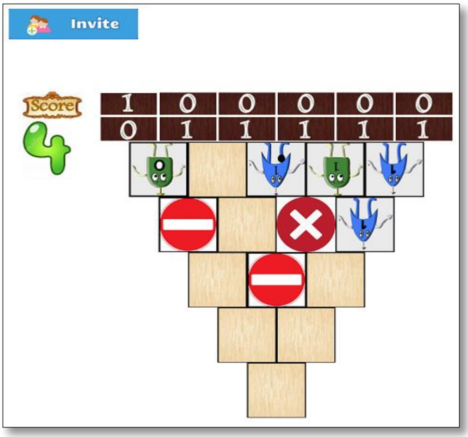


Figure 30 - Self training

During the development process of TrueBiters, we made sure to maintain those mechanics of the original b00le0 game that were suitable for the logical-mathematical intelligence. Additionally, the chosen interaction modality of TrueBiters (tablets and smart phones) is bodily-kinesthetically oriented (gestures on the smart phones and tablets can be mapped to the motion mechanic suitable for the bodily-kinesthetically intelligence). The analysis of the mechanics used in TrueBiters using our mappings is given in Table 23. The definitions for the mechanics used in TrueBiters are as follows:

- **Motion:** The players' bodily stances (postures, gestures, etc.) produce input to the game system or benefit in dealing with its challenges.
- **Repeat pattern:** The player must repeat a series of given steps.
- **Memorizing:** Tests the short-term memory of a player.
- **Submitting:** Submitting information (in a format specified in the rules) for evaluation by the game system or other players.
- **Points:** Points are a running numerical value given for any single action or combination of actions.
- **Quick feedback:** Shows the user what they have just done, and gives them instant gratification.

- **Modifier:** An item that when used affects other actions. Generally modifiers are earned after having completed a series of challenges or core functions.
- **Disincentives:** A game element that uses a penalty (or altered situation) to induce behavioral shift.
- **Companion gaming:** Games that can be played across multiple platforms.
- **Tutorial/first run scenarios:** Guided sequence of steps in the beginning for new users.
- **Logical thinking:** Thinking in a logical way would be a requirement for successfully fulfilling an objective.
- **Strategizing:** Planning ahead and/or devising a strategy for reaching a desired state before taking any action.
- **Browsing:** Browsing or moving through possible choices of instances of game elements.
- **Choosing:** The player is presented with making a choice between a number of options.

The majority of relationships of the game mechanics, utilized by this game, with the logical-mathematical dimension are positive relationships (7 out of 11). There is one game mechanic (i.e. Repeat Pattern) that has a dubious relation with this dimension, denoting that is mechanic is neither recommended to be used, nor recommended not to be used. We decided to keep this mechanic because the game is intended to practice the use of the logical operators and a good way to achieve this is by some form of repetition. Three mechanics are negatively for the logical-mathematical dimension: Disincentives, Browsing and Choosing. We didn't change these as they are part of the core gameplay of this game, and replacing them would have meant changing the core of the game.

Furthermore, half of the employed mechanics (5 out of 10) in TrueBiters that have a relationship with the bodily-kinesthetic dimension are of the type positive. There are three mechanics that have a dubious relation: Quick feedback, Modifier and Tutorial/first run scenarios. And there are two mechanics that have a negative relation with this dimension: Memorizing and Disincentives. Since the bodily-kinesthetic dimension was not intended as the main target dimension of our audience, we did not change any of these mechanics.

A cautious reader will notice that the proportion of the game mechanics that have a positive relation with the logical-mathematical dimension is higher than that for the bodily-kinesthetic dimension. Concerning the core mechanics, one of the core mechanics of the game (i.e. Memorizing) has no relation with the logical-mathematical dimension; the rest (i.e. Logical thinking, Strategizing) have positive relationships with this dimension.

Mechanic	Logical-mathematical Intelligence	Bodily-kinesthetic Intelligence
Motion	-	✓ positive
Repeat Pattern	✓ dubious	✓ positive
Memorizing	-	✓ negative
Submitting	-	✓ positive
Points	✓ positive	✓ positive
Quick feedback	✓ positive	✓ dubious
Modifier	✓ positive	✓ dubious
Disincentives	✓ negative	✓ negative
Companion gaming	✓ positive	✓ positive
Tutorial/first run scenarios	✓ positive	✓ dubious
Logical thinking	✓ positive	-
Strategizing	✓ positive	-
Browsing	✓ negative	-
Choosing	✓ negative	-

Table 23 - Analysis of TrueBiters's mechanics using the mappings between MI dimensions and game mechanics with respect to the logical-mathematical and bodily-kinesthetic dimensions of MI

Similar to LeapBalancer, we have analyzed the mechanics of this game with respect to all dimensions of MI. Table 24 shows this analysis. Based on this, we see that TrueBiters fits best the logically-mathematically intelligent players, as this dimension is the one having most positive relations with the core mechanics of this game (highlighted in blue).

Game mechanics	*Logical-Mathematical*	*Visual-Spatial*	*Bodily-Kinesthetic*	*Musical*	*Interpersonal*	*Intrapersonal*	*Linguistics*	*Naturalistic*
Motion	-	Negative	Positive	-	-	-	-	Positive
Repeat pattern	Dubious	Positive	Positive	Positive	Positive	Negative	Positive	Positive
Memorizing	-	Negative	Negative	-	-	-	-	-
Submitting	-	Negative	Positive	-	-	Negative	-	Positive
Points	Positive	Positive	Positive	Positive	Positive	Negative	Positive	Dubious
Quick feedback	Positive	Positive	Dubious	Positive	Positive	Positive	Positive	Positive
Modifier	Positive	Positive	Dubious	Positive	-	Positive	-	Dubious
Disincentives	Negative	Positive	Negative	Negative	-	Positive	Positive	Negative
Companion gaming	Positive	Positive	Positive	Negative	Positive	Positive	Positive	Positive
Tutorial/first run scenarios	Positive	Positive	Dubious	Positive	Positive	Positive	Positive	Positive
Logical thinking	Positive	Negative	-	-	-	Negative	Positive	-
Strategizing	Positive	Negative	-	-	-	Negative	Negative	-
Browsing	Negative	Positive	-	-	-	Positive	Positive	Negative
Choosing	Negative	Positive	-	-	-	Positive	Positive	-
Summary	1 Dubious 3 Negative 7 Positive	5 Negative 9 Positive	3 Dubious 2 Negative 5 Positive	2 Negative 5 Positive	5 Positive	5 Negative 7 Positive	1 Negative 9 Positive	2 Dubious 2 Negative 6 Positive
Core mechanic	2 Positive	3 Negative	1 Negative	-	-	2 Negative	1 Negative 1 Positive	-

Table 24 - Relationships between the game mechanics of TrueBiters and all dimensions of MI

7.4 Experiment

The experiment presented in this section focuses on testing the following hypotheses:

Hypothesis 1: *The logically-mathematically intelligent players have a higher learning outcome after playing TrueBiters compared to the rest.*

Hypothesis 2: *The logically-mathematically intelligent players have a better game experience playing TrueBiters compared to the rest.*

7.4.1 Methodology

We first investigated the learning outcome of the game as well as the game experience with a limited number of participants, i.e. students that failed the exam of the Logic course in the first session. After that, we extended the number of participants, and compared the differences in the game experience of logically-mathematically and bodily-kinesthetically intelligent players. We explain the reason for this two-step experiment in sub-section 7.4.1.2. For the first sub-experiment, the games were organized in the form of a tournament, in which each of the players played against all the other players, in order to avoid any potential negative influence caused by a weak player. For the second sub-experiment, each participant played two gameplays. We didn't use a tournament in this case, as we were not interested in measuring their learning outcome, but purely their game experience. For both sub-experiments, the game was first explained and the participants were given 10 minutes for self-training.

7.4.1.1 Data Collection

In order to see to what degree the participants' knowledge about the topic at hand improves after playing TrueBiters, we used a pre-test[20] and a post-test[21] for the first sub-experiment. In the tests, the students had to solve questions requiring the use of the truth tables for the standard proposition logic operators. The two tests were not identical, but did maintain the same level of difficulty. We measured the intelligence levels of our participants using the Multiple Intelligences Profiling Questionnaire (MIPQ) (Tirri & Nokelainen, 2011) (this is the same instrument as used in our survey (chapter 4 and chapter 6)).

Before the players started the game, they were asked to do the pre-test and fill out the MIPQ. After the play sessions, the participants were asked to do the post-test and fill-out the Game Experience Questionnaire (IJsselsteijn et al., 2008, 2007), composed of 33 statements (the core module) to be rated on a scale of 0 to 4

[20] Test available at: https://www.scribd.com/doc/316851385/Pre
[21] Test available at: https://www.scribd.com/doc/316851442/Post

(0: not at all and 4: extremely). This questionnaire was also used for the LeapBalancer (chapter 6). It measures the participants' experiences in terms of their competence, immersion, flow, tension, challenge, negative affect and positive affect. For a description of the metrics see sub-section 6.3.1.1. As it was mentioned previously, the play sessions took place in form a tournament. The schedule of the tournament is depicted in Table 25.

Session Number	**Matches**	
Session 1	*player1 VS. player2*	*Player 3 VS. Player4*
Session 2	*Player 1 VS. Player 3*	*Player 2 VS. Player 4*
Session 3	*Player 1 VS. Player 4*	*Player 2 VS. Player 3*

Table 25 - Tournament schedule

For the second step of the experiment, the participants were asked to fill out the GEQ questionnaire once the gameplay sessions were over.

7.4.1.2 Participants

In order to be able to measure learning outcome, we invited the students from our logic course who failed their exam in the first session, to participate in this study. Because those students clearly didn't manage to master the course, they would be a good audience to test the effect of the game. Despite offering incentives and assuring complete anonymity, only four students (out of 38) volunteered to participate. All of them were male students.

For the second part of the experiment, focusing on game experience, we invited students from the 2nd Bachelor Computer Science who have already passed the logic course. This way, a lack of knowledge about proposition logic could not be an influencing factor on their game experience. Seven students participated in the second step of the experiment, of whom six were male and one was female.

7.4.2 Analysis

In order to investigate the difference in the learning outcome of the players after playing TrueBiters, we compared the results of the pre and post-tests. We also compared the GEQ results of the bodily-kinesthetically and logically-mathematically players against the rest of the population to determine if there were any differences in terms of game experience. These results were investigated in more detail using a two-tailed T-test performed on the metrics of game experience between the two groups. These tests were performed in IBM **SPSS** Statistics 22.

7.4.3 Results & Discussion

7.4.3.1 Learning Outcome

The comparison between the pre and post-test results of the four participants is shown in Figure 31. Note that the maximum possible score for either of the tests was 100.

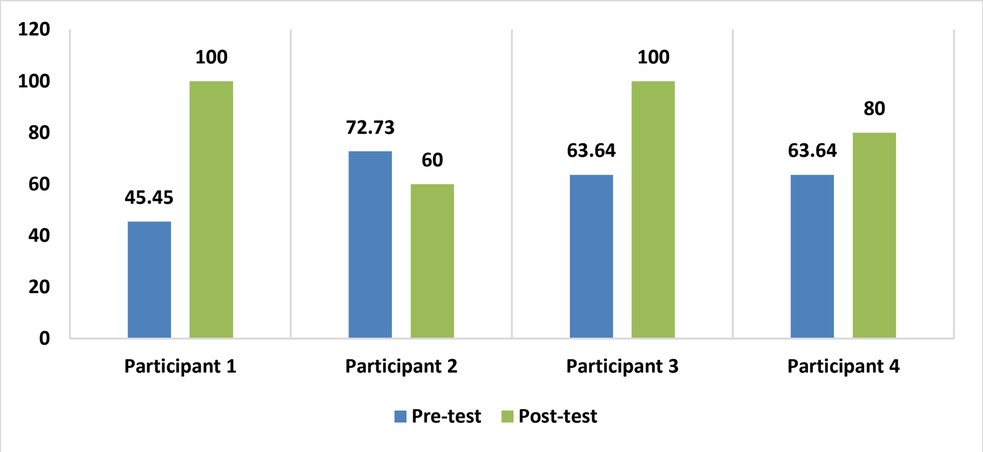


Figure 31 - Results of the pre and post-test

The results of the post-test were significantly better for all participants except for participant two. To try to understand why participant two didn't improve (in fact he did worse), we investigated the results of the MI questionnaire, and noted that participant two exhibits linguistics intelligence as dominant intelligence, whereas all other participants exhibit the logical-mathematical intelligence as one of their dominant intelligences. The logical-mathematical intelligence is defined as the capacity to conceptualize logical relations among actions or symbols, while the linguistic intelligence is defined as sensitivity to the meaning, order, sound, rhythms, inflections, and meter of words (Gardner, 2015). This difference may explain why participant two did not show the same improvement as the other three participants in the same amount of time. Whether he would be able to improve after more practicing or he would never be able to master the topic within a reasonable time cannot be derived from this pilot study. We will investigate this with a larger-scale study lasting at least one complete academic year. This is part of future work.

7.4.3.2 Game experience

In accordance with our prediction, the results of the MIPQ of both steps of the experiment showed that 9 out of the 11 participating students had the logical-mathematical intelligence as one of their dominant intelligences. A comparison between the game experience results of the logically-mathematically dominant participants and the rest of the population indicates (see Figure 32 and Table 26) that the former were experiencing more challenge, more competence, immersion and flow.

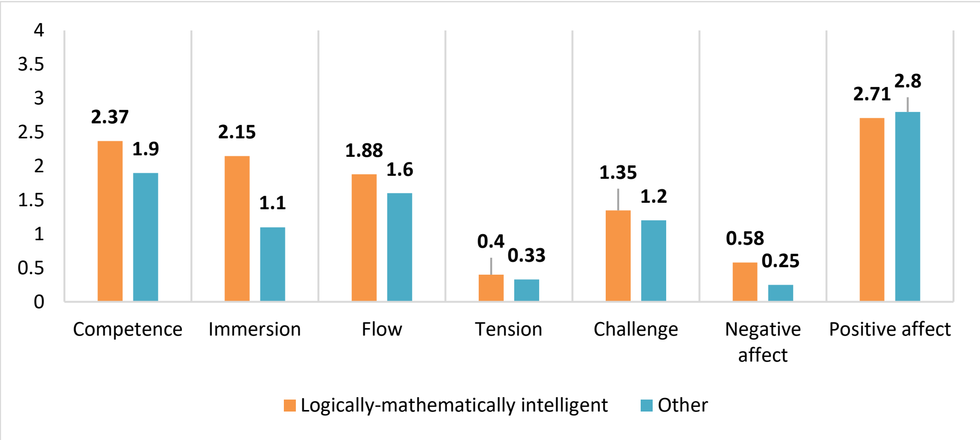


Figure 32 - Comparison of the game experience of logically-mathematically intelligent players with the rest of the population

This suggests that TrueBiters is providing a proper balance between challenge and competence for the logical-mathematical dominant participants. They were more immersed (significantly based on the results of T-test $P < 0.05$) in the game than the other participants, and were experiencing the flow state more. They were also feeling slightly more tension, less positive affect, and more negative affect. This could be due to the fact that the interaction modality of TrueBiters is gesture-based and thus inherently kinesthetic.

	Logically-mathematically intelligent		Other		T-test
	Mean	*Standard Deviation*	*Mean*	*Standard Deviation*	*Sig. 2-tailed*
Competence	2.37	1	1.9	0.42	0.54
Immersion	2.15	0.52	1.1	0.14	**0.024**
Flow	1.88	0.71	1.6	0	0.59
Tension	0.4	0.7	0.33	0.47	0.89
Challenge	1.35	0.5	1.2	0.56	0.7
Negative affect	0.58	0.5	0.25	0.35	0.4
Positive affect	2.71	0.54	2.8	0.28	0.83

Table 26 - Comparison of the game experience of logically-mathematically intelligent players with the rest of the population

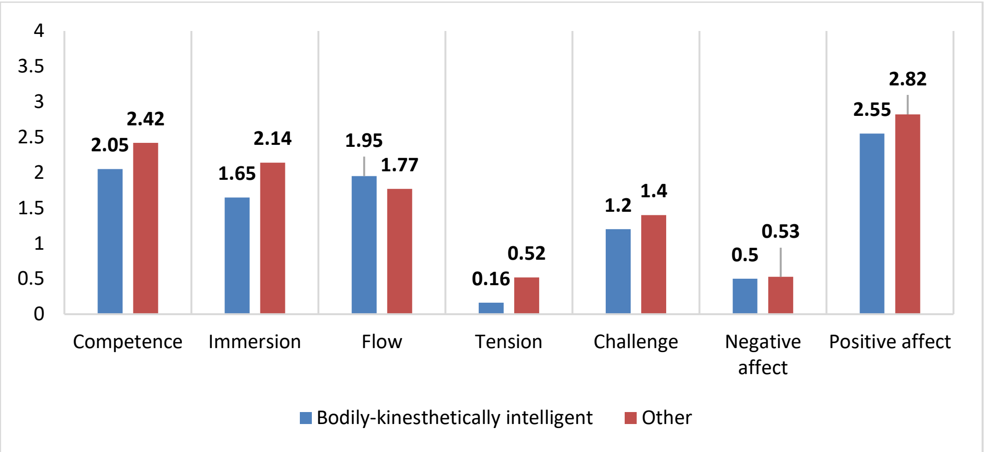


Figure 33 - Comparison of the game experience of bodily-kinesthetically intelligent players with the rest of the population

In light of this observation, we also checked for high bodily-kinesthetic intelligences. The results of the MIPQ showed that 4 participants had a high bodily-kinesthetic intelligence. A closer look at the game experience results of these participants compared to the rest of the population (see Figure 33 and Table 27) shows that they were experiencing less tension and less negative affect, perhaps because the gesture-based interaction suits them better. This further supports our assumption that the participants who do not have bodily-kinesthetic intelligence as one of their dominant ones experience more tension and negative effect due to the use of the gesture-based controls.

	Bodily-kinesthetically intelligent		**Other**		**T-test**
	Mean	*Standard Deviation*	*Mean*	*Standard Deviation*	*Sig. 2-tailed*
Competence	2.05	0.44	2.42	1.13	0.54
Immersion	1.65	0.71	2.14	0.56	0.23
Flow	1.95	0.92	1.77	0.5	0.68
Tension	0.16	0.33	0.52	0.76	0.4
Challenge	1.2	0.58	1.4	0.46	0.54
Negative affect	0.5	0.35	0.53	0.56	0.91
Positive affect	2.55	0.52	2.82	0.49	0.4

Table 27 - Comparison of the game experience of bodily-kinesthetically intelligent players with the rest of the population

The game mechanics used in the design might provide a potential explanation as to why the logical-mathematical participants felt tension and negative affect while experiencing the flow state at the same time. As indicated in section 7.3, TrueBiters employs a lot of game mechanics that are appropriate for the logical-mathematical dimension of MI. However, the mechanics *browsing*, *choosing* and *disincentives* (i.e. lose points) are negatively related to the logical-mathematical dimension. Similarly, the game mechanics could explain why the kinesthetic participants were experiencing less competence and immersion. Indeed, the key gameplay mechanics (*strategizing* and *logical thinking*) are logical-mathematical oriented and not kinesthetic-oriented, and there is a negative relationship with the *memorizing* mechanic (i.e. remembering the truth tables, which is vital for being successful).

Furthermore, three out of eleven participants have a high value for both the logical-mathematical and bodily-kinesthetic dimensions. The comparison between the game experiences of the participants who were both logically-mathematically as well as bodily-kinesthetically intelligent against the rest of the population (Figure 34 and Table 28) shows that the players that exhibit a high value for both dimensions, seem to have the highest difference with the rest of the population with respect to flow and tension.

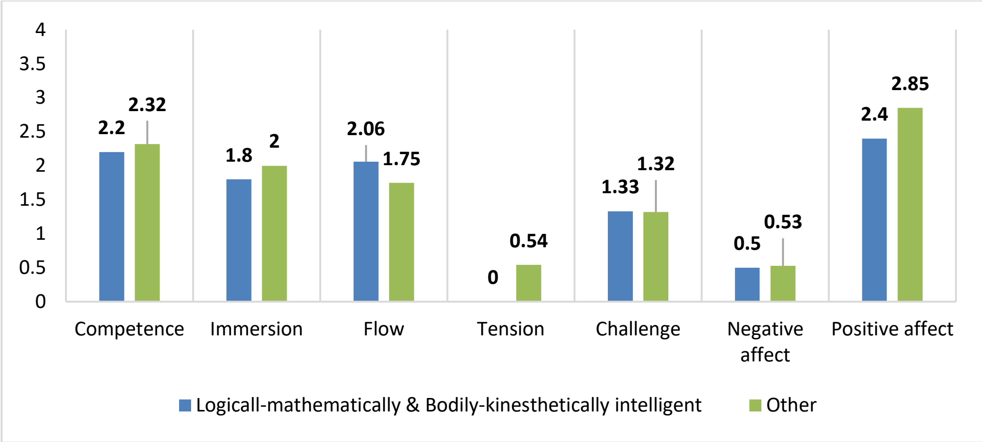


Figure 34 - Comparison of the game experience of logically-mathematically & bodily-kinesthetically intelligent players with the rest of the population

	Logically-mathematically & Bodily-kinesthetically intelligent		**Other**		**T-test**
	Mean	*Standard Deviation*	*Mean*	*Standard Deviation*	*Sig. 2-tailed*
Competence	2.2	0.4	2.32	1.08	0.85
Immersion	1.8	0.7	2	0.65	0.77
Flow	2.06	1.10	1.75	0.47	0.67
Tension	0	0	0.54	0.71	0.06
Challenge	1.33	0.64	1.32	0.47	0.98
Negative affect	0.5	0.43	0.53	0.52	0.92
Positive affect	2.4	0.52	2.85	0.46	0.19

Table 28 - Comparison of the game experience of logically-mathematically & bodily-kinesthetically intelligent players with the rest of the population

Based on the T-test analysis for each metrics of game experience between all groups, we observed a significantly higher level of "immersion" for the logically-mathematically intelligent players compared to participants with other dominant intelligence dimensions (last column of Table 26). The results of T-test analysis between participants exhibiting both logically-mathematically intelligence and bodily-kinesthetically intelligence, and the other people within the population did not show any significant differences (see last column of Table 28). Nonetheless, it is worth noting that the results with respect to "tension" were almost significant with a P-value of 0.06. We are confident that a bigger sample size would have resulted in a significant result. Thus, it is worth considering the results for tension, which indicate that players who exhibit both MI intelligences experienced less tension compared to others in the tested sample. Based on these tentative results from the first step of the experiment, we are inclined to accept the hypothesis that *the logically-mathematically intelligent players have a higher learning outcome after playing TrueBiters compared to the rest*. Based on the results of the second step of the experiment, we can also accept the hypothesis that *the logically-mathematically intelligent players have a better game experience playing TrueBiters compared to the rest.*

7.5 Conclusions

This chapter presented a learning game developed to help students practicing the truth tables of the standard logical operators of proposition logic. The game was mainly tailored to the logical-mathematical intelligence dimension. A pilot study was conducted to investigate the learning outcome and game experiences of participants with different MI intelligences. The results of a pilot study suggest that the dominant MI intelligences of players do play a role in the effectiveness of a learning game. Although the number of participants was rather small, the results of the pilot study were promising: 3 out of 4 participants performed better in a logic test after playing the game. The common denominator of the participants who showed improvement was their *strong* logical-mathematical intelligence. In terms of game experience, we saw that people with a high logical-mathematical, body-kinesthetic, or both MI intelligences exhibit different game experience. We observed some negative influences on specific game experience metrics, possibly induced by the use of some negatively related game mechanics. These results stress the importance of taking the target audience's high MI intelligences into consideration when designing a learning game. Though we cannot make any definitive claims that can be safely generalized, for the pilot study performed in the context of TrueBiters we can provide a positive answer to the third and fourth research question: **RQ3**: *Can player-centered game design based on the findings of RQ2 contribute to better game experience? and* ***RQ4:*** *Can player-centered game design based on the findings of RQ2 contribute to higher learning outcome?* Of course, the results presented in this chapter are only a partial validation of the proposed mappings in terms of the effect they have on game experience and learning outcome. The conclusions made in this chapter are limited to the MI dimensions under study, the game used, and the population used in the experiment.

In order to generalize our findings, a large-scale experiment should be set up. This experiment should run over a longer period of time and include a control group. Moreover, the used quantitative research approach could be complemented with qualitative measures (i.e. interviews, observations) in order to gain a deeper understanding of the game experiences of the players, and their gained level of knowledge. Finally, in order to present a comprehensive picture, the experiment should also focus on additional MI dimensions other than the ones evaluated in this chapter.

Chapter Eight:
Tool Support

"The game of science is, in principle, without end. He who decides one day that scientific statements do not call for any further test, and that they can be regarded as finally verified, retires from the game."

Bertrand Russell

8.1 Introduction

Chapter 6 and chapter 7 have demonstrated and partially validated the application of our mappings in the process of player-centered game design. These mappings (results of chapter 5) are in the form of eight relatively large tables, each dedicated to a MI dimension and addressing 116 game mechanics. This form might be hard to use in practice. In this chapter, we present a tool that visualizes these mappings. This visualization (see Figure 35) is aimed at making these mappings more easily accessible to game designers and developers. This tool provides an answer to the question ***RQ5:*** *How can our findings of RQ2 be provided to game designers and developers in a more accessible way?*

The main objectives of this tool are to enable game designers and developers to obtain an easy overview of our mappings, and to quickly find game mechanics for particular MI dimensions or to see the relationships of game mechanics with different MI dimensions. Furthermore, the tool also allows the game designers and developers to create a report of game mechanics they want to include in their game and how these are related to the different MI dimensions. With this report they can detect possible conflict is terms of suitable game mechanics when different MI dimensions are targeted.

In section 8.2, we present a description of the tool that visualizes the proposed mappings. In section 8.3, we discuss its implementation. In section 8.4, we provide a summary and address future development plans for the tool.

8.2 Description of the Tool

The tool[22] allows users to select one or more MI dimensions. Based on this selection, the system compiles and visualizes an overview of all game mechanics correlated with the selected MI dimensions. The system uses the "concept network"[23] visualization technique to display the overview.

In the overview, the 8 intelligence dimensions are positioned in the middle of the figure (see Figure 35). All the related game mechanics are placed around them. Lines are used to represent the relationship between an MI dimension and game mechanics. The user can browse over the MI dimensions to see which game mechanics are related with each individual MI dimension. The selected MI dimension and the lines are highlighted in blue; see Figure 35 and Figure 36. Figure 36 shows a part of the visualization depicted in Figure 35.

To avoid burdening the user with too much information at once, we added a selection panel at the top of the screen (see Figure 37). The user can use this panel to select one or more MI dimensions on which to focus. In Figure 37, the Bodily-Kinesthetic and Logical-Mathematical dimensions are selected. The selected dimensions and the related game mechanics will be shown on the screen, while the other dimensions and game mechanics are hidden.

[22] Available at: wise.vub.ac.be/dpl
[23] https://github.com/d3/d3/wiki/Gallery

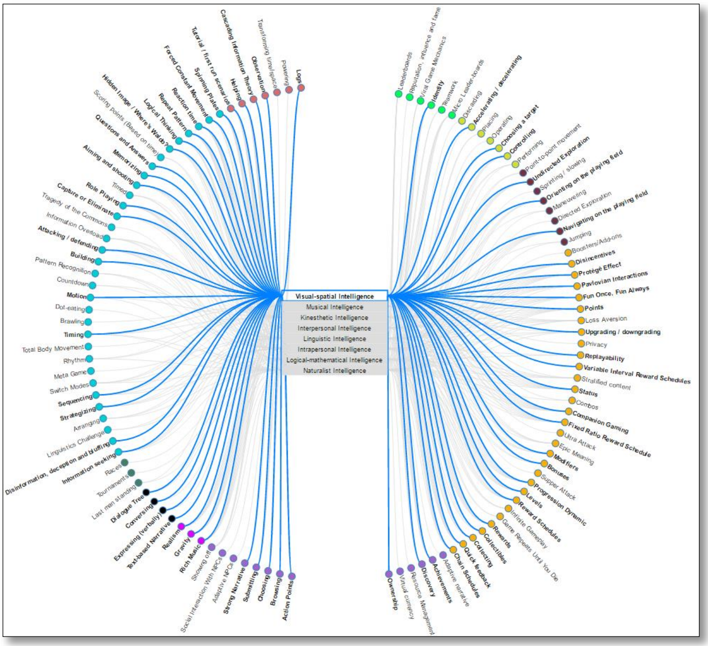


Figure 35 – Main visualization: Visualization of all MI dimensions and game mechanics

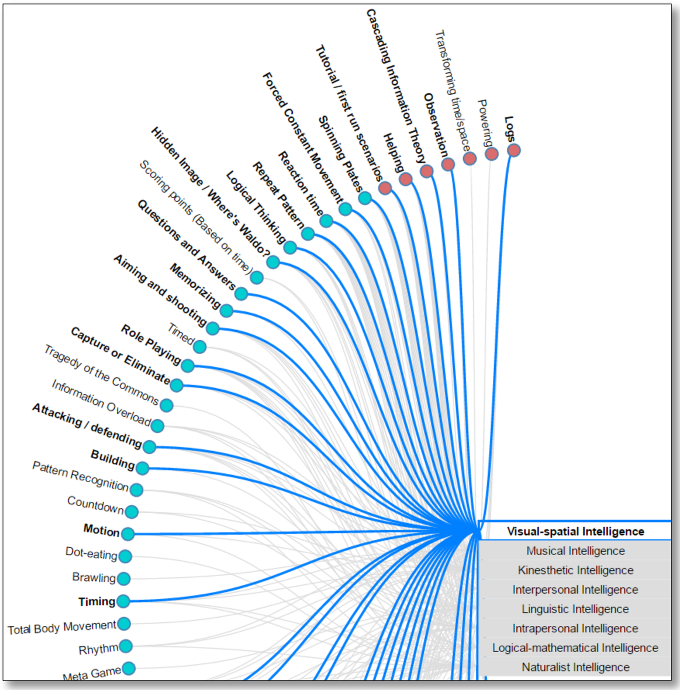


Figure 36 - Part of the main visualization (shown in Figure 32)

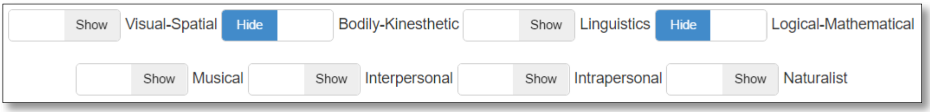


Figure 37 - MI dimension selection panel

The game mechanic nodes are grouped by color. The colors represent different classes of mechanics, e.g. blue is used for game mechanics in the “challenge” class. The classes represent groups of mechanics that can be placed under the same umbrella and represent an important aspect of a game. There are 10 classes in total: “Involvement”, “Challenge”, “Motivation”, “Competition”, “Assistance”, “Player movements”, “Object manipulation”, “Dialogue”, “Game environment”, and “Relatedness”. Classes can be used as a filtering mechanism in the tool by selecting or deselecting the classes from the panel on the left hand side (Figure 38). The mechanics belonging to the deselected classes will be excluded from the visualization (see Figure 39). The panel can be collapsed. This panel allows the game designers and developers to focus on different types of game mechanics one by one.

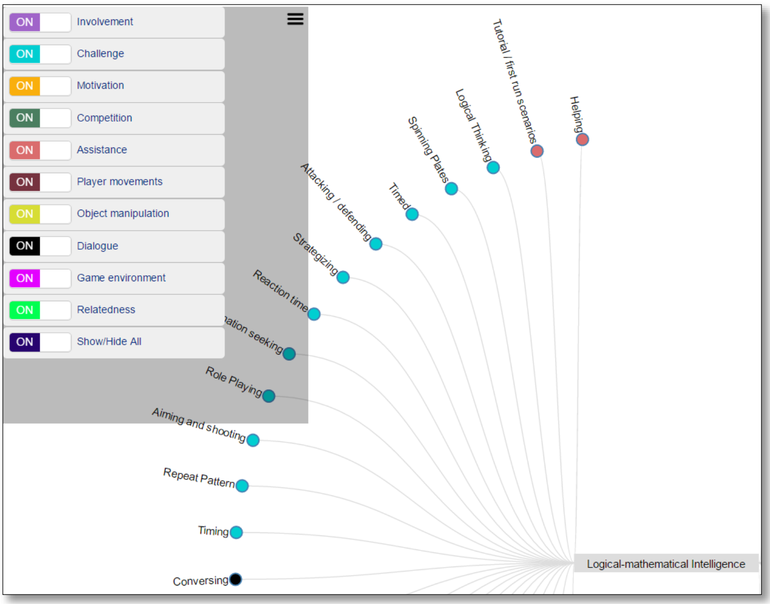


Figure 38 – Game class filtering panel and unfiltered mechanics of Logical-mathematical dimension of MI

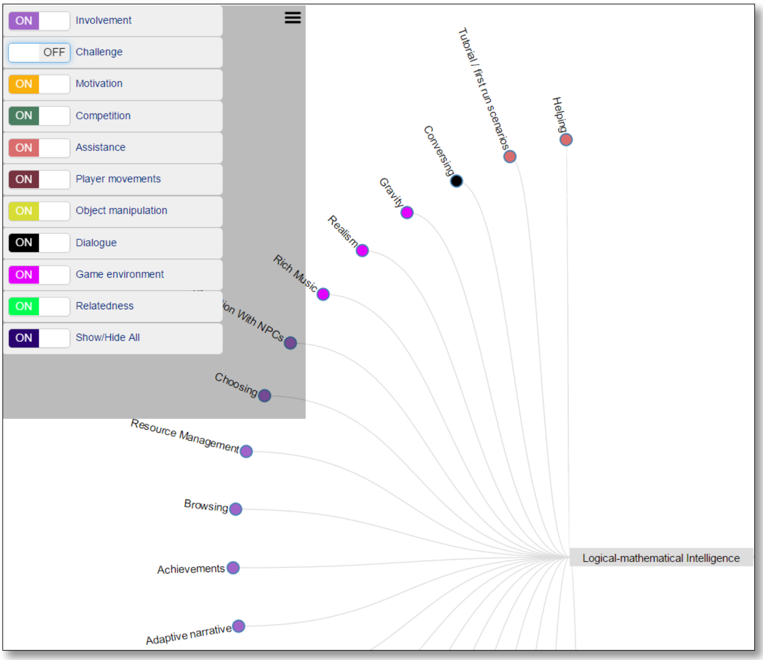


Figure 39 - Filtered mechanics for the Logical-mathematical dimension of MI

To see the nature of the relations (i.e. positive, negative or dubious) between a MI dimension and the associated game mechanics, users can click on the MI dimension. The system will then display a different visualization that indicates the nature of the relationships by using 3 different colors for the relationships: green for positive, yellow for dubious, and red for negative (see Figure 40).

In this visualization, the classes of the different game mechanics are also denoted by means of their color. To reduce the cognitive load, we have added a legend that explains the different colors (see Figure 41). The legend is hidden by default, but users can call up this legend at any time by clicking the 'help map' button. This visualization also includes the definition of the dimension of MI that is currently displayed, as well as the statements of MIPQ used for measuring it (see top left corner of Figure 41).

The user can get quick access to the definitions of the game mechanics by clicking on the label of a game mechanics. Doing so will result in a new visualization, in which the definition of that mechanic (as well as its source, if taken from one of the sources mentioned in sub-section 5.4.1) and the relationships it has with the dimensions of MI are shown (if any) (see Figure 42). As for the previous visualizations, the colors, green, red and yellow are used to indicate positive, negative or dubious relationships.

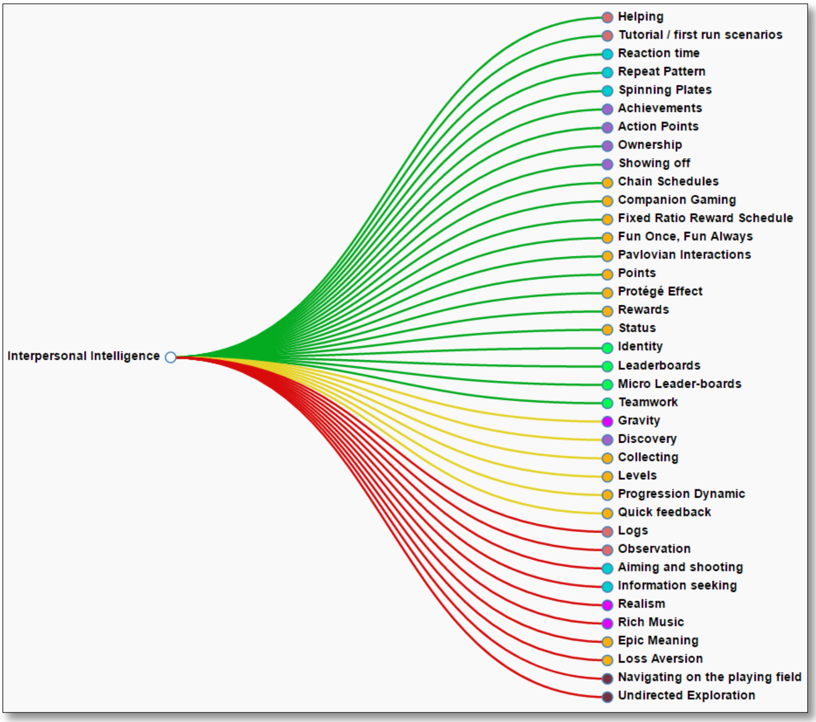


Figure 40 – Dimension visualization: Visualization of the nature of the relations between an MI dimension and game mechanics

The game mechanic visualization functionality is also available in the main visualization screen (Figure 35). Meaning that if the user clicks on a game mechanic in the main visualization (Figure 35), the visualization of that mechanic, as given in Figure 42, will be shown. Moreover, in the MI dimension visualization (Figure 40 and Figure 41) hovering over a game mechanic will result in a pop-up window that contains the definition of that mechanic (see Figure 44). This functionality is made available to ease the process of report generation that will be explained in the coming paragraphs.

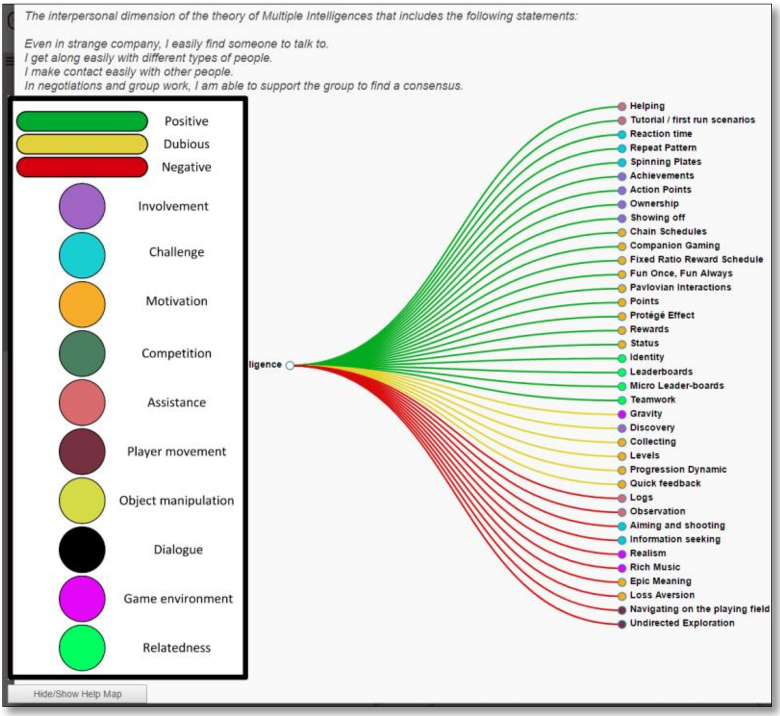


Figure 41 – Dimension visualization with the color map and the definition for the MI dimension

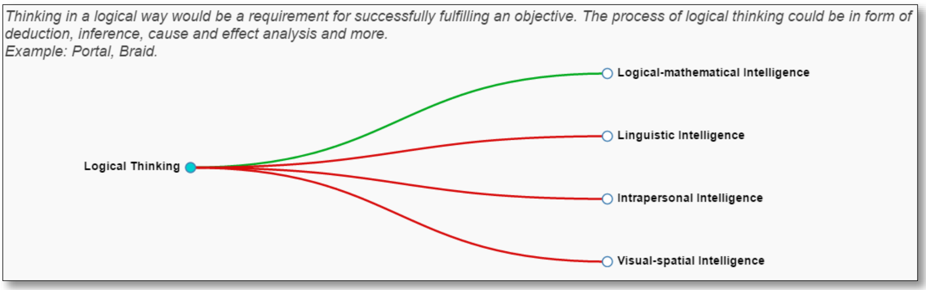


Figure 42 - Example of a game mechanic visualization

To ease the process of searching for a particular game mechanic, the system also features a search functionality. Using this functionality, the user is able to search for any game mechanic that is available in the tool by means of a combo box, which provides suggestions based on the input entered in the search field (see Figure 43).

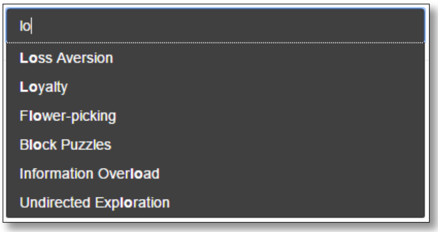


Figure 43 - Example of searching for a mechanics

As mentioned, the users can use the system to draw up a report of their exploration with the tool. This report contains the selected game mechanics, their relationship to the selected MI dimensions, as well as the nature of the relationship. We illustrate this with an example. Consider a scenario where a game designer is interested in designing a game for logically-mathematically intelligent players. She or he can use the tool to explore all the relations between this MI dimension and game mechanics. The game designer can use the MI dimension filter to focus only on the logically-mathematically dimension. She or he can then search or explore and select the game mechanics she/he wants to incorporate in the game by clicking on the corresponding nodes. The selected game mechanics (nodes) are highlighted by a blue circle (see Figure 44). Once the selection process is over, the tool provides the "generate report" functionality. The result of this function is shown in Figure 45.

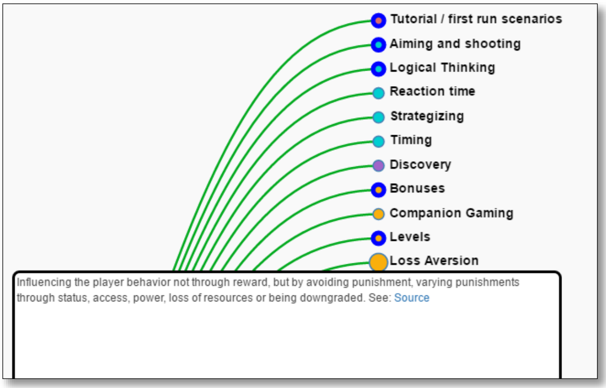


Figure 44 - Example of selecting game mechanics, while inspecting their description

Mechanic(s)	Logical-mathematical Intelligence
Tutorial / first run scenarios	positive
Aiming and shooting	positive
Logical Thinking	positive
Bonuses	positive
Levels	positive
Quick feedback	positive
Spinning Plates	dubious
Action Points	dubious
Fixed Ratio Reward Schedule	dubious

Figure 45 - Report for the selected mechanics related to the logical-mathematical dimension of MI

Furthermore, if the game designer decides to consider more than one MI dimension, he can filter on more than one MI dimension in the visualization (e.g. logical-mathematical as well as bodily-kinesthetic). Of course, selecting particular game mechanics that have relations to both of these MI dimensions can raise conflicts. These conflicts arise when a game mechanic is positively related to one dimension, and negatively related to another. The color use in the report allows the designers and developers to quickly spot them (see Figure 46). Note that the system does not offer or suggest a final decision on what to do with the conflict. It is up to the designer to decide how to deal with it: to keep the mechanic or to replace it by another one.

Mechanic(s)	Logical-mathematical Intelligence	Kinesthetic Intelligence
Tutorial / first run scenarios	positive	dubious
Aiming and shooting	positive	negative
Logical Thinking	positive	
Bonuses	positive	positive
Levels	positive	negative
Quick feedback	positive	dubious
Spinning Plates	dubious	dubious
Action Points	dubious	
Fixed Ratio Reward Schedule	dubious	dubious

Figure 46 - Report generation for multiple dimensions of MI

8.3 Implementation

The tool is implemented as a web application using the D3js JavaScript library[24]. The D3js is a library for producing dynamic, interactive data visualizations in web browsers. The implementation allows us to easily add and/or remove a MI dimension or game mechanics, i.e. to alter the repository of MI dimensions and the game mechanics. This also includes the definition of the MI dimensions and the game mechanics, as well as their relationships and the nature of those relationships.

The definition of the MI dimensions and the definition of the game mechanics and their relationship to the different MI dimensions, are stored in separate JSON files (see Table 29 and Table 30 for some fragments). The general architecture of the tool is visualized in Figure 47.

[24] https://github.com/d3/d3

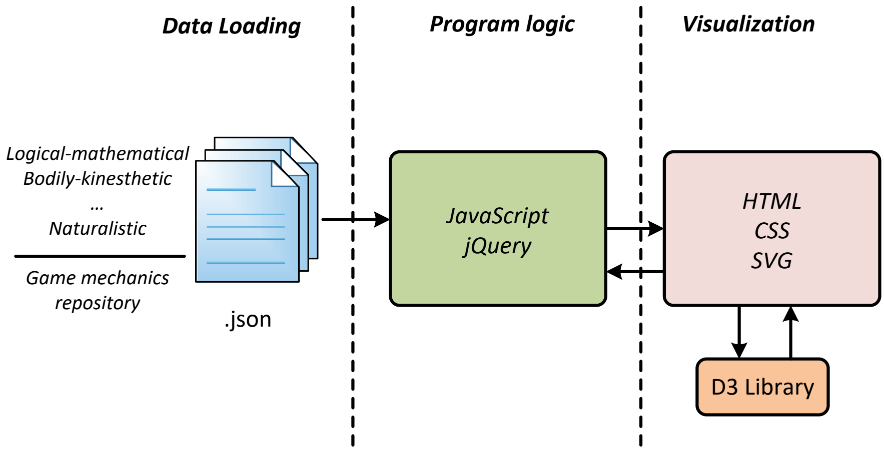


Figure 47 - Components of the tool

```
{
      "name": "Achievements",
      "description": "Achievements are a virtual or physical representation of having
accomplished something... See: <a
href=\"https://badgeville.com/wiki/Game_Mechanics/Achievements\"
target='_blank'>Source</a>",
              "code": "involvement"

 },

 {
      "name": "Bonuses",
      "description": "Bonuses are a reward after having completed a series of challenges
or core functions... See: <a
href=\"https://badgeville.com/wiki/Game_Mechanics/Bonuses\"
target='_blank'>Source</a> ",
              "code": "motivation"
 },
```

Table 29 – Example of game mechanics repository file

```
[
{
"nodeName": [
{
"name": "Logical-mathematical Intelligence",
"description": "The logical-mathematical dimension of the theory of Multiple Intelligences that includes the following statements: <br><br>At school I was good at mathematics, physics or chemistry.<br>I can work with and solve complex problems.<br>Mental arithmetic is easy for me.<br>I am good at solving logical problems and games that require logical thinking."
}
],
"relations": [
{
"with": "Achievements",
"type": "dubious"
},
{
"with": "Bonuses",
"type": "positive"
},
```


Table 30 - Example of defining the relationships between game mechanics and a dimension of MI

The tool is programmed in a way that the JSON file representing the repository of game mechanics can be reused for other theories than MI. As such, it can accommodate data from other studies focusing on the relationship between game mechanics and, for example, learning styles (e.g. VARK). To adapt the tool to a new mapping, for example for VARK, the researchers only need to create new JSON files for each learning style of that theory. With a few lines of codes in the script of the tool, the newly added JSON files can be visualized in the same fashion.

8.4 Summary & Future Work

This chapter presented a tool that visualizes the proposed mappings between MI dimensions and game mechanics. This tool is aimed to ease the process of utilizing the proposed mappings by game designers and developers in their design of player-centered games. To achieve this, the tool visualizes the mappings between the MI dimensions and game mechanics and allow to filter the mappings on different aspects. In addition to visualization, this tool also provides a report generation functionality when users (game designers) select the game mechanics they desire to incorporate in their design. This report provides an overview of their selection. Furthermore, the report shows potential conflicts between game mechanics from the viewpoint of their suitability for the different selected MI dimensions.

As such, we have presented an answer to ***RQ5:*** *How can our findings of RQ2 be provided to game designers and developers in a more accessible way?*

Chapter Nine:
Conclusions & Future Work

"There are no facts, only interpretations."

Friedrich Nietzsche

9.1 Summary

In this dissertation we started by discussing the context of the work and motivating our goal, i.e. to investigate the different attitudes that people with different pedagogical-oriented characteristics might have towards specific games, and how these findings can be used for advancing the state of the art in the individualization of learning games. This goal was derived from a literature review on individualization of learning games, which showed that there is a lack of considering pedagogical-oriented differences between players, such as their intelligences with respect to the "theory of Multiple Intelligences" (MI) for individualization. We hypothesized that individualizing certain aspects of games with respect to the MI intelligences of the target audience, would positively affect both the game experience and learning outcome of the players.

To position the work of the dissertation in the large body of work on player-centered game design, personalization and adaptation in learning games found in the literature, we delineated a conceptual framework for the individualization of learning games, which identifies the different contributing factors and the different ways individualization can take place. Our work is oriented towards the process of player-centered game design, which we identified as one form of individualization.

Although theoretical mappings exist between game constructs and different MI dimensions, empirical evidence on the topic was lacking. This incentivized us to first establish in a more empirical way, *mapping* between the MI dimensions and game constructs, and only then incorporate these mappings in the process of player-centered game design. Therefore, a survey study was conducted to unveil correlations between MI intelligences and preferences for games. Our results indicate that each dimension of MI is correlated with preferences for different games. Seeking for an explanation, we found that the genres of the games on their own could not be used to explain the preferences. To understand the reasons behind the observed correlations, we decided to consider the game mechanics used by the games and investigate whether certain game mechanics could be related to one or more MI dimensions, which was indeed the case. In this way, we were able to draw relationships between MI dimensions and the building blocks of games, i.e. game mechanics. These relationships, called mappings, can on their turn be used in the process of player-centered game design to adapt the game mechanics to the MI dimensions of the targeted players. The nature of these mappings is positive, negative or dubious (uncertain). This means that the game mechanics that have a positive relation with an MI dimension can be recommended to be used in the design of a game targeting people with that particular MI dimension. Similarly, the mechanics that have a negative relation are the ones that are recommended not to be used, and the mechanics that have a dubious relation are neither recommended to be used nor recommended not to be used. Although the mappings are derived from the results of the survey study, they are based on our interpretations of the empirical data and data available elsewhere, and thus should not be considered as hard rules, but rather as a first set of recommendations for the use of MI dimensions in the context of individualization.

In order to test the effectiveness of these mappings, we utilized some of them in the process of player-centered game design. More in particular, we used them for the design of two games: a game called LeapBalancer, which was designed for testing their effect on bodily-kinesthetically intelligent players; and for a game, called TrueBiters, which was developed for testing their effect on logically-mathematically intelligent people. We hypothesized that these games would positively affect the game experience and for the second game also the learning outcome of their intended audiences. Both games were implemented and the hypotheses were tested with experiments. The results confirmed our hypotheses. As such, these two case studies provide a partial validation of the proposed mappings.

Lastly, in order to make our mappings accessible to game designers and developers in an easy way, we developed a tool that visualizes the mappings and provided functionalities such as filtering, search and reporting.

9.2 Conclusions

Throughout this dissertation, we have answered four research questions, pivotal for reaching our main aim, which was formulated as:

To investigate whether individualization based on player's intelligences (according to MI) and the game's mechanics has a positive influence on the game experience and learning outcome of the players.

The first research question that was investigated was: ***RQ1:*** *Are there any correlations between player's intelligences (with respect to MI) and their preferences for games?* The answer to this question is yes. Based on the results of our survey study, we unveiled a series of (positive or negative) significant correlations between each dimension of MI and a list of games. As starting point, we used a multivariate analysis (principal component analysis) on the dataset and reveal the presence of patterns. Furthermore, using bivariate correlation analyses, we managed to unveil a series of significant correlations between each MI dimension and preferences for one or more games. These correlations support the claims of scholars such as (Becker, 2007; Starks, 2014) stating that MI can be mapped to game characteristics. However, our results indicate that these suggested theoretical mappings could be refined. As far as we are aware, our survey study is the first research that proves the existence of statistically significant correlations between the different MI dimensions and preferences for games. Further analysis showed that the aforementioned correlations could not be attributed to the genre of the games.

Next, the second research question was tackled: ***RQ2:*** *If there are correlations between players' MI intelligences and their preferences for specific games, can they be attributed to the game mechanics and if so how?* This question was also answered positively. Based on the results of the survey we were able to draw direct relationships (positive, negative, or dubious (uncertain)) between MI dimensions and game mechanics. This process resulted in the establishment of mappings between each MI dimension and game mechanics, which can be used to tailor the game mechanics to the MI intelligences of the target players.

The answers given to **RQ1** and **RQ2** enabled us to investigate the third research question: ***RQ3:*** *Can player-centered game design based on the findings of RQ2 contribute to better game experience?* We investigated this question in the context of LeapBalancer, a game designed using our proposed mappings, and specifically targeting bodily-kinesthetically intelligent players, and specifically developed for the purpose of our research. In the context of this game, the question **RQ3** was answered positively by means of an experiment. More in particular, we have seen that the game experience of bodily-kinesthetically intelligent players were significantly better with respect to *competence, negative affect, immersion* and *tension* compared to non-bodily-kinesthetically intelligent players.

Apart from game experience, the ultimate goal and objective of learning games is to positively affect the learning outcome of their audience. This goal was considered in the fourth research question: ***RQ4:*** *Can player-centered game design based on the findings of RQ2 contribute to higher learning outcome?* This question was investigated in the context of a learning game TrueBiters. TrueBiters targets logically-mathematically intelligent players and is mainly using game mechanics labeled as positive in our suggested mappings for this intelligence dimension. Also this game was specifically developed for the purpose of our research. In the context of the experiment performed, we could indeed see a higher learning outcome. Furthermore, it was also observed that the logically-mathematically intelligent players were significantly more *immersed* in the game.

Based on the answers given to the four research questions, we can claim that we have achieved our main aim. We investigated how we can attain individualization based on player's MI intelligences and the game's mechanics, and we showed that for the cases of LeapBalancer and TrueBiters, this individualization has positively influenced the game experience of the intended audiences of these games, and the learning outcome in the case of the TrueBiters learning game.

Lastly, research question five was answered: ***RQ5:*** *How can our findings of RQ2 be provided to game designers and developers in a more accessible way?* The solution is given in the form of a support tool that visualizes the aforementioned mappings, provides its users with the capability of searching and browsing through the different relationships between MI dimensions and game mechanics, and selecting the desired ones for inclusion in the game design. Furthermore, a reporting functionality is available, which provides an overview of the selected game mechanics and highlights possible conflicts that may arise as a result of targeting several dimensions of MI.

The findings from this dissertation will help game designers to create (learning) games that are better tailored to particular MI intelligences, with the objective to result in better game experience and possibly better learning outcome.

9.3 Research Contributions

The research presented in this dissertation has contributed to the state of the art in individualizing learning games in the following ways:

1) It provides a comprehensive overview of the state of the art in individualization (player-centered, personalization, and adaptation) of learning games. (chapter 2)
2) It provides a review of the different aspects of a player used to drive the individualization process, and highlights the most frequently used ones and the neglected ones. (chapter 2)
3) It provides a conceptual framework for dealing with individualization of learning games that can be used for personalization and/or adaptation, as well as for designing player-centred games targeting a specific audience. (chapter 3)
4) It provides empirical evidence for the existence of correlations between MI intelligences and preferences for certain games. (chapter 4)
5) It provides mappings between MI dimensions and game mechanics, which can be used to tailor the game mechanics to the MI intelligences of the target players. (chapter 5)
6) It provides a partial validation of the proposed mappings by means of their use in two games, specifically developed for this purpose. In particular, we have seen a positive effect on game experience of bodily-kinesthetically intelligent players in the game LeapBalancer (chapter 6) and a positive effect on learning outcome and game experience of logically-mathematically intelligent players in the game TrueBiters (chapter 7).
7) It provides a support tool for researchers, game designer and game developers to search, browse, and inspect the mappings in a visual way, and for selecting appropriate game mechanics targeting specific MI dimension(s). (chapter 8)

9.4 Limitations & Future Work

9.4.1 Limitations

1. Entertainment games as starting point

A first limitation concerns the use of entertainment games and a population of gamers in the survey study, while we were in the first place interested in learners in general and learning games in particular. It remains a question whether we are allowed to generalize our findings (based on entertainment games) towards learners and learning games. The TrueBiters case is an indication that this might be the case. However, more experiments with learning games and learners with different intelligences are needed to verify this. Moreover, learning games, similar to entertainment games also utilize game mechanics to evoke feelings such as fun, challenge, and immersion. If not identical, there is a rather huge overlap of the game mechanics utilized by both entertainment and learning games, and this insinuates that there is a high chance that players with different MI intelligences would have the same attitude towards these mechanics.

Another approach to investigate whether the findings are also applicable to learning games could be by replacing the entertainment game titles used in the survey study, with a compilation of learning games. However, as explained in section 4.4.1.1, a compilation of learning games instead of entertainment games would introduce the risk of reducing the familiarity of participants with these games and thus would significantly reduce the participation, since learning games are not as widely available and played.

2. Selection of game titles

Secondly, we recognize that our selection of game titles used in the survey study represent a snapshot of the current landscape of popular video games. Although we carefully selected a broad range of games, the selection of different game titles would unavoidably influence the outcome of the study. However, we are confident that if a selection of different game titles would result in differences, they would be minimal. We carefully selected a broad range of games to avoid any bias. In addition, we were aided in this process by avid gamers and academic experts on games, and we took into consideration various theoretical suggestions presented in the academic literature.

3. Influence of self-evaluation

Thirdly, we acknowledge the potential influences of the use of self-evaluation methods on the reliability of our results. Throughout this dissertation, the MI intelligences of our participants were measured using MIPQ. Although the recommended approach for measuring MI intelligences is a combination of methods (triangulation) as was discussed in section 4.2, given the sample size and the location of participants (particularly with respect to the survey study) and the available resources, the use of the MIPQ was the best approach. Since MIPQ is a validated instrument, we are confident that despite not being perhaps the best method for measuring the MI intelligences of people, it is still reliable to a good extent.

4. Subjectivity

Next, the relationships between MI dimensions and game mechanics are implicitly derived from the results of the survey study and are based on our subjective interpretation of what mechanics play what role in the games. Additionally, the protocol used for establishing the mappings also represents a subjective opinion on how these mappings can be done. These relationships could be explicitly verified by examining the explicit preferences of gamers for different game mechanics. On the one hand this can be seen as a limitation, but on the other hand, as already indicated, it is known that self-evaluation is also not always reliable and would also require quite some effort from the participants (i.e. rating 243 distinct game mechanics). In addition, the experience with a game mechanic is dependent on the context in which it is used. For example, a game mechanic such as “Discovery” might be slightly different in a game like *Portal* where the player needs to discover the correct strategy for overcoming the individual obstacles, compared to a game like *Heavy Rain* where discovery is more related to completing the overall story of the game. Also taking this into consideration would result in an effort that cannot be asked to volunteers. A possible approach to deal with this subjectivity by means of involving game-experts into the process was discussed in section 5.6.

5. Partial validation

Finally, the effectiveness of our mappings have only been partially demonstrated. The number of participants, as well as the number of MI dimensions targeted in the experiments, were limited and do not allow us to draw definitive conclusions for the effectiveness of proposed mappings. This is particularly the case for the learning outcome where we could only perform a pilot study. More experiments, on larger scales (both in terms of the number of participants and the duration of the experiments), are needed to confirm our findings.

9.4.2 Future Work

In order to obtain more reliable results for measuring the MI intelligences, triangulation, as proposed by Gardner, could be used. This is possible for experiments where the number of participants is limited. Furthermore, it is also possible to replace MIPQ with a more comprehensive instrument like MIDAS (C. B. Shearer & Muenzenmayer, 1999). MIDAS (Multiple Intelligences Development Assessment Scales) is a commercially available instrument that is used either through self-assessment or by interview. It is composed of 119 questions for measuring the eight dimensions of MI. MIDAS provides a series of sub-scales for each dimension of MI. For instance, the dimension logical-mathematical is composed of the *school math, logic games*, *everyday math,* and *everyday problem solving* sub-scales. Using this instrument, it would be possible to investigate the relations between each sub-scale of each dimension, and preferences for games, and game mechanics. Moreover, the participants could be clustered based on their scores for each sub-scale in future experiments to investigate the effects of our mappings. Nevertheless, using an instrument such as MIDAS as part of a survey study might introduce the risk of reducing participation because using this instrument would require too much time from the participants. More precisely, the version of MIDAS designed for adult users (above 20) will take between 35 to 45 minutes through self-assessment and 60 to 90 minutes through structured interview. Therefore, in the context of this dissertation, a decision was made to use MIPQ which requires less time.

The focus of this dissertation with respect to individualization has been on player-centered game design. Personalization and adaptation can also benefit from our mappings. In these cases, a generic game can be designed and developed. This generic game can then be personalized based on the MI intelligences of its player before each play session, or dynamically adapted in real-time and during gameplay, by including/excluding different game mechanics.

To automate the process of assessing the MI intelligences of the players and then performing personalization and/or adaptation accordingly, stealth measurement techniques can be used. This means inferring the MI intelligences of the players based on the in-game decisions, actions, choices and other behaviors. This could be partially based on our mappings, as these mappings indicate preferences for certain game mechanics by people with certain MI intelligences. This opens the door for an interesting and challenging research topic.

Furthermore, as was explained in chapter 2, some researches have focused on the use of games for the improvement of (one or more) of the MI intelligences. Our knowledge about which game mechanics are negatively, and which are positively related to a certain MI dimensions, could be used to force players to practice skills related to MI dimensions for which they score less high.

Finally, the support tool could be evaluated on its usability. This will help us to improve the tool. This can be done by asking a group of game designers to use the tool for their game designs.

Moreover, the limitations mentioned in the previous section could be tackled in future research.

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Appendices

A: Maze Commander[25]

In order to explore the possible relationships between MI and games, we performed a study that investigated whether people with certain MI intelligences exhibit different attitudes towards games that utilize different types of interaction modalities. To investigate the mentioned, we created a game, called "Maze Commander" and set up an experiment using this game. This game is a two-player game that requires both players to constantly communicate and collaborate in order to overcome the challenges posed by the game. Maze Commander can be considered as a learning game since it promotes 21st century skills (Dondlinger, 2007) such as communication and collaborative work. However, the learning aspect of Maze Commander was not the subject of evaluation in this experiment, but nonetheless turned out to be an important characteristic, as it affected the results of our study to a great extent.

Maze Commander accommodates bodily-kinesthetic interaction through the use of Sifteo Cubes, as well as visual-spatial interaction through the use of Oculus Rift virtual reality glasses. We hypothesized that *people who score high for the bodily-kinesthetic dimension of MI, would enjoy the game more when using an interaction modality that promotes physical movements like the Sifteo Cubes*. And, similarly, *people who score high for the visual-spatial dimension of MI, would enjoy the game more when using an interaction modality that focuses on visual-spatial aspects of a game such as the Oculus Rift*[26]. Based on the results of the experiment performed with Maze Commander, we failed to see any significant correlations between players' MI intelligences and their enjoyment and attitude towards the game with respect the selected interaction modalities. We believe that the reason behind this was the collaborative aspect of Maze Commander. Based on our observations, we realized that the collaborative aspect of this game had a great influence on the experiences of the players in the game in terms of their enjoyment and attitude. This was due to the reason that if one player underperformed, it affected the other player's experience. For this reason, we abandoned the use of the game for the rest of the research work.

[25] Large parts of this appendix is taken from our publication about this game available at (Sajjadi, Cebolledo Gutierrez, et al., 2014)

[26] https://www.oculus.com/

Sifteo cubes are an interactive gaming platform composed of physical cubes (see Figure 48). The cubes are 1.5 inch and have a clickable screen. The users can perform gestures with the cubes, including shaking, rotating, and tilting. The cubes can be placed next to each other (on any side), and depending on the game being player on them, the cubes will become connected and game objects can move from one cube to another.

Figure 48 - Sifteo Cubes[27]

Figure 49 - Oculus Rift[28]

The Oculus Rift is an immersive virtual reality glasses that also supports positional and rotational tracking of the head (see Figure 49).

To some extent, the choices for the interaction modalities were made based on the theoretical suggestions of Becker (2007) and Starks (2014). Both authors provide a mapping between visual-spatial intelligence and how the graphical environment and visual elements of games are perceived through the screen. These mappings indicate that in-game graphics engage a person's visual intelligence, while the way a player moves in the game environment engages their spatial intelligence. Similarly, bodily-kinesthetic intelligence is mapped to games that promote physical movement as well as the different physical states a player experiences while playing a game, like for instance *Dance Dance Revolution*. These mappings suggest that in-game actions requiring actual physical movement engage bodily-kinesthetic intelligence.

Before using Maze Commander to test our hypotheses, we tested the game on 16 players to ensure that it provided them with a good game experience. We compared the game experience of the players based on the interaction modality they used to assess the impact of the interaction modality on the players' game experience. The results indicated that the game was well perceived by the majority of the players. The results of this experiment can be seen in (Sajjadi, Cebolledo

[27] Taken from https://github.com/sifteo/thundercracker
[28] Taken from https://www.oculus.com/

Gutierrez, et al., 2014). In order to test our hypothesis, we ran a second experiment to identify possible correlations between players' intelligence levels and their enjoyment of, and attitude towards the game with respect to the interaction modalities.

Maze Commander[29] is a two-player collaborative tile-based maze game (see Figure 50 for a view of the maze). The objective of the game is to escape from a maze while avoiding enemies and hazards (explosions and traps). The enemies are patrolling over specific paths (they do not chase the character). In addition, certain tiles explode after a certain time interval. Traps are tiles that kill the character upon contact. These traps are not visible until the character steps over them. Of course, there are also a number of safe tiles, which are not hazardous and allow the players safely position the character on that tile for as long as they want. This gives them time to communicate and strategize. The game is over when the player ends up on the same tile as an enemy or a trap, when the player is on a tile when it explodes, or when the player reaches the exit tile.

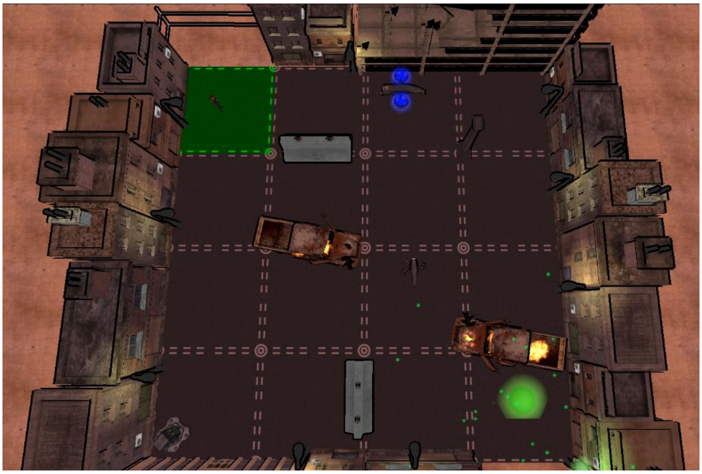

Figure 50 - Maze through the Oculus Rift

The two players use different interaction modalities to play the game: one uses the Oculus Rift and the other uses the Sifteo Cubes. The players' enjoyment of, and attitude towards the game is expected to be different since the view of the game, as well as the possible actions, are different for each interaction modality. The player using the Oculus Rift cannot move the character in the game, but has a 3D top down view of the whole maze and can see the enemies, the character, and the

[29] https://www.youtube.com/watch?v=55TaHKHgFDU

explosions. The maze is visualized to this player as a grid of tiles (see Figure 50). The Sifteo Cubes also provides a visualization of the maze but in a different way (see Figure 51). A single Sifteo Cube visualizes a tile, showing possible paths for moving (colored white) (see Figure 53). However, the player using the Sifteo Cubes does not get a complete view of the maze. She or he only has four cubes: one showing the tile containing the character (i.e., the character cube, see Figure 52); the three other cubes can be used to move the character to the right direction.

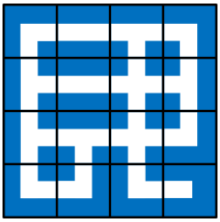

Figure 51 - Complete Maze on the cubes

Figure 52 - A Sifteo Cube showing the tile where the character is

Figure 53 - The 5 different patterns that the cubes can have

The role of the player with the cubes is to move the character through the maze by manipulating the cubes based on the instructions given by the player with the Oculus Rift. The role of the player using the Oculus Rift is to provide detailed instructions to the other player on which direction to move to, and when to do so in order to reach the exit of the maze (indicated with a green light, see Figure 50).

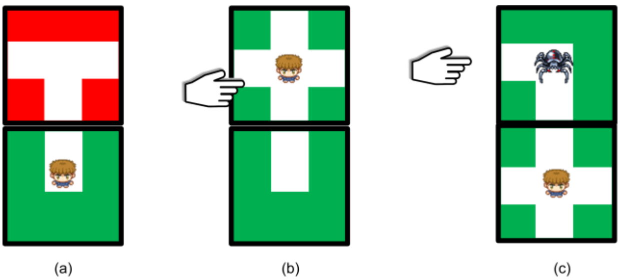

Figure 54 - Character movements

At the start of the game, the character cube shows the tile where the character is at the start of the game, and the other three cubes show random patterns. There are five possible tile patterns (see Figure 53). In order to move the character to a new tile, the player needs to join the character cube with another cube showing the desired direction for the move. As part of the rules of the game, only one cube can be placed next to the character cube. In order to change the pattern on a cube (if the desired pattern is not available on one of the three cubes), the player can pick up a cube and shake it. The shaking motion will switch between the different patterns. The cube can also be rotated in order to have the desired orientation.

When the player connects a cube to the character cube, and the pattern and orientation of the cube do not match the ones of the tile in maze on that position, the cube color will switch to red (see Figure 54 (a)) to show the player that this is an invalid combination. If the combination is valid, the cube color will switch to green (see Figure 54 (b)). Once a correct combination is recognized, the player can observe the ongoing activities on the connected tile (e.g., the existence of an enemy, see Figure 54 (c)). The character will not move to the desired destination tile unless the player clicks on the destination tile (see Figure 54 (b)). Once this action is finished, the destination tile becomes the new character tile and the same procedure can be repeated.

Maze Commander has three levels with increasing difficulty, as each subsequent level has a bigger grid, more enemies, and less safe tiles that are further apart. The first level has 13 tiles, five of them are safe, and the shortest path between two safe tiles has a maximum distance of three steps. There are two enemies and one explosion hazard on this level. The first two tiles of the maze are safe to allow the players to get familiar with the tiles and the way of moving around the game. The second level has 16 tiles arranged in a 4x4 grid, five of them are safe, and the shortest path between two safe tiles has a maximum distance of four steps. There are two enemies and one explosion on this level. The players do not start on a safe tile and need to move at least two tiles to reach a safe tile as soon as the game commences. The third level has 25 tiles arranged in a 5x5 grid, three of them are safe, and the shortest path between two safe tiles has a maximum distance of eight steps. There are four enemies, one explosion, and a trap. The player starts on a safe tile. The other two safe tiles are positioned at the center of the grid and at the exit.

Maze Commander was designed based on the collaborative game design guidelines proposed in (Wendel, Gutjahr, Göbel, & Steinmetz, 2013). Four of these guidelines were considered relevant and therefore taken into account during the design process of the game. We list them below and provide a brief explanation how they were applied in Maze Commander.

- **Common goal/success:** The game must be designed in such a way that both players have the same goal, and succeeding in the game means success for both. In Maze Commander both players have the same goal, i.e., escaping from the maze. Since accomplishing this requires rather close collaboration between the players, the success and failure in terms of achieving the objective is common.
- **Heterogeneous resources:** The game must be constructed in such a way that each player has a unique tool or ability that would enable that player to perform unique tasks. In Maze Commander, this guideline is clearly followed. The player who interacts with the game using the Oculus Rift is in possession of a unique resource, being an overview of the whole maze, enabling him/her to strategize and provide instructions to the other player. The player who interacts with the game using the Sifteo Cubes, is in possession of a different unique resource, being the ability of moving the character and viewing patterns that can be used.
- **Collaborative tasks:** The game must contain tasks that are only solvable when the players collaborate. Maze Commander follows this guideline. It is virtually impossible for either player to finish a challenge without the help of the other. Although the player interacting with the Sifteo Cubes actually moves the character, without a strategy and guidance from the player with the Oculus Rift, accomplishing the task would not be possible. These two roles are equally vital for accomplishing the task.
- **Communication:** Communication is a vital component in collaborative tasks. In Maze Commander, players have the possibility to communicate with each other in different ways; the most common one is verbal communication. On the other hand other modes of communication have also been observed in our evaluation, for example using hand gestures to describe the pattern of a tile that is required. This game is designed in such a way that bi-directional communication between the players is needed. The player with the Sifteo Cubes also needs to communicate certain information to the other player, for example describing the shape of the patterns he or she sees on the cubes in order to help the other player recognizing the tiles in the maze.

The decision to use only four cubes was made in order to create a balance between the levels of challenge the players would experience and their skills. If more than four cubes were given to the players, planning all the moves ahead would have become easier after a few tryouts of the game. By only providing four cubes the player has only a limited number of possibilities for prearranging the movements they want to make and therefore they have to act fast on finding the correct pattern and orientation while they are on the move. On the other hand, if less than four cubes were used, the game would have become extremely challenging, since the players had to switch between tile patterns and orientations extremely fast. Trial sessions showed that based on the difficulty levels we designed for this game, four Sifteo Cubes seemed to be the best trade-off.

As mentioned previously, a tile in each level may explode after a specific time interval, but the information about the frequency of the explosions is not given to the players. First of all, this challenges the player with the Oculus Rift to find the timing in order to give the "go ahead" signal to the other player, as well as challenging the player with the Sifteo Cubes to act quickly on moving the character before a new explosion occurs. Secondly, this encourages the players to communicate effectively, efficiently, and in a timely manner. Furthermore, as previously mentioned, the game starts on a safe tile in level one and three and on an unsafe tile in levels two. This decision was taken to challenge the players to act faster in the second and third levels in order to avoid losing the game. This decision was made based on the assumption that after finishing the first level, the players have already established an effective communication protocol and are able to communicate more effectively and efficiently.

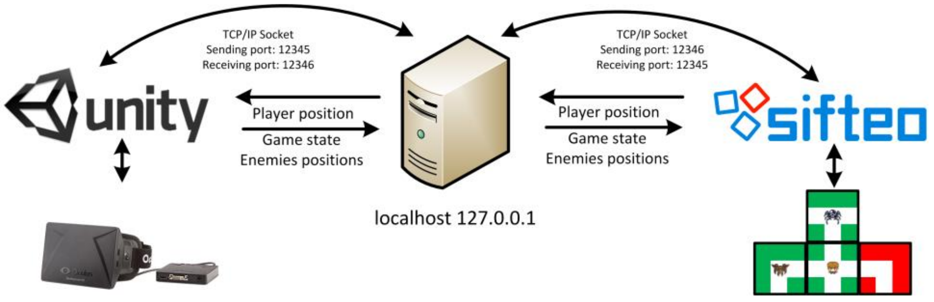

Figure 55 - Architecture of Maze Commander

Maze Commander is composed of two applications running simultaneously: the Oculus Rift and the Sifteo Cubes applications. The Oculus Rift application is written in C# in Unity3d, while the Sifteo Cubes application is written in C# using the Sifteo SDK. In order to synchronize both applications, sockets using TCP/IP are used. Each application connects to two ports, one for sending information and one for receiving information. The communication between the two applications is in the form of a full duplex, meaning that both applications act as client and server.

The Oculus Rift application needs to notify the Sifteo application when a new level is loaded or when the game is over. It also constantly streams the position of the enemies. The Sifteo Cubes application receives the commands and executes the corresponding actions. If the player uses the Sifteo Cubes and moves the character to a different tile, this movement and hence the new position of the player is send to the Oculus Rift application. The graphics on the Sifteo Cubes have five different sprites, one for the character and four for the different enemies. The paths are generated using Sifteo SDK primitives. We did not include animations in this version to avoid lags on the cubes. Although our tests were made using one computer, acting as both server and client, the chosen communication architecture allows us to run the two applications on different computers.

To investigate whether the enjoyment and the attitude of the players for the interaction modalities used in Maze Commander would be different based on their intelligences, we designed an experiment that would allow us to develop a first general understanding of the impact of the theory of MI on games. To do so, we tested the following hypotheses:

- Bodily-kinesthetic intelligence is positively correlated with enjoyment of an attitude towards Maze Commander when using the Sifteo Cubes.
- Visual-Spatial intelligence is positively correlated with enjoyment of an attitude towards Maze Commander when using the Oculus Rift.

Before we started the experiment, participants were asked to fill out two questionnaires. The first questionnaire contained 8 questions covering general info about age, gender, native language, level of education, field of study, frequency of playing games, preferred hardware to play games on, and how well the participants knew their team mate. The second questionnaire was designed to determine whether a player is bodily-kinesthetically and/or visually-spatially intelligent. In order to do so, we asked the players to fill out a short questionnaire before the start of the experiment. The instrument was designed based on the questionnaire of McKenzie ((McKenzie, 1999), see also (Marefat, 2007; Naeini & Pandian, 2010) for example uses of this instrument). McKenzie's questionnaire is composed of 8 series of 10 questions. Each series corresponds with one of the intelligence dimensions. Given the focus of our experiment, we only used the series related to Bodily-kinesthetic and Visual-spatial intelligence. In order to improve readability for non-native English speakers, we slightly adapted the wording of the questions. Of course, we were careful not to alter the content of the questions themselves.

Each team played 3 rounds in the first session, and then switched modalities (see Figure 56). Each team was given the opportunity to try out the game. Furthermore, the participants were asked to fill out two questionnaires that measured their enjoyment of attitude towards the game with respect to the two interaction modalities (see Appendix F) after they completed the final round of the second session. These questionnaires were tailored to inquire about the participants' enjoyment in relation to the specific features and possibilities of the interaction modalities. The questionnaire on the Sifteo Cubes contains 9 questions, and the one on the Oculus Rift 10 questions, all using a five-point Likert scale.

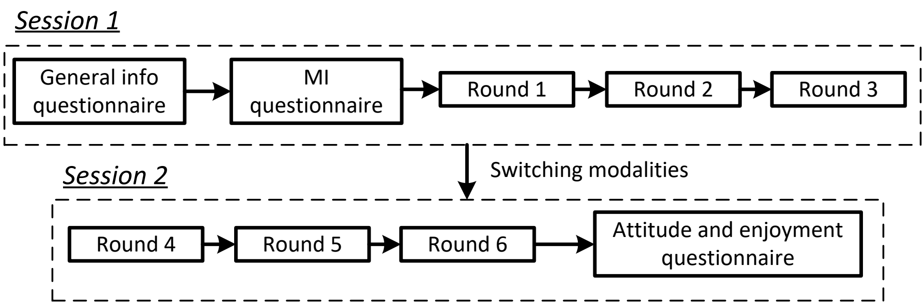

Figure 56 –Setup of the experiment on correlation between MI and enjoyment of the interaction modalities

In addition to the questionnaires, we also recorded the players in game behavior during the sessions using a video camera. This was done with the consent of the players. For this experiment, we recruited 30 participants: 15 teams of 2 players. The participants were recruited through university mailing lists, social media pages related to our institute, and word of mouth. The participants were between 18 to 31 years old. The sample included 6 females and 24 males. In terms of experience, 14 participants reported to play games "often"; 14 reported to play games "sometimes", and only 2 reported to play games "never". It is also important to note that 13 teams reported to be "friends" with each other, while one team reported to be "acquaintances", and one team "strangers".

The MI questionnaire contains 20 questions on a 5-point Likert scale from "strong agree" to "strong disagree". By balancing the answers related to each dimension we were able to determine a trend for each participant. That trend can be either agree (A) disagree (D) or neutral (N). As an example if a player has 6 "agrees", and 4 "disagrees" with respect to all 10 questions related to bodily-kinesthetic intelligence, then we consider the trend to be towards "agree" (trend = A). On the other hand, if a player has 4 "agrees", and 6 "disagrees" with respect to all 10 questions about body-kinesthetic intelligence, then we consider the trend to be towards "disagree" (trend = D). If the number of "agrees" and "disagrees" is equal the trend is neutral (tend=N). Based on this information, we were able to determine whether a participant could be considered as bodily-kinesthetically intelligent and/or visually-spatially intelligent.

The same principle is applied for the questionnaires that measure the enjoyment: 'A' represent the "agree" trend for enjoyment (i.e. the player enjoyed the use of the device for playing the game), 'N' is neutral, and 'D' means a "disagree" trend (i.e. the player did not enjoy the use of the modality for playing the game). In order to test the existence of possible correlations we performed a series of regression analyses. Two multiple regression analyses, using the scores for enjoyment and attitude with respect to modality as the dependent variable, and the scores of both intelligence dimensions as the independent variables were performed. The first one focuses on the Sifteo Cubes and the second on the Oculus Rift. The same test has also been performed to investigate possible correlations between the intelligence dimensions and the enjoyment and attitude with respect to the Oculus Rift.

Based on our analysis, 26 participants were considered to have a positive trend towards bodily-kinesthetic and 29 towards visual-spatial intelligence dimensions. The results for the bodily-kinesthetic intelligence, and enjoyment and attitude with respect to the use of Sifteo Cubes can be found in Table 31, and the results for the visual-spatial intelligence and enjoyment and attitude with respect to the Oculus Rift in Table 32.

Participants		**Bodily-kinesthetic Intelligence**				**Enjoyment with respect to Sifteo Cubes**			
Team	**Player**	**Agree**	**Disagree**	**Balance weight**	**Kinesthetic trend**	**Agree**	**Disagree**	**Balance weight**	**Enjoyment and attitude trend Sifteo Cubes**
T 1	P 1	6	4	**2**	*A*	7	2	**5**	*A*
	P 2	6	1	**5**	*A*	8	1	**7**	*A*
T 2	P 1	3	3	**0**	*N*	7	1	**6**	*A*
	P 2	5	3	**2**	*A*	2	4	**-2**	*D*
T 3	P 1	6	3	**3**	*A*	7	2	**5**	*A*
	P 2	6	3	**3**	*A*	7	1	**6**	*A*
T 4	P 1	5	0	**5**	*A*	9	0	**9**	*A*

	P 2	3	4	**-1**	*D*	8	1	**7**	*A*
T 5	P 1	6	0	**6**	*A*	9	0	**9**	*A*
	P 2	5	3	**2**	*A*	6	2	**4**	*A*
T 6	P 1	4	3	**1**	*A*	6	1	**5**	*A*
	P 2	6	2	**4**	*A*	7	2	**5**	*A*
T 7	P 1	9	0	**9**	*A*	7	0	**7**	*A*
	P 2	8	0	**8**	*A*	7	2	**5**	*A*
T 8	P 1	5	3	**2**	*A*	8	1	**7**	*A*
	P 2	8	1	**7**	*A*	7	1	**6**	*A*
T 9	P 1	5	3	**2**	*A*	9	0	**9**	*A*
	P 2	8	1	**7**	*A*	8	1	**7**	*A*
T 10	P 1	8	2	**6**	*A*	7	1	**6**	*A*
	P 2	9	0	**9**	*A*	9	0	**9**	*A*
T 11	P 1	3	5	**-2**	*D*	8	0	**8**	*A*
	P 2	6	1	**5**	*A*	8	1	**7**	*A*
T 12	P 1	4	3	**1**	*A*	8	1	**7**	*A*
	P 2	6	2	**4**	*A*	9	0	**9**	*A*
T 13	P 1	6	3	**3**	*A*	7	0	**7**	*A*
	P 2	7	1	**6**	*A*	9	0	**9**	*A*
T 14	P 1	5	5	**0**	*N*	5	2	**3**	*A*
	P 2	9	0	**9**	*A*	7	2	**5**	*A*
T 15	P 1	8	0	**8**	*A*	2	3	**-1**	*D*
	P 2	5	1	**4**	*A*	6	1	**5**	*A*

Table 31 - Trend of the kinesthetic dimension in the population and enjoyment with respect to the Sifteo Cubes

Participants		Visual-spatial Intelligence				Enjoyment with respect to Oculus Rift			
Team	**Player**	**Agree**	**Disagree**	**Balance weight**	**Visual trend**	**Agree**	**Disagree**	**Balance weight**	**Enjoyment and attitude trend Oculus Rift**
T 1	P 1	7	1	**6**	*A*	9	1	**8**	*A*
	P 2	5	1	**4**	*A*	10	0	**10**	*A*
T 2	P 1	4	2	**2**	*A*	10	0	**10**	*A*
	P 2	5	1	**4**	*A*	7	1	**6**	*A*
T 3	P 1	4	3	**1**	*A*	8	2	**6**	*A*
	P 2	4	4	**0**	*N*	7	3	**4**	*A*
T 4	P 1	4	3	**1**	*A*	9	1	**8**	*A*
	P 2	5	1	**4**	*A*	8	1	**7**	*A*
T 5	P 1	7	1	**6**	*A*	8	1	**7**	*A*
	P 2	7	0	**7**	*A*	7	2	**5**	*A*
T 6	P 1	4	1	**3**	*A*	6	0	**6**	*A*
	P 2	6	1	**5**	*A*	10	0	**10**	*A*
T 7	P 1	5	1	**4**	*A*	7	0	**7**	*A*
	P 2	5	3	**2**	*A*	9	0	**9**	*A*
T 8	P 1	6	2	**4**	*A*	9	0	**9**	*A*
	P 2	7	2	**5**	*A*	10	0	**10**	*A*
T 9	P 1	7	1	**6**	*A*	7	1	**6**	*A*
	P 2	5	0	**5**	*A*	10	0	**10**	*A*
T 10	P 1	8	0	**8**	*A*	9	0	**9**	*A*
	P 2	8	0	**8**	*A*	10	0	**10**	*A*
T 11	P 1	5	2	**3**	*A*	8	1	**7**	*A*
	P 2	4	2	**2**	*A*	10	0	**10**	*A*
T 12	P 1	5	3	**2**	*A*	9	0	**9**	*A*
	P 2	5	0	**5**	*A*	5	2	**3**	*A*
T 13	P 1	5	2	**3**	*A*	8	1	**7**	*A*
	P 2	5	4	**1**	*A*	9	1	**8**	*A*

T 14	P 1	4	2	**2**	*A*	7	1	**6**	*A*
	P 2	6	1	**5**	*A*	8	0	**8**	*A*
T 15	P 1	7	1	**6**	*A*	5	3	**2**	*A*
	P 2	6	1	**5**	*A*	8	0	**8**	*A*

Table 32 - Trend of the Visual dimension in the population enjoyment with respect to the Oculus Rift

The results of the first regression analysis showed that the bodily-kinesthetic intelligence is positively correlated with the enjoyment and attitude towards Maze Commander with respect to the Sifteo Cubes, but this correlation is very weak (barely above 5%). Similarly, we observed that the visual-spatial intelligence is negatively correlated with the enjoyment and attitude towards Maze Commander with respect to the Sifteo Cubes, but this correlation is also weak (6%). In short, our results indicate that the intelligence dimensions only accounts for 0.9% of the variations in the enjoyment and attitude towards Maze Commander with respect to the Sifteo Cubes. The test showed that no significant correlation between the bodily-kinesthetic intelligence dimensions and the enjoyment and attitude with respect to the Sifteo Cube exist (P-value > 0.05 (0.703)) if we continue to do more testing). Thus, we cannot reject the null hypothesis. This means that there are in fact no significant correlations between the bodily-kinesthetic intelligence and the enjoyment with respect to the Sifteo Cubes.

The results of the second regression analysis showed that the visual-spatial intelligence is positively correlated with the enjoyment and attitude towards Maze Commander with respect to the Oculus Rift, but this correlation is very weak (barely above 2%). Similar, we observed that the bodily-kinesthetic intelligence is positively correlated with the enjoyment with respect to the Oculus Rift, but this correlation is also not very impressive (17%). In short, our results indicate that the intelligence dimensions only account for 3% of the variations in the enjoyment with respect to the Oculus Rift. The test showed that no significant correlation between the visual-spatial intelligence dimensions and the enjoyment and attitude with respect to the Oculus Rift exist (P-value > 0.05 (0.882)) if we continue to do more testing). Thus, we cannot reject the null hypothesis. This means that there are in fact no significant correlations between the visual-spatial intelligence and the enjoyment with respect to the Oculus Rift.

The main reason behind failing to see any significant correlations is from our point of view, the collaborative aspect of Maze Commander. While observing the players during the experiment, we realized that this feature of the game had a rather large influence on the attitude and enjoyment of the players towards the game. This is because the performance of one player (competence in effectively communicate, or constructing paths) affected the experience of the teammate.

Lessons Learned

Based on the work done with Maze Commander, we have learned a few valuable lessons. Firstly, in order to examine the effect of some aspects, the influence of other aspects should be limited as much as possible. For games, this means that we should keep the games used for experiments as simple as possible. This also counts for the number of MI dimensions targeted in the game. This is the main reason why we have developed our own games to perform experiments with, in the context of the evaluation. Once effects of individual aspects are clear, more aspects could be combined to investigate whether this has an impact on the results. Secondly, we have learned that it is best to first have some evidence-based facts before designing and developing games for experiments, rather that designing them based on theoretical claims. Moreover, designing games for experiments, solely relying on intuition and theory could be a tedious, time consuming and wasted endeavor.

B: MIPQ

Linguistics:

1) *Writing is a natural way for me to express myself.*
2) *At school, studies in native language were easy for me.*
3) *I have recently written something that I am especially proud of, or for which I have received recognition.*
4) *Metaphors and vivid verbal expressions help me learn efficiently.*

Logical-Mathematical:

1) *At school, I was good at mathematics, physics or chemistry.*
2) *I can work with and solve complex problems.*
3) *Mental arithmetic is easy for me.*
4) *I am good at solving logical problems and games that require logical thinking.*

Visual-Spatial:

1) *At school, geometry and various kinds of assignments involving spatial perception were easier for me than solving equations.*
2) *It is easy for me to imagine and analyse complex and multidimensional patterns.*
3) *I can easily imagine how a landscape looks from a bird's eye view.*
4) *When I read, I form illustrative pictures or designs in my mind.*

Bodily-Kinesthetic:

1) *I am handy.*
2) *I can easily do something concrete with my hands (e.g. knitting and woodwork).*
3) *I am good at showing how to do something in practice.*
4) *I was good at handicrafts at school.*

Musical:

1) *After hearing a tune once or twice I am able to sing or whistle it quite accurately.*
2) *When listening to music, I am able to discern instruments or recognize melodies.*
3) *I can easily keep the rhythm when drumming a melody.*
4) *I notice immediately if a melody is out of tune.*

Interpersonal:

1) *Even in strange company, I easily find someone to talk to.*
2) *I get alone easily with different types of people.*
3) *I make contact easily with other people.*
4) *In negotiations and group work, I am able to support the group to find a consensus.*

Intrapersonal:

1) *I am able to analyze my own motives and ways of action.*
2) *I often think about my own feelings and sentiments and seek reasons for them.*
3) *I spend time regularly reflecting on the important issues in life.*
4) *I like to read psychological or philosophical literature to increase my self-knowledge.*

Naturalist:

1) *I enjoy the beauty and experiences related to nature.*
2) *Protecting the nature is important to me.*
3) *I pay attention to my consumption habits in order to protect environment.*

C: Social Network Pages

Facebook	
Independent Game Developers	https://www.facebook.com/groups/144438572289633/
UNITY3D Game Developers	https://www.facebook.com/groups/511573835572177/
Indie Game Chat	https://www.facebook.com/groups/IndieGameChat/
Indie Game Players & Develope rs	https://www.facebook.com/groups/1435669336648312/
The Gamers Den	https://www.facebook.com/groups/thegamersdenaw/
Game Development	https://www.facebook.com/groups/gamedevelopmentx/
Indie Game Developers	https://www.facebook.com/groups/IndieGameDevs/
UNITY3D	https://www.facebook.com/groups/unity3d/
✯GamerHolics™✯	https://www.facebook.com/groups/GamerHolic/
Utrecht Center for Game Resea rch	https://www.facebook.com/groups/860182270708904/
CHI Games Community	https://www.facebook.com/groups/244736775667232/
Society of Weird And Mad Peop le (SWAMP)	https://www.facebook.com/groups/14468900612/
Video Game Fans	https://www.facebook.com/groups/playvideogames/
Games Research	https://www.facebook.com/groups/gamesresearch/
Interactivography - the art of games	https://www.facebook.com/groups/interactivography/
Game Designers and Coders	https://www.facebook.com/groups/GameDesignersLearnAndTeach/
Game Research Lab Students	https://www.facebook.com/groups/gameresearchlabstudents/
Google+	
Gaming	https://plus.google.com/communities/106294677380036336853
Games	https://plus.google.com/communities/105973389818152904480
Games	https://plus.google.com/communities/107763515155146275377
Game Developers	https://plus.google.com/communities/101640237427303194102
YouTube Gamers	https://plus.google.com/communities/116853535163815141831

Games, Gaming and Gamers	https://plus.google.com/communities/115046792849609945963
Game Development Tutorials	https://plus.google.com/communities/114342050587612263650
Game Development	https://plus.google.com/communities/117475668671406824809
Naturist Gamers	https://plus.google.com/communities/113234782907477976215
PC & Console Gamers United	https://plus.google.com/communities/102575373964643047831
Gamers	https://plus.google.com/communities/113502821063184514561
Dublin Game Developer Hub	https://plus.google.com/communities/111387043756702873047
World Of Gamers	https://plus.google.com/communities/116309565906858332343
2D Game Development	https://plus.google.com/communities/110782843233718329546
Game Development	https://plus.google.com/communities/107274454425516763912
Game Audio and Sound Design	https://plus.google.com/communities/104860700446146054646
Game Design Feedback	https://plus.google.com/communities/104209995185265605633
Games User Research	https://plus.google.com/communities/104376342954803405775
Pro Game Analysis	https://plus.google.com/communities/106448587926631229762
Game Design	https://plus.google.com/communities/107042382950579703613
Video Game Design	https://plus.google.com/communities/110084258698732929339
Twitter	
Video Game Research	https://twitter.com/GamerResearch
Reddit	
Academic sample size – gaming	https://www.reddit.com/r/SampleSize/comments/3dzrw6/repost_academic_survey_on_game_preferences_gamers/
Academic mailing lists	
DIGRA	https://listserv.uta.fi/cgi-bin/wa?A0=GAMESNETWORK
IGDA	https://pairlist7.pair.net/mailman/listinfo/game_edu
DIGRA Australia	http://digraa.org/mailing-list/
IFIP	http://listserver.tue.nl/mailman/listinfo/icec
CHI-WEB	http://old.sigchi.org/web/index.html

D: Bivariate Correlations Between the Questions of MI and the 47 Game Titles

(* p < .05) (** p < .01).

Games	Intelligences																																	
	Linguistics				*Logical-mathematical*				*Visual-spatial*				*Bodily-kinesthetic*				*Musical*				*Interpersonal*				*Intrapersonal*				*Naturalist*	
	Q1	*Q2*	*Q3*	*Q4*	*Q1*	*Q2*	*Q3*	*Q4*	*Q1*	*Q2*	*Q3*	*Q4*	*Q1*	*Q2*	*Q3*	*Q4*	*Q1*	*Q2*	*Q3*	*Q4*	*Q1*	*Q2*	*Q3*	*Q4*	*Q1*	*Q2*	*Q3*	*Q4*	*Q1*	*Q2*
World of Warcraft					-.144*					.135*																		.138*		
Minecraft											.128*					.132*														
Dirt [series]										.186**	.123*						.116*												-.149**	
Portal [series]				.115*		.119*		.255**																	.124*	.181**	.121*			
Angry Birds	.132*			.134*									.120*		.157**	.161**								.114*						
Tetris													.125*	.153**									.118*							
Xbox Fitness							.115*																		.135*					
Street Fighter [series]	.118*																			-.135*										.112*
Just Dance [series]			.114*									.114*	.122*	.170**		.145*					.134*	.126*	.151**	.135*				.147**	.183**	

Dance Central Spotlight [series]										.135*		.117*	.117*																	
Dance Dance Revolution [series]														.144*			.142*			.112*				.134*						
Fantasia: Music Evolved							.132*			.132*							.114*													
Guitar Hero [series]																	.158**		.178**											
Audiosurf																										.165**	.115*			
Rock Band				.115*															.135*						.130*	.154**	.124*	.126*		
SingStar [series]			.125*						.128*								.132*			.128*	.163**			.125*						
Bit.Trip Runner																			.128*											
The Typing of the Dead [series]																-.138*				.161**										
Wordament						-.134*		-.115*																			-.122*			
Scribblenauts [series]																										.137*				
Wordfeud																														-.112*
Ace Attorney [series]									-.151**				-.125*	-.118*		-.123*														
The Room			.140*							.150**																				

[series]																														
2048		-.115*			.158**					.113*																		-.133*		
Braid	.150**					.113*	.135*	.156**																.122*					.114*	
Where's My Water?													.183**	.162**		.195**	.152**						.130*	.125*						
L.A. Noire												.135*					.131*	.113*	.120*											
Heavy Rain	.128*	.170**			-.128*																					.145*		.160**		
The Sims [series]		.127*			-.125*	-.154**	-.183**					.150**																		
DayZ											.138*				.123*									.114*						
Second Life									.126*	.162**															.117*	.127*	.133*	.162**		
Farmville [series]																						.172**				.121*		.165**		
The Walking Dead		.165**		.113*																						.115*	.130*	.149**		
Fable [series]								.147**			.112*															.118*				
Black & White [series]			.249**							.165**											.118*									
Infamous [series]																-.142*														
Mass Effect [series]																-.133*											.113*			
Fallout	.155**		.120*	.131*		.122*		.197**				.114*									.128*									

[series]																														
Endless Ocean				-.163**	-.113*	-.126*									-.127*									-.116*						
Spore										.260**	.129*								.116*									.114*		
Flower			.139*																							.143*		.116*		
Afrika							.129*			.147**																				

E: Game Experience Questionnaire (GEQ) modules

Core Module:

Please indicate how you felt while playing the game for each of the items, on the following scale:

not at all	slightly	moderately	fairly	extremely
0	1	2	3	4
< >	< >	< >	< >	< >

1	I felt content	
2	I felt skilful	
3	I was interested in the game's story	
4	I thought it was fun	
5	I was fully occupied with the game	
6	I felt happy	
7	It gave me a bad mood	
8	I thought about other things	
9	I found it tiresome	
10	I felt competent	
11	I thought it was hard	
12	It was aesthetically pleasing	
13	I forgot everything around me	
14	I felt good	
15	I was good at it	
16	I felt bored	
17	I felt successful	

18	I felt imaginative	
19	I felt that I could explore things	
20	I enjoyed it	
21	I was fast at reaching the game's targets	
22	I felt annoyed	
23	I felt pressured	
24	I felt irritable	
25	I lost track of time	
26	I felt challenged	
27	I found it impressive	
28	I was deeply concentrated in the game	
29	I felt frustrated	
30	It felt like a rich experience	
31	I lost connection with the outside world	
32	I felt time pressure	
33	I had to put a lot of effort into it	

In-game Module:

Please indicate how you felt while playing the game for each of the items, on the following scale:

not at all	slightly	moderately	fairly	extremely
0	1	2	3	4
< >	< >	< >	< >	< >

1	I was interested in the game's story		GEQ Core – 3

2	I felt successful		GEQ Core – 17
3	I felt bored		GEQ Core – 16
4	I found it impressive		GEQ Core – 27
5	I forgot everything around me		GEQ Core – 13
6	I felt frustrated		GEQ Core – 29
7	I found it tiresome		GEQ Core – 9
8	I felt irritable		GEQ Core – 24
9	I felt skilful		GEQ Core – 2
10	I felt completely absorbed		GEQ Core – 5
11	I felt content		GEQ Core – 1
12	I felt challenged		GEQ Core – 26
13	I had to put a lot of effort into it		GEQ Core – 33
14	I felt good		GEQ Core – 14

Social presence Module:

Please indicate how you felt while playing the game for each of the items, on the following scale:

not at all	slightly	moderately	fairly	extremely
0	1	2	3	4
< >	< >	< >	< >	< >

1	I empathized with the other(s)	
2	My actions depended on the other(s) actions	
3	The other's actions were dependent on my actions	
4	I felt connected to the other(s)	

5	The other(s) paid close attention to me	
6	I paid close attention to the other(s)	
7	I felt jealous about the other(s)	
8	I found it enjoyable to be with the other(s)	
9	When I was happy, the other(s) was(were) happy	
10	When the other(s) was(were) happy, I was happy	
11	I influenced the mood of the other(s)	
12	I was influenced by the other(s) moods	
13	I admired the other(s)	
14	What the other(s) did affected what I did	
15	What I did affected what the other(s) did	
16	I felt revengeful	
17	I felt schadenfreude (malicious delight)	

Post-game Module:

Please indicate how you felt while playing the game for each of the items, on the following scale:

not at all	slightly	moderately	fairly	extremely
0	1	2	3	4
< >	< >	< >	< >	< >

1	I felt revived	
2	I felt bad	
3	I found it hard to get back to reality	
4	I felt guilty	
5	It felt like a victory	

6	I found it a waste of time	
7	I felt energized	
8	I felt satisfied	
9	I felt disoriented	
10	I felt exhausted	
11	I felt that I could have done more useful things	
12	I felt powerful	
13	I felt weary	
14	I felt regret	
15	I felt ashamed	
16	I felt proud	
17	I had a sense that I had returned from a journey	

F: Adapted version of the McKenzie questionnaire

K means Kinesthetic and **V** Visual.

I enjoy making things with my hands (K 1.1)	Strongly agree — Agree — I don't know — Disagree — Strongly disagree
I can imagine ideas in my mind (V 1.1)	Strongly agree — Agree — I don't know — Disagree — Strongly disagree
I enjoy sports or games that involve plenty of physical activity (K 1.3)	Strongly agree — Agree — I don't know — Disagree — Strongly disagree
I find it difficult to sit still for long periods of time (K 1.2)	Strongly agree — Agree — I don't know — Disagree — Strongly disagree
I remember well using visual cues (V 1.4)	Strongly agree — Agree — I don't know — Disagree — Strongly disagree
I enjoy creating things using visual media, such as drawings, pictures, videos, … (V 1.3)	Strongly agree — Agree — I don't know — Disagree — Strongly disagree
I think that I learn best by doing (K 1.10)	Strongly agree — Agree — I don't know — Disagree — Strongly disagree
I enjoy rearranging a room (V 1.2)	Strongly agree — Agree — I don't know — Disagree — Strongly disagree
I like working with physical tools (K 1.8)	Strongly agree — Agree — I don't know — Disagree — Strongly disagree
I enjoy engaging in handicrafts as a pastime activity (K 1.6)	Strongly agree — Agree — I don't know — Disagree — Strongly disagree

I prefer music videos rather than plain music (V 1.7)	Strongly agree / Agree / I don't know / Disagree / Strongly disagree
I am good at reading maps and blueprints (V 1.9)	Strongly agree / Agree / I don't know / Disagree / Strongly disagree
I like interacting with 3d multimedia content (V 1.6)	Strongly agree / Agree / I don't know / Disagree / Strongly disagree
I like activities in which I have to be actively engaged (K 1.9)	Strongly agree / Agree / I don't know / Disagree / Strongly disagree
I think that I learn best by making/using maps, charts, graphs and tables (V 1.5)	Strongly agree / Agree / I don't know / Disagree / Strongly disagree
I often recall things in mental pictures (V 1.8)	Strongly agree / Agree / I don't know / Disagree / Strongly disagree
I value non-verbal communication such as gestures (K 1.4)	Strongly agree / Agree / I don't know / Disagree / Strongly disagree
I enjoy expressing myself through movement or dance (K 1.7)	Strongly agree / Agree / I don't know / Disagree / Strongly disagree
I enjoy communicating information through drawing (V 1.10)	Strongly agree / Agree / I don't know / Disagree / Strongly disagree

Questionnaire for assessing the enjoyment of the different interaction modalities.

Sifteo Cubes	
I enjoyed constructing paths by manipulating the cubes	Strongly agree — Agree — I don't know — Disagree — Strongly disagree
I barely noticed the passing of time when I was using the cubes	Strongly agree — Agree — I don't know — Disagree — Strongly disagree
I enjoyed shaking, rotating and joining cubes	Strongly agree — Agree — I don't know — Disagree — Strongly disagree
I liked how cubes allowed me to communicate information about the game to my team mate	Strongly agree — Agree — I don't know — Disagree — Strongly disagree
I enjoyed playing Maze Commander using the cubes	Strongly agree — Agree — I don't know — Disagree — Strongly disagree
I enjoyed interacting with a game through physical manipulation	Strongly agree — Agree — I don't know — Disagree — Strongly disagree
I like working with the cubes	Strongly agree — Agree — I don't know — Disagree — Strongly disagree
Playing the game with the cubes made me feel actively engaged with the game	Strongly agree — Agree — I don't know — Disagree — Strongly disagree
I found it easier to understand the working of the maze commander game after using the cubes than after using the Oculus Rift	Strongly agree — Agree — I don't know — Disagree — Strongly disagree
Oculus Rift	
I could easily visualize the route to escape in my mind	Strongly agree — Agree — I don't know — Disagree — Strongly disagree

I enjoyed visualizing many possible routes	Strongly agree / Agree / I don't know / Disagree / Strongly disagree
I enjoyed communicating the visual information I observed in the game	Strongly agree / Agree / I don't know / Disagree / Strongly disagree
I found it easy to remember the patterns and paths of enemies and traps	Strongly agree / Agree / I don't know / Disagree / Strongly disagree
I found it easier to understand the working of the maze commander game after using the Oculus Rift than after using the cubes	Strongly agree / Agree / I don't know / Disagree / Strongly disagree
I like the idea of being able to construct paths using the Oculus Rift too	Strongly agree / Agree / I don't know / Disagree / Strongly disagree
I enjoyed playing the three dimensional maze	Strongly agree / Agree / I don't know / Disagree / Strongly disagree
I preferred the rich visual animations of the Oculus version of maze commander rather than the low level graphics of the cubes	Strongly agree / Agree / I don't know / Disagree / Strongly disagree
I can still visualize the maze, enemies and hazards that I saw through the Oculus Rift	Strongly agree / Agree / I don't know / Disagree / Strongly disagree
I felt competent in discovering the enemys' patterns and finding the optimal route for the avatar using the oculus rift visualization of the maze	Strongly agree / Agree / I don't know / Disagree / Strongly disagree