Player Characteristics in Open Games for Learning

Doctoral Thesis

for the degree of a

Doctor of Informatics

At the Faculty of Economics,
Business Administration and
Information Technology
of the
University of ZURICH

by

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from

Glattfelden ZH

accepted on the recommendation of

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2009

Zurich, October 21, 2009

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2009

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

Plato

To Peter and Jacqueline, with love

Acknowledgments

First of all, I wish to thank my advisor, Professor Dr. Helmut Schauer, for supporting me throughout the course of this work. His novel inputs and his encouragement helped me get through several difficulties with the challenging research subject. Furthermore, I would like to thank Professor Dr. Kurt Squire for accepting to be my co-advisor, for his great interest in my work, for providing me many hints and leading me in a direction with a successful outcome.

A special thanks goes to Julian Ebert who never ran out of patience to answer my endless stream of questions regarding statistical analysis. Thank you also to Beatrice Hasler for advising me in planning the experiments and to Vania Guerra for her educational inputs. I also thank Tsuyoshi Ito for his great technical assistance and advice for my game Hortus. His critical questions prevented some disastrous outcomes during the game development and experiment phase.

Further thanks go to Philip Schaffner for programming the game Hortus, to Phil Fonberg for transforming my mother's sketches into beautiful graphics for Hortus, to Shree Durga for programming the entire test environment and the database queries, to Viviane Cantaluppi for the support of student recruiting, to Somala Mang for helping me with the think-aloud protocols and transcribing the interviews, and to Brigitte Rohrbach for reviewing my text. I immensely appreciated the fellowship and the support of the entire Educational Engineering Lab at the University of Zurich in Switzerland and the Games, Learning, and Society Group at the University of Wisconsin-Madison in the United States.

I am deeply grateful for the support by my parents and my sister.

However, my deepest thanks and greatest appreciation are reserved for my husband Peter. Without him I would never have finished my dissertation on time. Thank you for taking care of Jacqueline, our newborn daughter at that time, while I was sweating over my data. Your knowledge, analytical inputs, technical and also emotional support helped me get through these four tough years.

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Abstract

This thesis analyzes player characteristics in so-called “open games for learning”. Open games are authentic and complex learning environments that provide multiple solution paths. In such environments, players solve problems according to their individual backgrounds, preferences, and strategies.
Based on studies of the players’ actions, their decision-making process, and their learning progress, the goal of this thesis is to derive considerations and recommendations for a future design of a new kind of open game for learning.
Few references can be found in literature that propose learner-centered game-design approaches with the specific intent to improve the individual learning experience.
Open games specifically designed to be used as games for learning offer many challenges. Different players may approach a game differently, i.e., they focus on different aspects during play time and thus experience different contents. This may lead to uneven learning outcomes, which is not intended by the educational designer. In order to fulfill both requirements of supporting player characteristics and of ensuring that the designers’ learning goals are reached, it is crucial to formulate an understanding of how different players behave in learning game environments. Questions are asked concerning the strategies a player uses to solve a certain problem, their preferences in playing the game and what players learned during the play.
In this thesis, an online game called “Hortus” was developed, specifically designed to investigate questions of this nature. Hortus is a strategy and simulation game about horticulture that teaches fundamental principles of biology. Players’ actions are recorded and analyzed in accordance with certain events and situations. A mixed method approach is applied. First, the majority of user data is collected implicitly through the online game. Player characteristics are derived from the statistical analysis of quantitative information. Second, qualitative methods such as think-aloud protocols are applied to reveal user information that cannot be collected implicitly.
The results have shown the importance of planning ahead during the game and of developing a strategy for reaching the goal. Players who had no clear strategy were overwhelmed by unexpected situations and ended up losing the game. Furthermore, the results indicated how the players’ strategies influenced their playing efficiency. Moreover, player characteristics such as cautiousness were not stable during the game, but were rather connected to certain events.
The results confirmed the concern that the players reached different levels of learning outcomes. Several players never did achieve the designers’ intended learning goals. Finally, the results led to two concepts for achieving even learning outcomes despite the variations in player characteristics. In the first approach, the game environment is adapted such that the player is indirectly guided towards the learning goal. The second approach proposes the introduction of an autopilot system that can assist the player in the decision-making process.
The future implementation of the recommended concepts will increase the accep-

tance of open games for learning. The implementation of these concepts will help to simplify and support the teaching of complex topics.

Zusammenfassung

In der vorliegenden Arbeit werden typische Spielerverhalten in so genannten “open games for learning” analysiert. Den Begriff “open games for learning” könnte man mit “Simulations- und Strategiespiele” übersetzen. Es handelt sich um authentische und komplexe Lernumgebungen, wobei zahlreiche sehr unterschiedliche Lösungswege zu einem Ziel führen können. Jeder Spieler kann je nach persönlicher Erfahrung und Vorlieben eine eigene Strategie wählen, um das gestellte Problem zu lösen.

Ziel der vorliegenden Arbeit war es, die Handlungen, die Entscheidungsprozesse sowie den Lernerfolg eines Spielers zu untersuchen und daraus Empfehlungen für Entwickler von zukünftigen Lernspielen abzuleiten.

In der Fachliteratur können nur begrenzt Hinweise gefunden werden, wie ein lernerorientiertes Spiel zu gestalten ist, um den Lernerfolg zu optimieren. Simulations- und Strategiespiele, welche speziell als Lehrmittel verwendet werden sollen, bieten neue Herausforderungen. Zum Beispiel können Schüler einen ganz unterschiedlichen Zugang zu Spielen haben. Sie können sich auf unterschiedliche Aspekte des Spiels konzentrieren, und sie können daher unterschiedliche Lernerlebnisse und Lerninhalte davon tragen. Letzteres führt dazu, dass der Lernerfolg von Schüler zu Schüler unterschiedlich ausfallen kann, was unter Umständen nicht im Sinne des Spielentwicklers oder des Lehrers ist.

Um den Zielkonflikt aufzulösen, einerseits das individuelle Verhalten des Spielers unangetastet zu lassen und gleichzeitig den gewünschten Lernstoff zu vermitteln, muss das Verhalten von Spielereigenschaften in Lernumgebungen besser verstanden werden. Antworten müssen gefunden werden auf Fragen wie “Welche Strategie wählt ein Spieler um ein konkretes Problem zu lösen?”, “Welche Eigenschaft ist wichtig für ihn?” oder “Was hat sie gelernt?”.

Ein wichtiger Aspekt der vorliegenden Arbeit war es deshalb, ein Onlinespiel zu entwickeln, um Fragen dieser Art beantworten zu können. Das Spiel mit dem Namen “Hortus” und bezeichnet ein Strategie- und Simulationsspiel über Gartenbau, wobei grundlegende Prinzipien der Biologie anhand eines Gartens vermittelt werden. Die Datenerfassung erfolgte anhand von quantitativen sowie qualitativen Verfahren. Einerseits wurden sämtliche Spieleraktionen während des Spielverlaufs laufend aufgezeichnet. Andererseits wurden mit Hilfe von “think aloud” Protokollen Informationen gesammelt, welche nicht implizit erfasst werden konnten. “Think aloud” ist eine qualitative Methode, bei der die Versuchspersonen während einer Aktivität ihre Gedanken aussprechen. Die Spielerverhalten in bestimmten Schlüsselsituationen wurden anschliessend quantitativ analysiert, indem statistische Verfahren auf die grosse Menge von Messdaten angewendet wurden.

Anhand der gewonnenen Resultate konnte bestätigt werden, wie wichtig es ist, dass ein Spieler voraus plant, um das Ziel zu erreichen. Spieler, welche keine klare Strategie hatten, scheiterten häufiger, nachdem sie von unerwarteten Situationen überrascht wurden. Zudem weisen die Resultate daraufhin, dass effizienter spielt, wer eine Strategie hat. Des Weiteren konnte gezeigt werden, dass sich Persönlichkeitseigenschaften wie “vorsichtig” eher mit Schlüsselereignissen verbin-

den lassen, als dass sie konstant während des gesamten Spiels beobachtet werden können.
Die Ergebnisse bestätigen die Erwartungen, dass verschiedene Spieler unterschiedliche Lernerfolge hatten. Eine Anzahl Spieler haben die vom Spielentwickler vorgesehenen Ziele nicht erreicht, obwohl sie das Spiel erfolgreich beenden konnten. Aus diesen Resultaten wurden zwei Konzepte abgeleitet, welche trotz individuellen Spielerpräferenzen und unterschiedlichem Spielverhalten vergleichbare Lernerfolge garantieren sollen. Im ersten Konzept wird die Spielumgebung so angepasst, dass der Spieler indirekt zum gewünschten Lernziel geführt wird. Im zweiten Ansatz wird ein Autopilot-System beschrieben, welches den Spieler in Entscheidungsprozessen unterstützt.
Abschliessend bleibt zu hoffen, dass die zukünftige Implementierung der in dieser Arbeit präsentierten Konzepte die Akzeptanz von "Open Games" erhöhen und dass diese mithelfen können, komplexe Lerninhalte zu vermitteln.

Chapter 1

Introduction

Educators face new challenges in designing original games for learning for a broad audience. Much attention has focused on adventure games and storytelling (Burgos et al., 2008; Kickmeier-Rust et al., 2008) or role-playing games where players take over roles of professional identities (Shaffer, 2006). Unfortunately, little is known yet about so-called open games (Squire, 2008) and their design in an educational context. These kinds of games offer a lot of freedom of choice for learners. Therefore, it is difficult to provide learning with anything like a guarantee of learning success for each learner. Each individual has a personal learning experience depending on the choices made in the game.

In order to enhance a successful learning outcome, and most of all to reach the designer's intended learning objectives, it is crucial to know how players behave in such an open environment, how they make decisions, and what motivation lies behind their choices.

In this introductory part of the thesis, the motivation of doing research on player characteristics in open games is explained. Characteristics in this educational context consider *how* players act, think and make decisions in a learning environment. Furthermore, main research goals of this study are described, and the structure of this thesis is explained.

1.1 Motivation

Many educators and researchers agree that games are motivating and provide deep learning. Through play, people dare to take risks, explore possibilities, and even test boundaries (Resnick, 2007). It is within this kind of activity where long lasting and inner motivation, called intrinsic motivation, can evolve. If people are not enjoying learning, they will only learn the minimum required to accomplish goals. Today's learners face a world of globalization and international competition. Innovation and creativity have become essential abilities, in order to be successful (Friedman, 2005; Resnick, 2007; Shaffer, 2006).

Although skepticism towards digital games as a learning instrument is slowly fading, the utilization of games for learning is still a young research field. Especially in the area of original games for learning, little is known of how to design these games and how to assess learning. Original means to design games specifically for educational purposes. There are several reasons why games for learning are so challenging to realize. Commercial games are designed for a specific target audience: gamers. Learning environments have to be designed for a much wider audience. The "learner group" consists of various kinds of people such as hardcore and casual gamers, as well as non-gamers. If a learning environment resembles a famous commercial game too closely, gamers might reject it because of its likeness to the original. On the other hand, for non-gamers, it might be difficult to understand the concept of learning through a game; goals in the game must make sense.

Adventure games and role-playing games are the most common genre found in the research of games for learning. They are used for subject-specific learning. Social skills as a learning content is often found in role-playing games as well (Shaffer, 2006). Open games, such as educational versions of *Sim City*, an urban planning game, or *Civilization*, a game about world history, are very rare. A reason might be that these kinds of games are very complex and take more time and costs to develop than adventure games, for instance. For adventure games, there exist already game editors, where educational designers are able to create their own games without having any advanced technical knowledge (Burgos et al., 2008). Stories in adventure games are very engaging and might encourage players to explore and learn. However, in current design of adventure games for education, there are only restricted choices for players (Peirce et al., 2008; Burgos et al., 2008). It is the *educational designer* who is in control of the story progress, not the player. Adventure games or story-based games belong to a game group called linear or guided games (Squire, 2008). They are also called "games on rails" because players are guided through a story. Educational designers have more control over the learning outcome if everybody's experiences are similar. This is most likely the reason why so many educational games are linear. However, their application is more suitable for learning contents that are not very complex. A deep learning experience requires a certain degree of interaction between the learning system and the learners (Mandl and Krause, 2001; Meier and Seufert, 2003). Open games provide deep conceptual learning because the interaction for players is high (Squire, 2008). They are more suitable for complex learning contents.

In open games, it is the *players* who are more in control over their "story" and their choices. They decide where to go and what to choose. Every experience is individual. This kind of control is very engaging and motivating.

However, there seems to be a trade-off between the level of player control and learning objectives. This conflict may be resolved by adapting the game to the player characteristics. The goal of this adaptation is to provide the freedom of choices players have in open games, while leading them towards learning goals desired by educational designers. Hence, adaptation is a means for the educational designer to guide players towards a certain learning goal while players still have control over their story.

There has not been a lot of research in the fields of adaptation and open games for learning. Adaptive technologies and player profiles were mainly reported in commercial games for entertainment, such as real-time strategy games (Charles et al., 2005; Bateman and Boon, 2005; Hunicke and Chapman, 2004). Known profiles for players in this area are "rushers" and "turtlers" (Burke, 2009). Rushers prefer a fast game pace while turtlers prefer to create and build things. Profiles describing player characteristics such as "rushers" or "turtlers" have not been mentioned in formal research as yet; rather, they have appeared in informal game developer articles. Adaptive technologies in games research are mainly integrated into players' obstacles or artificial characters (Spronck et al., 2006). They mostly impact the level of difficulty in the game (Hunicke and Chapman, 2004).

Theories of player characteristics with a special focus on open games in an educational context are not known to the author. This study initiates a first step in the direction of analyzing player characteristics for learning in open games. The adaptation of the game system for open games will be introduced according to these player characteristics.
Since there was no such game available nor was there any literature to be found as a basis for this study, a prototype was developed specifically for this research. The game *Hortus* is a strategy and simulation game that teaches certain basics of biology. The goal is for the learners to understand plant characteristics and the dynamics in a garden system which they have to create themselves. With the support of this prototype, the following questions are to be answered:

- What do players learn in open games?
- What strategies do they use for reaching the goal?
- How do players make decisions in these kinds of environments?
- What is important to them?

These questions are necessary as a start to analyze player characteristics. The answers lead to concepts of how to support different players and their needs in open games for learning.

1.2 Contributions

The contributions in this study are due in part to empirical findings and in part to ne concepts. This thesis makes the following original contributions to the area of player characteristics in open games for learning:

- **Development of a prototype, specifically designed to analyze player characteristics and learning outcomes.**
  The design and realization of the prototype *Hortus* was an important precondition of this work. The idea for this game was initiated by the author. Since the content of *Hortus* serves as metaphor for real-life garden systems, a

model had to be developed that simulates a horticultural habitat. In order to analyze player characteristics, a database was designed to store every action a player takes in the game.

- **Series of Experiments with a mixed method approach.**
  In order to maximize the output information provided by players of *Hortus*, think-aloud experiments were conducted to identify certain strategies that cannot be found by analyzing user actions only. The combination of extensive think-aloud tests with online experiments is quite new in this field of research. Earlier, qualitative or quantitative studies were conducted but not combined. For a specific player characteristics, an online version of a psychological test (MFF20 - (**?**)) had to be developed and evaluated in collaboration with the School of Psychology, Ulster, UK. This test turned into a "product" used worldwide by various researchers in the field of psychology.

- **Results of experiments lead to findings for the design of open games for learning.**
  Results of the series of experiments revealed three major findings. Many players did not experience all important events necessary for learning goals because of distinct player characteristics and not because of the openness of the game. Planning and developing a strategy turned out to be vital for winning the game. Players who just rushed through the game without a strategy were overwhelmed by unexpected situations and lost the game. Finally, most characteristics, assessed in *Hortus* turned out to be highly situated and could not be categorized as stable over time.

- **Concepts for adaptive open games for learning are derived from the findings.**
  Based on these findings, concepts for an adaptive open game for learning were developed. There are two main approaches which support players in their strategies and their style. The first concept adapts the game environment if learning goals are not reached. The second adaptive feature provides players with dynamic and strategic feedback.

1.3 Structure of this Thesis

As a guideline to the reader, the structure of this thesis is briefly outlined. Figure 1.1 shows the main concept of this thesis.

The thesis consists of five main parts. Chapter 2 introduces fundamental principles regarding the field of open games for learning and player characteristics. Since the research field is still quite young, related work is discussed, and theoretical principles about learning and individual differences in learning are described. The central part of Chapter 2 is the learner attribute model. The model consists of the most important characteristics for learners with focus on open games for learning. This chapter ends with the introduction of an adaptive system for the field of open

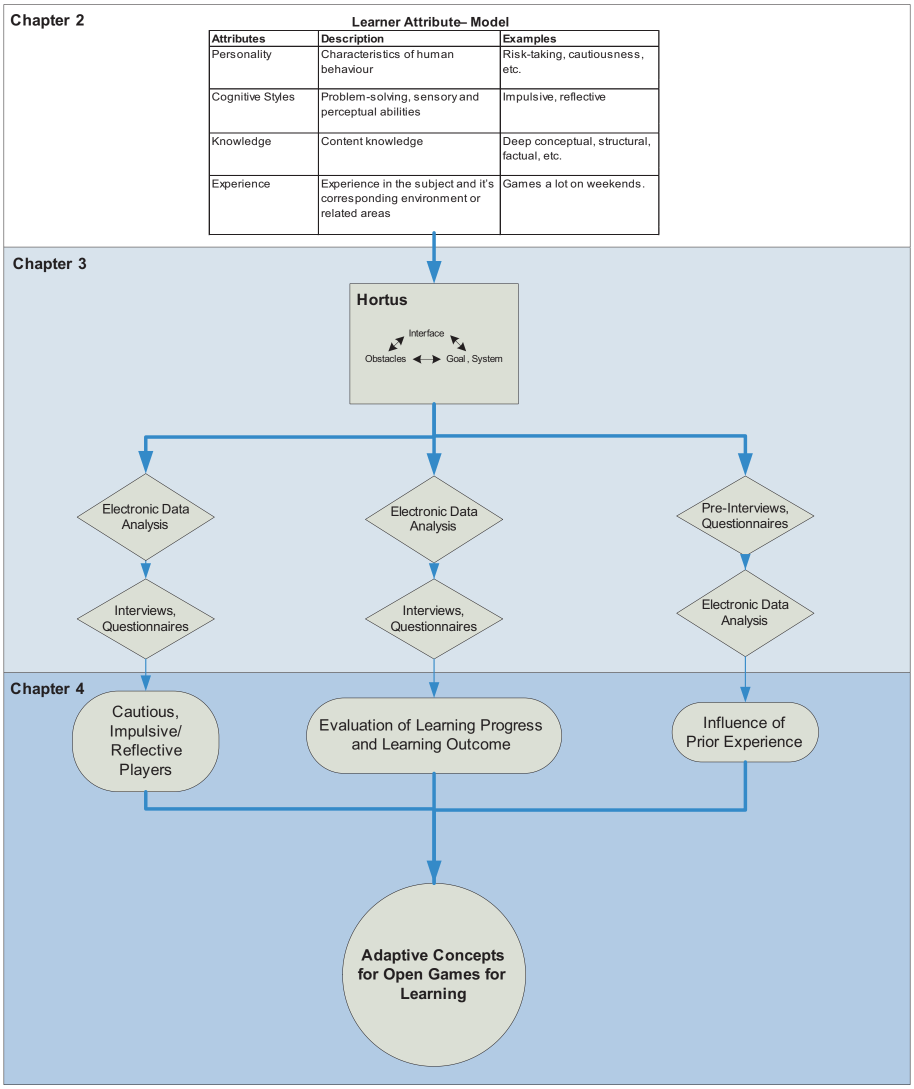


Figure 1.1: Structure of this thesis. (Explanation of forms: Rectangle=Treatment; Rhombuses=Research Methods; Round Rectangles=Results; Circle= Solution)

games and learning.

Chapter 3 describes the game *Hortus* and the methodological approach. The structure of *Hortus* is illustrated, and specific design decisions are discussed.
The mixed-method approach consists of a qualitative part containing think-aloud experiments and interviews, and a quantitative part containing online experiments with psychological tests and questionnaires. There were 163 players for the online experiment who completed the game successfully. Forty of these players also took part in the think aloud tests. Another 30 players lost the game because they ran out of resources.

In Chapter 4, the results of these tests are discussed. The findings are categorized according to the learner attribute model. In Fig. 1.1, those categories are displayed where the most important findings were found. As a major result of these findings, two concepts are introduced for the introduction of adaptations in open games for learning. The findings in the game *Hortus* showed that certain kinds of players need support while playing. Otherwise they lose the game or will not reach the intended learning goals.

Chapter 5 summarizes the key findings of this empirical study and points out specific limitations and problems that were encountered during this research. Since this thesis represents an initial step into a new research direction, future research is outlined. The thesis ends with some final remarks and the conclusions that can be drawn.

Chapter 2

Background

This chapter describes research fields related to open games for learning and player characteristics. Games for learning in general and open games in particular are introduced. There are many learning theories and principles integrated in games for learning purposes. In this study, only the most important principles concerning open games are explained. The origins of player characteristics are found in the research area of individual differences (Jonassen and Grabowski, 1993). Furthermore, various adaptive approaches are introduced. This chapter concludes with a learner attribute model that integrates the most relevant characteristics for players in the field of open games for learning.

2.1 Games for Learning

Since games can be seen as a form of simulation, a general definition for games for learning will be used that includes simulations. According to Shaffer (2006),

> ”Children are running simulations of worlds they want to learn about in order to understand the rules, roles, and consequences of those worlds.”

Every kind of play consists of a set of rules. This is true even for open-ended games that have no specific goals. Rules can be defined by game designers, or they can be expanded and changed by players as evolutionary games do (Spring-Keller and Ito, 2007). By playing according to some set of rules, players take over a certain role. Commercial games like *Sim City*, where players take over the role of a mayor, consist of a vast number of rules. *World of Warcraft* [1] is so complex that even after 50 hours of play time, the player does not fully know all the rules and stories in the game.

Learning in games is embedded in the game. This means that the better players understand the rules and can identify with their roles, the better they master the game and thus the intended learning content.

In order to provide an overview and to indicate the place of open games within the spectrum of games for learning , Table 2.1 shows a framework of games for learning.

[1] World of Warcraft is a massive multiplayer online game (MMOG), where thousands of people play in a virtual world and chat or resolve quests together.

This table does not represent typical categories such as action or role-playing games. It shows a framework of games for learning and how they can be interpreted. Each category might even require different learning approaches (Squire, 2008).

Table 2.1: This framework supports the analysis of games for learning (based on Squire (2008)

Game Genre	Typical Time to Completion	Replayability	Open-Endedness	Examples
Targeted games (puzzles, mini-games)	1-4 hours	sometimes	rarely	Mathblaster
Linear games	8-40 hours	rarely	rarely	Myst, Physicus
Open, sandbox games	40-1000 hours	extensive	yes	Civilization, Sim City
Persistent worlds	several 1000 hours	yes	yes	World of Warcraft, Quest of Atlantis

Targeted and linear games provide specific goals and clear paths for problem-solving. Examples of linear games would be adventure games where the user has to select from numerous options in order to progress in the narrative story. Games in this category are designed for a specific learning content. After playing the game, every player knows the same learning content. The definition of open games is quite versatile. Hence, not all games that fall into this category have open endings. Instead they provide an open environment where learners are loosely guided and can choose among multiple pathways. There are a variety of goals that have to be reached in order to win the game. Since the game represents an open world, every player plays a different kind of game. This means that the *players* choose what to play. In *Civilization*, players might be interested in developing cities and enhance cultural aspects, while others are more interested in building ships and explore more worlds. The fun is not only in playing the game but also in being a creator of new worlds and civilizations. Players are intrinsically motivated and learning happens along the way. In the end, every player knows a different learning content.
Persistent worlds are virtual worlds like *Second Life* where users move around in artificial worlds, chat, and communicate with each other, and solve different kinds of problems. Learning content is hardly controlled in these worlds. Tasks are rather of a collaborative nature.
In the next chapters, the theories and approaches are presented that are relevant to open games.

2.2 Learning in Open Games

Although several researchers and educators agree that games can actually teach something useful, there are still numerous skeptics who believe that games are fun, but neither efficient nor effective compared to other digital learning methods (Clark, 2007, 1983; Mayer, 2007). Rieber (1996) identifies this misconception as follows:

> "When one believes that what the learner needs to know has already been identified, the obvious course of action is to teach the learner this content as effectively and efficiently as possible. Play may be tolerated or even encouraged for short periods of time, perhaps in the belief that it will act as a 'motivating strategy'. However, play can quickly be viewed as a threat to instructional design efforts when it leads to learning sequences or learning outcomes other than those already determined or anticipated by the designer."

The debate of control and freedom of choices in open games is further discussed in Egenfeldt-Nielsen (2006). Players like to be in control of the game. However, if there is no educational guidance at all, some players feel lost and criticize the lack of learning. The balance between self-directed learning, learning from failure, maintaining control, and guidance or support is very difficult to keep. Guidance could quickly turn into patronizing, and learning from failure could lead to frustration.
A solution to this debate is to communicate educational goals to players. Players have to be aware of the educational context.
Aside from these conflicts, learning through games in general provides a deep and long lasting experience (Gee, 2005; Squire, 2008; Prensky, 2001). In particular, Gee (2003, 2005) analyzed existing commercial games and derived theories about learning. He found out that even though games for entertainment are very hard to learn, people love to play them for hours. He analyzed the learning found in those games and applied the findings to general learning principles for educational games. According to Gee (2005), game-like learning provides deep conceptual knowledge obtained in a situated way. Feedback is seen as instructions given "just in time" or "on demand". Mostly, learners take over a role in the game with which they can identify. Knowledge is distributed among learners, objects, or characters in the game. In *Sim City*, for instance, several advisors can be called upon for transportation or financial issues that support learners in their decisions.

Video games provide situations and opportunities where players have the chance to practice their recently learned skills. Other than in drill and practice games, these situations are embedded into the story of the game. Suddenly, practicing skills until they become a routine is not boring anymore, but rather meaningful in a situated context. For instance, in *World of Warcraft*, players learn different combat skills that they practice along their quests. By the time players reach Level 30, they have to master a variety of complex combat skills that include combinational usage of different weapons at the right time. Before a new skill can be achieved, players have to practice extensively and earn experience points in order to obtain the new skill. Gee defines this as *practice principle*. Players achieve a master level in certain skills. The new skills have to be learned or combined with

old ones in the next challenge. This is in no difference than, for instance, learning certain laws of physics on simple problems. If the problems are solved and the laws are understood, new situations are added. Learned skills serve as a base for the new challenges.
In order to progress in a game, players need to reflect on their actions. Gee (2003) describes this reflection in action as a *probing cycle* (Fig. 2.1). Players probe the

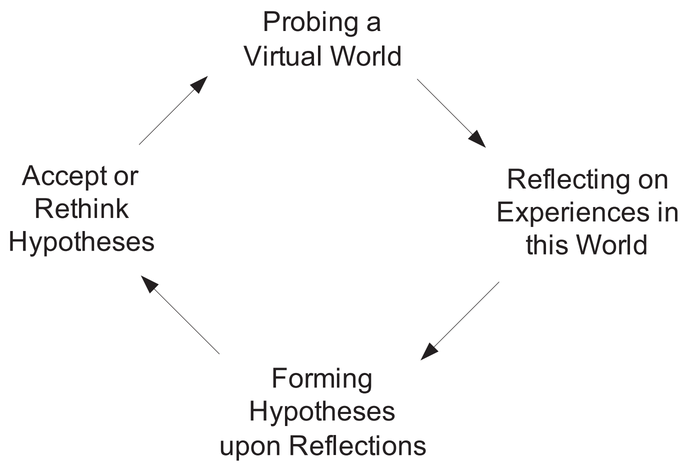


Figure 2.1: Four stages in Gee's probing cycle.

virtual world in the game. According to the players' actions, the game gives a feedback. They consider this feedback and form theories upon their reflections. After repeating these actions, they accept or have to correct their hypotheses. For instance, in Civilization, players can introduce certain aspects to their civilization which enhances their position within other civilizations. At a certain point in the game, religion can be introduced, for instance. This has a major impact on the entire civilization. Citizens are more peaceful, and the political power increases as well. According to these events, players reflect on their choice of integrating religion into their society. The consequence is that religion seems to be very important for a society (hypothesis). The player accepts this hypothesis since the political position of his or her country has increased.
This probing cycle is vital for learning. If a game does not encourage this cycle, players might not learn from the game (Gee, 2003). This is especially important in open games where there is hardly any guidance. Although this cycle should be true for every learning environment, in open games everyone acts differently. There might be players that do not reflect as much as others and still reach the end of the game, or they lose and are frustrated. How are these players supported? The "learner group" varies much more than players of commercial games. Games for entertainment only attract a specific group of people, while games for learning need to deal with a wide variety of people. Thus not everyone is motivated enough to think about their actions and to try to improve.
The next section will take a closer look at individual preferences and styles in learning.

2.3 Individual Differences

How to guide someone in games for learning differs from one individual to another. Every person has a different approach to retrieving and processing information. Everyone has a different attitude towards learning. Some players would rather try things out first and gain their understanding of a system's underlying rules through experimenting, while others first want to know something about the theoretical background before delving in. Time, for instance, is perceived differently by each person, and the amount of time required to learn something varies among people.

Opinions in literature of research in the field of individual differences and their influence on learning are very controversial (Coffield et al., 2004). In educational psychology several studies have dealt with learning types and styles and their impact on learning outcomes (Coffield et al., 2004; Juvina and van Oostendorp, 2006; McNutt and Brennan, 2005; Sadler-Smith, 1996). Empirical verification of the relevance of such learner types has been rare (Helmke and Weinert, 1997). In learning sciences, theories of specific learner types are more or less established, although they remain controversial. The most popular approaches have been described by Kolb and Fry (1975) and Keirsey and Bates (1984). Kolb's learner types are based on the constructivist learning theory, while Keirsey's temperament sorter refers to the *Myers-Briggs* personality types (Briggs and Meyers, 1987). However, the *Myers-Briggs* approach never had enough significant evidence on learning (Coffield et al., 2004) and Kolb's learning style could not be proved for digital learning environments (Coffield et al., 2004; Richmond and Cummings, 2005).

Motivation and challenge in a game also can be improved by adapting the game to the appropriate player type. The problems of player modeling are that a player type must be specific enough to allow different play styles, yet general enough to be applied to different game genres (Charles et al., 2005). Bateman and Boon (2005) propose four player types based on the typology by Myers and McCaulley (1985). This typology concentrates on player types for specific game genres, but it can also be adapted to play styles. The most popular player typology was found by Bartle (2006) and is focused on multiplayer online role-playing games. Bartle's typology consists of four player types where two focus on social aspects and two on the game itself. However, since this thesis focuses on single player games, this typology will not be taken into account.

Literature on individual differences in games for learning is still very limited. A study by Heeter and Winn (2008) showed different player types in a game for learning. The focus was on gender differences in particular. They found four player types, namely competitive, engaged, careless, and lost. Competitive players are those who play quickly and achieve a high score. Engaged players are those who spend a lot of time exploring the environment and also achieve a high score. Players are categorized as careless if they make many mistakes, but are very quick in playing through the game. Finally, the so-called lost players are those who play slowly and make many mistakes. Players were randomly assigned to a game version favoring either speedy play, exploration, or neither of the them (neutral). If a game version

favored speedy play, players received extra bonus points when they were fast. The study showed that boys were more competitive than girls. Girls were generally slower and made more mistakes. Heeter and Winn conclude that reward systems in educational games have to be selected carefully. While exploration should be rewarded, this is not necessarily true for speed.
Since players were assigned to different game versions, it would be interesting to see what their natural preferences and choices would have been. Scoring systems might influence players to a certain degree. Instead of focusing on their personal preferences, players might only focus on scoring well. Although it seems logical that speed is not necessarily good for learning, in many decision-making situations time is indeed very important. Thus, the generalization of not rewarding speed has to be treated very carefully.
The prototype used for this study has only a neutral scoring system, which is displayed at the end of the game. This should encourage the players to focus on their personal preferences.
There are two methods to analyze a player's profile: Explicit methods are based on questionnaires or question-based tests, whereas implicit methods are "in-game" assessments which analyze players while they are playing the game (without interrupting the game).
With explicit methods players either have to fill out a questionnaire before starting or during the game. Only information about the players' preferred player characteristics and about how they see themselves is gathered. Questions of classic learner-type questionnaires such as those described by Kolb and Fry (1975) or Gregorc (1985) are mostly very general and do not analyze learner characteristics in specific situations.
Implicit methods have the advantage that the user is not aware of the data gathering process. It is possible to gather information of players during the game and to adapt the system according to their actions and decisions. Another advantage is that the players' real behavior in a specific context can be analyzed, rather than being obtained in a general questionnaire.

2.4 Adaptation in Games for Learning

Adaptation in this context is defined as adjustments made by the system to the players' characteristics. In personalized systems, it is the player who actively manipulates the learning environment by choosing, for instance, personal learning goals. Adaptation, as opposed to personalization, is controlled by the system to improve a user's learning progress, engage the user's motivation, and react to the user's mental state.
A lot of literature is available about adaptation in digital learning environments as well as on games for entertainment. Research in adaptation and games for learning is still young.
The most common adaptive e-learning models are introduced in Burgos et al. (2006) and Moedritscher et al. (2004). Those approaches are:

- *Macro Adaptation:*
  This kind of adaptation adjusts rather general learning features according to a certain learner model. For instance, content presentation or learning goals are adjusted according to the learner's preferences and skill level.

- *Micro Adaptation:*
  This approach adjusts specific learning features on a micro level of the learning environment. This kind of adaptation is compared to one-on-one tutoring (Moedritscher et al., 2004). For micro adaptation, two steps of adjustment are involved. First, the learner's behavior is analyzed and evaluated with quantitative methods. Second, instructions are initiated according to the results of this analysis. Response sensitivity plays an important role with this adjustment. This occurs through response times, click frequency, eye movements, etc.

- *Aptitude-Treatment Interaction (ATI):*
  This approach adjusts instructions according to learner characteristics. The system proposes different types of instructions for different learner characteristics. They generally have three types of freedom in controlling learners. For low-prior-knowledge learners, control is very limited, while for learners with a higher prior knowledge, there is much more freedom in controlling tasks and learning pace.

- *Constructivist-Collaborative Approach:*
  This model focuses on constructivist learning methods where the learner is actively involved in the learning process. This model is implemented in systems with virtual coaches or with learning companions, respectively (Kort et al. 2001).

Most successful systems use a combination of the above approaches. For instance, intelligent tutoring systems consider a mixture of Micro-Adaptation and Aptitude-Treatment Interaction (Moedritscher et al., 2004). Instructions are based on learners' characteristics, but the adjustment happens on a moment-to-moment basis.

In Burgos et al. (2006), further adaptive approaches introduced that are more related to the content of adaptation. Eight different kinds of adaptation in e-learning are described that range from adjusting the interface to content-based adaptation over to adaptive feedback.

Most literature about adaptation in games for learning is concentrated on story-based games or on adaptive storytelling that should enhance learning. Commonalities of diverse the literature in this field are the preservation of the flow experience and thus the flow of the storyline. For this preservation, several architectural models haven been developed that describe the interaction between the game and the adaptive controller (Burgos et al., 2008; Law and Rust-Kickmeier, 2008; Peirce et al., 2008; Spring-Keller and Ito, 2007). In most cases, the game and the controller are separated. The practical reason is to keep the adaptive controller

generic so that various instructional theories can be integrated without influencing the game structure. Further explanations about the most current architectural model can be found in Peirce et al. (2008).
Generally, controllers deal either with the adaptation of instructional feedback in the game (Law and Rust-Kickmeier, 2008; Peirce et al., 2008) or adaptation of scenarios according to a players skill level (Burgos et al., 2008).

However, there is a thin line between patronizing players with well-intentioned instructional feedback and guiding learners towards the intended learning goal by supporting a learner's personal path. Games already provide situated and meaningful feedback as center characteristics (Gee, 2003). The challenge is to integrate educationally valuable feedback so that the game play is not interrupted and while providing the illusion of freedom of choice.
As a suggestion, the adaptive controller should only contain rules of how to adjust the game system itself according to learner characteristics. This is very difficult in story-based games. The story should not be interrupted, yet it still needs to make sense despite adjustments being made in the game system. However, in open games, this problem is not as complicated as in story-driven games since there is usually only a loose story line. Therefore, open games are more convenient for this kind of adaptation. For instance, complexity could be increased or decreased. In *Sim City*, players have to handle multiple tasks in parallel. The regulation of traffic, for instance, is quite overwhelming for beginners. This feature could easily be introduced later in the game when players are more used to the environment of *Sim City.*
The next section introduces a model that serves as a guide for defining player characteristics for adaptive open games for learning.

2.5 Learner Attribute Model for Adaptive Open Games

According to findings in the literature cited in Section 2.3 and 2.4, a model for analyzing player characteristics in open games is defined. Adaptive concepts in this study are based on macro- and micro-adaptation and aptitude-treatment interaction approaches.
Since learning styles are so controversial and no style theory is really established in literature, the focus lies on single learner attributes. An important requirement for analyzing player characteristics is that attributes can be measured in-game according to players' actions, choices, or reactions. There are many attributes that describe only preferences. For instance, visualizers or verbalizers have preferences for how information should be displayed. Many attributes do not really fit into the setting of games because they were created for more traditional learning environments. Figure 2.2 illustrates all the attributes, chosen for the analysis of player characteristics. The selection of attributes is based on the theories by

Jonassen and Grabowski (1993).

Table 2.2: The learner attribute model modified for games based on Jonassen and Grabowski (1993).

Learner Attribute – Model

Attributes	Description	Examples
Personality	Characteristics of human behavior	Risk-taking, cautiousness
Cognitive Styles	Problem-solving, sensory, and perceptual abilities	Impulsive, reflective
Knowledge	Content knowledge	Conceptual, procedural
Experience	Experience in the subject and its corresponding environment or related areas	Gaming experience, gardening experience

2.5.1 Risk-Taking and Cautiousness

Risk-taking and cautiousness are based on personality traits. They are defined as a person's choice of high-payoff/low-probability (risk-taking) or low-payoff/high-probability (cautiousness) alternatives. In educational contexts, there are numerous situations with actual or just perceived risk. Making mistakes by learners is seen as a weakness to be eradicated. The punishment is a bad score. Thus, there are people who have a higher fear of failure than others. Low-risk-taking behavior is also connected to low self-esteem. Extreme cautiousness is connected to perfectionism. People who are too cautious are risking to miss opportunities for learning experiences and are not able to find creative solutions for a problem (Jonassen and Grabowski, 1993).

Failure takes on a different meaning in a playful learning environment. In a game like *World of Warcraft*, the word "failure" does not have such a bad connotation. If players fail in the game, the worst that could happen is the death of their character. But after resurrecting it, they can try again. Playful learning allows failure without hard punishment. This allows trying out different things and going to the limit of the system while remaining on the safe side without risking any real-world damage. However, not everyone plays games and is used to experiments in a safe environment. Some people might still be cautious in games because they do not want to lose the game or do not like to make mistakes. Thus, such a behavior might have a major impact on learning in games if players are too cautious.

One problem with measuring cautiousness is the generalization of tests. They usually assess all kinds of situations that have nothing to do with the actual treatment. Tests that were found by the author, were either low in reliability (e.g., Tension Risk Adventure Inventory by Keinan et al. (1984)) or were not freely accessible.

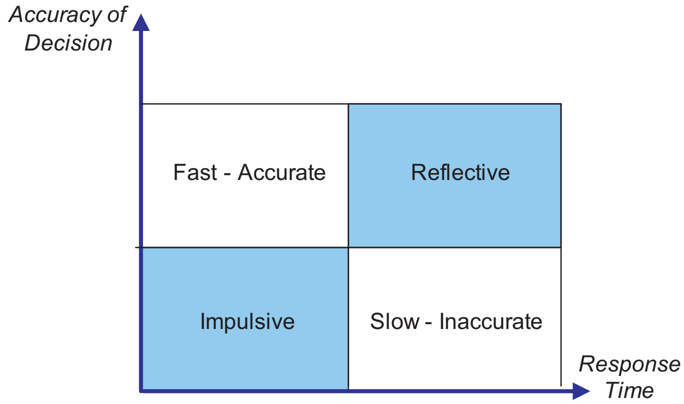


Figure 2.2: Four categories resulting from the MFF20 test.

Therefore, this attribute will be directly analyzed in the prototype of this study in specific situations or tasks.

2.5.2 Impulsive and Reflective Style

In problem-solving environments, there are a lot of situations where learners have to make decisions under great uncertainty. Some people tend to study all the possible solutions before they make a decision. If many tasks are to be dealt with under time constraints, such people would rather solve just a few problems than tackle all of them in order to avoid a high error rate. They are afraid of making mistakes and want to avoid them. Other people rush over the whole situation and choose the next best solution. They do not care as much for the optimal solution as the first group of people does. Their goal is to solve as many problems as possible in the given amount of time. If they are not all perfectly solved, it is not important to them. The first group of people belongs to the category of the reflective style. The latter group is defined as impulsive (Sternberg and Zhang, 2001; Jonassen and Grabowski, 1993).

In classic learning environments, impulsive learners are trained to re-think and change their behavior into a more reflective approach since the impulsive behavior is considered a weak behavior. Planning ahead and reflecting on actions thouroughly is not the preferable and efficient way from the point of view of an impulsive learner, nor is it always desirable in certain situations, for instance in making decisions under time pressure. Therefore this trait will be investigated in greater detail in the prototype of this study. Games tolerate "making mistakes". This crucial aspect is mostly not tolerated in classic learning environments.

The most popular measurement device for impulsive and reflective (I/R) behavior are the so-called Matching Familiar Figures Test (MFFT) by Kagan et al. (1964) and a revised and digitized version (MFF20) by Van Merrienboer and Jelsma (1988). Figure 2.2 illustrates the dimensions measured by the MFF20 test. The original MFFT had only 12 items and never showed sufficient reliability. The new computer-based MFF20 has 20 items and proved to be more reliable than the

paper-based original. The test requires people to select one from eight alternative pictures (adults) or six pictures (children), respectively, and to match it with the original picture. The time required by test persons for the first response is measured, and their mistakes are counted. There is only one correct solution for each 8-picture set.
There is a big discussion in literature whether this cognitive style is stable over time or not. In this research, impulsive and reflective are assumed to be stable over a certain amount of time. This has also been confirmed by several other studies (Sternberg and Zhang, 2001).
In this study, an online version of the MFF20 is used in order to find out if there is a correlation between results of this test and behavior during the game. The goal is to categorize playing patterns in the game as one of these four types. Recent studies have used the MFF20 or have transferred its dimensions to multiple choice questions (Mammar and Berard, 2002). Thus there is still a restricted number of choices that can be either right or wrong. However, a choice does not necessarily have to be right or wrong according to the definition of I/R. If looked at in a continuous dimension, there could be several optimal or good choices. In open games, optimal depends very much on the definition of the learning goal and cannot be generally defined.

The difference of I/R and cautiousness lies in the cognitive nature of I/R. Impulsive people do not consider all possible solutions. They usually do not care about the most optimal solution, while a risk-taking person might care about an optimal choice under the given circumstances. Theories of cautiousness and I/R have some overlaps in their definition, though. A cautious person tries to avoid making mistakes just as a reflective person does, for instance. Gee (2005) also mentions failure as part of the learning principles for game-based learning: The psychological moratorium. In games, real-world risks are generally lowered. Players dare to take risks without any serious consequences. However, for some people, this difference might not be so clear such that this behavior could be still visible in certain situations. Part of this research is to analyze if there are still players who are afraid to go to the game's limit or try out different things.

2.5.3 Knowledge

There are many different kinds of knowledge to be acquired in a learning environment. The most popular one is Bloom's taxonomy (revised by Anderson and Krathwohl (2001)). Bloom's taxonomy (Bloom, 1976) is defined as a classification of educational objectives. They are not hierarchical. According to Anderson and Krathwohl (2001), four different levels of complexity are defined to represent the content of a task: factual knowledge, conceptual knowledge, procedural knowledge, and metacognitive knowledge.

- Factual Knowledge:
  The knowledge tested in this category can also be regarded as "learning by

heart". Facts neither have to be understood nor combined, but just reproduced as presented.

- Conceptual Knowledge:
  Single elements that have been learned are put together as a whole. Schemas, structures, and models have to be recognized and explained. It is not the application of a certain rule that is important, rather it is the knowledge of its existence.

- Procedural Knowledge:
  Procedural knowledge means knowing how to do something. At this level of abstraction knowledge about processes and how they can be applied is tested, but the knowledge is limited to a specific field rather than being interdisciplinary.

- Metacognitive Knowledge:
  In contrast to procedural knowledge, metacognitive knowledge is distributed over various fields. The basic idea is to use personal experience to solve tasks, which requires know-how at deeper levels in order to be able to establish cross-links. It is important to know whether a learned strategy or method can be applied or not.

Games generally provide all these levels of knowledge. In this study, the game prototype considers mainly conceptual and procedural knowledge.
The assessment of knowledge in games depends on the kind of game and on the kind of knowledge that should be achieved. Some studies still use traditional evaluation methods such as multiple choice questions (Burgos et al., 2008). Kickmeier-Rust et al. (2008) used a so-called non-invasive assessment method. Non-invasive means that players are implicitly assessed while they are playing. All possible solutions are stored as a set of solution states for each task and are rated with according competence states. Thus, depending on what path a player chooses, it appears more or less competent. This kind of assessment only works for a countable number of solutions for specific problems.
Assessing knowledge in open games is quite challenging. Solutions to problems might be finite but not countable anymore. There could be solutions that not even the game designer had thought of. Therefore, implicit and explicit assessment methods are applied to the prototype. There will be a non-invasive test scenario. Afterwards, players will either fill out a questionnaire or be interviewed.

2.5.4 Experience

Experience is defined as prior knowledge that players bring to the game environment prior to playing. This can be either experience in playing games (media-related experience) or knowledge about the subject or related areas. Many studies on individual differences had only significant results of the influence of prior knowledge (Coffield et al., 2004; Jonassen and Grabowski, 1993), but no other

learner trait. Prior knowledge in the subject has a strong influence on learner characteristics. Media-related knowledge did not have a significant influence in digital learning (not game-based) environments (Foerster, 2004). However, games provide a special environment and interface to which non-gamers first have to get accustomed. Therefore, media-related experience might have an influence on players' characteristics in open games.
In more traditional learning settings, experience in the subject determined the degree of guidance for learners. The more experienced learners were, the less guidance they needed (Jonassen and Grabowski, 1993). The influence in open games for learning is uncertain. There was no study or literature found on this topic by the author. A feature that might replace this approach is a dynamic level of difficulty or complexity in games. This means that the more experience a player has in the subject, the more complex or difficult the game would be.

2.5.5 Adaptive Open Games System for Learning

The goal of an adaptive game-based learning system is to improve the interactive communication between the system and the player. Thereby the educational game system takes the role of a coach. Adaptation cannot occur by coincidence. It must be focused on specific player characteristics. Therefore, adaptation must follow specified rules that regulate adjustments in the game system if the situation requires it. Such rules are derived from findings of the experiment with the game prototype. The exact specification of such rules will be investigated during this study. The technical transformation of such rules is effected by a control module. As shown in Figure 2.3, the functionality is as follows:

1. There is a constant interaction between player and game. The player provides inputs through mouse clicks. The game provides feedback by visual or other multimedia means.

2. Information of the game and the player are stored in a database. Selected information such as click speed, objects clicked, or certain game events are analyzed and categorized according to the learner attribute model. This means that it also assesses learning progress of players according to their knowledge.

3. According to the respective characteristic, the information is sent to the control module, which then adjusts the respective game feature. For instance, if players did not experience a certain event, a rule in the control module could adjust the game parameters such as to ensure that the player is experiencing that event.

4. Rules are then executed in the game. For instance, an event is occurring and is visualized to the player. Eventually, the process starts over with (1).

The advantage of this adaptive game system is that it is versatile enough to deal with continuously changing characteristics. Characteristics do not necessarily have

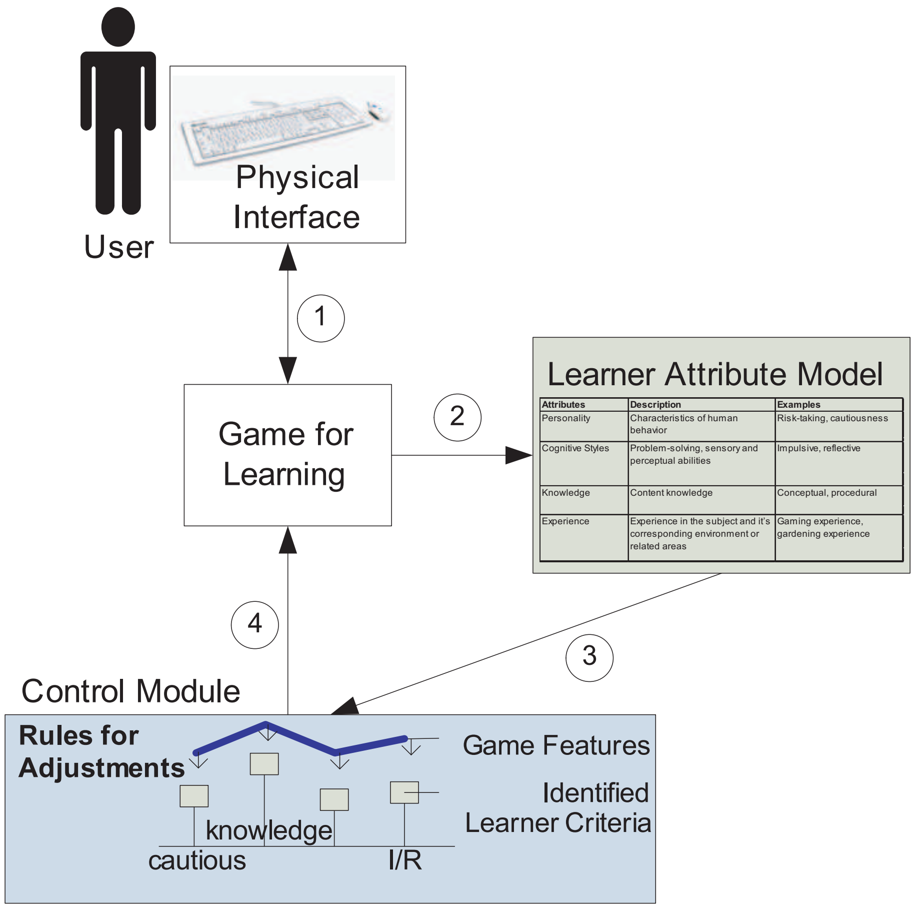


Figure 2.3: Player characteristics are continuously analyzed and evaluated. The control module adjusts certain game features such that the game matches optimally with player characteristics.

to be stable over time. Cautiousness, for instance, can also be used for just specific situations. If a player changes his or her characteristics, the system adapts accordingly.
Learning progress also is not bound to a certain level in the game since open games do not provide a guided system. Thus, players reside in the game environment and explore different things without the need to repeat certain scenarios. Learning is embedded in events and actions that repeat from time to time.

Chapter 3

Methodology

The learner attribute model is applied to a specifically designed open game as a case study and evaluated with a series of experiments. The experiment consists of three exploratory studies. The game prototype was developed to explore player actions, thoughts, and learning in open games, but not to measure distinct player characteristics. The focus lies on the exploration of for learning. The learner attribute model is serving as a guide to find patterns of player characteristics. Only players are analyzed who play the game for the first time so that they can be compared to each other.

Figure 3.1 presents an overview of the research design, which uses a mixed method approach consisting of quantitative and qualitative analysis elements. The goal of the pilot study was to discover major problems and bugs in the game system. Furthermore it was to reveal general tendencies of learning outcomes and play behavior. Players shared their thoughts with the testing person, and both screen and voice were recorded with a video camera. The second study with think-aloud protocols revealed more distinct patterns and learning outcomes. Think aloud tests are vital for this kind of method because certain behaviors can only be identified by player's thoughts. Some player actions are intentional, while others are purely accidental or occur without the player thinking of a strategy. On top of the electronic data collection, the think-aloud protocol allows to gain further information as to why players showed a certain behavior. As a third study, an online experiment was conducted where exclusively electronic data was collected. This last study was to confirm certain findings from the think-aloud protocols. The goal was to reinforce patterns and verify conclusions drawn from the electronic data that were revealed by the think-aloud tests.

The design of the prototype needs to fulfill certain requirements. It should provide enough complexity so that distinct play patterns can be analyzed. Games such as *Civilization* or *Sim City* take hours to play and learn, while *Sudoku* or *Tetris* are too abstract for analyzing player characteristics. In order to compare behavior patterns among players, they should all have the same game goals. However, pathways to reach goals should be open. Players are invited to explore the environment. Guidance is reduced to a minimum such as help sites.

Since the author was unable to find a game for learning that meets these conditions, *Hortus* was developed specifically for this purpose.

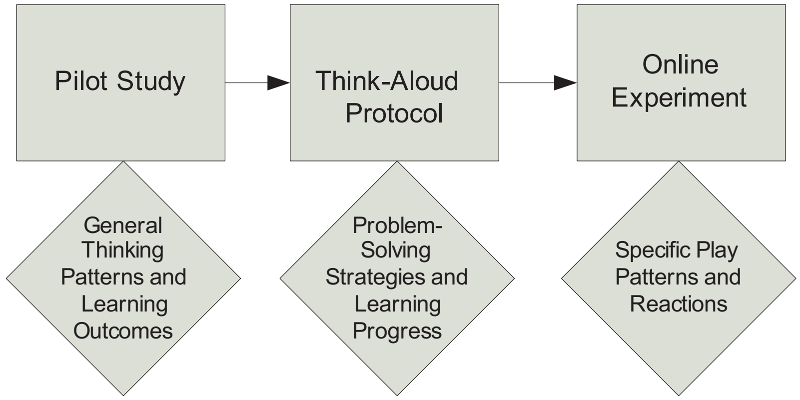


Figure 3.1: Design of experiment.

3.1 Hortus, a Strategy and Simulation Game

Hortus' system represents a metaphor for horticultural or eco-systems. The author wanted to avoid a strong influence of prior knowledge since this changes learning strategies (Jonassen and Grabowski, 1993). Everyone is a novice in the beginning of the game. Hence, game characters do not consist of real flowers and animals. However, as in real life, some plants can harm each other if they are planted too close to each other. Some parasites are attracted to certain kinds of plants, while other plants attract and eat parasites.

3.1.1 Learning in Hortus

There are three levels of learning involved (Fig. 3.2). First, players have to familiarize themselves with the *game interface* and gain an orientation in the game. There is no tutorial, only a quick starter help with the most important information. The reason behind this design choice is to better analyze how players help themselves. Do they find out quickly where everything is? Or do they rather experiment or use the game help? Second, they need to know the *game goal* of each level and

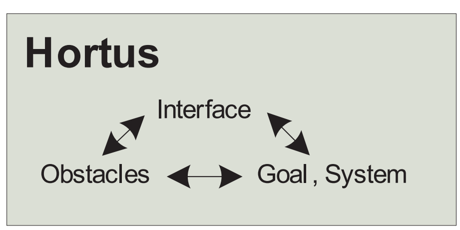


Figure 3.2: Three learning levels of Hortus.

learn about the *system dynamics*. The overall learning goal is to understand the characteristics of the plants and the rules, causes, and effects of this garden system. The feedback in the game visualizes interactions among plants if they are too close together. The state of each plant, i.e. how many leaves it has, its health and the

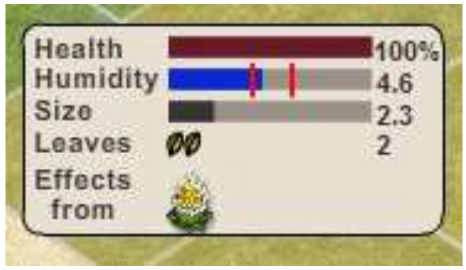


Figure 3.3: Quick information about the most important plant features for one plant.

humidity range for optimal growth is displayed. The learning process first involves the player's awareness of these features, and second, if the player understands them (Fig. 3.3). Eventually, players should be able to deal with the given information and take advantage of certain features such as the optimal humidity range for a healthy plant or how plants affect each other.
The third step of learning involves obstacles that players encounter during their play time. In *Hortus* there are parasites that eat the plants (Fig. 3.4) or parts thereof. They are real-time controlled, as opposed to the turn-based features. Hence, the last learning step involves dealing with a real-time action feature that jeopardizes the plantings. Players should learn to take care of their plants despite parasites.
The game has five levels. Each level provides players with new knowledge by only

Figure 3.4: There are two different kinds of bugs in Hortus, Matronata (purple) and Trojanis (red), and one bug-eating plant, Fortis Noctis.

introducing one or a maximum of two new plants. Thus, players learn just-in-time (Gee, 2003) when they need the information. There is also an encyclopedia with all the plant descriptions in case someone needs more information or help. Otherwise, players can find out a plant's characteristics by just playing and experimenting by placing it on the field and water it or placing it next to another kind of plant to see

their interaction.
Generally, the game provides different sources of knowledge and learning. This is to enhance the freedom of choice for players to find their own personal way of learning. There are no guidelines or norms for how to reach a specific goal. Players are free to choose their own path in their own time. This freedom of choice enhances the analysis of authentic player characteristics because the choice is controlled by players themselves. There are many different ways of solving a problem. In authentic problem-solving environments such as *Hortus*, there is rarely a right and a wrong choice.
The fifth level is a final test scenario that is embedded in the game system. Thus, the test is not recognized as such by players, but is seen as another challenging scenario. The level confronts players with a completely different situation and introduces one new plant. In this scenario, the system analyzes whether players are able to transfer their knowledge to an unfamiliar situation. Players should have learned up to the last scenario how to treat different plants and how to place them on the field.

3.1.2 Player Identity in Hortus

The entire game is accompanied by a main storyline about sick people in a small village who need to be healed by the player. Thus players take over the role of a herbal healer who has to fight against several diseases that have come over the village. In order to create an identity, players have to choose their personal herbal healer and give him or her a name. The picture with its name is displayed throughout the entire game (Fig. 3.5). The role of the herbal healer should give players a higher

Figure 3.5: The players character shows 100% health.

motivation and a purpose for playing the game. Thus, it is not only about planting some flowers but also about doing good and healing people.
The identity of the player's character is addressed several times in the game play: In the storyline when a new level is introduced and while the player is experimenting with certain plants. In the storyline, players receive applause if they made it to the next level. In the description of the new goal, players are addressed directly in their role as healers. During the play, there are certain plants that might attack the player if they grow too big. One kind of plant, *Canibalis*, even can be fatal if players do not pay attention to its attack. Other plants, such as *Dormitus* and *Dulcita*, rather put players into a different state of consciousness like making them drowsy or dreamy. This is visualized by a dark screen or a blurry screen for dreaminess. The idea is based on board games where players usually are blocked for several rounds if they come to certain fields. The direct referral to players by game characters is

unique in this game genre of open strategy games for learning. Thus, not only the game character is addressed, but also the players.

3.1.3 Scenario in *Hortus*

For a better understanding of *Hortus*, an example scenario is described. In Level 1, players get familiar with the interface and with basic tools for growing plants such as watering and harvesting. Players practice these things on the plant *Cukoas*. It is one of the easier plants in the game and represents a kind of weed. It also has weedy characteristics such as robustness and insensitivity to bad soil and it spreads easily. In the second level a new disease appears. The goal for this level is displayed (Fig. 3.6, snapshot no. 1). Two new kinds of plants are introduced (Fig. 3.6, snapshot no. 2). *Dormitus* is more sensitive to its environment and needs more care than *Cukoas*. It also has an effect on other plants by drowsing them and thus slowing their growth. *Fortis Noctis* is introduced one level before the bugs are introduced to familiarize the player with this plant. *Fortis Noctis* spreads a smell that changes in cycles. For three turns, it will attract bugs and for another three turns it will not have any protection against bugs.
Players need to harvest a certain number of leaves for each healing potion (Fig. 3.6, snapshot no. 3). The necessary ingredients are displayed on the right top corner of the play screen. If players do not pay attention they will experience a "player attack" that is caused by Dormitus in Level 2. In picture no. 4 of Figure 3.6, it puts the player in a sleepy state. Players can only escape from this state if they click "next turn" twice. During this blockage, many things happen in the garden. Picture no. 5 shows the results after the blocked turns. One of the main learning goals of Hortus is to experience these attacks and to learn how to deal with them. If players collect all the necessary leaves, they can finally brew the potion for healing sick people (Fig. 3.6, snapshot no. 6).

3.1.4 Design Choices and Technical Information

In this section, a brief overview of distinct design choices are explained that might differ from popular game design in this genre. Furthermore, the data collection and online technology behind *Hortus* is described.

Turn-Based vs. Real-Time

As mentioned before, *Hortus* is a turn-based strategy game. This means that players' actions only take effect when the button "next turn" is clicked. This takes away the time pressure in the decision-making process about plant care. For this research, it is important to see if players have a natural time preference even if time pressure is not provided by the game itself. However, there are certain real-time features in the game. Real-time means that an effect is immediately visible. In *Hortus*, the bugs' movements are independent of turns. While the effect of plant attacks is turn-based, the attack itself is not dependent on turns. Tools are effective the moment they are

Figure 3.6: Excerpt of playing Hortus in level 2.

used. If a player uses the "prune" tool on a plant, all modifications (size, health, leaves) are effective immediately. A plant can even die the moment it is pruned if its health drops to 0 or below because of the action. Another immediate effect occurs when plants are harvested. There is an instant display of the number of leaves harvested. However, watering plants has a delayed effect on humidity because it is influenced by several aspects such as type of soil or evaporation. Thus, the actual level of humidity is visible in the next turn.

Data Collection and Online Technology for *Hortus*

The reason for developing an online game is to reach a wider audience and more participants for this research than for a controlled experiment in the lab. Thus the results are expected to be more significant. For a quantitative analysis it is important to have a certain number of participants for each criterion. Since the number of characteristics depends on the learner attribute model and is yet open, the number of participants should be as large as possible. It is also independent of place and time. Participants can take part whenever and wherever they want. They only need a personal computer and an internet connection. However, online experiments also have certain disadvantages. There is no control over participants and the environment in which they are taking the experiment (Fritz, 2002). Thus the number of participants aborting the experiment is much higher than during a laboratory experiment. Duration is also a critical aspect and can keep potential participants away. Since *Hortus* takes approximately 60 minutes of play time this might be a disadvantage for an online experiment. *Hortus* is a game, though, and therefore might attract more participants than usual for such a long experiment.
The most convenient software for online games is *Adobe Flash*[1] because most people already have a flash plug-in in their web browsers. This increases the playability of *Hortus* because there is no big effort to "install" the game. Instead, players only need to wait a few seconds or minutes until the game is loaded. The goal is to minimize the effort required by potential participants in order to induce them to want to play the game.
The entire game is first loaded on the client (computer of player) and only player data is stored in a database at an online server. A more detailed description of the database is found in Appendix C.

3.2 Validation of Learner Attribute Model

For each category in the learner attribute model, various criteria are used to analyze learner characteristics. A detailed description of the criteria's calculation is found in Appendix D.

3.2.1 Cautiousness

For the personality attributes, cautiousness and risk-taking behavior, no suitable test could be found by the author that would identify these characteristics in a learning or playing context. Most tests are too general or were not publicly accessable. Therefore, those attributes are analyzed in *Hortus* directly. Game criteria that are linked to the personality attributes "cautiousness" and "risk-taking":

- **Average size of plants**
  The size of a plant influences the strength of an effect on a neighboring plant

[1] http://www.adobe.com/products/flash/

or its need for water. Some plants are fatal for their neighboring plants when they are too big. The resistance of plants to over- and underwatering caries as well. However, for players it is important to experiment with the size of a plant and to find out what works best for their play style. Some players might be cautious from the beginning and leave plants small during the entire play time, while others might be less cautious and let them grow bigger. As a learning goal in the game, it is important for players to experience the effects of big plants and to learn how to react to those effects.

- **Field Setting**
  Plants interact with each other on the field. Some of the plants such as *Canibalis* or *Cukoas* have an harmful effect on certain neighboring plants. Other plants such as *Dormitus* and *Dulcita* affect the growth cycle of plants. It is assumed that some players might set all their plants far apart from each other so that no interactions occur. Similar to player attacks, plant interactions are a learning goal as well. It is important that players experience these interactions rather than just reading about them in the game help.

- **Dealing with budget**
  In the beginning of the game, all players start with the same amount of money. It is entirely up to them how they want to spend the money or how they want to manage this resource. There might be players who do not care and will just spend money until nothing is left. Others might carefully manage their budget and keep it always at a high level. If players are too careless with their budget they might lose the game because of miscalculation.

All these criteria are electronically logged. Additionally, statements from think-aloud protocols and interviews are analyzed and compared with the electronic data.

3.2.2 Cognitive Styles

For cognitive styles, *impulsive and reflective behavior* are chosen as characteristics in Hortus. These criteria are first measured with the MFF20, and results are then compared with actions in the game. The first four of the following criteria are evaluated electronically. The last criterion is evaluated with the qualitative method of think-aloud tests.

- **Number of Plants Died**
  Since impulsive players might not be very careful with their plants, it is assumed they will have more dead plants than reflective players.

- **Use of budget**
  Impulsive players spend more on plants and bug treatments than reflective players. Impulsive players have more dying plants. Furthermore, they generally have more plants on the field, and thus more bugs are appearing. So they might spend more on bug treatments.

- **Time per Action**
  It is assumed that impulsive players click faster or have a higher click frequency than reflectives. This is based on the notion that impulsive players are less patient than reflective players and thus click more or faster.

- **Number of Player Attacks**
  The assumption is that impulsive people have more player attacks because they will pay less attention to plant sizes.

- **Dealing with Unexpected Situations**
  The real-time feature for bugs represents an unexpected situation for players. The think-aloud protocols and post interviews with players reveal what they first thought and how they reacted. Some players stay calm and quickly develop a strategy, while others just react to bugs and forget to pursue their game goal. There also might be statistical differences in the electronic data. For instance, a criterion for the dying rate of plants that were eaten by bugs is assessed. There is a difference if there are many plants and only a few bugs or few plants and many bugs that eat all of the plants.

3.2.3 Prior Experiences

Every player has a specific experience regarding the learning content or areas related to it. For *Hortus*, prior experience in gaming and gardening is analyzed. Although the eco-system and its plants in *Hortus* are not real-world plants, gardening knowledge might have an influence on how players care about their plants. Gaming experience could have an influence on how fast someone learns the game interface. Prior knowledge and experience is assessed by interviews for think-aloud tests and by questionnaires for the online experiment before playing the game.

3.2.4 Learning Outcome

Since the game is based on fictional rules, no player starts the game with prior knowledge of its content. Hence, knowledge concerns measuring the *learning outcome* in *Hortus*. A qualitative analysis is conducted by post-interviews of participants. Since learning in *Hortus* occurs in an informal way, the evaluation of learning should be indirect, too. Thus the questions concern specific scenarios or situations in the game.
For the quantitative evaluation, three criteria are created:

- Optimal Watering
  The level of humidity should always be in the optimal range. If humidity is in the optimal range, a plant grows and is healthy.

- Affected by Neighboring Plants
  Some plants attack or affect the health or size of other plants. Thus, they should rather not be placed next to each other. Distinguishing from cautious

behavior, it is important to learn not to place plants next to each other. The system measures if interactions decrease over the levels or stay very low.

- Reaction to Player Attack
  The system measures how long it takes players until they react after a player attack occurred. Furthermore, it measures how long it takes until they prune this plant so an attack is prevented.

These criteria are particularly analyzed in the last scenario of *Hortus* which represents an in-game test scenario. Since player attacks could already be learned in the prior levels, in Level 5, the system evaluates if there is a player attack at all. If there still is a player attack, the reaction to this attack is measured.

3.3 Participants

For each of the three experiments, several participants had to be recruited. For the pilot study, eight people were personally asked to take part in the experiment. Their age ranged between 21 and 40 years. Seven of them were graduate or post-doc students and one worked as an engineer.
For the think-aloud experiments, 34 people were recruited by personal invitation. All but five of the 32 are graduate and post-doc students from Switzerland and the United States. The other five worked in the corporate world. Their age ranged from 18 to 48.
For the online experiment, over 240 participants were recruited through several sources such as announcements in classes and online ads on psychological test sites. The majority of players were computer science students from Switzerland and Austria. The age of the players was between 18 and 42. All the candidates voluntarily participated in all three studies. There were no incentives given to them. Table 3.1 shows an overview of the number of valid participants in this study. The requirements for valid candidates were players who only played Hortus once until they reached the final goal or lost the game in level 4 or 5[2]. A prior experience in the

Table 3.1: Overview of player data.

Category	Total	Valid
Electronic Data (Game Won)	240	163
Electronic Data (Game Lost at Level 3-5)	62	22
Questionnaires	General: 375 Feedback: 255	137
Think Aloud Protocol	42	31
MFFT	281	126

[2]Two players from the think-aloud experiment lost in level 3. They were also taken into account because it was clear that they honestly made a certain effort to win the game.

game should be prevented with this restriction. Players who quit or lost the game before level 3 were omitted because it was not clear if they made an honest effort to win the game. Only losing the game due to running out of funds was considered valid. Other players who lost because of a player attack were omitted. The reason is that losing because no resources were left might be caused by wrong strategic decisions. Losing because of a player attack is usually accidental. Players lost their "lives" without realizing they were in danger. A reason for aborting the game was not evaluated. Players who lost up to level 3 were not taken into account because there was not enough data to be compared with the rest of the group.
Some players showed an inconsistency in the database where time stamps or certain turns were missing. This might have been caused through by unstable internet connection. These players were also invalid candidates for further evaluation. The difference between the numbers of total users and valid users for both questionnaires is due to users who filled out the questionnaire although they only tried out the game and played up to level 2. There were also many users who only played *Hortus*, but did not fill out any questionnaire. The candidates that dropped out from think-aloud protocols either had no database entries due to a technical malfunction, or the video/audio quality was too bad to be evaluated. For the MFF20, only those users were taken into account who also played *Hortus* and would fall into the valid category for electronic data evaluation.
Table 3.2 shows an overview of the countries of origin and the gender of the participants. Only the 163 valid participants were taken into account since they provided the most relevant data.

Table 3.2: Countries and gender of valid Hortus players.

			country				
			Austria	Switzerland	U.S.A.	Other	Total
gender	male	number	79	34	1	6	120
		%	66	28	1	5	100
	female	number	14	25	2	2	43
		%	33	58	5	5	100
	Total	number	93	59	3	8	163
		%	57	36	2	5	100

3.4 Procedures of the Three Studies

The pilot study and the think-aloud experiment were both conducted under laboratory conditions. The time requirements for the two studies ranged from two to three hours for each participant. The interview with general questions took about five minutes. The time to conduct the MFF20 test ranged between 10 and 20 minutes. Playing *Hortus* took anywhere from 50 minutes to around 140 minutes. For the post-game interview, participants required about 15 minutes to answer all the questions.
Participants were invited to a specific room where the experiment took place.

There was only one participant with one experimenter in the room. For think-aloud experiments, this privacy was very important so that participants were not distracted or influenced by outside factors. First, the entire procedure was explained to them. General questions were then asked about personal information, about attitudes toward video games, and experience with playing such games and with gardening. The interviews were recorded with a digital audio device. After the first interview, the think-aloud procedure was explained to them. Most people felt rather uncomfortable with speaking out their thoughts about actions. Some participants had to be encouraged repeatedly during the game play to either say what was on their minds or also to speak louder. It was very difficult for them to think aloud for over an hour. Most people forgot to speak when they were concentrated on playing the game. In the pilot study, the game play was recorded with a digital video camera. In the think-aloud experiment, the game play was recorded with the screen recording tool *Camtasia*[3]. Inputs like mouse actions were stored in the game database.

After playing the game, participants were asked about their impressions of *Hortus*, memorable moments and strategies, and about what they learned. These interviews were also digitally recorded.

For the online experiment, participants recruited from computer science classes received instructions via email. The instructions advised them in which order they should fill out the questionnaires, the MFF20 test, and play the game. Participants who where recruited via websites received the same instructions.

[3]http://www.techsmith.com/camtasia.asp

Chapter 4

Results and Interpretations

The results of the three studies – pilot study, think-aloud tests and online experiment – are categorized according to the learner attribute model.

4.1 Cautious and Risk-Taking Players in *Hortus*

Only a few "stable" characteristics were found in *Hortus* regarding cautiousness. Most of the players changed their strategies and actions over time according to certain situations.
The following criteria describe cautious behavior in the specific context of *Hortus*.

4.1.1 Plant Size

In *Hortus*, many players did not let their plants grow big. Some players harvested their plants immediately and pruned them right afterwards. Others let them grow big and harvested more leaves at once. Table 4.1 shows so-called ranking probabilities. For instance, players with a small-sized *Dormitus* in one level will have a small sized *Dormitus* in the next level as well. A detailed calculation of all the average plant sizes is found in Appendix D. A Spearman coefficient of 0.508

Table 4.1: Ranking probabilities for *Dormitus* plant sizes

Correlations

			MeanOfMax SizesDormiL2	MeanOfMax SizesDormiL3	MeanOfMax SizesDormiL4
Spearman's rho	MeanOfMaxSizesDormiL2	Correlation Coefficient	1.000	.508**	.382**
		Sig. (2-tailed)	.	.000	.000
		N	163	163	163
	MeanOfMaxSizesDormiL3	Correlation Coefficient	.508**	1.000	.598**
		Sig. (2-tailed)	.000	.	.000
		N	163	163	163
	MeanOfMaxSizesDormiL4	Correlation Coefficient	.382**	.598**	1.000
		Sig. (2-tailed)	.000	.000	.
		N	163	163	163

**Correlation is significant at the 0.01 level (2-tailed)..

means that players will have the same sizes of *Dormitus* in level 3 with a probability of approximately 50% compared to other players. It does not mean that they always have the same sized plants. They are likely in the same rank of plant size as in the previous level. The rank coefficient gets stronger (0.598) from level 3 to 4. Since players are introduced to *Dormitus* in level 2, they first have to get accustomed to this plant. This might be the reason for the rather weak rank correlation of 0.382 from level 2 to level 4. Another reason might be that people who first had big plants and thus more player attacks became more cautious in future levels.
However, players with rather small-sized plants rarely had any large-sized plants. This tendency is illustrated in Fig. 4.1.

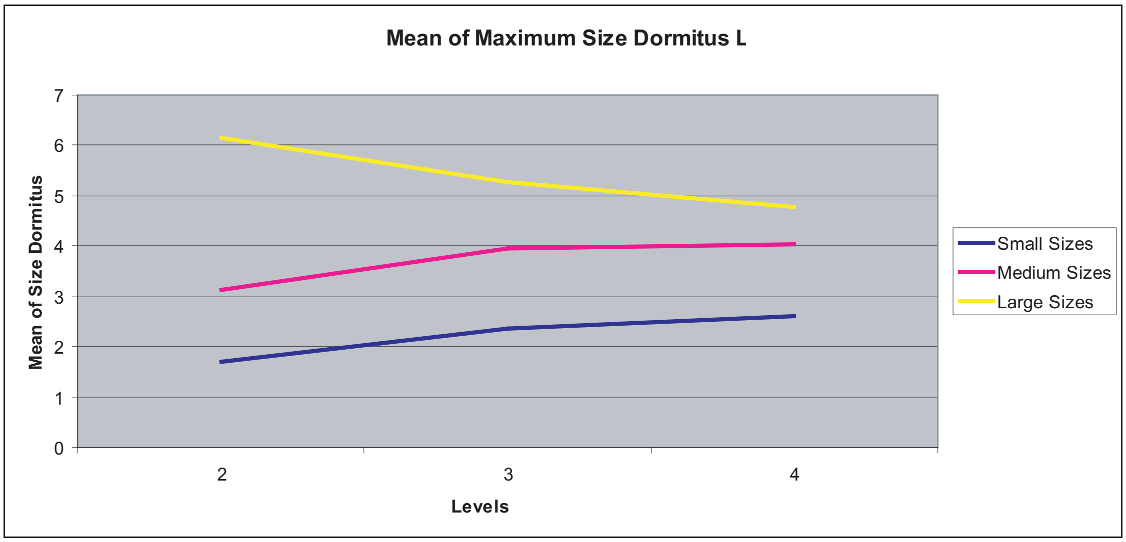


Figure 4.1: The three groups illustrate a tendency of ”stable” plant sizes for one plant *Dormitus* that can cause player attacks if it is too big.

The three groups result from splitting the entire sample into three equally sized groups ordered by plant sizes of level 2. The lines show the average of plant sizes for each group. The “Large Size” line represents the group that has the largest plants in level 2. It shows that players who first had big plants tend to keep their plants smaller throughout levels. But players with already small-sized plants (Small Size in Figure 4.1) keep their plants mostly small. This tendency for one plant is also seen in other kinds of plants, but not in all of them. Table 4.2 shows the Spearman correlation across levels for all six plants in the game. The strongest correlation is seen from level 2 through level 4 with 0.648. This means that someone with small plants in level 2 has small plants (compared to the other players) in level 4 with a probability of 65%. The tendency of sizes for all plants (Fig. 4.2) illustrates this relation from level 2 to level 4. In level 5 a change appears which is also seen in Table 4.2 where the correlation is only 0.416. This means that most of the players who at first let their plants grow big kept their plants smaller in the last scenario.
There are various reasons why players kept their plants small. The following are two differing statements from cautious players. One player stated:

Table 4.2: Ranking probabilities for all plant sizes

Correlations

			TrueMaxSizeL1	TrueMaxSizeL2	TrueMaxSizeL3	TrueMaxSizeL4	TrueMaxSizeL5
Spearman's rho	TrueMaxSizeL1	Correlation Coefficient	1.000	.653**	.498**	.433**	.335**
		Sig. (2-tailed)	.	.000	.000	.000	.000
		N	163	163	163	163	163
	TrueMaxSizeL2	Correlation Coefficient	.653**	1.000	.759**	.648**	.416**
		Sig. (2-tailed)	.000	.	.000	.000	.000
		N	163	163	163	163	163
	TrueMaxSizeL3	Correlation Coefficient	.498**	.759**	1.000	.817**	.452**
		Sig. (2-tailed)	.000	.000	.	.000	.000
		N	163	163	163	163	163
	TrueMaxSizeL4	Correlation Coefficient	.433**	.648**	.817**	1.000	.603**
		Sig. (2-tailed)	.000	.000	.000	.	.000
		N	163	163	163	163	163
	TrueMaxSizeL5	Correlation Coefficient	.335**	.416**	.452**	.603**	1.000
		Sig. (2-tailed)	.000	.000	.000	.000	.
		N	163	163	163	163	163

**. Correlation is significant at the 0.01 level (2-tailed).

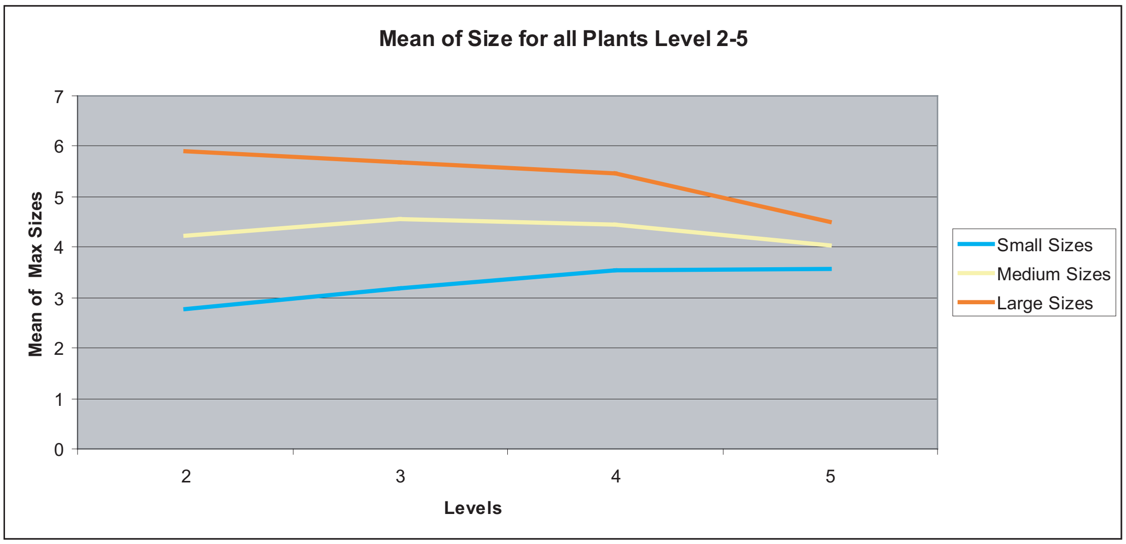


Figure 4.2: The three groups illustrate a tendency towards "stable" plant sizes for all plants.

> "I could have let these leaves grow longer, but the risk was too high that I would lose them. That's why I always radically pruned them ..."

The second player who was asked whether he intentionally kept his plants small answered as follows:

> "... Then I started thinking that pruning them isn't a bad idea because if everything is low then I don't know what the full effects are going to be when they are big and the other ones are around it. So I kept them kind of low so that they wouldn't affect other ones nearly as much – at least that's what my theory was. But also I kept them low because I was always pruning them because I needed money."

This player actually meant ”harvesting” since pruning would be cutting back plants without taking their leaves.
The reason for keeping plants small thus is twofold. Some players kept their plants intentionally small while others did it without a purpose. Players of the first group were afraid of the effects that big plants could have on other plants. Another reason for keeping plants low intentionally is because they do not have to be watered as often as big plants. Finally, some players looked up this feature in the game help, which stated that the plants might attack the player if they become too big. But it did not say how big they have to be.
Other players unintentionally kept their plants small because they kept harvesting the leaves, which also decreases a plant's health. Hence, there is always a trade-off between harvesting as many leaves as possible and keeping plants healthy. If plants are unhealthy they do not grow, but stay at their actual size. This effect is also seen when bugs appear. Players tend to quickly start harvesting as many leaves as possible before the bug eats them.
Whatever reason lies behind small or large sized plants, Figure 4.2 shows the tendency that this behavior remains stable from level 2 through level 4 with a probability of 65% (Table 4.2) for all plants. The result of this was that many players who had small-sized plants did not experience any player attacks. A player attack only occurrs with large plants. In the case of *Dormitus*, there is a probability of 60% that someone who has small-sized *Dormitus* in level 3 will not experience a player attack of *Dormitus* in level 4. Since *Dormitus* is only required from level 2 to level 4 for brewing potions, it is likely that a *Dormitus* player attack will never occur and thus players will never learn about player attacks and how to react to them.

4.1.2 Field Setting

The health or size of a plant is affecte if a different plant is placed in the next field for a couple of turns. Figure 4.3 shows trends for all players' average values for a *Dormitus* field setting. The groups are equally sized in three parts. The value ”0” means that there were no interactions with neighboring plants throughout the entire lifetime of *Dormitus* whereas ”1” means that there were constantly one or more neighbor plants that affected *Dormitus*. For instance, if a *Dormitus* exists for six turns and it is affected by *Canibalis* during all of these six turns, it is a 100% influence for Dormitus' lifetime. If *Canibalis* is replanted after three turns or dies, this represents only a 50% influence. Trend lines indicate a general decrease in plant interactions for all three groups. This means that they all improved so that *Dormitus* was less affected by neighboring plants. Figure 4.4 shows an excerpt of one turn for two different players in more detail. Table fields represent the respective plant fields. *Dormitus* from player ID492 was affected by *Canibalis* for two turns. Since it was the only *Dormitus* and had been there for totally 10 turns, its health was affected for 20% of its lifetime.

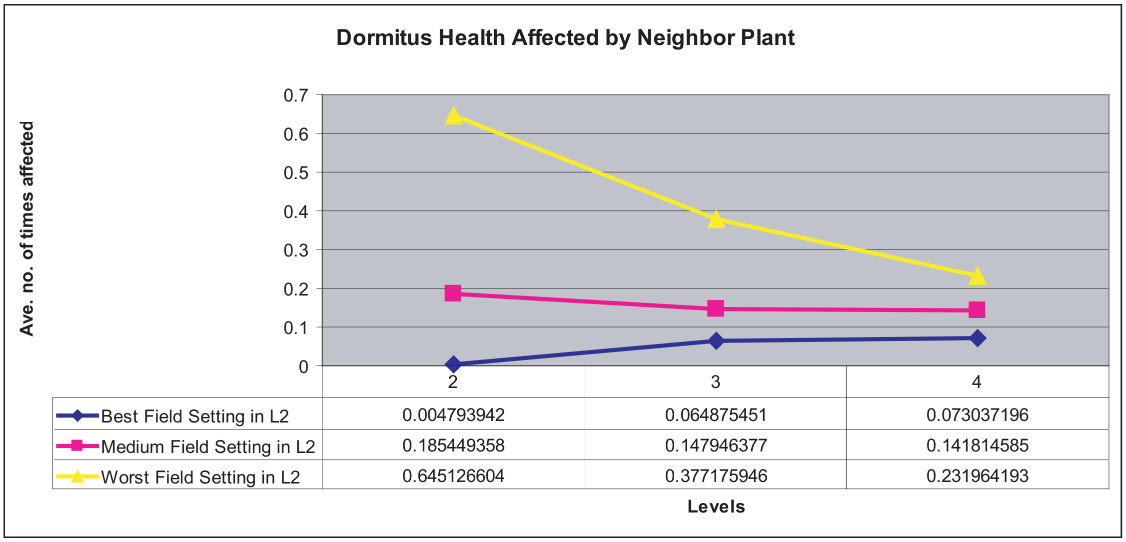


Figure 4.3: The three player groups illustrate a tendency toward an average number of plant interactions.

gameID468

Turn Nr: 40				
Canibalis	---	---	---	---
---	---	---	---	---
---	---	Fortis Noctis	---	Cukoas
Dormitus	---	---	Cukoas	Cukoas

gameID492

Turn Nr: 88				
Cukoas	---	Cukoas	Cukoas	Cukoas
Cukoas	---	Cukoas	Cukoas	Cukoas
---	Dormitus	---	Cukoas	Cukoas
Fortis Noctis	Canibalis	---	---	Cukoas

Figure 4.4: These excerpts of field settings in one turn shows that player ID468 had his plants set far apart from each other, unlike player ID492. Plants in diagonal positions cannot influence each other.

There were many players like ID468 who hardly had any interactions. Unfortunately, this trend cannot be statistically confirmed as "stable" with plant sizes. However, the data shows several players who always had values around "0" which means hardly any interactions. As with plant sizes, plant interactions are a learning goal in *Hortus*. Since some players never had any interactions, they failed to achieve this goal.

4.1.3 Dealing with Budget

In Hortus there are certain resources that have to be managed, such as a budget. Every player starts with a budget of $100 for the four levels. In the fifth level, it starts again with a budget of $50. For every potion sold, players receive an some additional amount. They can also sell leaves to increase their budget. There were players who spent almost all their budget in the first level and had to play with hardly anything through the rest of the game. This made it more challenging, especially when bugs arrived and destroyed their plants.
The results showed that players change their behavior with budget over the levels. There is no consistency among levels. The Spearman coefficient for a low budget shows a higher correlation from level 1 to level 2 and from level 2 to level 3 (Fig. 4.3). This correlation means that players who had, for instance, mostly a low budget in

Table 4.3: Ranking probabilities of low budget

Correlations

			BudgetFreq 0To9RecL1	BudgetFreq 0To9RecL2	BudgetFreq 0To9RecL3	BudgetFreq 0To9RecL4	BudgetFreq 0To9RecL5
Spearman's rho	BudgetFreq0To9RecL1	Correlation Coefficient	1.000	.667**	.332	.193	.085
		Sig. (2-tailed)	.	.000	.079	.334	.753
		N	29	29	29	27	16
	BudgetFreq0To9RecL2	Correlation Coefficient	.667**	1.000	.554**	.440*	.084
		Sig. (2-tailed)	.000	.	.002	.022	.757
		N	29	29	29	27	16
	BudgetFreq0To9RecL3	Correlation Coefficient	.332	.554**	1.000	.416*	.268
		Sig. (2-tailed)	.079	.002	.	.031	.316
		N	29	29	29	27	16
	BudgetFreq0To9RecL4	Correlation Coefficient	.193	.440*	.416*	1.000	-.215
		Sig. (2-tailed)	.334	.022	.031	.	.424
		N	27	27	27	27	16
	BudgetFreq0To9RecL5	Correlation Coefficient	.085	.084	.268	-.215	1.000
		Sig. (2-tailed)	.753	.757	.316	.424	.
		N	16	16	16	16	16

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

level 1, mostly had a low budget in level 2 as well. On the other hand, it also means that players who rarely had a low budget in level 1 rarely had a low budget in level 2.
As Table 4.4 shows, high correlations for high budgets indicatea slight shift with increasing levels. Players had a constantly high budget from level 2 to level 3 (0.521) and from level 3 to level 4 (0.667). The high budget in level 5 had to be split because the starting budget was $50 and hardly anyone was over this amount since it was the last level. The high ranking correlation from level 2 to level 3 cannot be explained. The assumption was rather that bugs appearing in level 3 would cause players to be more cautious or to spend more money to fight against them. One interpretation might be that some players stayed with a low budget when bugs were coming and others tried to keep a high budget. Thus, bugs neither improved nor worsened the situation. Perhaps they prevented players with mostly a low budget to gain more money.
The importance of watching over the personal budget is reflected in single levels of

Table 4.4: Ranking probabilities of high budget

Correlations

			Budget Freq70AndUpL1	Budget Freq70AndUpL2	Budget Freq70AndUpL3	Budget Freq70AndUpL4	Budget Freq30To69L5	Budget Freq70AndUpL5
Spearman's rho	BudgetFreq70AndUpL1	Correlation Coefficient	1.000	.348	.243	.280	.333	.
		Sig. (2-tailed)	.	.065	.204	.157	.207	.
		N	29	29	29	27	16	16
	BudgetFreq70AndUpL2	Correlation Coefficient	.348	1.000	.521**	.303	-.144	.
		Sig. (2-tailed)	.065	.	.004	.125	.595	.
		N	29	29	29	27	16	16
	BudgetFreq70AndUpL3	Correlation Coefficient	.243	.521**	1.000	.667**	-.185	.
		Sig. (2-tailed)	.204	.004	.	.000	.493	.
		N	29	29	29	27	16	16
	BudgetFreq70AndUpL4	Correlation Coefficient	.280	.303	.667**	1.000	-.315	.
		Sig. (2-tailed)	.157	.125	.000	.	.235	.
		N	27	27	27	27	16	16
	BudgetFreq30To69L5	Correlation Coefficient	.333	-.144	-.185	-.315	1.000	.
		Sig. (2-tailed)	.207	.595	.493	.235	.	.
		N	16	16	16	16	16	16
	BudgetFreq70AndUpL5	Correlation Coefficient	.	.	.	.	.	.
		Sig. (2-tailed)	.	.	.	.	.	.
		N	16	16	16	16	16	16

**.Correlation is significant at the 0.01 level (2-tailed).

the game. One player who was not among the players with the highest budget, but who is considered as cautious stated:

> Player ID692: "Well, I really think that this is important and that you should learn something from it. Most of all in games, you have to manage your income. You have to watch that you have an income and save it so that you are not going broke."

Figure 4.5 shows this player's frequencies of budget values. Most of the time it was in the high areas, except in level 5. The low budget in level 5 is because the

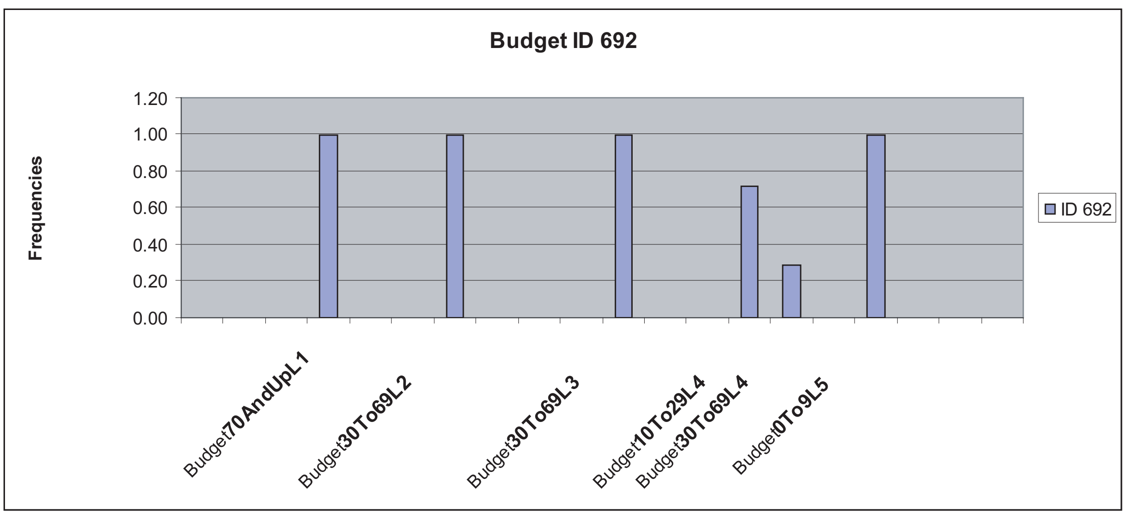


Figure 4.5: This player's budget is constantly high except in level 5.

player knows that this is the last level and that the money did not need to be saved anymore. Another player was very special because he showed a strong interest in "not wasting money" at the end of the game:

> Interviewer: "... the money is in the center although you knew that you had reached the end of the game and you continued to collect money?" Player (ID 503): "Yes, I still sold some (leaves) because they would have been lost otherwise without any use. Of course, I could have continued to play more rounds before I ... continued to grow and grow and sell. But it wasn't worth it. Time was more precious. But to let them just die ... I thought, well."

The status of ID 503's budget is displayed in Figure 4.6. While the budgets of

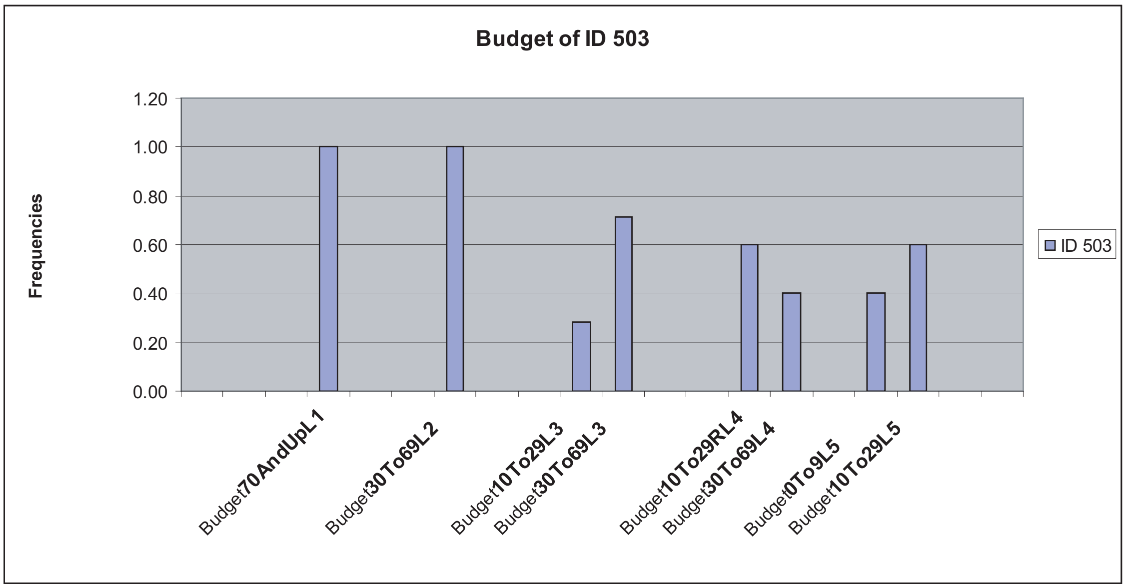


Figure 4.6: This player was cautious with his budget until the end of the game.

most of the players was in the range of \$0 to \$9 in level 5, this player had most of his budget in the range of \$10 to \$29. Hence, the data reflects this care for saving money, especially in level 5 where it was not important anymore to save money.
Generally, there is no stability with the budget over all the levels. Players change their behavior according to individual circumstances and situations. Everyone deals differently with money in certain situations. Some people did not understand the game design and thought that the game would restart after each level. Thus, they did not care about the money and bought many plants in the beginning. However, as soon as they realized that the levels built on each other, they started to be more careful with their budget.
A conclusion that can be drawn from these findings is that the care for monetary resources might be visible in level 5 if the budget is above \$10 most of the time. It is questionable though how this knowledge might be useful for supporting players in the future. No relation was found with losing the game because of a constantly low budget. Losing the game has more complex causes.

Cautiousness is supposed to be a stable personality trait. However, even the pertinent literature is questioning its stability across all situations (Jonassen and Grabowski, 1993). The electronic data in *Hortus* shows several criteria that are categorized as cautiousness. With a certain probability, they are stable over all five game levels. However, the results confirm concerns found in literature. No generalization is possible because the group of players for each criterion is not the same. Every player reacts differently in certain situations. Thus it is not possible to define a general profile for cautious players.

4.2 Impulsive and Reflective Styles in *Hortus*

Analogously to personality traits such as ”cautiousness”, cognitive styles claim to be stable over time. Results from the MFF20 compared to certain characteristics in *Hortus* led to only a few significant results. Although many more criteria were analyzed than are discussed here (more than 100). Since none of them provided any significant results, only a significant selection is analyzed further. For other relevant criteria, a short summary is given.
Besides the quantitative analysis of impulsive and reflective (I/R), a qualitative criterion was analyzed as well. Therefore, dealing with unexpected situations is described separately in Section 4.2.4 below.

4.2.1 Results from MFF20

All candidates that made the MFF20 also played *Hortus*. However, not all of them were valid candidates for the game analysis. Since the MFF20 is strongly dependent on the sample size, all 281 subjects were taken into account as a basis for the categorization of I/R in *Hortus*. Figure 4.7 shows a summary of these candidates. As a result of the double median split, impulsive and reflective groups are of equal size. The median for total errors out of 20 picture sets was 8. The median for the average response time until the first image was clicked was 15.608 s. The correlation

Table 4.5: Pearson Correlations between the two variables.

Correlations

		AvgRT1	TotErrors
AvgRT1	Pearson Correlation	1	-.427**
	Sig. (2-tailed)		.000
	N	281	281
TotErrors	Pearson Correlation	-.427**	1
	Sig. (2-tailed)	.000	
	N	281	281

**.Correlation is significant at the 0.01 level (2-tailed).

between total errors and a reaction time to first response is –0.427 and it is significant (as shown in Table 4.5). A negative correlation means that someone, for instance,

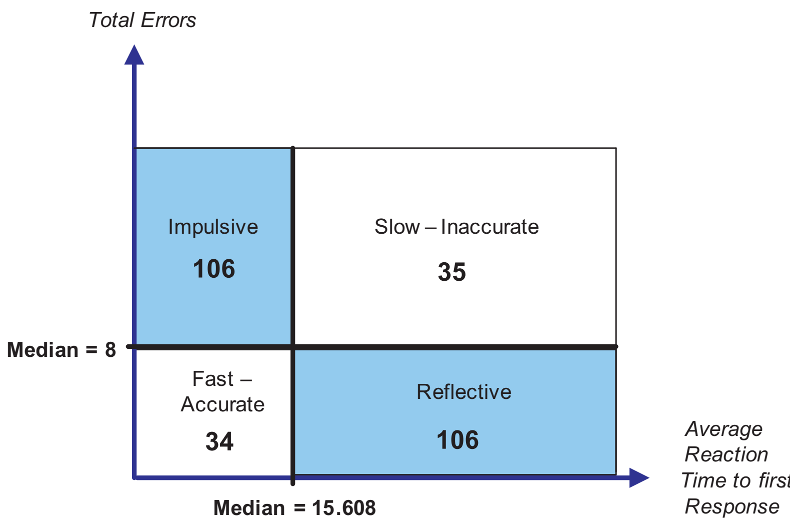


Figure 4.7: Overview of the MFF20 results of all the candidates who accomplished the MFF20.

who had only a few errors, had a longer reaction time to first response. However, a value of –0.427 is quite low compared to other MFF20 test versions or other samples of this online version. Other samples resulted in correlations between - - 0.57 and - - 0.68. This means that there is only a weak correlation between total errors and reaction time in this MFF20. One possible explanation is that this sample of people is more heterogeneous than other samples that were tested with the same online version. Other samples had a more consistent age group, field of work, and nationality. The age group of the sample for *Hortus* ranges from 17 to 48 years. The field of work consists of education, psychology, computer science, and a few other fields such as financing or physics. The nationalities ranged from United States, UK, Austria to Switzerland and some other countries represented by one citizen each.
The fact that the MFF20 is not standardized and strongly sample dependent might be an indication for the weak results obtained. Furthermore, it could have an influence on the few significant findings for several criteria in *Hortus* in relation with the MFF20. The following two subsections summarize quantitative findings in *Hortus* related to I/R.

4.2.2 Significant Differences

None of the criteria proposed in Section 3.2.2 resulted in significant differences between impulsive or reflective styles in *Hortus*. Therefore, further criteria were analyzed, which led to the few findings described here. There is a significant

difference between impulsive and reflective players regarding the number of turns in levels 1, 5, and in the total game. This means that impulsive players had more average turns in these levels.
Table 4.6 illustrates this finding from a statistical point of view. The top table shows means of the two groups on the variable "NrTurnsLXY". The bottom table evaluates if there is a significant difference between these mean values. In order to prove a significant difference, an independent t-test was conducted. This t-test describes the means of two groups (impulsive/reflective) on a given variable (in this case the number of turns). The "group statistics" clearly show

Table 4.6: Statistical data about differences in turn no. for I/R

Group Statistics

	I/R	N	Mean	Std. Deviation	Std. Error Mean
NrTurnsL1	0 (impulsive)	41	14.61	13.321	2.080
	2 (reflective)	47	8.70	4.403	.642
NrTurnsL5	0	41	38.15	39.448	6.161
	2	47	24.11	22.615	3.299
NrTurnsGm	0	41	90.10	56.015	8.748
	2	47	66.66	39.074	5.700

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Upper	Lower
NrTurnsL1	Equal variances assumed	16.487	.000	2.868	86	.005	5.908	2.060	1.813	10.002
	Equal variances not assumed			2.713	47.612	.009	5.908	2.177	1.529	10.286
NrTurnsL5	Equal variances assumed	2.350	.129	2.080	86	.040	14.040	6.749	.624	27.456
	Equal variances not assumed			2.009	61.807	.049	14.040	6.988	.070	28.010
NrTurnsGm	Equal variances assumed	2.421	.123	2.299	86	.024	23.438	10.195	3.171	43.705
	Equal variances not assumed			2.245	70.172	.028	23.438	10.441	2.615	44.261

that impulsive players (group 0: 14.61) play a higher average number of turns than reflectives (group 2: 8.7). The *Levene's test for equality of variances* is conducted to see whether the variances of these means are significantly different or not. The highlighted values indicate a significant difference for NrTurnsL1 and a significant equality for NrTurnsL5 and NrTurnsGm. According to these results, the highlighted fields in the sample t-test show a significant difference because they are all below 0.05, which is the threshold for a significant difference.
Another significant difference between impulsive and reflective players was found for the amount spent in level 5. Since everyone had the same budget to start with in level 5, it is easier to compare different strategies than in previous levels. Although in level 1, everyone starts with the same budget as well, players still are

at the beginning of a learning process. In level 5, most of the players understood the interface and the main concept in the game.
Therefore, the assumption of impulsive players spending more money than reflective players is only proven for level 5.

Finally, for the group fast-accurate and slow-inaccurate, there was a significant difference in duration of level 2. The mean time value for the slow group was 823.5 s and for the fast group it was 532.1 s. The sample t-test resulted in a significant value of 0.03, which indicates a significant difference between slow and fast players for the duration of level 2.

4.2.3 Non-Significant Differences

Most of the criteria introduced in Section 3.2.2 for impulsive and reflective players did not lead to a significant outcome. This means there was no significant difference between impulsive, reflective or slow, and fast styles.
Table 4.7 summarizes the results of the sample t-tests for the criteria number of plants that died, use of budget (amount spent), time per action, and player attacks. For display purposes, groups of slow and fast, and criteria for each level are not shown. All the criteria have no significant differences between impulsive and reflective players. The criteria "SpendingsGm" is almost significant with a value of 0.54. The mean values shown in Table 4.8 confirm the results

Table 4.7: No significant difference for I/R variables

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Upper	Lower
TotalPlantsDiedRateGm	Equal variances assumed	1.418	.237	.068	86	.946	.00056	.00835	-.01603	.01716
	Equal variances not assumed			.068	85.658	.946	.00056	.00824	-.01581	.01694
SpendingsGm	Equal variances assumed	6.294	.014	2.016	86	.047	39.683	19.681	.559	78.808
	Equal variances not assumed			1.962	67.705	.054	39.683	20.222	-.672	80.038
AvTimePerActGm	Equal variances assumed	1.614	.207	-1.274	86	.206	-.7025085	.5516021	-1.7990572	.3940401
	Equal variances not assumed			-1.340	61.061	.185	-.7025085	.5241537	-1.7505976	.3455805
NrPlayerAttGm	Equal variances assumed	3.525	.064	-.994	86	.323	-3.152	3.170	-9.453	3.149
	Equal variances not assumed			-1.012	84.686	.314	-3.152	3.114	-9.343	3.039

shown in Table 4.7. Most of these means are very close together. The means of "TotalPlantsDiedRateGm" describe the average percentage of plants that died in relation to plants that were totally planted on the field. Most of the mean values are very close together, except for SpendingsGm. For amount spent, the difference is almost significant. Thus, impulsive players tend to spend more money in general

Table 4.8: Mean values for non-significant differences

Group Statistics

	ImpulsivReflektiv	N	Mean	Std. Deviation	Std. Error Mean
TotalPlantsDiedRateGm	0	41	.0752	.03472	.00542
	2	47	.0746	.04249	.00620
SpendingsGm	0	41	285.85	110.204	17.211
	2	47	246.17	72.780	10.616
AvTimePerActGm	0	41	2.763630	1.2839534	.2005198
	2	47	3.466138	3.3200692	.4842819
NrPlayerAttGm	0	41	7.98	12.656	1.977
	2	47	11.13	16.493	2.406

than reflective players throughout the total game.

Based on the few significant findings for I/R in relation to the MFF20, it seems that *Hortus* supported both types equally. There are several possible explanations for this. The base sample of the MFF20 did not have a high correlation between the two variables. Since this relation was already weak, it might have resulted in weak differences between *Hortus* and MFF20 as well. The MFF20 online version is neither established yet, nor are there any other MFF20 tests. They are highly sample-dependent.
Another possible explanation might be found within*Hortus* itself. There is a high possibility that *Hortus* evaluates something different than the MFF20. The MFF20 measures incorrect and correct answers, whereas *Hortus* looks at different performances while gamers are playing the game. *Hortus* is designed according to the original definition of I/R; i.e. making decisions in problem-solving environments under great uncertainty (Jonassen and Grabowski, 1993). Thus, *Hortus* contains a problem-solving and decision-making environment with several possibilities for a solution. There is no optimal or worst solution to a problem, only less and more optimal ways to solve a problem.
The following criteria shows the most promising results for the research in impulsive and reflective styles.

4.2.4 Dealing with Unexpected Situations

To most players the real-time effect of the *bugs* was surprising. The insects in the game did not move in every turn. Rather, they moved straight to one plant and either ate their leaves or the entire plant. Thus players had to react quickly in order to avoid losing many plants. Some players stopped playing and just observed bugs. They wondered where they would go and what they would eat. All of them had the bug-eating plant *Fortis Noctis* in their garden. Not all of them realized this feature, though. Those who realized it and watched this bug-eating event said that

this was their favorite moment in the game or that *Fortis Noctis* was their favorite plant. Other players reacted quickly and immediately started a treatment against the bugs.
In order to better understand the different kinds of player reactions, two distinct players are discussed in more detail.
Figure 4.8 shows a player's reaction after the first bug appeared. Player ID513

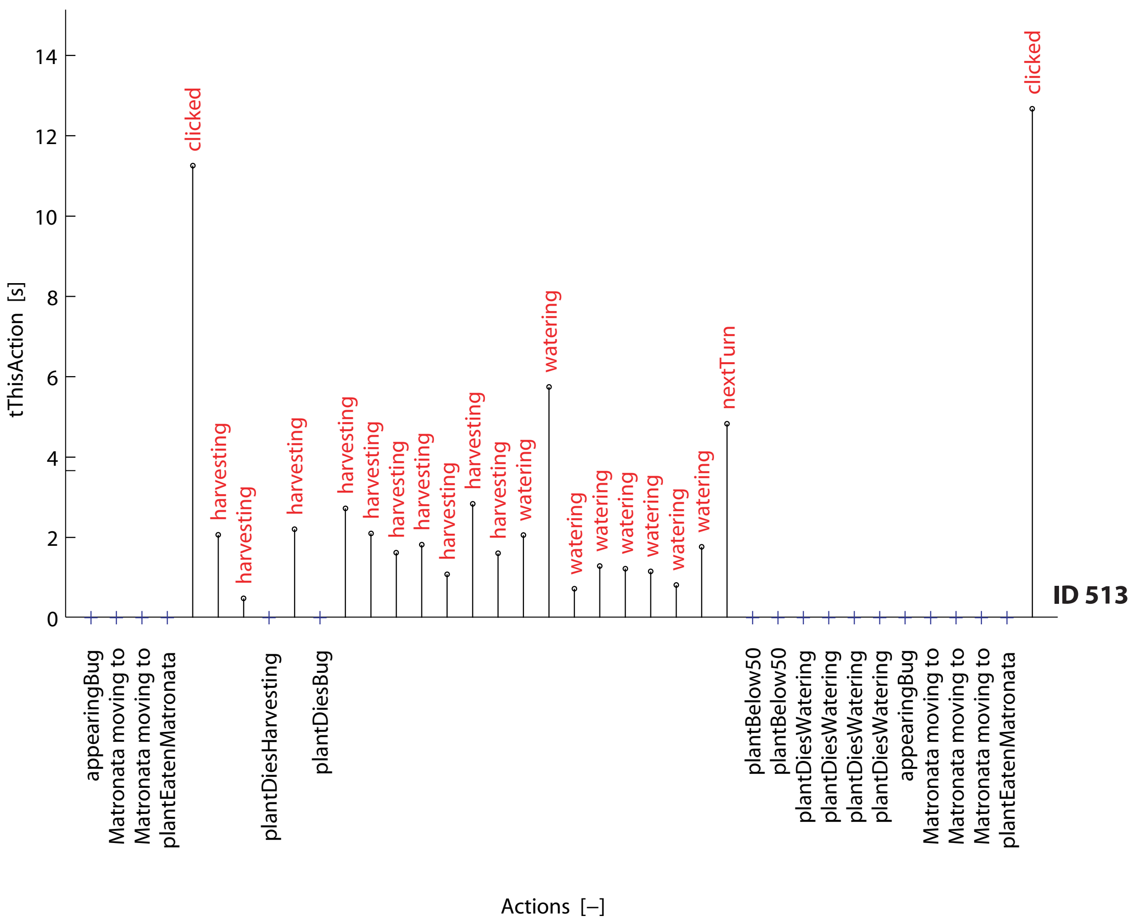


Figure 4.8: This player's reaction to bugs is harvesting and watering as much as possible after the first bug appeared. (Explanation of variables: Matronatamovingto = Bug "Matronata" moves to; plantDiesXX = plant dies because of reason XX; plantBelow50 = plant health is below 50%; plantEatenMatronata = plant was eaten by bug)

waited only a short time after *Matronata* appeared. Her response time was 11.3 s, which is neither short nor very long compared to the reaction of other players who all took more than 15 s to react. What followed was a series of quick actions consisting of harvesting and watering. As a consequence, several plants died from over-watering. When *Matronata* was moving towards another plant, the reaction time became longer (12.7 s). The longer reaction time is explained by the player's watching and following *Matronata's* movements.
Another player (ID508) had a similar style as 513, but she learned fast and adjusted her strategy to the respective situation. Figure 4.9 shows her reaction when the first

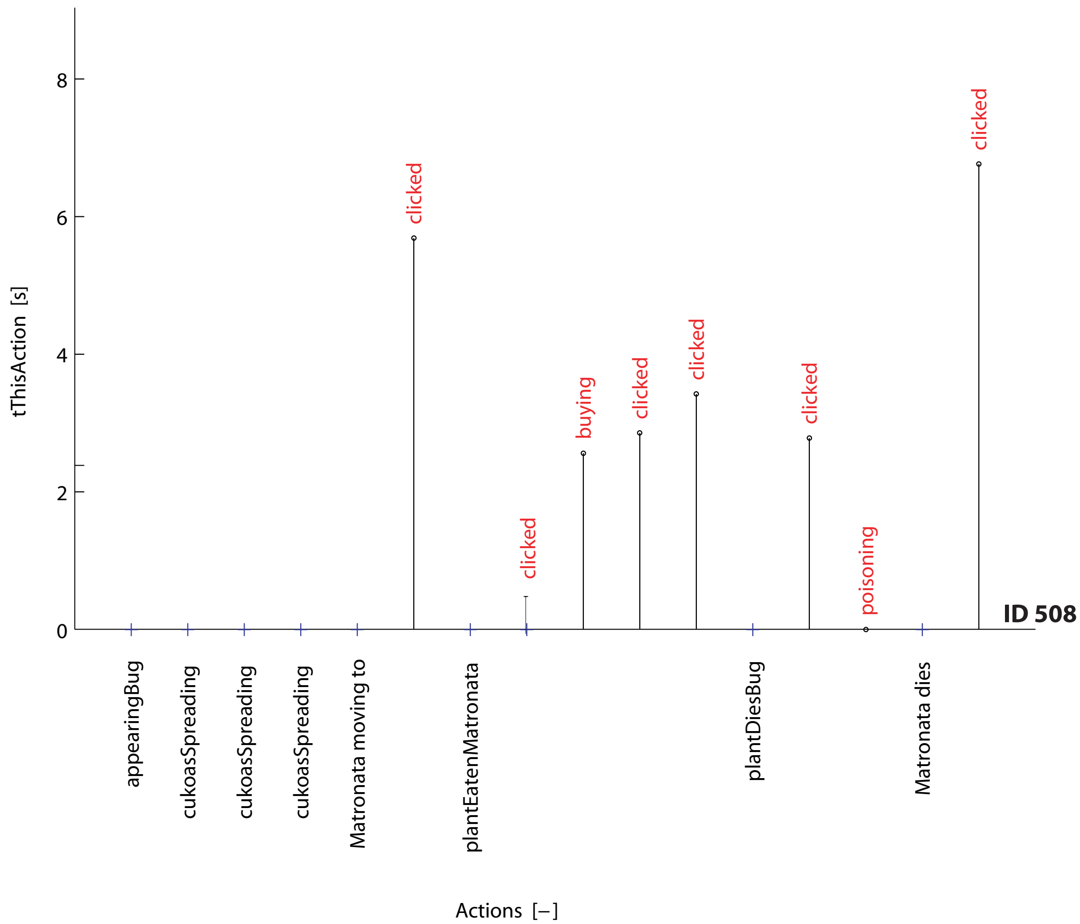


Figure 4.9: This player reacted very fast by buying poison and using it on the bug. (Explanation of variables: cukoasSpreading = plant "Cukoas" is spreading to neighboring field)

bug appeared. She had an immediate reaction (5.7 s) after *Matronata* appeared. Her first reaction, though, was to buy poison in the shop. After 17.3 s, the bug was poisoned, and she continued with her routine of growing herbs. The two screenshots shown in Fig. 4.10 and Fig. 4.11 visualize the situation when bugs were appearing. The think-aloud protocol of player 513 revealed that instead of thinking about a strategy, she started to harvest as much as possible before the bug could eat all the leaves. She changed her focus to reaching the game goal as fast as possible no matter what it would cost. Thus she was not careful with plants and their health. The field shown in Figure 4.10 shows small plants, and most of them were not really healthy. The information bar next to the plant *Cukoas* shows too much humidity which results from too much watering. Thus its health is only 10% and the plant is about to die. Since this player only has two *Cukoas* plants, losing one is a big loss. The player took many actions until "next turn" was clicked. Since she did not change her kind of careless playing, she lost the game. Many actions between turns are most efficient if players are already experienced with their tools

Figure 4.10: There are only small and unhealthy plants on the field (player 513).

and the garden system. They should be able to assess the effect of their actions. However, player 513 showed this kind of careless style from the beginning and did not adjust to this new situation. She only had two bugs appearing in level 3, while others managed to deal with over twenty bugs.
Player 508 had a different strategy and collected many leaves for making money in order to have some savings. Therefore, she used *Cukoas*, a weedy plant, as a generator of cash. Since *Cukoas* is quite a robust plant, it does not have to be treated carefully. In the beginning of the game, this player accidentally planted too many *Cukoas* because she did not know how the game worked. Instead of pruning down these weedy plants, she started to use them as an investment source which helped her in level 3 with bugs. This precaution saved her from a lot of the problems that player 513 encountered such as a low budget and running out of plants. Her strategy of dealing with the bugs was not very cost-efficient. Poisoning bugs is the most costly method. Using *Fortis Noctis* as bug trap would have been the cheapest method. Although the glass for catching one bug at a time is more expensive to buy than the poison, it is more efficient if used cleverly and it only has to be bought once. One bag of poison costs only slightly less than the glass, but it can only be used once on a bug.
Since player 508 had half of the field crowded with *Cukoas* plants, though, she could afford to use this costly method. Therefore, unlike player 513 who lost the

Figure 4.11: This player (508) is using *Cukoas* as an investment source.

game, player 508 could use her strategy to finish the game.

These two examples showed two different strategies for dealing with this unexpected situation. One strategy led to losing the game and one lead to winning the game. Both were not the most efficient and time-saving methods.
However, there were other players who did not panic and just remained calm when bugs appeared. Post-game interviews revealed some very elaborate strategies, but also some totally wrong assumptions about bugs.
One player (ID1064) used the glass as trap and fed the bug to *Fortis Noctis*. Normally, it takes three turns until the glass can be used again for catching bugs. Feeding them to *Fortis Noctis* tricked this feature and thus could be used more often than it was actually intended by the game designer.
Another player (ID505) remained calm and devised several bug treatment alternatives:

> "... I read about this somewhere and I immediately thought about what I could do against it. There were two things, the glass and the poison. And then I saw how expensive it is. And then I remembered a plant that I planted recently that is connected to insects and that it eats them. So I compared prices and chose the plant ... I totally focused on this feature

and did without the glass and the poison."

This strategy payed off on his spendings, and he hardly had any plants that died because of bugs.
Table 4.9 shows a summary of the most important criteria regarding bug treatment strategies. For player 508, the strategy of just using poison causes her above-average

Table 4.9: Summary of bug treatment strategies for the four described players. Highlighted values are caused by more and less efficient strategies.

GameIDs	SpendingsL3 ($)	SpendingsL4 ($)	SpendingsL5 ($)	AppBugPerPlantL3 (no./plant)	AppBugPerPlantL4 (no./plant)	AppBugPerPlantL5 (no./plant)	PlantByBugDyingRateL3 (%)	PlantByBugDyingRateL4 (%)	PlantByBugDyingRateL5 (%)	UserIndActionsL3 (no. clicks)	UserIndActionsL4 (no. clicks)	UserIndActionsL5 (no. clicks)
Average	58	58	69	0.97	1.02	1.62	0.39	0.53	1.09	277	308	395
ID505	55	20	35	1.16	0.45	0.20	0.10	0.00	0.00	367	141	146
ID1064	60	55	40	1.05	2.29	0.21	0.07	0.03	5.26	379	567	161
ID508	90	165	95	0.88	0.56	1.23	0.26	0.10	0.28	528	534	426
ID513	25			0.54			7.69			151		

spendings. The inefficiency of this method is visible in the number of clicks. The efficient strategy of player 505 is visible in spendings and clicks that are below the average. He also had the least number of plants dying because of bugs compared to the three other players. Although the method used by player 1064 is a very creative solution, it is not the most efficient one. Spendings and clicks are quite high compared to those of other players. However, not as many plants died because of bugs. Only in level 5, this rate changed for reasons unknown to the author.
Player 513 had the highest rate of plants that died because of bugs. She only had one bug for two plants (ratio of bug : plants of 1:2), while most of the other players had at least one bug per plant appearing (bug:plant; 1:1). This value is quite low compared to her rate of plants dying because of bugs [1], which is the highest among these players. These two values confirm her bad strategy which was discussed above.
In relation to the MFF20, players 508 and 513 are categorized as impulsive, while player 505 was reflective. Player 1064 was categorized as slow and inaccurate.

This section discussed different bug strategies. There are more and less efficient strategies. Since this is a learning game, it is questionable if efficiency is very important in regards to learning. However, some players are more creative than others and again other players have a more sophisticated strategic thinking compared to other players.

[1] The rate is calculated by no. of bugs appearing per turn and plants died because of bugs in relation to total plants on the field per turn.

4.3 Influence of Prior Experience and Field of Work

In order to exclude the influence of prior knowledge as much as possible, *Hortus* is based on modified rules for the garden system. In this section, results show if there is still an influence of prior knowledge in subject-related areas such as real gardening and media-related knowledge such as playing video games. The results presented here stem from interviews from think-aloud experiments and online questionnaires. For ***gaming experiences***, players were categorized according to their play time. Categories are defined as follows:

- Non-gamer.
  Non-gamers do not have any prior experience with games or have played other non-digital games a few times in their lives.
- Casual-Rarely.
  Players who play once a month, a couple of times a year, or who had played video games a few years ago.
- Casual-Often.
  Players who play a few minutes a day or once a week.
- Hardcore.
  Players who play several hours a week or even per day.

Table 4.10 presents an overview about player distributions of gaming and gardening experience, and how they liked the game. For the overview, only those candidates were evaluated who completed the game and also filled out the feedback questionnaire or participated in interviews after playing the game. The majority of

Table 4.10: Overview of attitude towards video games and gamer, gardening experience.

Overview of Prior Experience

likeVideoGames	yes	141
	not sure	9
	no	19
GamerCategory	Casual-Often	54
	Casual-Rarely	37
	Hardcore	60
	Non-Gamer	18
haveExperienceIn Gardening	no	112
	yes	57

candidates liked video games in general. This high number is not surprising since

taking part in the experiment was voluntary. Hence, mostly gamers were attracted to this experiment. However, there is still a remarkable number of people who did not like video games and tried out the game anyway. The majority of gamers were casual or hardcore gamers who played video games several times a week or month. From a gender perspective, female players were evenly spread through gamer categories, while male gamers were concentrated in the hardcore and casual-often category. From a cultural perspective, only Swiss players were concentrated in the categories with less gaming experience (non-gamer and casual-rarely).
Gaming experience had some influence in the beginning of the game (see Table 4.11). The biggest difference of mean values between non-gamers and hardcore gamers is found in level 1. Hardcore gamers were significantly faster (twice as fast)

Table 4.11: Gaming experience and play time

Gaming Experience vs. Play Time

	GamerCategory Rec	N	Mean (s)	Std. Deviation
timeL1	Non-Gamer	11	1157.95364	750.099834
	Hardcore	50	514.63714	298.347831
timeL2	Non-Gamer	11	890.33800	512.971408
	Hardcore	50	519.08984	294.320878
timeL3	Non-Gamer	11	819.32491	461.505342
	Hardcore	50	620.10258	505.383808
timeL4	Non-Gamer	11	830.26173	515.263516
	Hardcore	50	662.06412	401.896089
timeL5	Non-Gamer	11	1030.01482	434.756788
	Hardcore	50	1214.22758	3108.643948

than non-gamers at the first level. At the second level, hardcore gamers are still significantly faster. These characteristics disappear though in levels three and up.

Table 4.12 shows the distribution of *gardening experience* and nationalities of players. Most of the US citizens and players from other countries had gardening experience, while the majority of Swiss and Austrian players had no gardening experience. This difference might be explained by Swiss and Austrian players who mainly live in big cities such as Vienna or Zurich. Most of the players of the US grew up in single-family houses and had to help their parents with garden duties.
Since *Hortus* has non-real plants, gardening experience had no influence on play performance. This was an expected result. Although it was assumed that people with an affiliation for gardening might be more careful with their plants or would not use any poison for bug treatment, there was no difference to be seen between these groups.
However, think-aloud protocols revealed that players with gardening experience tried to connect their knowledge of real-life gardening with the phantasy content of

Table 4.12: Overview of gardening experience in relation to nationalities

haveExperienceInGardening * country Crosstabulation

			Country				Total
			A	CH	Other	USA	
haveExperienceIn Gardening	no	Count	60	45	3	4	112
		% within country	72.3%	70.3%	37.5%	28.6%	66.3%
		% of Total	35.5%	26.6%	1.8%	2.4%	66.3%
	yes	Count	23	19	5	10	57
		% within country	27.7%	29.7%	62.5%	71.4%	33.7%
		% of Total	13.6%	11.2%	3.0%	5.9%	33.7%
Total		Count	83	64	8	14	169
		% within country	100.0%	100.0%	100.0%	100.0%	100.0%
		% of Total	49.1%	37.9%	4.7%	8.3%	100.0%

Hortus.
One player commented on *Cukoas*, the weedy plant:

> "I suspect that it will spread more soon. Because it's like mint and you can't kill mint."

Another player with gardening experience summarized her learning experience in the game:

> "... care in planting things next to friendly neighbor plants, controlling plants that spread aggressively, taking care in amount of water, not over-pruning or over-harvesting are all real-world gardening principles."

Some real-life attitudes were so strong for this player that they even influenced her decision-making in the game.

> "It became frustrating when I couldn't seem to control the bugs – the jar wouldn't capture them anymore, and I hate using pesticides."

For this player, this ethical decision affected the outcome of the game. She lost the game in level 5 because there were too many bugs to handle with the jar.
Some players had assumptions that a mono-culture is not healthy for plants so they planted different plants close together. This had a damaging effect on plants in *Hortus*, though. In the *Hortus* world, a mono culture of plants is desired. Other players were of the opposite opinion and planted everything far away from each other. Since the system in *Hortus* is developed for this behavior, they were more successful with keeping plants healthy from neighboring attacks.
Certain players who had no experience in gardening did not even water the plants in the first few levels. They did not know that it is necessary to water plants for growth and health. Therefore, many plants died in the beginning and spendings for buying new plants increased. They only realized the necessity of watering when their budget got short and they were forced to rethink their strategy.

However, the overall results of gardening and gaming experience show a major influence on playing only in the first two levels. As soon as players became familiar with the game and its rules, this difference evened out. Thus, there is no extensive impact of gardening and gaming experience on the learning progress in the game. This also means that the intended exclusion of prior knowledge was quite successful.

4.4 Learning Progress and Learning Outcome

Learning in *Hortus* was measured by interviewing players after playing the game and as in-game measurement by analyzing the online data collection.
Measuring learning progress or learning outcome in an open game is very challenging. Learning should happen in a playful way. This means that players play *Hortus* and learn something about the plants and the system while playing. *Hortus* does not openly inform players what they should learn. The same was designed to leave open what players would focus on if no specific learning goal was given. The learning goals intended by the designer are integrated in the game play.
In Section 3.1.1, a cycle with three different learning goals was introduced (Fig. 4.12). The two features interface and dealing with obstacles of this cycle have been discussed earlier in Section 4.3 and Section 4.2.4. Most of the players learned how to handle the game interface and orient themselves. As stated in Section 4.3, prior gaming experience slightly accelerated this learning process. However, that advantage evened out in subsequent levels.

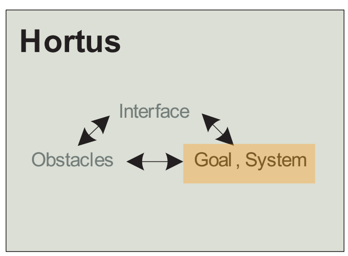
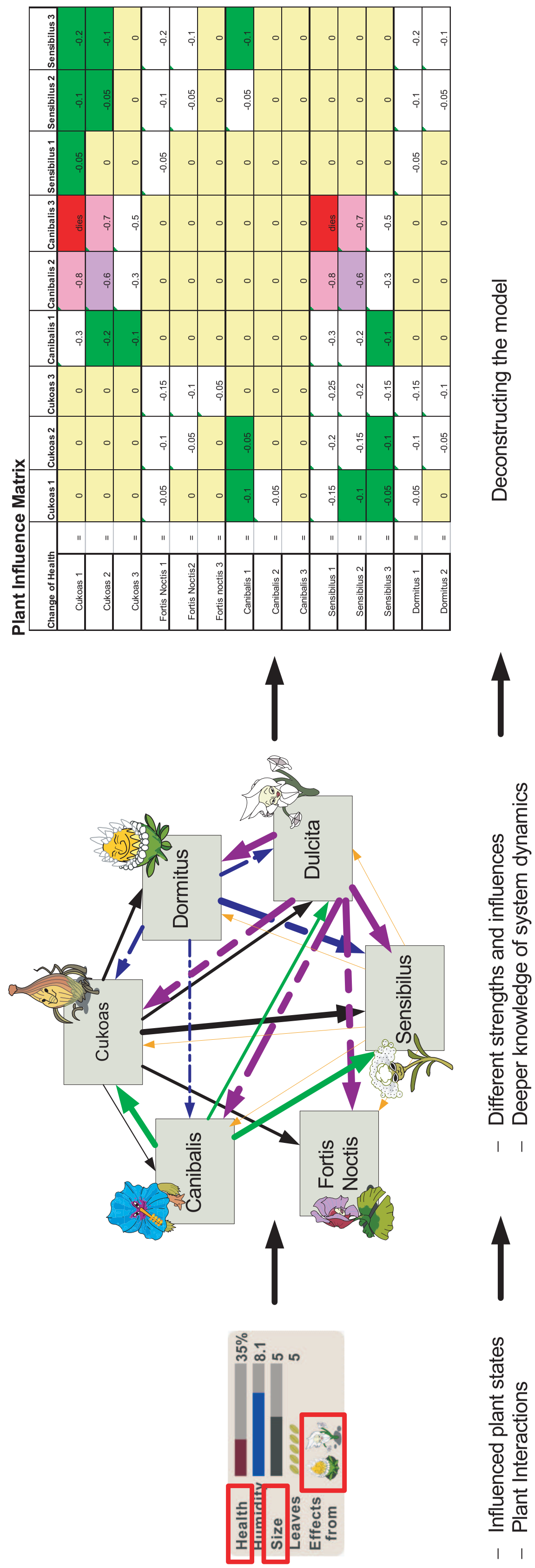


Figure 4.12: The focus of this section lies on characteristics of the plants and dynamics of the system.

The emphasis in this section lies on the second learning step: Learning about the characteristics of plants and the dynamics of the system.

4.4.1 Results from the Pilot Study

The pilot study revealed a more detailed picture of possible learning goals achieved in Hortus. Figure 4.13 illustrates three learning goals that resulted from the pilot study. In the first learning level, players learned the basics about each plant. They learned about different states such as health or humidity that they can influence. Humidity depends on the amount of water poured on a plant in each turn. Health increases or decreases if humidity is too low or too high, etc. Basically, players



Change of Health		Cukoas 1	Cukoas 2	Cukoas 3	Canibalis 1	Canibalis 2	Canibalis 3	Sensibilus 1	Sensibilus 2	Sensibilus 3
Cukoas 1	=	0	0	0	-0.3	-0.8	dies	-0.05	-0.1	-0.2
Cukoas 2	=	0	0	0	-0.2	-0.6	-0.7	0	-0.05	-0.1
Cukoas 3	=	0	0	0	-0.1	-0.3	-0.5	0	0	0
Fortis Noctis 1	=	-0.05	-0.1	-0.15	0	0	0	-0.05	-0.1	-0.2
Fortis Noctis2	=	0	-0.05	-0.1	0	0	0	0	-0.05	-0.1
Fortis noctis 3	=	0	0	-0.05	0	0	0	0	0	0
Canibalis 1	=	-0.1	-0.05	0	0	0	0	0	-0.05	-0.1
Canibalis 2	=	-0.05	0	0	0	0	0	0	0	0
Canibalis 3	=	0	0	0	0	0	0	0	0	0
Sensibilus 1	=	-0.15	-0.2	-0.25	-0.3	-0.8	dies	0	0	0
Sensibilus 2	=	-0.1	-0.15	-0.2	-0.2	-0.6	-0.7	0	0	0
Sensibilus 3	=	-0.05	-0.1	-0.15	-0.1	-0.3	-0.5	0	0	0
Dormitus 1	=	-0.05	-0.1	-0.15	0	0	0	-0.05	-0.1	-0.2
Dormitus 2	=	0	-0.05	-0.1	0	0	0	0	-0.05	-0.1

Figure 4.13: Three different complexities in Hortus (increasing from left to right) dependent on the number of times played the game.

learned that each plant is different and has different needs.
On another level, players learned that plants influence each other when they are close together. Not every plant is harmful to all other plants, though. Some plants have a stronger effect on certain plants than others.
Thanks to some players who volunteered as test players, the third and most complex learning level could be discovered. Most of these players could de-construct only certain parts of the model, though.
The following player statements demonstrate different learning depths:
The first statement is from a player with vague knowledge about specific game features.

> "I used plants I don't need anymore as a decoy for the bugs."

The second statement is from a player with a deeper conceptual knowledge about game features.

> "I used *Fortis Noctis* as bug decoy because it attracts them in certain stages. I also planted them in different turns so that at least one plant is always in the attraction mode."

Some players already had quite an accurate picture of *Fortis Noctis* after only playing once. They observed that *Fortis Noctis* changed cycles every third turn.
The depth of learning depends very much on players and on how willing they are to reflect on events in the game. Many players only remained in the first learning level and never went further to the second level. This confirms that learning in open games is very individual and is hard to control by the educational designer. However, for future studies, it is important to incorporate the encouragement of reflection in the game design.

4.4.2 Results from Think Aloud Experiments

Some players (from think-aloud experiments) experimented with their plants in order to find out how they react and how sensitive they are. One player (ID472) had a small *Dormitus* on the field with only one leaf. He was wondering how much its health would go down when the leaf is harvested. As it went down from 100% to 30% he was surprised but knew he had to be careful with harvesting those plants. Most of these players who liked experimenting had only a few plants on the field and systematically tried out different things to see the immediate effect.
This confirms Gee's learning principle of the *probing cycle* (Gee (2003)). Certain players tried out something specific. Depending on the system's reaction, they derived hypotheses about the system. When a similar situation was returning, but the reaction of the plant was different, a new hypothesis was formed. In the case with *Dormitus*, the player found out that the drastic decrease in health is affected by plant size. Thus, a bigger *Dormitus* is less sensitive to harvesting than a smaller one. Also, only harvesting the last leaf causes such a drastic effect. This learning outcome was confirmed by another player with the following statement in an interview right after playing the game:

> "You know you have control (over plants) because, for example, you always leave one leaf on them. Because when I take the last leaf it hurts them a lot more than before."

Although most players had a probing cycle in their learning process, many of them formed wrong hypotheses at first. If several things happened at once, it was difficult to distinguish between single events. Thus, a player thought bugs were intelligent and would get more and more intelligent with the progress of the game. This was caused by a series of coincidental actions and reactions between bugs and plants. In reality, bugs are attracted to certain plants with certain sizes or health states. There was no intelligent behavior involved.
Another player planted four *Fortis Noctis* plants in different turns. Since at least one of them always was eating bugs, he assumed that *Fortis Noctis* always does that without considering the two cycles this plant had. In the test scenario though, he planted them all at once and thus they were all in the same cycle when bugs came. This was confusing at first because the entire time he had the theory that *Fortis Noctis* always eats bugs. Therefore, in the last level he had to correct his hypotheses.
Players who systematically experimented and tested things had a very accurate image of the characteristics and needs of the plants. Players who planted many different plants at once and had many plant interactions had a less accurate image of the garden system. However, the latter group had a better understanding of plant interactions because plants were planted closer to each other. Players who were more careful and intentionally planted all different plants far from each other never had any interactions and thus did not learn how plants react to other plants. One player was quite the opposite of player ID472. He had a rather crowded plant field. However, he had many plant interactions and categorized *Cukoas* as quite strong and indestructible. Size had a rather negative effect because the influence on neighboring plants became stronger and more damaging.
Having phantasy plants also had a downside. It was very difficult to gather learning experiences of players in post-game interviews. If asked if they learned anything, many players answered that they learned nothing. Since the garden system of *Hortus* had only little to do with a real-world garden in their opinion, many players had problems to talk about phantasy learning content. They wanted to compare it with things they knew from real life. One player who claimed not to have learned anything stated:

> "... because it is only a game for me. [...] Well, I believe that this helps a couple of people with learning but for me the link to reality is missing. Because in that moment, it's not clear at all if these plants really exist in real life. And I don't have a picture of how they really ... if there were photos of them, it might have been different."

Therefore it was especially interesting to watch players playing the game and let them find out various things about plants while playing. Also, if asked indirect questions, like about specific experiences in the game and their thoughts about them, a lot of information could be gathered about what they learned. However, the same players claimed not to have learned anything when they were asked directly in post-game interviews.

Think-aloud protocols also confirmed findings from the pilot study. Most of the players who reflected on game events also learned something about the system and plants. Players who just played around and somehow reached the goal did not learn a lot. At least, neither think-aloud protocols nor post-game interviews could discover any learning outcomes.

4.4.3 Results from Online Experiment

The third study consisted of 163 players who successfully ended the game the first time. Players from the think-aloud experiment are included in this number because their game data was stored in the database as well.

For the in-game measurement of learning outcomes three different criteria were analyzed:

First, it was analyzed how players watered their plants so that the humidity level was in an optimal range. Second, it was evaluated if plants were affected by their neighboring plants and how many times. If this issue was learned, it should have improved in level 4 or in level 5. The third criterion is about player attacks and how players deal with it. They should learn to prune their plant after a player attack.

Since only four kinds of plants are planted in level 5 (*Fortis Noctis, Canibalis, Dulcita, Sensibilus*), only these are analyzed for the criteria optimal watering and plant affected by neighboring plant. For player attacks *Dormitus, Canibalis,* and *Dulcita* were taken into account. These are the only plants that provoke a player attack.

Optimal Watering

Since *Fortis Noctis* did not need a lot of watering, it was one of the easiest plants to take care of. The trend lines shown in Fig. 4.14 for *Fortis Noctis* illustrate this aspect. The three groups are equally sized (each 1All three lines of each group are improving towards level 5; even those who started weak in the first level improved during the play.

For *Dulcita* the effect is stronger. There are players who started quite good but worsened in level 5. Others stayed the same, and the group that started bad improved during level 5. Since these lines only represent general tendencies, this is not valid for single players in particular. There are all kinds of variations. One reason why the watering worsened in level 5 could be that players did not care so much anymore because the goal was about to be reached soon. Another reason is that some plants were more robust than their humidity level actually indicated. Thus, they did not need the optimal amount of water. This mostly occurred with *Cukoas*.

Every plant has different needs for humidity though. Since some players watered

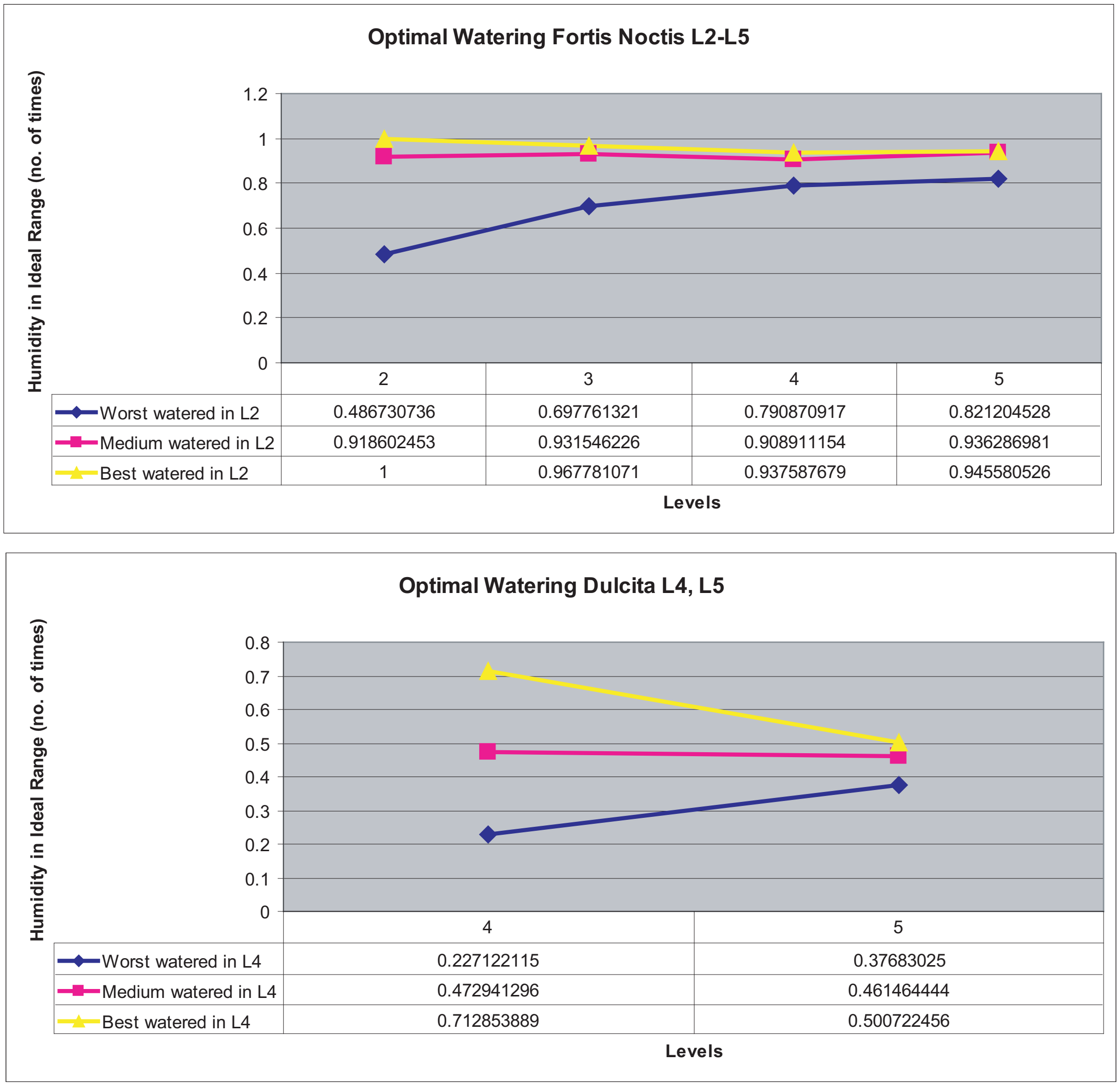


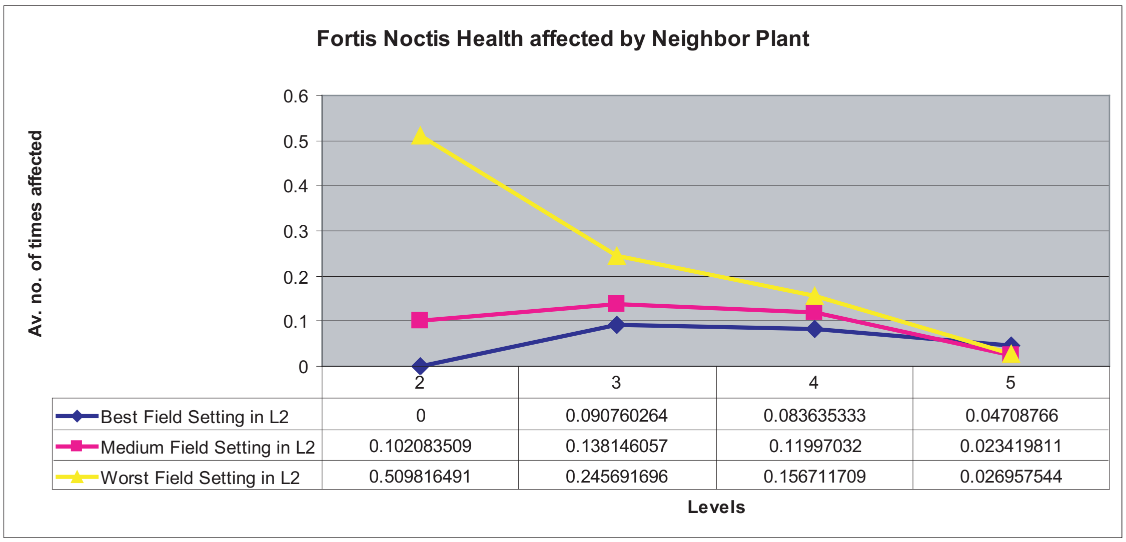
Figure 4.14: Players generally improved in watering *Fortis Noctis*. With *Dulcita*, the results are mixed.

all their plants the same, some plants had worse values than others. *Canibalis*, for instance, is very sensitive and needs a lot of water. Generally, it can be said that there are players who improved in watering certain plants or at least particular plants, while others worsened in watering and thus lost many plants with over- or under-watering.
More detailed results are displayed in Appendix E.

The results of optimal watering as a learning goal turned out to be very mixed and contradictory. Several reasons might have caused a distraction of really caring about optimally watering plants. For instance, bugs were very distracting such that players concentrated more on treating bugs than on caring for their plants. Optimal watering was an "internal" learning goal that should have been achieved while playing the game. Since it was not openly communicated to players as a learning goal, they did not care enough about watering their plants as necessary.

Plants Affected by Neighbor Plants

In order to learn about different plant interactions and how the plants affect each other (either in size or health), players actually need to plant certain plants next to each other. Otherwise, there will not be any interaction. Certain trends in field setting have already been discussed in Section 4.1.2, with a focus on cautious behavior. Therefore, the emphasis in this chapter lies on learning. The trends shown



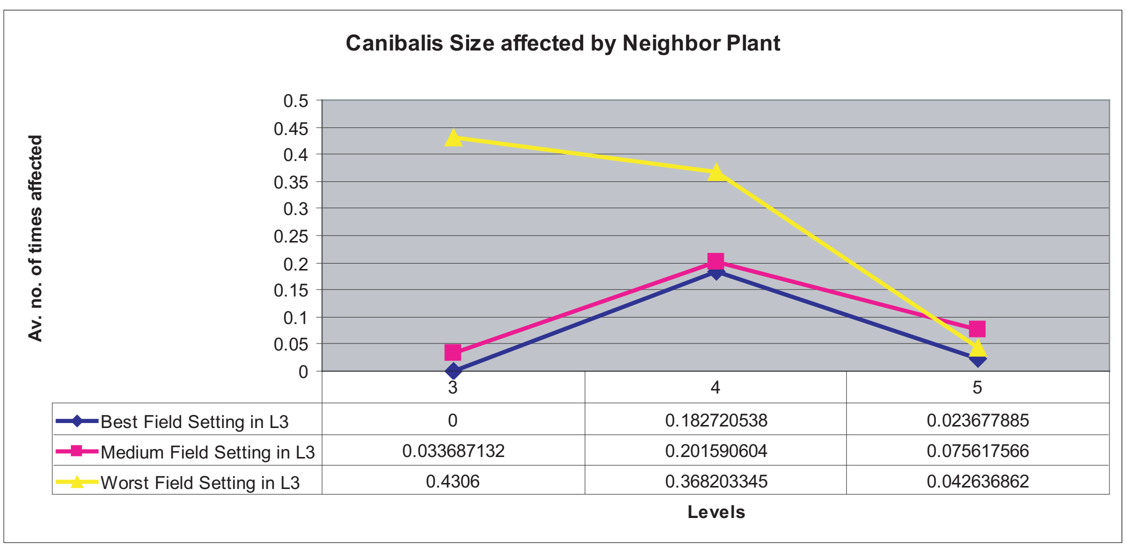


Figure 4.15: Health of Fortis Noctis and Size of Canibalis affected by neighbor plants generally improved. The three groups are equally sized.

in Figure 4.15 indicate that *Fortis Noctis* had interactions with other plants that affected *Fortis Noctis*' health. This is shown for two groups in the slight worsening

in levels 3 and 4 . However, in level 5, lines fall towards "0" which means that *Fortis Noctis* plants were planted so that there were no interactions with other plants anymore. Trend lines of *Canibalis* show an increase of interactions in level 4 and a decrease in level 5. This could indicate a learning progress. In order to see if there was a successful learning progress, values should clearly be over "0" at a certain point in the game. They should decrease though towards "0" at the end of the game.
Results show that most of the players learned to deal with plant interactions. Analyzing individual players showed that some players also worsened and interactions among plants increased at higher levels. Think-aloud protocols revealed that some players made wrong assumptions. Some players were assuming that certain plants would positively influence each other and placed them next to each other on purpose. Figure 4.16 shows a scene where player 492 did not learn about the interaction between *Dormitus* and *Canibalis*.

After two turns, *Dormitus* dies of over-watering, and it probably was also weakened by *Canibalis*. In turn 86, a new *Dormitus* is planted next to *Fortis Noctis* but is replanted right next to *Canibalis* on the same place. This shows that player 492 did not realize a negative interaction between *Canibalis* and *Dormitus*.
A positive learning progress became mostly visible in level 5. At that level, the soil was the same everywhere, such that the plants could be placed anywhere. Those players who still planted damaging plants next to each other did not really think about their actions. They were not aware that some plants can damage other plants or slow down growth.
In order to learn these features, it is important to first have some interactions. However, it is also important to learn from the interactions and avoid them in the future.

Player Attacks

Many players were confused when their screen was locked all of a sudden because a plant attacked them. This feature is out of the game context because it symbolized an attack directly on the player. Normally, players take over an observer role from a "god" perspective. It is unusual to involve the player directly in such a setting.
However, as learning goal, players needed to react to a player attack by pruning the respective plant. Therefore, it is measured how many actions and how much time it took for pruning the plant that had caused a player attack.
Around 36% of players never experienced a player attack while 20% of the players that had one or more player attacks never reacted to it. This means they either never had to prune the plant because it died, or somehow they managed to play on with too big plants. In any case, this group did not learn how to react to player attacks. Players who did react had between one and 355 actions and showed reaction times of between 0.142s and 1069.6s until they pruned this plant. The time is measured until the plant is pruned. It is doubtful, though, if players with 355 actions and a reaction time of 1069s really understood that they had to prune the plant in order to prevent further player attacks.

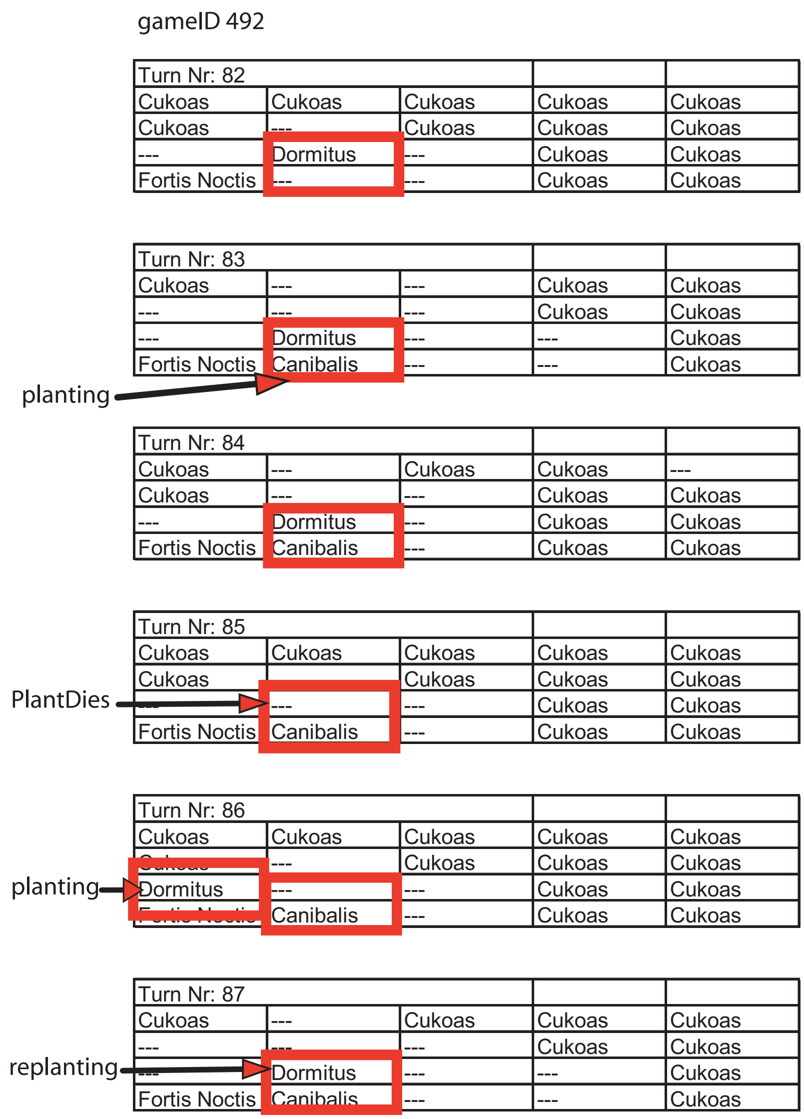


Figure 4.16: The fields represent the plant field. First, all different plants were away from each other. After planting *Canibalis* next to *Dormitus*, an interaction between them occurs which causes *Dormitus* to die. After two turns, a new *Dormitus* is replanted on exactly the same place.

The reason why so many players did not have any player attacks at all is because their plants never reached a critical size for player attacks. Some reasons for this are explained in Section 4.1.1. Thus aside from cautious players, others had read in the game help about player attacks and tried to avoid them.

4.5 Concepts for Adaptive Open Games for Learning

According to the results reported in this section, two approaches for adaptation in open games for learning are introduced. They mainly refer to the attribute of cautious behavior. The first approach is a direct adaptation of the game system according to the player's behavior. The second approach is a form of dynamic feedback and supports players in a personalized way.

4.5.1 Adaptation of Game Environment

Several findings for cautious behavior lead to the conclusion that players who are too cautious do not learn everything they are supposed to learn in an open game for learning. If they always have small plants in *Hortus*, for instance, they will never learn about features of big plants. In *Hortus*, this was the player attack of plants that are too big. Cautiousness also influences the issue with plants affecting their neighboring plants. Some players never saw any plant interactions because their plants were spread too far apart in the field from the beginning.
How can these features be introduced to these kinds of players?
The adaptive system introduced in Section 2.5.5 is modified according to these findings. Figure 4.17 illustrates an example with a player who is cautious in several areas in the game. Since *Hortus* has a phantasy content, it would be easy to simply adjust game parameters so that the game is literally brought closer to the player. For too small plants this would mean that features that are only available for big plants could be integrated into smaller plants. Hence, cautious players would experience a player attack even with small-sized plants. For plant interactions, this would mean to extend the interaction radius of plants so that even those plants that are far apart interact with each other.
However, the problem with adjusting game parameters is that the learning content is manipulated and might even be falsified. These kinds of adjustments work well with unreal content, but not with real-world learning content. Otherwise players get the impression that small plants could be aggressive, too, although only adult plants are aggressive.
One possible solution for this problem is to adjust the game environment rather than changing system parameters.
In the case of plant interactions, this could mean to reduce the size of the plant field, for instance. Hence, players are forced to plant their herbs closer together so that there are more interactions. These changes should be done when a player is constantly planting plants far away from each other.
In order to change a game environment without confusing players, this change has to be integrated into the storyline of the game. If the game is constructed with separate levels that are not connected, the change of scenarios is implemented in the next level. For *Hortus*, this change is introduced through an event like the last scenario with the drought.

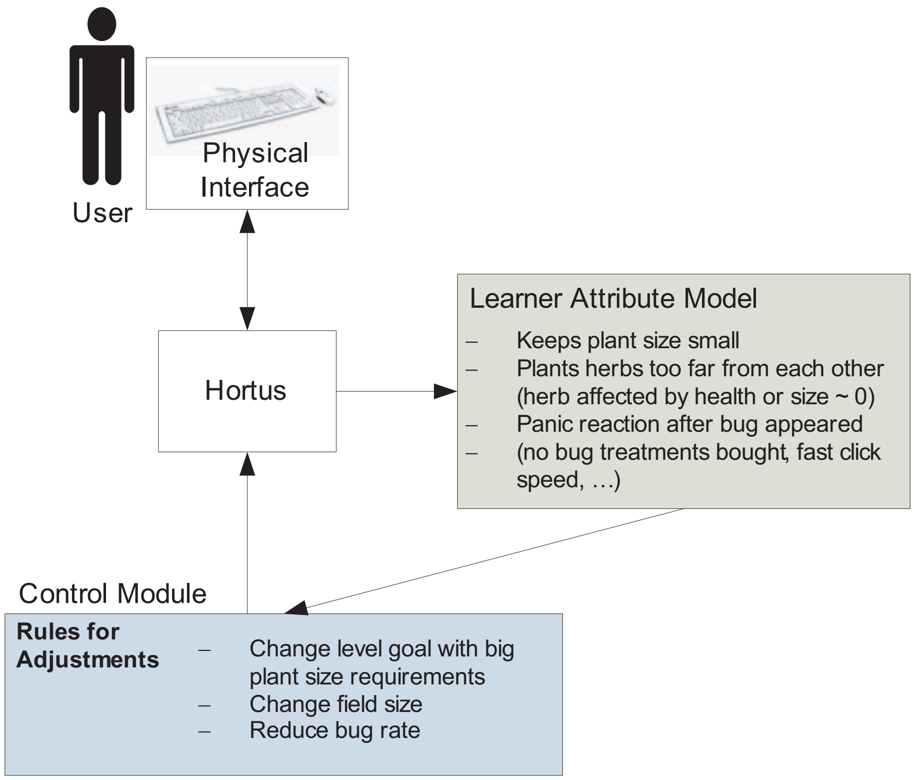


Figure 4.17: The adaptive system, modified for *Hortus*.

As for characteristics such as never having big sized plants, the game level goal has to be adjusted. The goal of having bigger plants in order to experience adult plant features should be made more attractive or necessary. For instance, the goal is to include specific requirements that are only available through adult plants. In *Hortus*, there are potions that are only made with leaves from adult plants.
All these scenarios in *Hortus* are connected by storyline and built up on each other on the level of difficulty by introducing one or two new plants per level. If scenarios are changed all of a sudden or goals are adjusted, they still need to fit in with the rest of the game play structure.
For a versatile connection of different game levels, the concept described by Spring-Keller and Ito (2007) is modified and applied. Thus, depending on a player's behavior (e.g. too cautious), he or she could have a different learning scenario than a player who is average in cautiousness. Figure 4.18 illustrates the modified version of a personal learning module integrated in the open game for an average player. An average player who learns all different kinds of features as expected will have non-modified levels in the game. Neither the learning goal nor the game environment have to be adjusted. *Hortus* currently implies this structure. For an adaptive version focused on cautious players, the structure needs to be modified as shown in Figure 4.19. In this modified structure, several parts in the game are adjusted according to cautious behavior. For instance, a player has never had big sized plants and thus never experienced the characteristics of a big sized plant as a

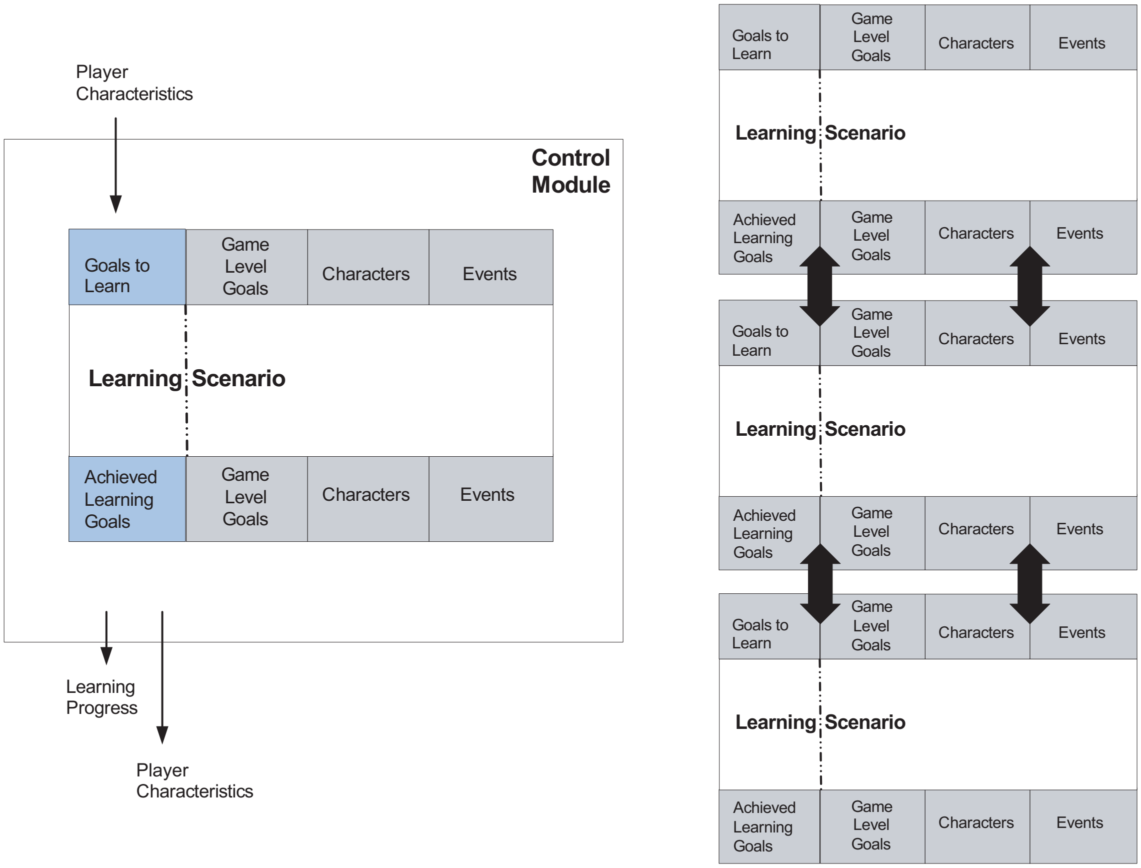


Figure 4.18: Structure of a standard scenario for an average player. Each scenario represents an entire game level.

learning goal. This input causes the level goal to be adjusted. Hence, a potion has to be brewed with leaves of adult plants. The output information for the next level will be if this player actually had a player attack and how he or she dealt with it. If the player learned to prune this plant, the next level can be changed back to the standard game.

This example can also be more complex if several features have not been learned or if players did not learn anything after one level. The adjustment is occurring as long as certain learning goals have not been reached yet.

The same is valid for bugs. This feature belongs to the ”event” part of the learning scenario. If someone has many bugs and also many plants that die because of bugs, this feature has to be adjusted.

However, adapting the complexity of events so that players are able to deal with bugs is quite challenging. Failure is an important issue in the learning process. The question is whether players need to lose the game in order to learn about bugs or if the lack of learning can be handled differently. It is very challenging to keep a balance between boring players and not overwhelming and thus frustrating them.

The most crucial requirement for this kind of adaptation is to know how to measure learning outcomes. What is the right time to conclude that a player will not

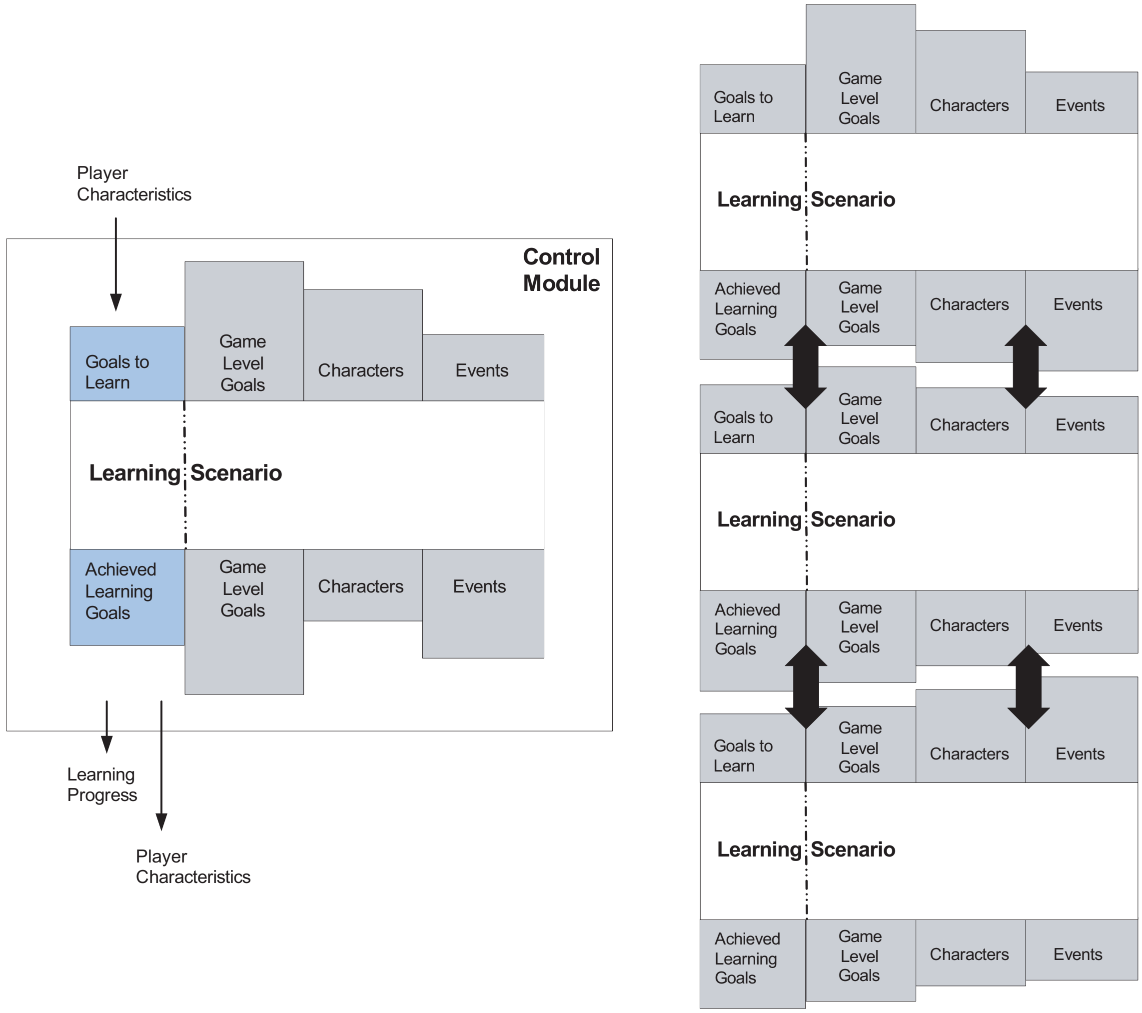


Figure 4.19: Adjusted structure for a cautious player.

experience plant interactions? The first level is too soon and the last possible level is too late. These are the challenges faced with adaptation for this specific feature. In the case of plant sizes it is easier because there was a certain stability detected, as described in Section 4.1.1. For stable attributes such as plant sizes, forecasts can be made to predict with a high probability whether players will keep plants low or not. This feature is thus adjusted in the consecutive level.

4.5.2 The Autopilot – A Personalized Pathfinder

An alternative method for cautious or anxious players is some kind of autopilot. If players do not know how to continue playing the game or do not dare to try out anything, they could switch on an autopilot feature. This feature would then show them a couple of steps of a possible path to continue the game. After the autopilot has stopped, the game would either rewind to the moment where the autopilot started, or players could continue where it stopped.

The idea is compared to a learning method called apprenticeship method (Steinkuehler (2004)) but without a real person who is showing players how something works. Another interpretation is originated in cheat modes for gaming. For commercial games, there have always been cheat codes around for specific situations. Most of this information was created by players themselves.
For this concept, the cheat mode is integrated in the game as a support system.
There are several games such as *Civilization* or *Sim City* that have an internal movie function. Players can watch their personal game in a replay mode. However, this feature usually is available at the end of the game and only from their own game.
The autopilot shows a possible path on-demand in the current situation before players start playing. It can also be used as a "what if I did this" tool to figure out certain things without testing them and risking something.
Although the idea behind the autopilot conflicts with the approach of playful learning, it might be necessary in order to reach target groups other than gamers or game enthusiasts. The motivation behind this personalized pathfinder is to support people who get stuck in a certain situation and do not dare to experiment. The think-aloud experiment revealed certain types of people who are not used to experimenting or who do not want to experiment much. Whether this attitude is age-dependent or depends on gaming experience has not been evaluated as yet. Some players needed more assistance (in *Hortus* using the game help) than others. There is the possibility that the group of non-gamers who aborted *Hortus* in a very early stage would have been better supported with such an autopilot feature and thus might have dared to continue playing the game. The rule system for this

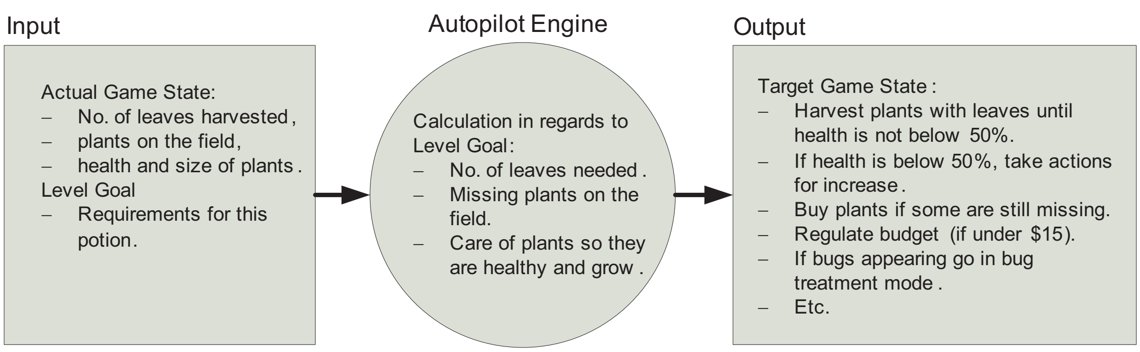


Figure 4.20: Functionality of the autopilot on the example of Hortus.

feature only stores current information about the game and the player. When the autopilot is started, it retrieves the actual state of the game and the level goal and calculates the target state. For instance, it calculates how many leaves are left for brewing the potion. Depending on this information, a virtual player starts to take care of the plants in the field for a couple of turns until the autopilot stops. As indicated in Figure 4.20 in the output window, the goal serves as a guideline for where actions of the autopilot are targeted.
There is a risk of overusing this feature so that players only lean back and watch

the entire game like a movie. This should be prevented by a restriction on the use of this feature. One possible restriction would be that every player has a few credit points for using the autopilot. Once these credit points are used up, players either cannot use the autopilot anymore or they somehow have to earn credit points again. Earning credit points could be combined with a learning goal that has not yet been achieved. Hence, players would not just hunt for points but learn something at the same time.
Another possible restriction is to integrate learning goals into the autopilot's rule system. Hence, the movie would lead into the direction of teaching the player something. In Hortus, this could be towards plant sizes and player attacks. Thus, if a plant already has a certain size, the autopilot could provoke a player attack to demonstrate this feature to the player.

Eventually, both of the above concepts could be implemented together. They are not mutually exclusice. Both are targeted to cautious players. The first is a more indirect way of guiding players towards the desired learning goal. The other concept is more a direct way of demonstrating to players some possible ways of how to solve their current problems. Thus, the autopilot rather deals with suggestions than with guidance. The overall goal of these concepts is to find a balance between open playing and self-direction and providing loose guidance towards a desired learning goal.

Chapter 5

Summary and Conclusions

This chapter discusses the most important findings of this research.
Furthermore, there will be a closer look at several problems or design issues that could have been improved in *Hortus* and in the data collection.
This study represents only the beginning of research in open games for learning. Experiments with *Hortus* provided many insights, but many questions evolved as well. Therefore, some selected topics will be discussed in this chapter for future research.
Eventually, this thesis closes with general conclusions and implications for researchers who want to continue to do research in this direction.

5.1 Summary of Key Findings

This study analyzed player characteristics in open games for learning based on a learner attribute model derived from the theory of individual differences by Jonassen and Grabowski (1993). For this research, the strategy and simulation game *Hortus* was developed. It is a new game about horticulture that teaches fundamental ideas in basic biology. *Hortus* was specifically developed for analyzing player characteristics. The game is played online and its design shows similarities to games like *Sim City* or *Civilization* that are very popular as classroom games. For questions such as how learners solve problems or make decisions and how they learn, a series of explorative studies had been conducted. The goal of this method was to explore and observe players in an authentic environment. Think-aloud experiments and interviews were investigating the questions in further depth. The final online experiments were to statistically validate certain results, but they confirmed only a few of the results obtained from think-aloud protocols.

Certain learner attributes such as ***cautiousness*** could not be generalized. Some players were cautious in a specific situation while in other situations they were not cautious. There were players with cautious characteristics for planting their herbs so far away from each other that there were no interactions among plants. Since experiencing plant interactions belongs to a learning goal in *Hortus*, this could not be achieved by these players.

Others kept their plants low most of the time. Since there are certain characteristics, such as player attacks, that are only experienced with big plants, these players never experienced them. Keeping plants low turned out to be the most stable characteristic from a statistical point of view. As a result, it is possible to make a forecast for cautious players with low plant sizes in level 2 for consecutive levels with at least 50% probability. A general tendency of keeping all plants small can even be predicted with a probability of 65% after level 2. If a player did let the plant grow to a certain size in Level 2, then the player would show the same behavior in Levels 3, 4, and 5. The first level is seen as a training level where players had to become familiar with the game.
Due to cautious behavior, it is concluded that not everybody learns the desired learning goals in an open game like *Hortus*, even though the choices in *Hortus* are more restricted than in other open games.

Statistically significant results from cognitive styles such as ***impulsive/reflective*** were not found in *Hortus* as measured in the MFF20 test. There might be certain play behaviors that indicate impulsive or reflective behavior, but none could be related to the MFF20 test (Matching Familiar Figures Test). Since the MFF20 test only measures wrong/right situations, while the game provides a range of different choices, neither good nor bad, or right or wrong, it is difficult to compare these two treatments. Another reason could be the quality of test results from the online MFF20 test. The correlation of total error and response time was only 0.4, which is considered as a medium correlation. Thus, the MFF20 delivered already a mediocre base for I/R.
Qualitative results, though, were quite promising. One of the analyzes evaluate how players would deal with an unexpected situation in the game. In *Hortus*, bugs were introduced in level 3. They were real-time as opposed to the turn-based structure of *Hortus*. Results showed that players with already sophisticated strategies had fewer problems fighting bugs compared to players with no obvious strategies. Many players with no clear or inefficient strategy could be categorized as impulsive.
Other players had unconventional strategies. Although their strategies were not very efficient, they found solutions for bugs that were not intended by the game designer. It was interesting to see that even in a restricted environment, creative solutions were possible.
This also confirmed an advantage of open games in that they support creative problem-solving.

Measuring ***learning progress and learning outcomes*** in an open game for learning is very challenging. Since learning happened in an informal way, many players did not recognize specific things as learning success or ignored certain learning goals. The latter happened because players were not informed about learning goals in the game. For this research, it was rather important to see how players would choose their own priorities and preferences if nothing was predefined or no score would influence them.

This led to the result that certain learning objectives, such as optimal watering, were achieved well in the beginning. Players concentrated on other events and issues in the game later, though so that some of the players no longer watered their plants as well as they had in the beginning. Some players might be good in the beginning by pure coincidence. However, some players really did not care anymore, although they understood the principles behind watering. If learning goals have to be achieved, players need to care more about them. Therefore, the game design in open games should better incorporate learning goals and make them more valuable for players.

These results form the basis for developing ***adaptive concepts for open games for learning***. First, an adaptation of the game environment was introduced. For instance, if plants are always too small, the game goal is adjusted so that players need to work with bigger plants.
A general structure for these kinds of adaptations was proposed with a series of learning scenarios that are interconnected. Each learning scenario, which in *Hortus* is a game level, has adjustable beginnings. Players end each level differently. Some achieved certain goals and some did not. The game levels need a flexible structure so that every scenario is logically connected to those above and below and is able to adapt to individual player achievements.
The other concept considers an autopilot system that provides players with a personalized outlook for possible pathways. Thus, no matter at which point in the game the player is, the autopilot can be activated. The idea behind this feature is based on a mixture between the apprenticeship method and a cheat mode in games. It functions as another player who could show a possible solution to a specific problem in the game. This feature is best suited for players who are quite cautious or even anxious and do not dare to take risks or to ask other players.

Player characteristics and learning preferences produce new challenges to designers. This study indicates that open games enable different players to approach games differently, meaning that they will focus on different aspects during play time, leading to uneven learning outcomes. This issue is particularly important in open-ended simulation games that provide multiple pathways toward a goal. Part of adaptation then becomes supporting these behavior patterns and providing possible tools or adjustments in the game so that learning objectives still are achieved.

5.2 Limitations

After finishing these series of experiments, an entire iterative cycle could have been added in order to improve results. Several details did not work properly as they were intended to, and the game design could have used another revision.

5.2.1 Technical Limitations

Certain data that was intended to describe certain behavior patterns in the game failed to do this because of technical issues in the data collection.
Online experiments can hardly be controlled. Since players cannot be controlled, the environment and data collection should be as controlled as possible. However, online connections encounter time-outs, no matter how good the connection is. Due to several interruptions, some players had missing turns or single entries. Single entries are hard to detect and mostly do not have a big influence on the total amount of data per player. The data of those players who had missed entire turns, had to be omitted. This could have been prevented by developing an application which stores the data temporarily if no connection is available. Another solution might have been that the data was stored entirely on the player's computer (client side instead of server side) and sent to the server automatically at the end or when players had lost the game.

Other things that were detected early but could not be resolved for a long time were some errors in the game system.
Dying plants sometimes produced "ghost-like" plants on the field. The image was there and occupied the field, but the plant could neither be removed, nor did it have any functionality left. The ghosts were produced especially when the plant was attempted to be replanted while it was dying. Parts of the problem were due to *Flash* and *Actionscript* technology and to the process of removing images or movie clips from the scene. In think-aloud experiments, certain players were not able to replant any of their plants because of this problem. Thus, they had to work around this feature and find alternatives. Their ghosts covered the plant field and usually disturbed them in their playing process. They even stayed in the last level, the test scenario where everything was re-initiated again. Fortunately, this problem was resolved for the online experiment. Hardly anyone encountered this problem again. For analyzing play behavior, this problem was taken into account. Every criterion that included the replanting activity was omitted. In think-aloud experiments, experimenters said that they were aware of the problem and considered it in their analysis.

Finally, one of the most troublesome issues is still the real-time feature in a turn-based game. The bugs in *Hortus* are hardly controllable. They start to act strange after being released from the glass (which is catching them). Also, they are not completely removed by the program in level 5. This made it hard to compare the test scenario of different players because they had different starting conditions. This issue remained unresolved at the end of this study.

5.2.2 Design Limitations

Several difficulties evolved from design misconceptions or ambiguous questions in questionnaires.

Feedback questionnaires were created for the online experiment. For think-aloud protocols the same questions were used, but answers contained more details. Interviewers could rephrase questions to avoid misunderstandings during the experiment phase.

In feedback questionnaires, German speaking people misunderstood certain expressions in English. For instance, many of the players did not understand the word "challenging" in the sense of "difficult". Thus, players answered the question of the most challenging plant in the game with the same answer as the easiest plant in the game, this did not make any sense. Also, questions that were to provide information on whether anything and how much was learned in the game were not stated clearly enough. In interviews of think-aloud experiments, interviewers could correct themselves and reformulate their questions. This was not possible in online questionnaires, though. The questions were formulated as clearly and specifically as possible. However, players did mostly describe only one aspect that they learned if any at all. In interviews, players talked about having learned several things in the game.

Generally, it is always a problem to induce players to describe what they learned or why they did not learn anything in the free text fields in online questionnaires. Usually, only a few people are really responsive and are willing to write down several issues they encountered in the experiment.

These flaws in questionnaires limited the amount of information gathered from players.

Another problem was incipient in the game design itself. The designers of *Hortus* were not professionals in the game development area and thus made a number of beginner's mistakes in the game design.

Many players were bored after three levels and claimed that the game was repetitive. This might also have had some impact on the performance and learning in the game. The strength of impact, though, could not be evaluated within the scope of this study. Also, play time was initially intended to last for one hour at the most. Players in the pilot study more or less confirmed this play time. Unfortunately, many players in the main studies took much longer, such that play time varied from 40 minutes to over 120 minutes.

Although animations in the game were quite appealing to players, many of these animated interactions were too weak to be recognized clearly. They are thus suspected to have a major impact on the learning outcome of being aware of any plant interactions. Also, the fact that this was a turn-based feature was quite hard to understand for some players in the beginning. Since certain game features, such as pruning or harvesting, had an immediate and visible effect, other features had a delayed effect that did not show up until "next turn" was clicked. For instance, the information display of the humidity range for a plant changed after "next turn" because several parameters had to be calculated for the new humidity data. Thus, many players watered their plants too much in the beginning because they wanted to see an effect.

As for learning, the game did not incorporate any real knowledge. The garden system served as a metaphor for real plants, but the plants were in fact phantasy products. Any prior knowledge of the subject of gardening could thus be prevented from influencing player behavior in the game. However, in real situations with a real learning content, prior knowledge is always present and is influencing players' decisions. Therefore, this issue should be taken into account in future studies.

Despite all these limitations, it was still possible to conduct experiments and evaluate data. For a future project, these flaws can hopefully be corrected and changed in such a way that results and player experiences can be improved.

5.3 Future research

As a next step after this research, *Hortus* should be redesigned implementing the players' feedback from these experiments. If open games are to be applied for targeted learning, it is important to do more research on how learning goals can seamlessly be integrated and assessed. It is very difficult to assess informal learning as it occurred in *Hortus*. Learning goals should be communicated better to players, for instance in the form of a scoring system.
The two adaptive concepts are to be implemented in *Hortus* as well. Since open systems provide more freedom in choices than targeted or guided games and players behave differently, it cannot be expected that players will experience all the intended learning goals. In order to find out what kinds of adaptations work and which do not, further experiments with players have to be conducted. It is uncertain, for instance, whether an autopilot is really desired by players and whether it is effective for learning.
Two criteria have not been described in this study yet because there are too many things uncertain about their interpretation, namely *response times* and *click frequency*.
Response times to certain events such as when "next turn" is clicked or when a bug appeared could not be interpreted due to a lack of information. There is an assumption that it might be possible to detect if players reflect on events due to their response times. Other players might reflect less on events in the game and thus learn less.
The click speed or click frequency between breaks is always the same throughout the entire game. Breaks are defined as longer (usually 10s and more, depending on the player's click speed) response times between a series of fast (always less than 10s) user-induced actions. The average speed remains similar in relation to other players' click speed (Table 5.1). This means that a player with the fastest click speed in level 1 will have an almost 60% chance that he or she will still be the fastest in level five compared to other players. The assumption was to find that people with too many breaks are overwhelmed by the game, while those with hardly any breaks longer than 10s considered the game to be too easy. Unfortunately, there were also players who took very long, yet still thought that the game was too easy. Strangely, some of them lost the game and gave as feedback that the game

Table 5.1: Ranking coefficient of click speed data shows a high correlation, which means that clicks speeds are mostly "stable" over levels.

Correlations

			AvTimePerActL1	AvTimePerActL2	AvTimePerActL3	AvTimePerActL4	AvTimePerActL5
Spearman's rho	AvTimePerActL1	Correlation Coefficient	1.000	.744(**)	.717(**)	.587(**)	.558(**)
		Sig. (2-tailed)	.	.000	.000	.000	.000
		N	164	164	164	164	164
	AvTimePerActL2	Correlation Coefficient	.744(**)	1.000	.783(**)	.684(**)	.654(**)
		Sig. (2-tailed)	.000	.	.000	.000	.000
		N	164	164	164	164	164
	AvTimePerActL3	Correlation Coefficient	.717(**)	.783(**)	1.000	.804(**)	.717(**)
		Sig. (2-tailed)	.000	.000	.	.000	.000
		N	164	164	164	164	164
	AvTimePerActL4	Correlation Coefficient	.587(**)	.684(**)	.804(**)	1.000	.740(**)
		Sig. (2-tailed)	.000	.000	.000	.	.000
		N	164	164	164	164	164
	AvTimePerActL5	Correlation Coefficient	.558(**)	.654(**)	.717(**)	.740(**)	1.000
		Sig. (2-tailed)	.000	.000	.000	.000	.
		N	164	164	164	164	164

** Correlation is significant at the 0.01 level (2-tailed).

was too easy. If the click speed does not change due to certain events in the game, what can be said about it? Is this a rhythm of play people have? Could players be classified according to their play rhythm? Or is it just a click speed without any particular meaning?
It would be interesting to find out if players could be identified according to their click speed and if learning could be assessed by analyzing the time breaks after certain events. Unfortunately, in this study, there was not enough data to establish a relation between learning, mastering the game, and click speed and breaks in-between.

Dealing with unexpected situations was only qualitatively analyzed in this study. Instead of categorizing this criteria as impulsive and reflective, it could also be part of the personality trait "adaptability or flexibility" of a person. How fast can a person adapt to new situations? New situations are for instance bugs appearing in *Hortus*, or the last test scenario. Although a message in the game announced the change, the totally new field conditions were surprising for many players.
However, an explorative method is not the most suitable approach to assess this specific characteristic. For such an assessment, a designed experiment would be required. In order to evaluate and correlate the behavior in the game with these personality traits, scenarios have to be singled out. A big challenge is the quantification of players' reactions. There should be several specifically designed scenarios that only assess the flexibility of players in different situations.
The next step would be from find a relation to learning. Does a flexible player learn more of the game than an inflexible one?

The analysis of how players dealt with bugs showed how complex and difficult it is to assess such situations and the reactions of players. Problem-solving skills in learning games are not researched very well as yet. Some research has been published in the areas of assessments and problem-solving skills with respect to job recruiting. Some approaches of these studies might be applied to open games for learning. In order to support players in finding strategies and solving complex problems, more research is needed in this area. Questions such as "Can strategies for problem-solving tasks be classified?" or "How can players be supported when they do not have any sophisticated strategies for solving a problem?" need more attention in the field of open games and learning.

Some of these issues specifically relate to *Hortus*. Others, such as dealing with unexpected situations or click speeds, could be generalized to other games as well. Generally, research in open games is still an uncharted territory and only few studies have been published so far. The study on *Hortus* revealed some very important issues in this research field, but also more open questions were uncovered that are worth investigating in greater depth.

5.4 Conclusions

This thesis provides novel approaches and insights towards the assessment of player decision-making, actions, and learning in open problem-solving environments. Questions such as "What strategies would players use to solve a problem?", "What was important to them?" or "What did they learn?" have been answered.
The combination of qualitative and quantitative methods generated results that would not have been established with only the single use of a research method.
The results of these combinations showed that players with a more sophisticated strategy succeeded better in the game than others who rarely had a strategy to solve problems. Many players who lost the game were just playing and reacting in the moment rather than planning ahead. Therefore, special attention has to be drawn to players who appear "impulsive" because they are not prepared for unexpected situations and thus tend to lose the game. This can easily lead to frustration and quitting of the game in general.
Furthermore, even though the learning environment of *Hortus* was of a restricted nature and thus not entirely open, the results proved a more situated play behavior than stable traits. Depending on the situation or on changing preferences, players usually did not show any stable characteristic throughout the entire game. For instance, it was not possible to classify players as cautious. They were only cautious in specific situations, while in others they did not show this behavior. This means that in open game-based learning environments, characteristics cannot be easily classified. Players focus on current situations, their interest is connected to events in the game and their chosen strategy.
Open games are usually designed so that players explore the content by themselves. Hence, it is difficult to measure learning outcomes or compare the results among players. For targeted learning, where learning goals are pre-defined, a mixture between targeted and open games might lead to a satisfying result. *Hortus* is not

a completely open game. While it provides a somewhat targeted structure with several sub-goals, it still encourages individual and creative problem-solving due to its freedom of paths.

Even with this structure, players are difficult to compare with each other. Therefore, similar situations and the respective players' reactions are compared. However, due to certain cautious behavior, not everyone attained the intended learning goals, despite the semi-targeted structure.

Thus, one of the open question is still whether learning goals should be communicated to players. If yes, should they be specified or just remain very general so that players have only a loose learning goal? What happens if they know the learning goal but never come into a situation to learn it? For this last question, this study suggests a solution by adapting the game environment to player characteristics or to provide a personalized autopilot which provides them with a glance into the options and their consequences.

For educational designers, it is important to think about all these issues when designing a game for learning. Although open games truly have their difficulties when it comes to targeted learning, this is an obstacle that can be overcome. Advantages, such as encouraging creative problem-solving or engaging curiosity, outweigh disadvantages such as being able to fully control the learning progress.

For learners it is crucial to find personal ways of how to solve specific problems. In real life, it is unlikely that a few specified alternative solutions are presented. Usually, problems are complex and often have an uncertain number of optimal pathways. The ability to find creative solutions is vital in a world of globalization and international competition. Therefore, learning environments should promote and encourage this ability.

Appendix A

Glossary

Open Games for Learning
Open games provide non-linear pathways for challenges in a game. These kinds of games allow more freedom of how to play the game and choice of various pathways than linear games, which tend to provide a fixed sequence for solving challenges. Some open games are more sandbox-like, while others include certain integrated sub-goals.
Popular games with an open game structure are *Civilization* or *Sim City*.

Targeted and Linear Games for Learning
Targeted games are applied to specific learning objectives. Open games can also be used for specific learning goals, but the definition of these learning goals tends to be rather loose because they are less controllable. Targeted games tend to focus on detailed objectives. They are often integrated in linear games which provide a preset path for challenges.
A common form of targeted games are mini-games or puzzles, such as Tetris.

Real-Time and Turn-Based Strategy Games
In real-time strategy games, the game progresses without the player's input, while in turn-based games players have to actively initiate the "next turn" in order for something to happen.
Popular real-time strategy games are *Sim City* and *Age of Empires*. A favorite turn-based game is *Civilization*.

Adaptation and Personalization
Adaptation in this context is defined as adjustments made by the game system. In personalized systems, it is the player who actively manipulates the game or learning environment.

Personality Traits
Personality traits are defined as established patterns of actions, thoughts or emotions.

Cognitive Styles

Cognitive styles describe how people think, perceive or process information during problem-solving activities.

Practice Principle and Probing Cycle

These two learning principles are based on Gee's theory (Gee, 2003). In the practice principle, players practice in similar tasks until they master them. These tasks are embedded in the game environment. In the probing cycle, players experience things in the game, reflect on them, form a hypothesis, and test their theories in the game again.

Appendix B

Questionnaires

For the online experiment, a test environment was created. The test environment had to be protected from the outside in order to keep student data private. Furthermore, certain game features such as music was copyright-protected so that it could be played in a restricted environment only. In this part of the appendix, screenshots from the main entrance page of the test environment, questionnaires, and the MFF20 test are displayed.
Figure B.1 shows part of the main entrance page for users. Users first had to register to create a personal account. The orange arrows indicate questionnaires that had not been filled out yet by users. They change to a green check mark if users filled out the respective questionnaire.

Figure B.2 shows the determination of prior knowledge in the field of gaming. Figure B.3 shows a screenshot of assessed learning in the game Hortus. There are many free text fields encouraging users to fill in their thoughts as detailed as possible.

The screenshot in Figure B.4 displays one set with eight images out of a total of 20 sets. The cowboy figure belongs to a more difficult group of images.

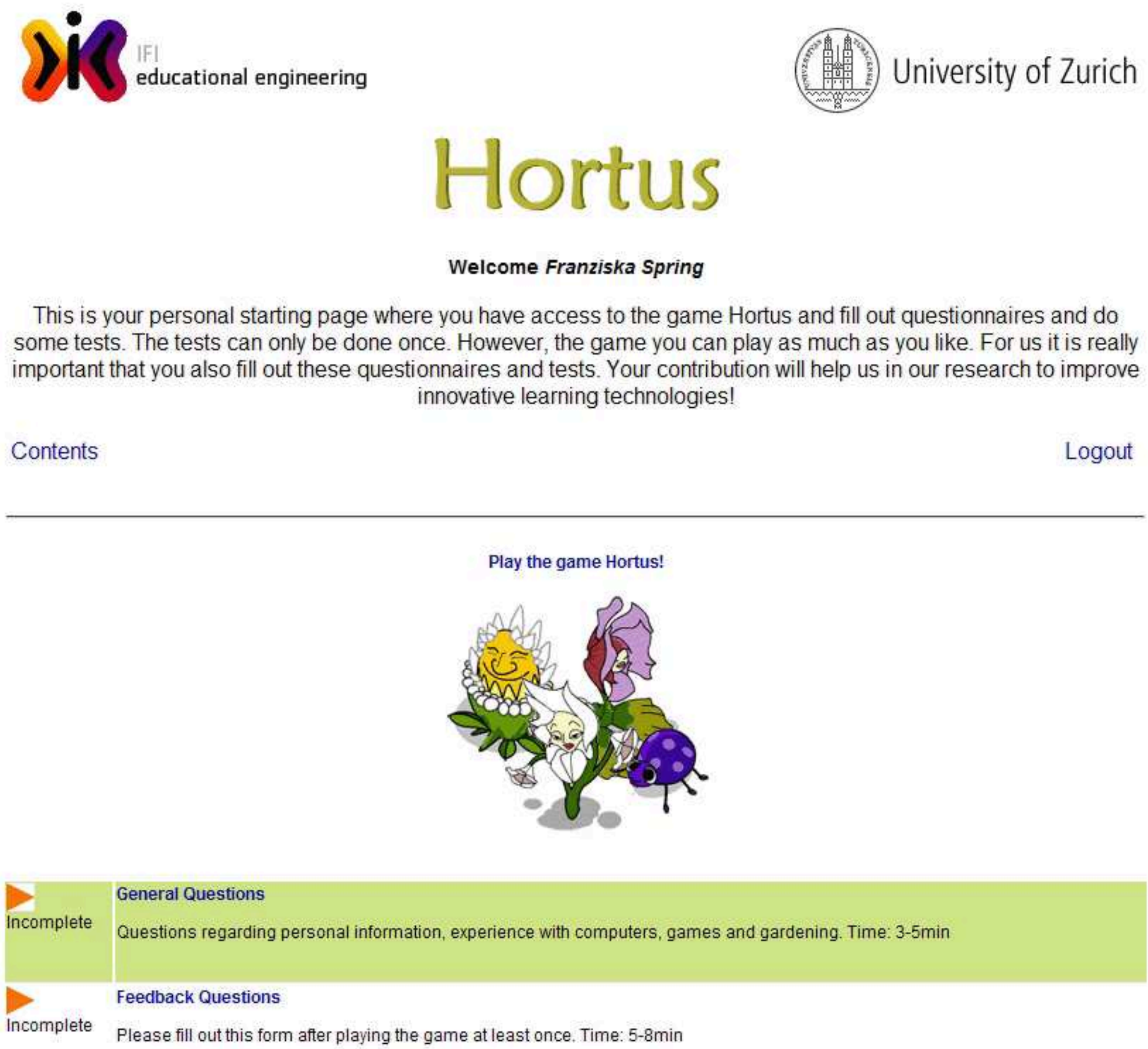
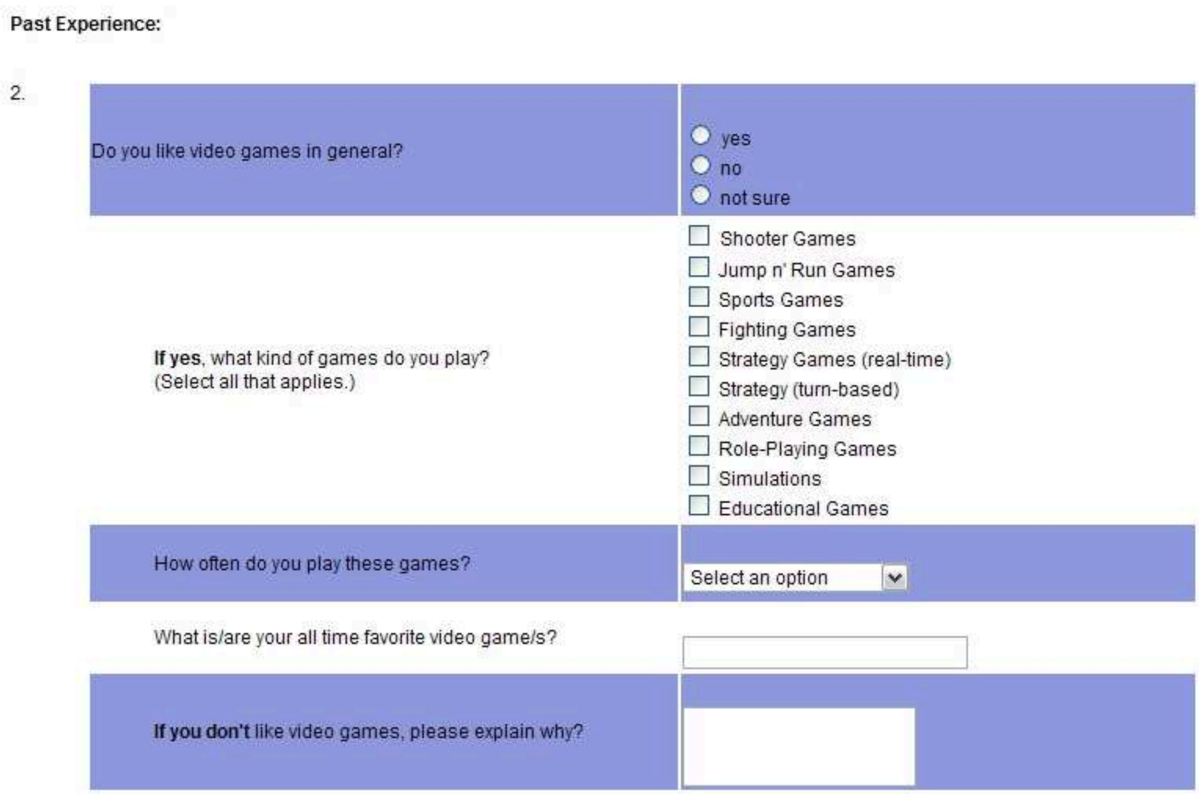


Figure B.1: Screenshot of main entrance page of test environment.

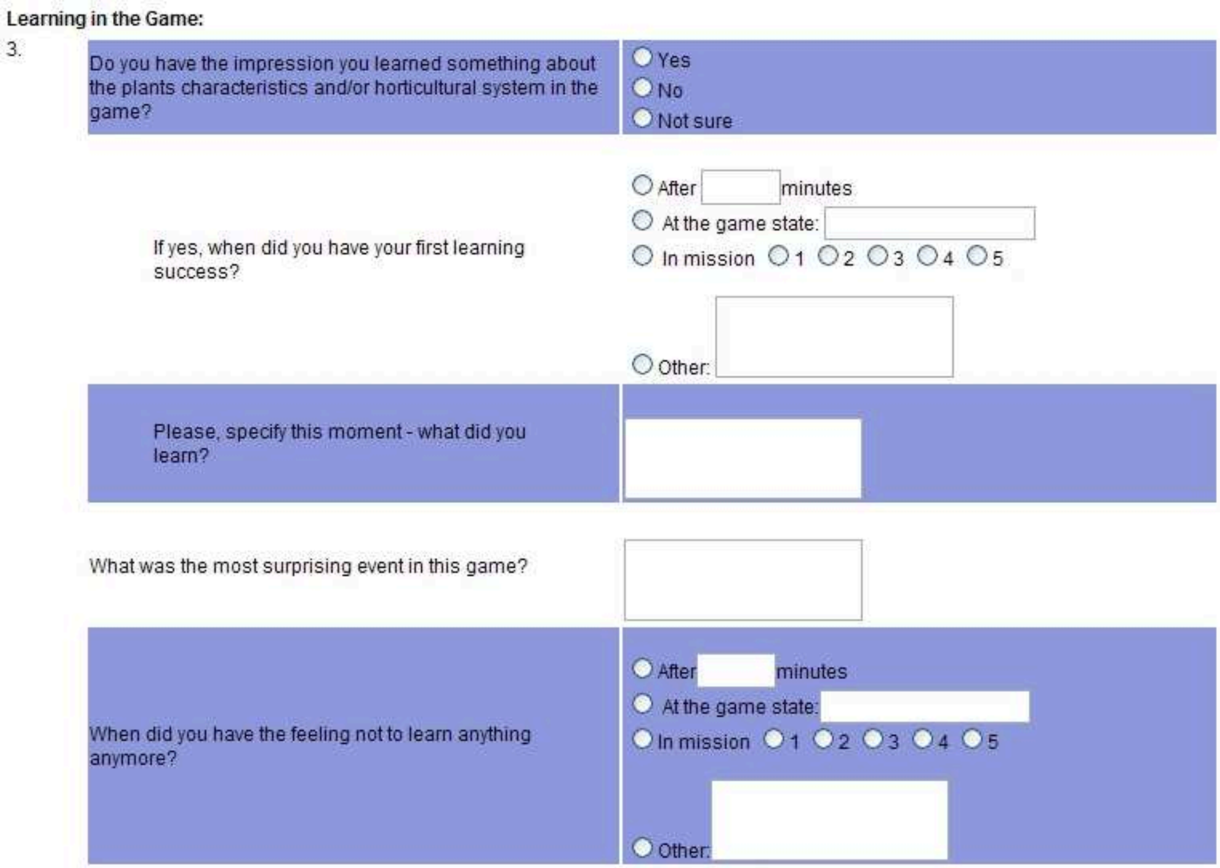


Past Experience:

2.

Do you like video games in general?	yes no not sure
If yes, what kind of games do you play? (Select all that applies.)	Shooter Games Jump n' Run Games Sports Games Fighting Games Strategy Games (real-time) Strategy (turn-based) Adventure Games Role-Playing Games Simulations Educational Games
How often do you play these games?	Select an option
What is/are your all time favorite video game/s?	
If you don't like video games, please explain why?	

Figure B.2: Screenshot general questionnaire.



Learning in the Game:

3.

Do you have the impression you learned something about the plants characteristics and/or horticultural system in the game?	○ Yes ○ No ○ Not sure
If yes, when did you have your first learning success?	○ After [ ] minutes ○ At the game state: [ ] ○ In mission ○ 1 ○ 2 ○ 3 ○ 4 ○ 5 ○ Other: [ ]
Please, specify this moment - what did you learn?	[ ]
What was the most surprising event in this game?	[ ]
When did you have the feeling not to learn anything anymore?	○ After [ ] minutes ○ At the game state: [ ] ○ In mission ○ 1 ○ 2 ○ 3 ○ 4 ○ 5 ○ Other: [ ]

Figure B.3: Screenshot of feedback questionnaire.

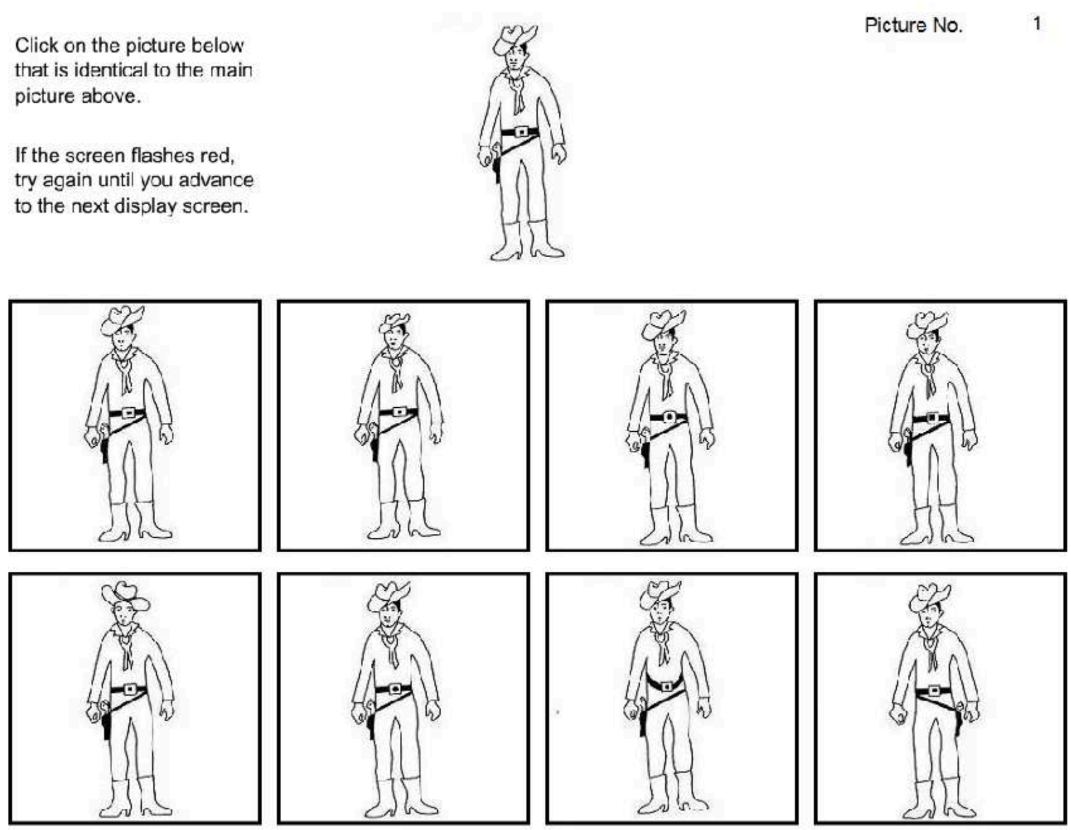


Figure B.4: Screenshot of one set out of 20 from the MFF20

Appendix C

Hortus Database

The database structure is modular so that it is more flexible for possible extensions. Generally, the structure is divided into game information and player information. Figure C.1 shows the main structure of the database.

There are seven entities and two side tables. The seven entities are:

1. user
   There can only be one user id. This id had to be unique. In this case, email addresses of these users were used.

2. game
   Users could play Hortus as many times as they wished. Thus each user has multiple game ids with the respective starting times.

3. action
   This table contains all the information that is generated by users during playtime or events that happen in the game. For example, a user waters a plant and at the same time, in the same turn, another plant dies because it was overwatered. These two events are stored as two entries in the table *action*. Turn number and level are also stored with each action.

4. savegame
   After ”next turn” is clicked by the user, all the current information of the inventory and of collected leaves is stored.

5. tile
   This table saves the state of each tile after ”next turn” is clicked. Amongst others, the information stored is the kind of plant, humidity of the ground, or what kind of soil is on this tile.

6. plant
   The table ”plant” stores all the data of each plant on the field after ”next turn” is clicked. Information such as the number of leaves or health of a plant is important.

7. bug
   This stores whether a bug is on the field and its location.

The two side tables belong to the entity *savegame*:

1. Inventory – Plants
   This table lists all current states for player resources. For instance, budget or amount of poison bought in the last turn.

2. Inventory – Reagents
   Reagents are items that users collected during a turn in the game such as leaves.

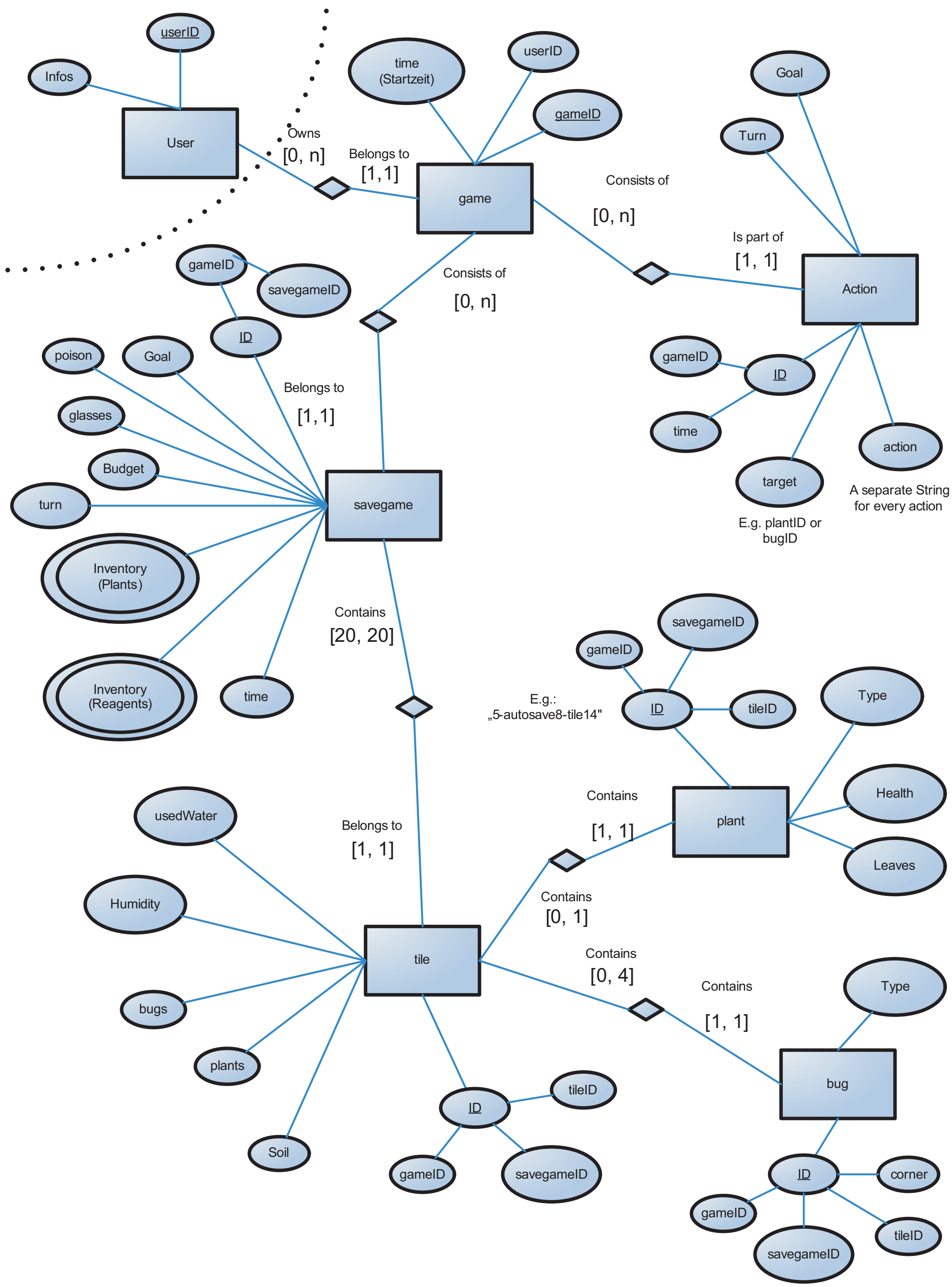


Figure C.1: Screenshot of feedback questionnaire.

Appendix D

Test Variables for Player Analysis

This section lists the explanations of how the criteria of Section 4 are defined.

D.1 Cautiousness

The data for these criteria were taken from game-related information rather than from any user-induced actions.

Average Size of Plants

Every plant has ten stages of growth. The maximum size of a plant in any level is taken and the average of those sizes is calculated. For instance, if a player has 3 *Dormitus* in Level 2 with maximum sizes of 6, 7, and 8, the average size would be 7. The maximum is taken mainly in regards to player attacks which happen at size 7 and higher.

Field Setting

Each plant has a maximum of four neighbors that can affect either its health or its size. There are thus the two variables health affected and size affected. Their values range from 0 to 1 where 0 means that this plant was never affected by any neighboring plants and 1 means that it was affected at every turn until it died. These values are relative to a plant's lifetime.

Dealing with Budget

This criterion considers how high or low a player's budget was most of the time at each level. There is no formula for the budget variable. A histogram provides this information for each player at each level.

D.2 Impulsive and Reflective Styles

For impulsive and reflective styles, a number of criteria were analyzed that involve player actions as well as game-related data.

Number of Plants that Died

This criterion shows the number of plants that died in relation to the number of plants that were planted. The values range from 0 to 1. For instance, if the player had planted 10 Dormitus and 10 Dormitus died, the value would be 1. If only 5 Dormitus died, the value would be 0.5.

Use of Budget

This variable counts how much each player spent in total. It sums up the value of all actions connected to buying something.

Time per Action

Time per action is measured in milliseconds between any two clicks a player makes.

Number of Player Attacks

This variable counts the number of player attacks each of the three possible plants (Dormitus, Canibalis, Dulcita) made on players. Since Canibalis stings players and thus usually attacks several times until players realize it, the values for this attack are much higher than for Dormitus and Dulcita.

D.3 Learning Outcome

Optimal Watering

A plant is optimally watered if the humidity is always in the given range of healthiness. The value 0 means never in the optimal range and 1 means that the humidity was always in the optimal range.

Affected by Neighboring Plants

The variable is the same as cautious behavior. Its interpretation is different, though. In this category, the variable gauges how the values evolve over the play levels.

Reaction to Player Attack

This value measures the time that it took players to react to a plant attack. It is measured from the time the player attack occurred until players ”prune” the plant.

Appendix E

Further Results of Player Characteristics

Average Plant Sizes

The tables illustrate further the results of Section 4. The Spearman coefficients show the rank probability for plant sizes. This means that the higher the probability, the more likely it is that does some players have equal-sized plants during the game.

Table E.1: Ranking probabilities for Canibalis in levels 2 to 5.

Correlations

			MeanOfMax SizesCaniL2	MeanOfMax SizesCaniL3	MeanOfMax SizesCaniL4	MeanOfMax SizesCaniL5
Spearman's rho	MeanOfMaxSizesCaniL2	Correlation Coefficient	1.000	-.096	-.057	.007
		Sig. (2-tailed)	.	.225	.470	.929
		N	163	163	163	163
	MeanOfMaxSizesCaniL3	Correlation Coefficient	-.096	1.000	.574**	.247**
		Sig. (2-tailed)	.225	.	.000	.001
		N	163	163	163	163
	MeanOfMaxSizesCaniL4	Correlation Coefficient	-.057	.574**	1.000	.372**
		Sig. (2-tailed)	.470	.000	.	.000
		N	163	163	163	163
	MeanOfMaxSizesCaniL5	Correlation Coefficient	.007	.247**	.372**	1.000
		Sig. (2-tailed)	.929	.001	.000	.
		N	163	163	163	163

**.Correlation is significant at the 0.01 level (2-tailed).

Table E.2: Ranking probabilities for Dulcita in levels 4 and 5.

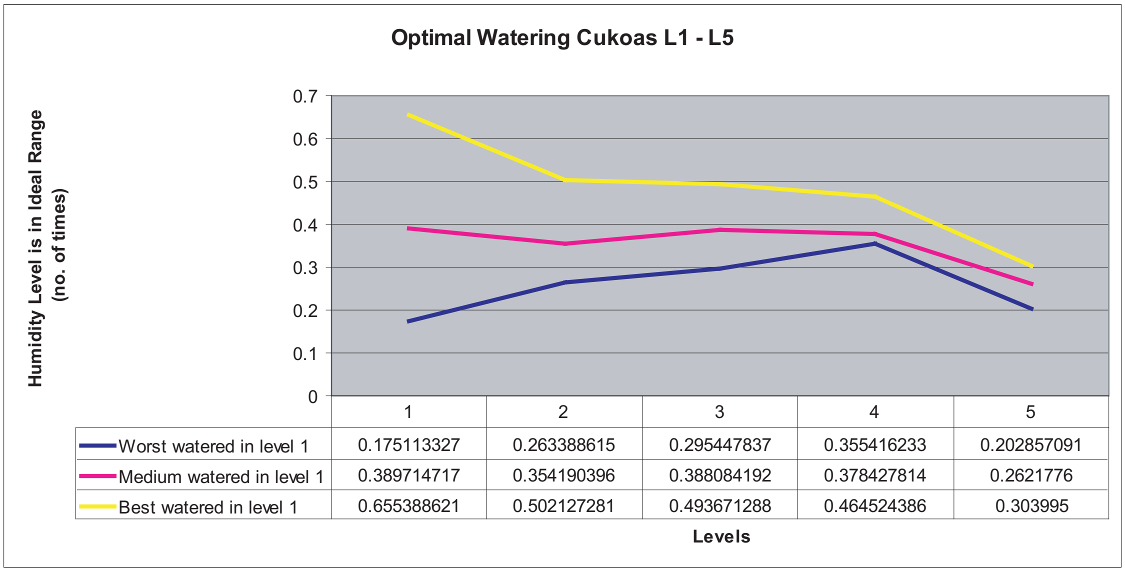
Correlations

			MeanOfMax SizesDulciL4	MeanOfMax SizesDulciL5
Spearman's rho	MeanOfMaxSizesDulciL4	Correlation Coefficient	1.000	.846**
		Sig. (2-tailed)	.	.000
		N	163	163
	MeanOfMaxSizesDulciL5	Correlation Coefficient	.846**	1.000
		Sig. (2-tailed)	.000	.
		N	163	163

**Correlation is significant at the 0.01 level (2-tailed).

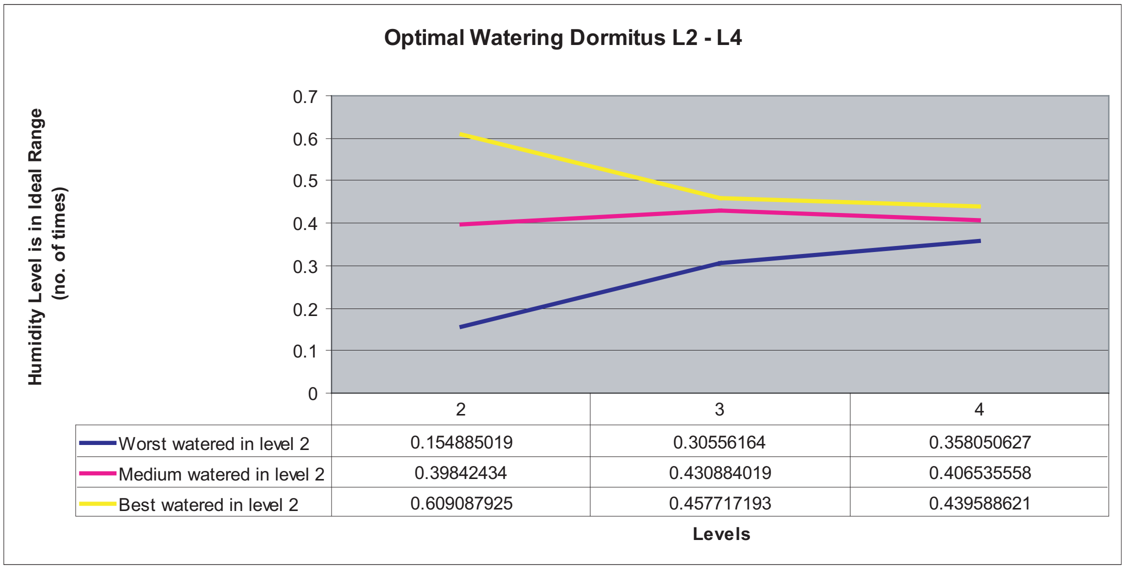
Learning Outcome – Optimal Watering

The graphs shown in this appendix illustrate results for further plants under the aspect of optimal watering. The lines in the graphs only demonstrate trends for plant sizes.



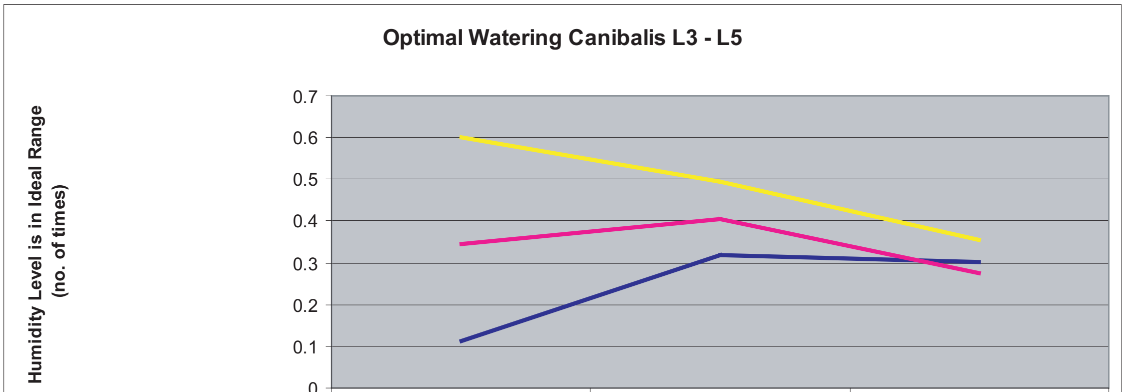
	1	2	3	4	5
Worst watered in level 1	0.175113327	0.263388615	0.295447837	0.355416233	0.202857091
Medium watered in level 1	0.389714717	0.354190396	0.388084192	0.378427814	0.2621776
Best watered in level 1	0.655388621	0.502127281	0.493671288	0.464524386	0.303995

Figure E.1: Average plant sizes for Cukoas.



	2	3	4
Worst watered in level 2	0.154885019	0.30556164	0.358050627
Medium watered in level 2	0.39842434	0.430884019	0.406535558
Best watered in level 2	0.609087925	0.457717193	0.439588621

Figure E.2: Average plant sizes for Dormitus.



	3	4	5
Worst watered in level 3	0.1123895	0.318927981	0.301388577
Medium watered in level 3	0.343911698	0.404291189	0.276551509
Best watered in level 3	0.599026316	0.495561897	0.355213448

Figure E.3: Average plant sizes for Canibalis.

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