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Johannes Konert

Interactive Multimedia Learning

Using Social Media for Peer Education in Single-Player Educational Games

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Johannes Konert

Interactive Multimedia Learning

Using Social Media for Peer Education in Single-Player Educational Games

Doctoral Thesis accepted by
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Springer

Author
Dr.-Ing. Johannes Konert
Department of Electrical Engineering and Information Technology
Institute for Computer Engineering, Multimedia Communications Lab (KOM)
Technische Universität Darmstadt
Darmstadt
Germany

Supervisors
Prof. Dr.-Ing. Ralf Steinmetz
Department of Electrical Engineering and Information Technology
Institute for Computer Engineering, Multimedia Communications Lab (KOM)
Technische Universität Darmstadt
Darmstadt
Germany

Prof. Dr. Regina Bruder
Department of Mathematics
Technische Universität Darmstadt
Darmstadt
Germany

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Book Chapters

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For the Digital Natives
and everyone feeling connected

Supervisor's Foreword

It is a great pleasure to introduce Dr. Johannes Konert's thesis, accepted for publication within Springer Theses and awarded with a prize for his outstanding original work. Dr. Konert joined our Multimedia Communications Lab at Technische Universität Darmstadt in July 2010. He started his doctoral program with a 14-month scholarship of the interdisciplinary DFG research training group *Feedback-based Quality Management in E-learning*. He continued his research within a full position as Research Assistant in Engineering. He completed it with an oral defense in December 2013. Dr. Konert's thesis includes significant original scientific contributions, representing a considerable advancement in the field of interactive multimedia learning. He published as first author in top journals and international well-recognized conferences most of his findings. The work has been widely recognized and awarded with several Best Full Paper Awards.

Social Media, as an information and communication technology, enables users to exchange information about experiences and insights in easy ways. Such exchange can be used for peer interaction among learners in E-learning scenarios or also to support players of educational computer games. The players profit from social media content interpreted as learning resources that are created, edited, and then shared by peers. Therefore, social media applications and concepts can serve as a way to bring peer education concepts closer to educational games in specific and to systems for technology enhanced learning in general. Appropriate information technology enhances the way learners share hints, assess each others' solutions, and give feedback in the learning and playing process. However, the intersection of serious games and social media appears to be a quite novel field of research with various uncertainties to be addressed by scientists.

With his thesis, Dr. Konert defines, to a much larger extent than before, this new research area of social serious games. He integrates the perspectives and findings from didactics, pedagogical psychology, social media, and educational games in order to enhance knowledge exchange among learners in virtual environments. His exceptional interdisciplinary work addresses several core problems of technology-enhanced learning. It includes the integration of user-generated content in learners'

interactions, the sophisticated diagnosis of problem solving competency, and a proper assessment of learners' solutions—especially to open-format problems. Additionally, Dr. Konert offers enhanced solutions for algorithmic peer learning group formation based on manifold criteria to improve learning effectiveness as well as quality of feedback among the peers.

This is the first time single-player games are enhanced by content integration and game adaptation based on social media interactions. The achievable improvements are shown by a multitude of conducted studies including field tests with pupils of secondary schools, laboratory studies with master's degree students, extensive simulative evaluation, as well as expert interviews with CEOs of video game development studios in Germany.

With his findings, Dr. Konert brings the field of serious games and technology-enhanced learning an enormous step forward. His insights allow the use of social media to establish effective circles for knowledge exchange between learners. Core aspects are the integration of user-generated content into the learning process and the algorithmic learning group formation in the application field of educational games.

Darmstadt, June 2014 Prof. Dr.-Ing. Ralf Steinmetz

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For the cheerful and supportive atmosphere, my colleagues of the Serious Gaming research group at KOM deserve a big thank you: Florian Mehm, Viktor Wendel, Sandro Hardy, Christian Reuter, Michael Gutjahr, and Tim Dutz.

I would also like to thank my colleagues at KOM, at the graduate school E-Learning, and elsewhere on this planet for their support, corrective hints, and deep discussions about research issues, especially: Henrik Bellhäuser, Kristina Richter, and Simon Olberding.

The whole KOM-team also deserves a lot of thanks, especially Marion and Klaus-Peter Ehlhardt, Jan Hansen, Monika Jayme, Frank Jöst, Sabine Kräh, Silvia Rödelsperger, Karola Schork-Jakobi, Gisela Scholz-Schmidt, and Christian Theiß.

It was a pleasure to supervise the theses of many great students, and especially I would like to mention Dimitrij Burlak, Martin Tjokrodiredjo, Rhaban Hark, and Nico Gerwien for the great cooperative work.

The proofreaders have earned their acknowledgments very much, thank you! To the best of my knowledge no remaining errors have been left before printing. Still, if any errors are found, please correct them with the best intentions.

I am forever grateful to my social network of family, friends, and acquaintances for their love and support. Without their continuous encouragement and faith in me, my studies and this thesis would have been hardly possible.

Darmstadt, October 2013 Dr.-Ing. Johannes Konert

Contents

About the Author

Dr.-Ing. Johannes Konert was born in Bad Nauheim, Germany in 1979. He graduated with a German *Diplom* in Computer Science from the Karlsruhe Institute of Technology (KIT), Germany in 2006. During these studies, he was granted a scholarship from the Baden-Württemberg foundation for his studies abroad at the Australian Catholic University (ACU), Sydney, Australia, where he studied relevant courses in telematics and electronic commerce. In the following years he successfully co-founded a German company for the development and operation of an online social network application and worked as a freelancer and employee in the field of social media and web applications. In 2010, he was awarded scholarship by the German Research Foundation (DFG) for his Ph.D. work in the research training group *Feedback-based Quality Management in E-learning*.

As lead author he won the Best Full Paper Award at the International Conference of Advanced Learning Technologies for the development of the Peer Education Diagnostic and Learning Environment PEDALE in 2011. Two years later, he won as lead author the Best Full Paper Award at the German E-learning and IT Conference DeLFI for the optimization algorithm GroupAL that addresses the problem of quality-optimized learning group formation. In 2013, he received his Ph.D. degree with *Summa Cum Laude* from the Technische Universität Darmstadt, Germany based on the thesis published in the book at hand.

He has co-acquired and co-lead several national and international research projects. Besides his activities as lecturer and thesis supervisor, he has successfully co-designed and coordinated an interdisciplinary, integrated course for students from architecture, psychology, and computer science working on project topics assigned from the field of serious games.

His current research is focused on the adaptation of learning resource recommendation and the interconnection of learners for knowledge exchange in social serious games and social media applications.

Acronyms

AJAX	Asynchronous JavaScript and XML
API	Application Programming Interface
BPT	Bartle Player Types
CBKST	Competency-Based Knowledge Space Theory
CEO	Chief Executive Officer
CI	Content Integration
CPI	Cohort Performance Index
ECD	Evidence-Centered Design
GA	Game Adaptation
GPI	Group Performance Index
GUI	Graphical User Interface
HTTP	Hypertext Transfer Protocol
ILS	Index of Learning Survey
JPEG	Joint Photographic Expert Group
JSON	JavaScript Object Notation
LSI	Learning Style Inventory
MBTI	Myers-Briggs Type Indicator
MIT	Massachusetts Institute of Technology
MOOC	Massive Open Online Course
MUD	Multi User Dungeon
NEO-PI-R	Neuroticism Extraversion Openess (NEO)-Personality Inventory Revised
NPC	Non-Player Character
PF	Peer Group Formation
PLE	Personal Learning Environment
PPI	Pair Performance Index
SNA	Social Network Analysis
URL	Uniform Resource Locator

UXQ	User Experience Questionnaire
VLE	Virtual Learning Environment
WBT	Web-Based Training
XML	Extensible Markup Language

Chapter 1
Introduction

You have to learn the rules of the game.
And then you have to play better than anyone else.
Albert Einstein

Playing is an inalienable part of human life, integral for understanding the rules this world follows. Mastering the challenges of life can be supported by playful practice and knowledge exchange among others. Thus, insights and methodical approaches are passed on from generation to generation. How the aspects of gaming, the related learning, and the field of social media are envisioned to be interconnected among each other is outlined in the following, covering the underlying motivation for the addressed topics (Sect. 1.1), a summary of the contributions (Sect. 1.2), the research approach (Sect. 1.3), and an outline of the thesis' organization (Sect. 1.4).

1.1 Motivation

As the process of learning is fundamental to human life, contributing research to this process is an ambitious endeavor in itself. Nevertheless, mankind passes knowledge from one to the next, therefore methods and concepts of effective teaching and learning necessitate investigation. Beside the transfer from more experienced individuals to novices, knowledge exchange among peers is likewise important for both: on one side, *peer tutoring* or assessing the other, facilitates the dissemination of insight pertaining to one's own level of understanding during *learning by teaching*; on the other side, for the peer to being taught, knowledge exchange leads to insight into anothers' methodical expertise about how to approach the discussed problem at hand in a linguistic usage both are accustomed to.

Each transfer of knowledge is based on the exchange of information, which requires a transport channel. As face-to-face communication is limited by spatial and temporal discrepancies, web-based E-Learning applications help to decouple

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such barriers to exchange. As individuals contemporarily consume yet also produce such knowledge holding information pieces, is seems reasonable to design software solutions as *social media applications*.

As mentioned in the beginning of the chapter, playing and practicing are core elements of knowledge acquisition. Due to the availability of highly developed technology and frameworks, it is contemporarily easier to create challenging and immersive simulations and training environments for specific learning topics. For example, pilots or medical personnel are trained in virtual simulations which facilitate practice before real operation. These examples focus on the training aspects, but have less focus on motivation and aspects of play. From the field of computer games, *serious games* combine the playful aspects of computer games with the serious aim of knowledge acquisition and practice for real world challenges. As such they are powerful tools to intrinsically motivate the player as they adjust to the challenges presented, based on the player's abilities. Beside this, the process of adaptation and personalization has its limitation in multiplayer scenarios as the learning speed and level of knowledge of all participants is seldom identical, especially in the fields of *exergames* and *educational games*. The former includes the use of computer games for physical training and the later focuses on the education sector. Hence, is seems suitable to provide challenging single-player serious games, but still integrate peer education benefits by loosely coupling the individual players in order to facilitate the exchange of knowledge (e.g. hints and descriptions of methodical approaches to problems) via an extra social media platform. Furthermore, such a coupling can be used to allow completely new types of serious games. It is a well-known problem to pedagogues and serious game developers that most learning happens if the presented tasks are open problems with manifold opportunities for solutions, as these challenge an individual's problem solving abilities and judgment to determine which approach might be the most suitable. Hence, with open problems existing misconceptions of the player about the learning topic are easier to identify. Unfortunately, computer algorithms cannot cope satisfactorily with such manifold possible answers to open tasks. Consequently, a promising solution can be to combine serious games, presenting such tasks, with the power of peer-based assessment. Such a combination can be supported via an inter-connecting social media application, thus resulting in a new type of game called *social serious game* (see Fig. 1.1).

The approach to bring serious games and social media closer together is a new research focus that seems to be not widely addressed yet. Concerning the aspects motivating this thesis, several missing topics in current literature to be addressed can be identified:

- An approach to connect participants of single player educational games for knowledge exchange using user-generated learning content;
- A concept and framework to use social media content in educational games;
- A solution using the characteristics and knowledge of the user to build learning groups for effective knowledge exchange in such social media enriched learning environments.

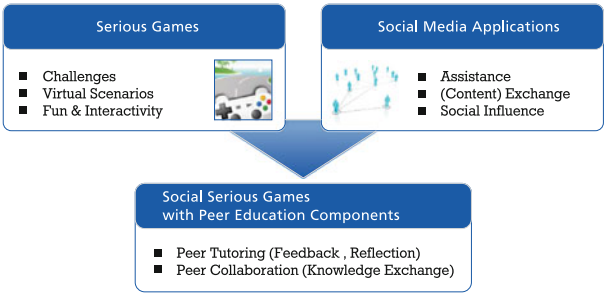

Fig. 1.1 The research field *social serious games* combines serious games and social media applications (image source: FreeDigitalPhotos.net: *Left* image courtesy of *Idea go*, *right* image courtesy of *jscreationzs*/http://www.FreeDigitalPhotos.net)

It is the aim of this thesis to show that it is possible to bring the fields of serious games and social media closer together by providing definitions, an architectural framework and algorithmic solutions for the creation of social serious games as illustrated in Fig. 1.2. Research disciplines involved—beside *Computer Science and Information Technology*—are *Communication Theory*, *Sociology*, and *Pedagogy*.

The author of this thesis is pursuing doctoral studies as a research assistant at Multimedia Communication Lab (KOM) of Technische Universität Darmstadt (TU Darmstadt). Originally, he held a scholarship from the German Research Foundation (DFG) and was member of the graduate school *E-Learning* at TU Darmstadt. Therefore the thesis is highly interdisciplinary and not focusing on technical aspects only. In fact, related work investigation, conceptualization and intended research impact is as well strongly influenced and driven by pedagogy and pedagogical psychology due to the close research exchange and work in research tandems with researchers from

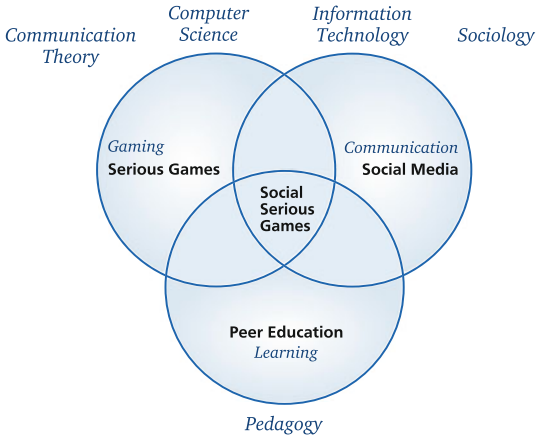

Fig. 1.2 Research focus of this thesis and the related fields

department of didactics in mathematics and department of pedagogical psychology at TU Darmstadt.

In this context the thesis does *not* focus on conversion and transition of multimedia content between both application areas of serious games and social media, even though it is an aspect that is addressed. Likewise, it does not claim to develop a holistic approach towards this connection, but rather contributes a sophisticated approach connecting serious games and social media from a technical point of view to provide game developers and researchers with first effective tools and models to use social media for peer learning aspects in the development of social serious games.

1.2 Contributions

This thesis introduces new concepts and mechanisms regarding the usage of social media interactions, artefacts, and metrics for peer education in educational games. The major outcomes and contributions are listed below. Their interdependency and structural composition is depicted in Fig. 1.3.

1. **Structuring the field for social serious games**
   (a) *Social serious games definition*: An analysis of the criteria essential for social network-connected casual games is realized to define the term *social serious game*.

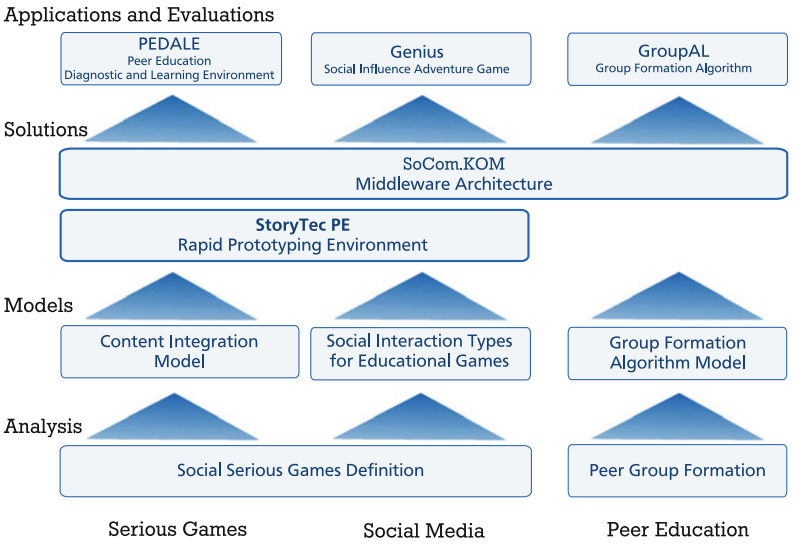

Fig. 1.3 Composition and sequential order of the contributions of the thesis with an abstract attribution to the fields of serious games, social media and peer education

(b) *Content integration model for user-generated game assets*: To facilitate the re-use of assets created by users while using a serious game, a model for game context and metadata usage is developed. It allows storage and retrieval of such content in order to assist the player(s) in similar game situations or when reaching the same (type of) game challenge.
(c) *Social game interaction model*: Based on interactions essential to social media usage, on one side, and a list of game phases of single player educational games on the other, a matrix of possible interactions is defined. Such interactions allow the description of possible influence types, to be used for personalization of a player's educational gaming experience, characterized by social media content, social media metrics, or by near-term content contribution from other individuals.
(d) *Peer group formation*: To foster the content-based knowledge exchange among peers, an algorithm is defined to form learning groups of these peers. A precedent analysis of the requirements highlights the need for the simultaneous allowance of two types of matching criteria: peers' criteria to be matched homogeneous as well as criteria to be matched heterogeneous. In addition, a quality measure is defined in the algorithm model to allow the comparison of group formation results.

2. **Designing solutions for social serious games**

(a) *Social serious games middleware architecture* SoCom.KOM: the results of the content integration model, the social interaction patterns for educational games, and the group formation algorithm facilitate an architecture, which provides a middleware to interconnect (existing) serious games and social media applications and make use of the three solution pillars.
(b) *Rapid prototyping environment* StoryTec PE: the results of the content integration model and the social interaction patterns for educational games, together with the related work of peer learning, lead to the architecture of a rapid prototyping platform that has the capacity to define open tasks for single players and allow for assessment and feedback, thus encouraging learning and diagnosis.

3. **Implementations and evaluations for social serious games**

(a) PEDALE (Peer Education Diagnostic And Learning Environment): Based on the analysis and the rapid prototyping environment, a concept, algorithmic extensions for the story-based authoring tool StoryTec, and an evaluation of the new software solution PEDALE, are provided. The software is designed for problem- based learning and knowledge transfer using peer education concepts in the context of math learning.
(b) Genius (Game ENabling Interaction of Users by Social media): The SoCom. KOM middleware, using the social interaction model, allows for the creation of a prototypical adventure game in the project Genius that use social media profile data and influential contributions of other individuals from a social media application to the gameplay of the player.

(c) GROUPAL (Group formation ALgorithm): Challenged by the limitations of existing group formation algorithms (as later described in Chap. 2) an implementation of a newly developed algorithm, named *GroupAL*, is presented to allow the simultaneous matching of the needed criteria as resulting from the analysis for peer group formation.

The following sections describe the approach towards the contributions and how they are structured in the different chapters of this thesis.

1.3 Research Approach

Based on the motivation to bring serious games and social media together, both research fields are first investigated to define their characteristics and possible intersections. As a result the relatively new game genres of social network games and casual games are identified. Unfortunately an elaborated definition of criteria for these genres could not be found in the academic literature. Consequently, the genre of social games was defined based on existing literature and models naming criteria and aspects of social network games and casual games.

To further define the combination of serious games and social media, social games are critically investigated to find characteristics of such games with serious aspects. Such games turn out to be educational games or social aspect games based on the instances found during the research for this work. As a result the term *social serious game* is defined for the following work.

With a clear definition of social serious games, it is aimed to broaden the insight into these games and contribute to the creation of such games. Academic research on this field is sufficiently lacking. Hence, concepts and paradigms from which educational games could profit, specifically pertaining to the usage and integration of social media content and applications, are investigated. Drawn from the fact that most of the existing social serious games are educational games, pedagogics and didactical implications are utilized as a base. Models on group learning and peer education concepts are discussed. Finally, support for peer tutoring (content based), peer assessment (to be seen as task-based peer interaction) and criteria-based learning group formation is identified as the most promising enhancement for the development of social serious games.

Though other research fields related to the creation of serious games, such as art, sociology, or communication theory, could have been a rewarding base to find concepts and paradigms to enhance social serious games.[1] This work cannot claim to investigate all possible enhancements to this new research field. As a result, pedagogy as a closely related field has been chosen as a suitable starting point due to the fact that both fields—serious games and social media—have the aspiration to provide

[1] Specifically, topics like criteria-based learning group formation interfere with e.g. sociology concomitantly.

pedagogical benefit in selected application scenarios (as discussed in Sects. 2.1.6 and 2.2.2).

On the contrary, a different approach would use the existing models of social network games and elaborate these further by enhancing them with concepts and paradigms from serious games on one side and social media on the other. By doing so, the risk of supporting concepts, unsuitable for the field, is minimized, but at the same time the pedagogical claim can be lost. As this thesis focuses on educational games and social media, pedagogical aspects are inherently involved in the research resulting in less suitability of such an approach enhancing existing social network game models.

As the underlying research focuses on a relatively new field, no architectural models on information technology were found for the interconnection of (existing) serious games and social media applications. Accordingly, an individually developed model is proposed, interpreting the pedagogical requirements and resulting in the provision of a middleware architecture with components for exchange of user-generated content (*content integration*), peer interaction and personalization support (*game adaptation*), and assistance for learning group formation (*group formation*). The benefits and drawbacks of technical architecture solutions residing within the connected game client(s) or the social media application(s) are accordingly discussed.

Each of the proposed components adapts and enhances existing models and concepts, introduced in Chap. 2. With game developers as one of the main target groups, the suitability of the architectural design is verified by the conducted expert interviews.

The model conception and architectural design are conduced by an iterative process model, as requirements are fraught with uncertainty. This is not a weakness of the chosen approach, but is rather attributable to the novelty of the field. Thus, iterative improvement and agile development are chosen to be more suitable as a classical linear model (e.g. waterfall model [1, p. 11]).

With the first architectural design (without group formation functionality), two prototypical implementations have been realized with different foci:

PEDALE, a Peer Education Diagnostic And Learning Environment. It focuses on the use of user-generated content in the social network of a school classroom within a task-based diagnostic and learning environment, designed based on an authoring framework for serious games. The findings are related to quality aspects of user-created task results, and provided peer feedback (and peer assessments). Additionally, motivational aspects related to the provision of peer feedback are investigated as well as conditions promoting good feedback. The results assist in the future design of similar applications and deliver parameters and design issues for the group formation algorithm (Chap. 6).

GENIUS, a Game ENabling Interaction of Users by Social media. It focuses on the use of user-generated content as contributions from outside the game which are integrated into the game (interaction). Additionally, the game can use social media metrics and profile information to personalize the game experience for the player. As this approach focuses on the circle of information flowing between

the game and social media it posts results (game to social media) and requests interaction participation or fetches content (social media to game). The findings are related to acceptance of such new functionality, motivational aspects, and technical functionality.

Based on the findings from the evaluation with PEDALE, it was investigated how group formation for learning groups can be enhanced by learner profiles. As existing approaches do not completely suit the requirements to assist learning group formation in the social serious games field, an individually developed model and algorithm, called **GroupAL**, is proposed. The performance and effectiveness are investigated using simulation. The findings are assumed to be valuable for group formation in future learning scenarios.

Finally, this research approach concludes with a critical reflection on the findings and results, outlines limitations of the results, and proposes possible future improvements.

1.4 Organization of the Thesis

Aligned to the research approach the subsequent chapters of this thesis are structured as illustrated in Fig. 1.4 and described in the following.

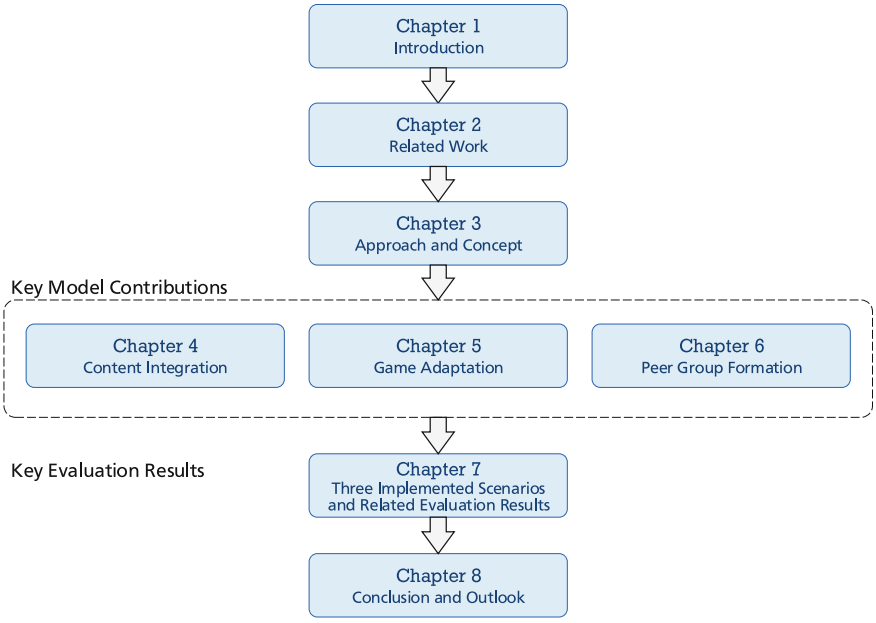

Fig. 1.4 Organization of the thesis' chapters

Chapter 2 describes the related work in the research areas of *learning theory*, *social media*, and *serious games*. As this interdisciplinary work relates to a magnitude of related research aspects, the chapter focuses on the models and applications related to the intersections of these research areas. Therefore, in Sect. 2.1 personal learning environments are introduced as well as the term social media and the pedagogical concepts relevant for the further chapters of this thesis. Section 2.2 outlines the aspects of learning with educational games in the intersection of serious games and learning theory. Before concluding the related work overview, Sect 2.3 discusses the intersection of serious games and social media that is the most closest to the topic of this thesis. As it is a quite new field of research, a first definition of criteria necessary for social (network) games is provided. Key outcomes of the related work are the identified game aspects demanded for deep learning with educational games (Sect. 2.2.4): social interaction, peer tutoring, peer collaboration, and suitable tasks. Furthermore, the analysis of the group formation algorithms reveals the open issues of the group formation problem (Sect. 2.1.3).

Chapter 3 outlines the overall concept and architecture to address the needed functionality for educational games. It aims to be a step towards the use of social media for peer education in educational games. Based on the boundary conditions and the definition of social serious games, hypotheses are formulated to be focused on in the following chapters. The target groups are analyzed. After discussion of the alternative possible solutions, the architectural design for SoCom.KOM is defined with the components *content integration*, *game adaptation* and *peer group formation*. It's aptitude is investigated with a preliminary expert evaluation.

Chapter 4 explains the approach and solution of the *content integration* model which offers the use of metadata and the game context information for storing and retrieving content. Additionally, a dual achievement system is described to combine game-based and community-based achievements.

Chapter 5 points out the two facets of the approach towards *game adaptation*. First, the adaptation by social media profile information and second, the adaptation by social interaction patterns for educational games. For the later, a thorough derivation is described as no existing research provides a list of suitable interactions from social media to be used for interactions between social media users and players of educational games.

Chapter 6 defines the proposed approach for the *group formation* algorithm on a mathematical basis. After an analysis and description of a suitable modeling of matching criteria, two main metrics are defined: *Group Performance Index* and *Cohort Performance Index*. They take into account not only the homogeneity and heterogeneity of matching criteria, but also the aim of a uniform formation quality among all groups. Additionally, matching algorithms are designed and proposals are made for optimization cycles and incremental update of group formations.

Chapter 7 maps the afore described approach and models to implemented prototypes, which are evaluated in two user studies and one simulation-based

evaluation. PEDALE (Sect. 7.1) provides indicators that content-based peer tutoring indeed can support knowledge transfer. Questionnaire results show the acceptance by the 183 participants. Moreover, PEDALE lead to findings about relevant matching criteria for the group formation algorithm. GENIUS (Sect. 7.2) proves that the attitude towards social media interaction significantly differs when it is indeed experienced based on the underlying study design. Still, only tendencies are found that game adaptation by social media interaction improves the user experience. In general, from both perspectives, social media side and game side, the 70 participants value the functionality of content-contribution and participation positive. Finally, GROUPAL (Sect. 7.3) represents the implementation of the group formation algorithm and is evaluated with generated participants' data in several setups and variations. The comparison with related work outlines that GROUPAL constructs mostly better group cohorts as the algorithms compared to. Only in several cases the results are equally good. Even if assessed by metrics of related work algorithm TeamMaker [2] the results are still better.

Chapter 8 summarizes the fundamental findings after a critical assessment of the thesis' aim. It ends with the outlook on future work to be conduced related to the addressed topics.

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Chapter 2
Related Work

As depicted before in Fig. 1.2 several research fields contribute to the results of this thesis. As such, one of the opportunities of this work is the interdisciplinary work and application of findings from pedagogy and sociology to the field of computer science. Thus, this chapter starts with the findings relevant for this thesis from the field of pedagogics intersecting with social media (Sect. 2.1) and afterwards with serious games (Sect. 2.2). The last section (Sect. 2.3) is most closely related to the thesis topic and states the findings on social network games in the intersection of serious games and social media (illustrated in Fig. 2.1). Each section will introduce the terms and models of pedagogy, serious games, and social media in the opening of each respective part.

Finally, the chapter concludes with the key aspects to be addressed in the following chapters.

2.1 Social Media and Learning

This section contains the pedagogical aspects of the work, focusing on different learning models and theories about learning. Based on this, group learning and its didactical implications are addressed. Beside pedagogy, social media is explained according to its difference from classical media and the characteristics for the use of social media in the learning context. Consequently, the intersection of both learning and social media is addressed and the different types of Personal Learning Environments (PLEs) are similarly attended to. The section concludes with an overview investigating the types of support for peer education concepts and social media functionality.

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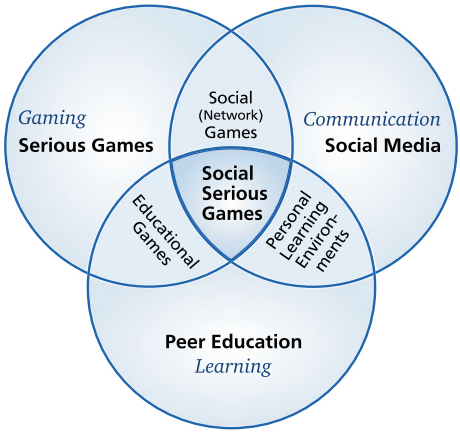

Fig. 2.1 Research fields and intersecting areas for the combination of serious games and social media using peer education concepts

2.1.1 Learning Theories and Models

The underlying theories about learning originate from the field of pedagogical psychology. The main researchers to name here are *Jean Piaget*, *Lew Vygotsky*, and *Albert Bandura*. Their models and empirical findings lead to recommendations, models, and guidelines in didactics, underlying learning with social media and serious games. While Piaget and Vygotsky belong to the school of constructivism, Bandura has his foundation in behaviorism. Still, it is argued that both schools of learning theories and all three researchers' models should not be considered isolated or as being disparate, as the didactic design of situations to support learning and the learning progress might profit from results of all of them.

2.1.1.1 Jean Piaget's Perspective of Socio-Constructivism

The three main aspects of Piaget's model of cognitive development are (1) maturation, and the strong influence of one's (2) physical and (3) social environment. By interaction with this environment the individual develops cognitive models of it. A basis for this cognitive development is the appearance of cognitive conflicts caused by interaction with the environment. These conflicts are eliminated by a mediating fourth factor, moderating all factors important for learning and development. By *assimilation* and *accommodation* an individual solves the conflicts and reaches a next step in development. Assimilation in this context means the integration of new aspects into the existing mental models. If such a synthesis is not possible or the

model appears to be inadequate to suit the new aspects, accommodation processes re-structure the existing model accordingly [1, p. 56].

As Piaget explicitly names physical and social interaction as factors, he claims that physical and social activity of the learner are essential for development. As such, traditional forms of tuition, like teacher-centered teaching, are not suitable as learners remain passive and are constricted to consume the information *someone* (an instructor) presents. A key role for cognitive development is the interaction and exchange within a group, as it not only leads to activation of the individual, but also encourages the rise of conflicts and argumentation within the group as a positive mediator for cognitive development (cognitive conflicts) [2]. However, Piaget establishes that empirical foundations of the positive influence by group-learning are not easy to create [1, p. 196]. Still, from a Piagetian perspective Doise et al. [2, p. 377] could show that "social interaction leads to more complex structuring than does individual action."

2.1.1.2 Lew Vygotsky's Socio-Cultural Perspective

Vygotsky agrees with Piaget on the importance of interaction with the environment for cognitive development. For this interaction, individuals use culturally developed tools which are furthermore used collaboratively with others for interactions. His *activity theory* assumes that each self-development has a particular intentional activity as a basis. A learning activity, in specific, builds on existing learning prerequisites. These enabling prerequisites are created and enhanced by guidance and interaction with a more experienced individual (an instructor). This guidance broadens the possible mental development, that Vygotsky calls the *zone of proximal development* [3, p. 86ff].

Referencing Piaget's conclusions about the importance of social interaction for mental development, Vygotsky [4, p. 35] proposes that "the essential feature of learning is that it creates the zone of proximal development." He further points out the need for interaction of the learner with peers in the environment. In contrast to Piaget, Vygotsky sees interaction with others as an essential enabler for learning, whereas Piaget mentions it as one of the main factors, whose effect is mostly indirect, resulting in learning when resolved by the inner mediation process. In particular, the difference lies in the role of the interacting individual: while Vygotsky sees the interaction with a more advanced individual as even more effective than one with a peer on the same level for methodical skill training (externalization), Piaget sees the cognitive conflicts arising from peer interaction on the same level as the most beneficial (mental model and uncovering of misconstructions).

2.1.1.3 Albert Bandura's Social-Cognitive Perspective

With his background in behaviorism, Bandura sees an individual's development to be based on observations that result in more elaborated behavior. But these trained

behaviors are not adapted unreflected. Rather the observer notices and reasons about the consequences an observed behavior has for the initial individual. After this mental re-considering the behavior is either adopted or refused. If adopted, it is then practiced and will be aligned to requirements and conditions resulting from the critical evaluation and reflection during practicing. Depending on these conditions, the practiced behavior may occur more or less often in future [5].

As such, learning is described by Bandura as a model-based approach. If the behavior (skill, knowledge) observed is considered to be worthy, it will be adopted. Here Bandura describes the necessary cognitive aspect of one's development. Reasoning and decisions are part of learning. They happen based on the existing trained models. Consequently, the individual depends in his development on the environment's stimulation to be able to observe behavior and build such models. Broadening the observation to symbols and more complex models, Bandura's perspective can also be applied to more abstract concepts that can be observed (e.g. by reading) and then be learned.

Model Summary

All three models emphasize that social factors are important (Piaget) or even necessary (Vygotsky, Bandura) for cognitive development. By observing, self-practicing, and interacting with the environment a learner mentally develops. The process continually contains critical review, reconstruction, and refinement of the mental models and related conditions when they may be applied. Possible development is promoted by observing (Bandura), mediating peers (Vygotsky) or interacting in a social group (Piaget).

In learning scenarios, several phenomena can arise that are not explainable by only one of these perspectives. When learners are confronted with new approaches to a stated problem, which stimulate reasoning and inner re-structuring, the model and principles behind can be made more clear by mutual discussion. This may lead to a collective ability to solve a tasks that was not solvable for each one alone before. In such a scenario learning can happen by adopting others approaches in specific situations. Based on the description, all models's aspects can be considered to be relevant for learning, cf. [6]. A comparison from multimedia learning perspective and the resulting implications for the design of learning systems is given in Steinmetz and Nahrstedt [7, p. 179ff].

We can conclude that individuals can either provide exemplary artifacts, act as tutoring peers, or be part of a collaborative group experience for learning. This very dense summary of all three theories required significant simplification. Nevertheless the simplification will serve the further sections of this thesis, providing a conceptual understanding of the aspects that can stimulate learning. Although, the three cited authors mainly focus on mental development in early childhood, they argue that all mental development and learning rests upon these concepts and are further diversified during maturation and remain valid at all ages. Thus, the application of these authors' findings to learning of more mature individuals, as focused in this thesis, remains valid.

2.1.2 Peer Education

The potential of peer learning concepts and the circumstances under which they lead to desired results are discussed by Damon [8]. He revises the peer learning aspects of Piaget and Vygotsky and concludes, consistent with the argumentation of this work, that education can benefit from both insights. Additionally, he adds aspect from the work of Harry Stack Sullivan, an American psychiatrist who developed his interpersonal theory of psychiatry [9]. As such, social relationships are a core aspect for the coconstruction of new insights. Damon consolidates the theories and describes that the three core concepts to be considered for peer learning are *peer tutoring*, *cooperative learning*, and *peer collaboration* [10]. The use of these concepts differ from intended learning effects and skills of the involved peers. Suitable dimensions to diversify the approaches are equality and mutuality.

Peer tutoring is characterized by low equality and low mutuality, where a more advanced tutor explains and guides a novice tutee and the flow of information is mainly unidirectional. But the advancement of the tutor can as well be marginal and only in one aspect of skills. It is desired that both switch the roles in the course of learning, in case the tutee can as well teach their tutor something. Peer tutoring is most suitable for skill training or drill and practice, but not expected to raise new complex insights for the tutee.

In contrast, peer collaboration is characterized by high equality and high mutuality and thus more suitable for approaching complex problems in a group using *discovery learning*. Peers exchange ideas and concepts, justify their point of view and consider the feedback of others seriously. This collaboration is "only possible in an atmosphere of mutual respect" [8, p. 334] where a close matching of peers in knowledge and ability is a prerequisite. Consequently, collaborative learning groups should be matched with a *symmetry of knowledge* [11, p. 7], complementing one another in partitions of the *knowledge space* (cf. [12]). A somewhat specialized form of collaborative learning is the group discussion and exchange to individually produced results to the same tasks. This can be applied when practicing problem-solving, e.g. with math problems [13]. The problems are approached individually, then the result and chosen approaches are discussed afterwards in groups (cf. [14, p. 45]). All such methods, peer tutoring, peer group collaboration, and problem-based learning are identified to have high positive impact[1] on learning progress of involved participants, as shown by John Hattie in a substantial meta analysis of 736 studies on learning effects [16].

Cooperative learning lies somewhat between peer tutoring and peer collaboration, with high equality and differing mutuality, depending on the setup [10, p. 15] as illustrated in Table 2.1. Still, mutuality will always be more restricted than in collaboration, as tasks are subdivided and learners are doing their work individually. This can lead to strong specialization as each learner adopts the role and takes the subtask they are most experienced with. In further cooperative work they may stick to these choices, preventing them from mastering other skills or aspects of the divided

[1] Cohen's *d* effect size greater than 0.5 [15, p. 20].

Table 2.1 Peer education concepts and their characteristics

Aspect	Peer tutoring	Cooperative learning	Peer collaboration
Equality	Low	High	High
Mutuality	Low	Varies	High
Skill development	High	Varies	Low
Problem-solving	Low	Varies	High

task. To prevent this, Cohen and Goodlad [17] propose the program of *complex instructions* where peers in the group alternate between roles in the group, so that everyone has the chance to participate on every component of the task. Still, following the argumentation of Damon, cooperative learning is considered the least suitable concept for the course of this thesis due to its unpredictable outcomes depending on the setup and difficulty in administration.

In conclusion, and based on the findings about the effectiveness of peer tutoring and peer collaboration [18], peer education can be considered as the use of peer tutoring for tutoring of methodical knowledge and skill practice on one side and peer collaboration for the collaborative problem solving on the other side. Based on this understanding, the author of this thesis defines peer education as follows:

Peer Education is the concept of using peer tutoring and peer collaboration for learning. The former for skill practicing when equality and mutuality of the peers are low, the later for problem solving with high equality and mutuality among the learners.

2.1.3 Group Formation Algorithms

When peer education is about to be applied to learning scenarios e.g. in school classes, social media applications, or serious games, algorithms can be used to assist the instructors and learners in finding appropriate members of their learning group.

Group Formation Problem As discussed in Sect. 2.1.1.3, matching peers for learning heterogeneously by various aspects, like learning style preferences, stimulates cognitive dissonances, supports interaction due to socio-cognitive conflicts and can enhance learning effects [19–21, p. 5]. Unfortunately students prefer to select primarily friends and others of the same status and level of proficiency as their group members [17, 22]. This leads to homogeneous group formation instead of the desired heterogeneity in the group. Above all, instructors do not have the capacities to establish an optimized grouping as matching criteria are manifold. Moreover, students

"…tend to be rebellious if they are forced to work in groups that are not of their own choosing" [22, p. 1].

The challenge to optimize learning group formation from a given set of peers to match, while respecting homogeneously to match criteria simultaneously with heterogeneously to match criteria and aiming for a balanced quality of the build groups, will be called the *Group Formation Problem* in the following work.

Relevant Matching Criteria Paredes et al. [23, p. 2883] state that homogeneous groups perform better for specific tasks, whereas heterogeneous groups are better on broader tasks (e.g. problem-solving). Likewise, as mentioned above, for peer education an atmosphere of mutual respect has to be established [8, p. 334], where a close matching of peers in symmetry of knowledge and ability is a prerequisite [11, p. 7]. Thus, level of knowledge can be considered as a homogeneous matching criteria, whereas the area of knowledge should be complementing each others previous knowledge (as a heterogeneous criterion). Generally, learners should have similar learning targets and the intensity of learning should be matched homogeneously to avoid fast separation in knowledge symmetry [24]. For the matching of learner's age Damon [8] recommends a homogeneous matching. Gender can be matched homogeneous or heterogeneous, but should equally distributed within the group [25].

Learning style preferences are expected to be most suitably matched heterogeneous to support cognitive dissonances, argumentation among the learners, and insight into each others' different approaches to problem solving [26, p. 6].

Concerning the personality traits, Barry and Stewart [27] argue that openness for new experience and conscientiousness should be matched homogeneous, while the level of extroversion should be heterogeneous. Consistently, group roles of leaders and followers should be matched heterogeneously within a group for better team performance [28].

In brief, no general advise can be given which criteria need to be matched homogeneous or heterogeneous for improvements in group learning performance. This depends not only on the type of tasks, but also on the learning environment and the participants themselves. Consequently, it remains most valuable to aim for a general algorithmic solution that allows the instructor to set the specific criteria and weightings for each scenario a group formation is conducted for.

Existing Approaches As outlined in Konert et al. [29], from an algorithmic point of view, two differing groups of approaches exist for group formation: *semantic matchmakers* and *analytic optimizers*.

The former use ontologies for calculating how well two (or more) learners suit each other for an effective learning process. The ontologies allow for the formulation of manifold boundary conditions, e.g. learning goals and skills, to be respected during group formation [30]. If a suitable ontology is missing, the use of such matchmakers becomes very costly. Furthermore, most of these matchers do not provide a calculated measure of the group formation quality and will not consider the aspect of creating equal distribution of group formation quality. One algorithm providing equal distribution is *Fits/CL* [30]. It uses an opportunistic group formation approach to find suitable peers for collaboration based on learning goal ontology and peers' roles in

groups as tutor or tutee. In contrast, the *GroupMe* algorithm is able to calculate a group formation quality and supports weighting of the matching criteria [25]. To calculate possible valid solutions based on the semantic information in the underlying ontology the DLV logic solver is used [31].

In contrast to the semantic matchmakers described above, *analytic optimization* algorithms map the desired optimization criteria to a *n*-dimensional feature space of each learner. Comprehensive, group-specific criteria are respected as boundary conditions or they are integrated into calculation of the group formation quality (within their fitness function). Based on criteria to be matched homogeneously, similar learners can be grouped by cluster analysis using the feature space (e.g. Fuzzy-C-Means algorithm as used by Paredes et al. [23]). This approach appears to be limited if heterogeneous to match criteria exist in parallel to the homogeneous to match criteria. Then heuristics and iterative optimization procedures are used [24]. Such approaches use swapping of group members or calculation of groups in repeating cycles with varying starting conditions. This seems feasible for scenarios with a few hundred to thousand learners [24]. Seldomly existing approaches go beyond existing classical optimization procedures to address the issue of respecting heterogeneous and homogeneous to match criteria simultaneously.

The cited systems and their algorithms are compared according to the criteria of

- providing of a calculated measure for group formation quality,
- respecting the restriction to form groups with similar formation quality,
- allowing a theoretically endless number of criteria,
- providing the possibility to weight criteria's impact on group formation,
- allowing the use of several group formation algorithms depending on the desired group size and criteria characteristics,
- supporting the use heterogeneous criteria (clustering),
- supporting the use heterogeneous to match criteria (amendment), and
- supporting the use of both criteria types simultaneously.

As shown in Table 2.2 none of the researched approaches supports all of these eight criteria. Still, it might be suitable to consider further criteria, like interactive support and visualization for instructors, to manually influence the group formation as provided e.g. by *OmadoGenesis* in Gogoulou et al. [32]. Likewise valuable can be assessment of the capability to address the *orphan student problem* [25, p. 1] and handle missing data. As this thesis focuses on matching learners in the field of serious games and social media, a support for instructors is not the main focus. Nevertheless, it is expected that it could be possible to add support for instructors after the design of a pure automatic algorithmic solution. The problem of having unmatched participants will be partly addressed later by matching participants by group to prevent groups with only one member in the end. The aspect of missing data will not be addressed as participants′ profiles are expected to be complete as a basis for this thesis′ considerations. Investigating matching problems with missing data is an own research field that cannot be covered here in depth.

Table 2.2 Group formation systems and algorithms

	Calculation of group formation quality	Uniform group formation quality	Infinite number of criteria	Criteria weighting	Several algorithms available	Homogeneous group formation	Heterogeneous group formation	Mixed group formation
System *Algorithm*	*Qualities*							
Fits/CL [30] *Opportunistic group formation (Learning ontology)*	-	+	-	-	-	+	+	+
GroupMe [25] *DLV solver*	+°	-	+	+	-	+	+	+
I-minds [33] *VALCAM/agent system*	-•	-	-	-	-	+	+	-•
GroupFormation [34] *Fuzzy C means/random tool*	-	-	-	-	-	+	+	-
Together [23] *Far-away-so-close*	+*	-	-	-	-	-	+	-
OmadoGenesis [32] *Homo-A/Hete-A/genetic algorithm*	+	-	+	-	+	+	+	+
TeamMaker [24] *Hill climbing*	+⋆	-	+	+	-	+	+	+

• VALCAM's agent system evaluates the suitability of candidates iteratively based on prior task solutions for a previously selected homogeneous or heterogeneous strategy, ° statement about restriction violations, * using a threshold, ⋆ using a heuristic

2.1.4 Knowledge Transfer

The aim of peer education is to support each individual's progress (learning). From a didactical point of view, situations facilitating peer education are desired to lead to knowledge transfer among peers. Knowledge is here defined and considered as the sum of all capabilities and skills an individual identifiably applies for problem solving [35, p. 1]. A prerequisite for knowledge is the availability of data and—by contextualizing this data—the resulting information. This underlines the difference of information to knowledge, as knowledge is always personal. On account of this, knowledge, per se, is tacit and its transfer is difficult as the objective aspects are not clear. Tacit knowledge can still be transferred among individuals by social and personal experience (e.g. dancing can only be learned by interaction as the attitude, mood and timings needed are hard to describe). Tacit knowledge needs to be transformed into a explicit instantiation to be rational [36]. Such *knowledge externalization* leads to the creation of *knowledge media* that can be transferred among individuals (or systems). This data is then again interpreted in a context to read the containing information and then transformed into the recipient's implicit knowledge in the case that the data contained any new information (for the recipient) [37, p. 164f].

2.1.5 Social Media

"Social media is a group of Internet-based applications that build on the ideological and technological foundations of Web 2.0, and that allow the creation and exchange of User Generated Content" [38, p. 61]. To make this more clear, *web 2.0* can be seen as the foundational technology and ideology for social media. The technological aspects are the upcoming solutions for dynamic website creation, like Asynchronous JavaScript and XML(AJAX)[2] and the wide use of Adobe Flash for video and rich interactive content, just to name a few. Ideologically, as websites turned into platforms providing services, the web began to be a continuously developing software system with beta-versions and strong end-user involvement in application and content development (also called the *participatory web* [39]). When users visit social media application websites they do not simply browse, but actively create assets and contribute to the further development of these assets. These contributions are called *user-generated content* when (a) it is published or accessible to a wide range of other users, (b) its creation required some depth of creativity, and (c) it evolved out of a non-professional practice [40, p. 18]. It is important for the course of this thesis to differentiate social media, that are applications, from user-generated content, that is the outcome of using such applications.

The spectrum of applications in the social media landscape is manifold. The Parisean Internet consultant Fred Cavazza publishes each year his (subjective) view

[2] Even though mostly the XML data is nowadays a different format, e.g. JavaScript Object Notation (JSON) for easier parsing by receiving Javascript objects.

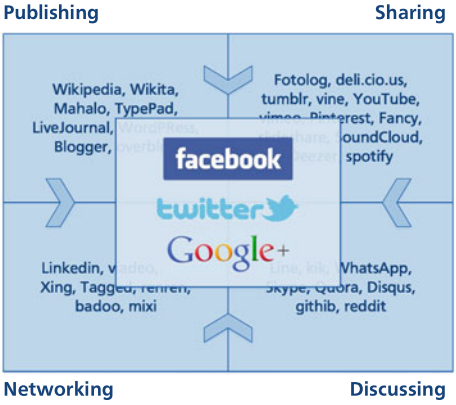

Fig. 2.2 Social media landscape 2013, based on circular illustration of Fred Cavazza (Fred Cavazza's Social Media Landscape 2013, source: http://www.fredcavazza.net/2013/04/17/social-media-landscape-2013/, last visited on August 13, 2013.). It shows the four main interaction patterns in social media and names exemplary applications with *Facebook*, *Twitter* and *Google Plus* in the center

of the development and trends in social media as a landscape that is illustrated in Fig. 2.2. Even though it is not academically founded, it is useful for a first insight, as academic resources on social media are very limited.

The major user needs addressed by these applications are publishing of individual content, sharing of own or found content, discussing opinions or content, and networking with other users.

Currently three applications are dominating the market: Facebook,[3] Twitter,[4] and Google+,[5] as these serve all the mentioned needs and provide an API for third party developers to integrate content into the application or read profile information and data. In 2012, Facebook reached about 700 million active users, Twitter about 280 million and Google+ 340 million as illustrated in [41]. All three emerged from the core service of social networking and function now as a hub for publishing, sharing, discussing and networking.

Julien [42] provides a list of 12 social interaction patterns that strongly relate to the four core interactions from Fred Cavazza mentioned above: Publishing is subdivided to posting and commenting. Sharing includes updating (of shared posts). Discussing contains voting and tagging. Networking groups the interaction patterns of chatting, inviting (to join), and joining (as response to invites). Additionally, Julien names the interaction patterns of buying and playing as his research is focused on users of online social networks applications. It can be argued that these two are quite special activities occurring in social network applications and even violate the conditions of interactivity that needs at least two individuals (sender, receiver). As such, buying

[3] http://www.facebook.com/, last visited on August 13, 2013.

[4] http://www.twitter.com/, last visited on August 13, 2013.

[5] http://plus.google.com/, last visited on August 13, 2013.

and playing are not considered as pure social interaction patterns in the further course of this thesis. All of the mentioned patterns can as well be found in the list of more than 100 social patterns described by Crumlish and Malone [43] for the design of social interfaces.

2.1.6 Social Media for Learning: Personal Learning Environments

Even before the rise of social media, web-platforms were created to support knowledge acquisition using the Internet as the fastest and most convenient transport channel for E-Learning content. As part of E-Learning, Web-Based Trainings (WBTs) became a popular way for institutions and companies to deliver their learning content to recipients in distance learning or blended learning scenarios. In WBTs the content is organized in a traditional way: learning units are arranged in chapters, pages and testing questions in the end of each unit. Therefore web-based trainings can be considered as unidirectional E-Learning (from institution to learner) without the ideological and technical aspects of social media.

A term of wider coverage in this context is Virtual Learning Environment (VLE), which is also called Learning Management System from an institutional perspective. A VLE allows for content management and alignment with a learner's curriculum and covers administration aspects. Modern virtual learning environments allow collaboration of learners in online learning communities within the environment [44]. A learner-centered perspective is provided by Personal Learning Environments (PLEs) (or Adaptive Personal Learning Environments). They evolved from VLEs and provide the learner with abilities to chose their favorite learning tools that interact with the learning environment, load the learning content and provides social media functionality for sharing, discussing, and networking [45, 46]. The idea of PLEs is to connect users with each other and with the learning content, but also allow the use of individual tools to grasp, manipulate, and create content. Here users can arrange their learning content in their own competency portfolios and review the topics continuously [47, p.101ff]. Exemplary in the use of high-quality PLEs are the learning-platforms offered by renowned universities, which provide free video-based lecture material in courses with schedules, assignments, and basic networking capabilities. Prominent examples are on *edx*[6] with lectures from the Massachusetts Institute of Technology (MIT), Harvard University, Berkley University of California and many more. Likewise, MIT Open Courseware,[7] Open Yale courses,[8] and Coursera[9] offer high-quality university course content. Commercial operators like

[6] https://www.edx.org/, last visited on August 14, 2013.

[7] http://ocw.mit.edu/, last visited on August 14, 2013.

[8] http://oyc.yale.edu/, last visited on August 14, 2013.

[9] Offered by University of California, Irvine at http://oyc.yale.edu/, last visited on August 14, 2013.

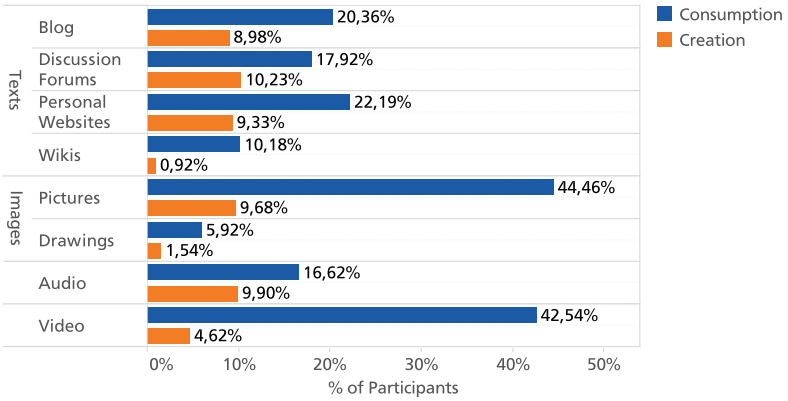

Fig. 2.3 Types of user-generated content with distribution of consumption and creation [51, 52]

Udacity[10] try to keep up by offering courses also for free, but charge for examinations that are approved for college credits or official degrees.

As social media changes the usage of the Internet, online learning environments change accordingly. In the sense of web 2.0, learners become consumers and creators of learning content simultaneously. Online applications supporting peer-learning and sharing of user-generated learning content emerge [48–50].

Most content created and shared online consists of text, images, audio or video [40, p. 34f]. On a daily basis, 87 % of web-users consume such content and 22 % of these create such content themselves [51, 52, p. 9ff]. In more detail, users prefer to consume primarily images (44 %) and videos (43 %), followed by text (up to 22 %). Users create primarily text-based formats as discussion forum comments (10 %), personal websites (9 %) and blogs (9 %), followed by pictures (10 %). An overview is given in Fig. 2.3 based on [51, 52]. In summary, text and images are the formats widely consumed and created, followed by video.

Platforms focusing on articles and learning videos[11] offer limited networking functionality as their focus is on content creation, sharing, and discussion. Other solutions focus primarily on creating a community environment for learners. With *PeerSpace*, Li et al. [49] have shown the positive influence on peer community building and provision of mutual feedback when social media applications are used alongside learning content provision. In *PeerWise* [53] students create questions to lecture topics, provide peer assessment on the quality of the questions, answer explanations, and give peer feedback for improvements. Unfortunately the authors neglected to measure the learning impact or effects the system usage had on student engagement and final marks. Nevertheless, the frequent usage of the system for exam preparation supports the findings on the positive aspects of social environments,

[10] https://www.udacity.com, last visited on August 14, 2013.

[11] Eg. http://www.ehow.com/, http://www.lynda.com/, http://www.ted.com, and http://www.youtube.com/education; all last accessed on August 14, 2013.

peer tutoring, and feedback for learning. Stepanyan et al. [54] have used a VLE to voluntarily allow students to access each others' work and provide peer assessment. In the specific setup of this study the provision of content to be assessed was low, but interest in accessing other peers' work was high. The authors point out the impact of anonymity and the provision of marks on the willingness to contribute. This indicates a sensitivity of content creators for privacy issues and an awareness of rewards.

More recently, the term Massive Open Online Course (MOOC) emerged for the new generation of learning resources available online. The term is not yet well defined and "since MOOCs are a relatively new kind of online learning, there are relatively few studies written about them" [55, p. 2396]. Still, as one key success factor for MOOCs Russell et al. [55, p. 2396] identified their "…engaged and socially active communities of students that pose problems, resolve questions, add additional material to the class, and support other students' learning"—key aspects supporting learning (cf. conclusion on learning perspectives in Sect. 2.1.1.3).

Currently, operating MOOC providers—offering PLEs with the social media functionality described above—are The Open University[12] with their SocialLearn platform, probably the oldest provider (since 1971), or KHAN Academy.[13] If the term MOOC is seen in a more strict definition, sticking to openness and considering less the social media publishing aspect, then the PLE examples of edx, MIT Courseware, and Open Yale courses mentioned above can be considered to be best-practice MOOC provider examples, too. The other (commercial) PLE providers do not offer their courses for free. Consequently openness is not fulfilled as needed for MOOCs.

The considerations of this work on the different types of learning environments and their support for peer education aspects and social media needs are summarized in Table 2.3. In conclusion, among the considered E-Learning platform variants, MOOCs appear to be the most close to the aspect of bringing social media and learning together. They are a good base for the intersection of educational games and social media.

Table 2.3 Examples of learning environment types and their support for peer education and social media

	WBT	VLE	PLE	MOOC
Peer tutoring	No	No	No	Yes
Peer collaboration	No	Basic	Basic	Yes
Publishing	No	No	No	Yes
Sharing	No	Basic	Yes	Yes
Discussing	No	Yes	Yes	Yes
Networking	No	Yes	Yes	Yes

[12] http://sociallearn.open.ac.uk/, last visited on August 14, 2013.

[13] https://www.khanacademy.org, last visited on August 14, 2013 providing all content for free in a social media application environment.

2.1.7 Section Summary

In this section (Sect. 2.1) the theories of learning have been compared and lead to the conclusion that all three theories can be used in conjunction to support learning scenarios. As described, social interaction for learning by *peer education* can greatly support knowledge transfer among peers. In the context of social media, the user-generated content can be used as the media for knowledge externalization and transfer among users of social media applications. Most promising types of applications—supporting the intersection of learning (by peer education) with social media—are Massive Open Online Courses as they allow all the social media interactions of publishing, sharing, discussing and networking as well as peer tutoring and peer collaboration.

2.2 Serious Games and Learning

> Tell me and I will forget,
> Show me and I will remember,
> Involve me and I will understand.
>
> (Confucius, 450 B.C. [56, p. 179])

By the time individuals in the United States have officially become an adult (achieving the age of 21) they have spent around 10.000 hours playing with computer and video games [57, 58, p. 266], all to become good in one set of skills: "cooperating, coordinating, and creating something new together" [57, p. 348]. Game researcher McGonigal summarizes this as one of 14 core aspects[14] that make games[15] more than fun and rather how they make individuals better.[16]

The term *serious games* evolved from the entertainment field of computer games (pure entertainment games). They build on the entertainment value of such games and add an extra value with an educational purpose [59, 60]. As such, they have a serious purpose which leads to the easily misunderstood term *serious games*. In the course of this thesis the term serious games is understood as digital games which are developed for another purpose beside pure entertainment (in relation to the discussion in [61, p. 6]).

Terms used instead of serious games and meaning something similar, but not an identical group of applications, are *edutainment* games as the broad intersection field of education and entertainment [62]; *games with a purpose* [63]; *game-based learning* [64]; and *applied games* [65]. The term *applied games* nicely points out the interdisciplinary aspect of serious games, which are used in application fields like knowledge gain, (social) skill development, health and medical treatment, fitness,

[14] McGonigal calls them *fixes* in her book.

[15] When referring to games in the course of this thesis it covers primarily electronic games in forms of video games, computer games, browser games, and mobile games, if not otherwise stated.

[16] With *better* McGonigal refers to improvement in the skills trained by the games.

collaboration, recruitment, or persuasion and attitude change [66, p. 119]. Most of the games have primarily academic educational content (63 %), followed by games related to social change (14 %), occupation (9 %) and health (8 %) [67, p. 14]. Serious games referring to the academic field—addressing knowledge gain and skill development—are called *educational games*. Before focusing on educational games in the further course of this thesis (Sect. 2.2.2), an overview over the research field serious games is given as it is understood and approached at Technische Universität Darmstadt.

2.2.1 Serious Games at Technische Universität Darmstadt

> All serious games are games; i.e. analogue to any other (pure entertainment) games serious games contain game play, goals and rules and use game technology. These elements are combined with further domain-relevant methods, concepts and technologies, e.g. pedagogic and didactic concepts for educational games or sensor technology for exergames and are applied within a broad range of serious game application fields.
>
> (Göbel and Gutjahr [59, p. 1])

The serious games group at the Multimedia Communications Lab (KOM) defines the understanding and approach to serious games as the use of game technologies as a basis, supplemented and enriched by the knowledge and models from related interdisciplinary fields around, to be applied in manifold application areas.

Reference examples for serious games cover a broad range of application domains including educational settings (from kindergarten to collaborative workplace training), sports and health applications (prevention and rehabilitation) or other societal relevant topics.

In particular, serious games technologies are used as 3D training and simulation environments for pilots, firefighters, medical staff, police women, bus drivers, train guards and service staff, as visualization and construction tools for architecture and urban planning, or as research tools for human perception and action. Serious games concepts are used to support learners and teachers in educational settings at school or university, to motivate humans for a healthy, active life, to encourage (especially young) people to explore their cultural heritage, to increase public awareness of societal issues (religion, politics, security, energy, climate, etc.), or to assess human behavior and experience in complex and dynamically changing environments.

Challenges and Research Areas

Serious games are a highly complex scientific area considering the multifaceted characteristics of pure digital games plus the dimension of the serious part: The key challenge of serious games is to reconcile and balance true gaming experience on the one hand and the fulfillment of the additional purpose beyond pure entertainment, on the other. Thus, research in serious games is necessarily multi-disciplinary, and most of the currently available systems are specifically designed for a particular target

application area. Such solutions for specific application areas have to be subjected to formative and summative evaluations considering the complex interplay of numerous factors.

Research objectives include an in-depth analysis of serious games, and the elaboration of new methodologies for (1) efficient, single-user or collaborative authoring of serious games, (2) personalized, adaptive, and context-sensitive control, and (3) empirical versus objective, technology-enhanced evaluation of serious games. Figure 2.4 shows the overall structure of research on serious games.

The serious games group at Technische Universität Darmstadt aspires to synthesize these objectives in a reference model for the description and evaluation of serious games, with the option to serve as a quality label in the long-term perspective [59, 68–70].

2.2.2 Educational Games

Educational games evolved by continuously adapting the evolved principles of various learning theories for serious games. First generations were limited to drill and practice tasks, respecting behaviourism-based theories. They had limited value for sophisticated knowledge acquisition or change of attitudes towards learning content, because the first generation of these applications did not support the adaption to the progression of learners. The second generation moved to constructivism-based theories focusing on the learners—not their behavior—and respecting their learner- and player-profile. Finally, the evolved third generation integrated a socio-cultural perspective to constructivism adding situations and settings to the games [71, p. 25].

Still, these types of games, supporting cognitive problem solving beyond knowledge gain through exploration, are only about 24 % of the available serious games.

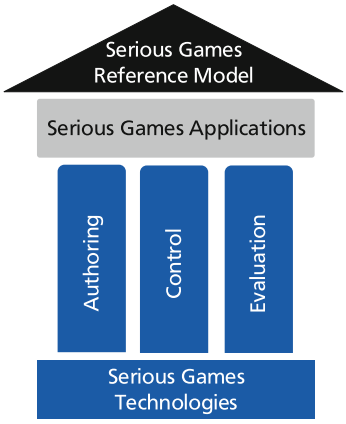

Fig. 2.4 Serious games research areas

Second generation games (exploration) are 21 % and first generation are still the biggest share of 48 %. The remaining 7 % are attributed to games beyond third generation, including social interaction for problem solving like collaboration [67, p. 17].

Gros [71, p. 26] names seven genres of educational games. Among them, adventure games seem most appropriate for peer education, as these games are characterized by tests the player has to solve to progress in the game. Educational adventure games therefore appear to be less action-laden or time-restricted than other genres. In the course of this thesis the focus is on such educational adventure games of third generation and beyond as they allow the social interaction, explorative learning, content exchange for *deep learning* [72, p. 89], and peer education concepts identified as most important in the preceding section of this chapter. Deep learning refers to the software- and game-based support of learners to develop skills "that prepare all learners to be life-long creative, connected, and collaborative problem solvers" [73, p. 6].

2.2.3 Player Modeling and Learner Modeling

For all aspects of serious games creation, support for suitable representations of players′ state are beneficial. The better the underlying models, the more accurate the game can control the players′ level of engagement and thus, the learning progress.

To provide a player with the best gameplay experience the game has to adapt to a player's mental state (needs) and cognitive development (abilities). The psychological theory of *flow* describes a channel of optimal experience where someone is engaged and immersed in an activity, if the current goal and presented challenges fit with their abilities [74]. For games where players develop their skills over time, this means that the game has to measure and detect such changes and adapt the difficulty and task characteristics accordingly.

As the theory originally has not been designed with games as its focus, Sweetser and Wyeth [75] propose and evaluate the *game flow* model. It builds on the flow theory and has eight elements, with seven of these linked to flow criteria to achieve the enjoyment of games. The eighth "(…) element of player enjoyment, social interaction, does not map[17] to the elements of flow, but is highly featured in the literature on user-experience in games. People play games to interact with other people, regardless of the task, and will even play games they do not like or even when they don't like games at all" [75, p. 4]. To achieve game flow, developers must adapt to the different personal flow zones users have—depending on preferences and skills [76]. When adapting to player preferences, adapting to different player types (player models) is meant. Adaptation to skills refers to different levels of ability and learning preferences (learner model).

For differentiating player types, two approaches can be identified. The first is a psychologically driven approach using established models on personality traits

[17] i.e. link (author's remark).

and personality types from psychological research. The second approach focuses on player preferences and their expected game experience.

2.2.3.1 Personality Models: Traits or Types

To differentiate the personality of individuals in general two widely used approaches have emerged.

On one side, the psycholexical perspective of [77] combined with the differential-clinical perspective of [78] has emerged and been further developed over the last decades [79]. Starting with the two personality traits of extraversion and neuroticism, it has been extended by Costa and MacCrae [80] with the concept of openness, and resulted in the 5 factor Neuroticism Extraversion Openess (NEO)-Personality Inventory Revised (NEO-PI-R) model, adding the dimensions conscientiousness and agreeableness. Its validity has been widely shown and is accepted worldwide as a stable method to describe human personality and is therefore also called the Big5 model.[18] A reliable 21-item short questionnaire to measure the dimensions is available from [82].

On the other side, the Myers-Briggs Type Indicator (MBTI) based on Jungs' types of personality measures individual's preferences with 93 items on four dimensions, resulting in 16 possible psychological types [83]. That said, the main difference lies in the measurements and scales. While with NEO-PI-R, personality traits themselves are measured on five independent scales, MBTI assesses personality types and then classifies a person into the most suiting category accordingly. As the categories can be used as stereotypes, the MBTI seems to be more accepted in the business field for classifying human resources and for career planing.

In summary, NEO-PI-R is a absolute measurement of personality itself (traits) with continuous results while MBTI is comparative and has discrete (preference) results as exhibited in Table 2.4.

Corroborated by manifold studies, these models can claim to be valid independent of application context, cultural aspect, or target groups. However, their direct application to games has to be investigated as it remains unclear what adaptation consequences a specific personality profile of such models has for the gameplay experience as the mapping to the game elements is missing.

Table 2.4 Examples of personality models (NEO-PI-R, MBTI)

Model	Dimensions	Measure	Items[a]	Result
NEO-PI-R [82]	5	Absolute	21	Continuous
MBTI [83]	4	Comparative	93	Discrete

[a]For MBTI listed in Myers-Briggs Type Indicator Explanation (Development Edge), available at http://www.dec.co.th/mbti_explanation.htm/, last visited on August 17, 2013

[18] And different from the Five-Factor Model (FFM) that appears to be less robust to cultural differences (cf. [81]).

2.2.3.2 Player Models: Preferences

Describing player interests, a widely known and frequently implemented model of player types, has been proposed by Bartle [84] based on his analysis of user-behavior and preferences in Multi User Dungeon (MUD) games. He classifies player interests onto the axes of acting versus interacting and player versus world, resulting in four[19] player types: achievers, explorers, socialisers, and killers. Players afford more or less peculiarities in each (ranging from 0 to 100%).

Achievers are acting in the world, focusing on completing game tasks. Explorers are interacting with the world, knowing secret features and gaining expertise in knowing what is possible where (and how). Socialisers are interacting with other players, using the game environment as the foundation for communication. Finally, killers are acting on other players aiming to be superior and applying game expertise to differentiate from other players. As Bartle [84] aims to argue how these types influence each other and can be balanced in MUDs, he points out the disharmony of killers with achievers and socialisers (and even among killers themselves). Therefore the only way to reduce the presence of killers is to strongly increase the number of explorers. For the course of this thesis, interest is given less to the balancing of such player types in multi-player games, but more so to modeling and tracking players' needs in order to serve the appropriate game content (or peer player). Surprisingly, no sophisticated direct method for measuring these player types could be found during the research underlying this thesis. Bartle [85, p. 145] himself mentions a set of test questions not yet academically published, but available as a web application [86]. For usage concerning this research, the authors of this test were contacted and asked for the questionnaire items and permission to use.

From traditional pen and paper role-playing games, similar models exist. Laws [87] (as cited in [88]) defines six player types of power gamer, butt-kicker, specialist, method actor, storyteller, and tactician. Unfortunately, a measure and underlying questionnaire items were not stated in the literature. From computer science theory, Charles et al. [89] propose a more dynamic model using pre-defined criteria and continuously adapting the model in a game control loop to match players to (pre)-defined clusters depending on in-game behavior. Consequently no questionnaire measuring the model criteria exists as it is calculated from in-game behavior directly.

The three models are listed in Table 2.5 for comparison. As apparent, the dimensions depend on the developer-defined amount of clusters. As this research did not reveal a questionnaire for the types of Laws and due to the fact that Charles et al. leaves open the definition of meaningful criteria and cluster-mappings to the developer, the model from Bartle seems appropriate to be used as a starting point to identify player type preferences of individuals.

[19] According to Bartle's blog there exists also a version with 8 players types that could not be found in academically publications unfortunately (cf. http://www.youhaventlived.com/qblog/2008/QBlog251108B.html, last visited on August 16, 2013.).

Table 2.5 Examples of player models [84, 87, 89]

Model	Dimensions	Measure	Items	Result
Bartle [84]	4	Comparative	39	Continuous
Laws [87]	6	N.S.	N.S.	Discrete
Charles et al. [89]	Variable	N.A.	N.A.	Continuous

N.S. for *not stated* in literature, N.A. for *not applicable*

2.2.3.3 Learner Models: Types or Preferences

Modeling learner types and learning style preferences is somewhat orthogonal to player types and preferences. It is specifically challenging for educational games to additionally include learner types and learning style preferences, compared to classical entertainment games. In theory, the models of player and learner are independent.[20] Hence all combinations need to be considered in a game while adapting the game flow.

As no single universally accepted method exists, several models and approaches have been developed. Still there is criticism that some of the existing models' dimensions or categories of learning types and preferences measure personality traits more than learning aspects. A concise overview considering the results, benefits, drawbacks, and limitations of four major models is given in [90]. Study results investigating which of the models appears to be better under certain conditions imply that the choice for once specific model does not matter much as long as the implications from each models' types are very similar from a didactic point of view [91]. Two of the most widely used models are briefly described below. Felder and Silverman [92] developed a model to classify their engineering students based on the approach to interpret learning as a two-step process in both perception and processing. At present, this model consists of the following four dimensions: (1) active versus reflective, (2) sensory versus intuitive, (3) visual versus verbal, and (4) sequential versus global. They abandoned the formerly existing fifth dimension (inductive versus deductive), concluding that in a sense of problem-based learning and discovery, learning inductively is always to be the favorite method for teaching college students. According to these dimensions, they created a self-scoring instrument, called the Index of Learning Survey (ILS), which, in the current version, has 44 items and has already been used multiple times even though it has not yet been validated [90]. It can be concluded that one reason for the model's popularity appears to be the provided direct mapping of preferred styles (diagnose result) to corresponding recommended teaching styles. That said, the index is a practical tool for adapting learning content delivery depending on a learners style. Additionally, a compact, adaptive questionnaire version exists from [93].

The second model described here was proposed by Kolb [94] and is named the *Learning Style Inventory (LSI)*. This model is not classifying, but identifying the learning style preferences on two axes: collection of experience as abstract

[20] For evaluation results see Sect. 7.1.6.

Table 2.6 Examples of Learner Models (ILS two times, LSI)

Model	Dimensions	Measure	Items	Result
ILS [92]	4	Comparative	44	Discrete
ILS [93]	4	Absolute	4–5	Discrete
LSI [94]	2	Absolute	12	Discrete

conceptualization (AC) versus concrete experience (CE) and processing of experience as active experimentation (AE) versus reflexive observation (RO). The LSI model results in the style preferences of accommodating (CE/AE), converging (AC/AE), assimilating (AC/RO), and diverging (CE/RO). The validity proven questionnaire for the Kolb Learning Style Inventory is not published and can be retrieved upon request from HayGroup.[21]

Both learner models are compared in Table 2.6 and are equally suitable. As [92] lack a validated questionnaire currently, the model of [94] is preferred, even though their questionnaire items are only available upon request.

2.2.3.4 Learner Assessment Models: Knowledge-Based or Evidence-Driven

Modeling of learners' progress to select the next most appropriate task is a separate aspect for maintaining flow experience with educational games. The behavioristic knowledge space theory has been complemented with constructivistic elements resulting in the Competency-Based Knowledge Space Theory (CBKST) [12]. The model contains the knowledge structure and the knowledge space. The structure consist of the set of problems $Q = \{q_1, q_2, \ldots, q_n\}$ and the binary transitive relation ρ defined as $\forall q_i, q_j, q_k \in Q : (q_i \leq q_j \wedge q_j \leq q_k) \Rightarrow q_i \leq q_k$. It can be interpreted that if a learner has shown the competence to solve the problem q_k, the deduction is reasonable that he also can solve problem q_i (and q_j) as it is a smaller problem and the required skill-set (knowledge) exists if a related (greater) task has been solved. The set of problems Q and the set of all instances of the defined relation $R = \{\rho_1, \rho_2, \ldots, \rho_m\}$ span the directed graph of prerequisites (e.g. q_i before q_j) and paths through the knowledge structure. This graph is called the knowledge space as it spans all possible trajectories to explore the structure as shown in Fig. 2.5. The model's simplicity and applicability has lead to its use in educational games and studies, as well as in the authoring tool StoryTec for single-player educational games [95–97].

As several researchers stated the importance of problem solving, interaction, and self-directed approaches towards problems,[22] it seems necessary to broaden the abilities of the underlying model to dynamically identify evidence for task solutions that are related to problems. As such the tasks do not need to be mapped directly to the

[21] http://www.haygroup.com/leadershipandtalentondemand/contact/, last visited on August 15, 2013.

[22] As learning tasks with several possible solution approaches.

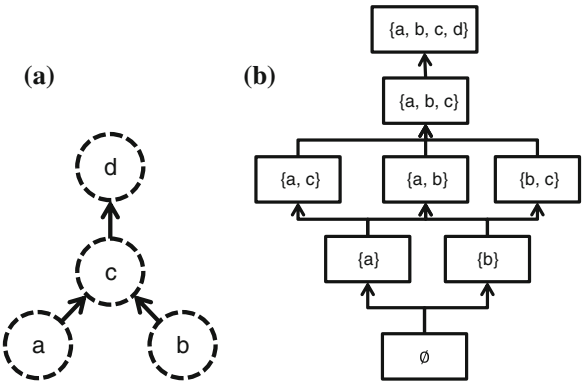

Fig. 2.5 Scheme of a simplified **a** knowledge structure and **b** resulting knowledge space from competency-based knowledge space theory [12]; *source* [97, p. 71]

knowledge in the knowledge structure, but activities (as evidence) moderate between game tasks and the competency model. Such a model of Evidence-Centered Design (ECD), to support creative problem solving assessment of learners' progress, has been developed and proposed by Shute et al. [98, p. 295ff]. Similar to the knowledge structure of Albert and Lukas [12] a competency model is created containing more specific constructs on a lower level, which are connected to more generalized constructs on higher levels (e.g. the concept of novelty informs creativity). Additional to this fully-connected, directed graph (a tree), the model consist of an evidence model and action model. The interdependence of these three components is illustrated in Fig. 2.6.

Actions are activities of a player, measurable in real-time, within the game environment. The actions are weighted by experts, machine learning, or continuous player adaption for all basic items in the competency model. A high value basically means a high relation to an aspect. The heart of the system is the evidence model in which one or more evidence indicators are defined as distribution tables collecting information on several actions and one of the action's aspects. The tables have programming code scripts attached, defining the scoring and accumulation rules for scores. This

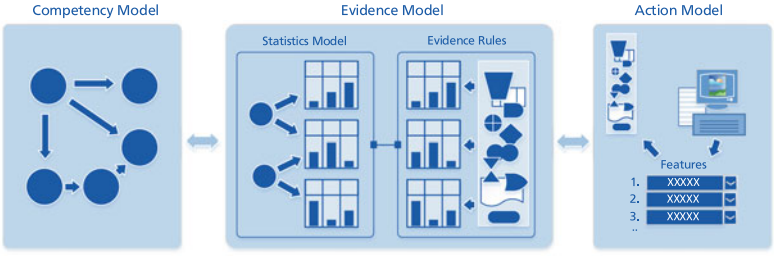

Fig. 2.6 Symbolic scheme of structures from Evidence-Centered Design assignment assignment, based on Shute et al. [98, p. 302]

evidence indicators are connected to one or more items in the competency model to update them when the observed distribution changes (e.g. a highly unexpected action for a specific problem may be encoded as an evidence table observing these actions and informing the competency of novelty if it occurs while working on this problem). Shute and Ventura [99] call the pervasive evidence based measurement of learner's progress *stealth assessment*.

2.2.4 Section Summary

Educational games have great potential to deliver what conventional teaching alone cannot: continuous, individual leaner support by providing the most suitable tasks. Essential are models that connect game activities to intended learning targets (skills) and the provision of tasks for creative problem solving. As games mean entertainment, fun is essential. Most important for this thesis is the finding that many researchers from game based learning research have stated the importance of peer education, creative solutions, and sociability as essential for effective deep learning and fun (flow) together.

Finally, game aspects that have a positive impact on players' motivated deep learning with educational games, considering specifically the aspects related to *peer education*, are identified as:

1. **Social Interaction** creating, sharing, discussing, networking of game content and game experiences.
   [100, p. 39] [101, p. 60]
2. **Peer Tutoring** explaining, documenting, and helping other players.
   [102, p. 71]
3. **Peer Collaboration** collaboration and cooperation on game problems.
   [103, p. 273] [104, 327]
4. **Suitable Tasks** creative problem solving assessment, open format tasks, and self-created tasks. This includes accurate modeling and tracking of players progress by stealth assessment.
   [98, p. 307].

2.3 Serious Games and Social Media

> Compared with games, reality is disconnected. Games build stronger social bonds and lead to more active social networks.
>
> Jane McGonigal, 2011 [58, p. 82]

As outlined in Sects. 2.1 and 2.2 serious games and social media have key benefits for learning. Now both fields are brought together in order to identify the potential of this connection. As the research on the intersection of serious games and social media is quite young, this section will predominantly rely on best practice examples.

In addition, concise definitions are currently missing. Thus, first the view is broadened on the intersection of entertainment games with social media to identify the characteristics of social games and existing technical solutions to use social media in games. Afterwards the view is narrowed to serious social games. Based on these findings, an individually-developed clarification of the term social (network) game as a base for later focused social serious games (in Chap. 3) is realized.

2.3.1 Social Games

The first steps towards the interconnection of entertainment games and social media were the manifold social casual games available free to play online. These were games that were casually played with easy to use interfaces, which were connected to online social networks [105]. Loreto and Gouaïch [105] identify *asynchronous play* as one important characteristic of such games. Players interact by e.g. exchanging items or favors, but do not have to be online or in the game at the same time.

As O'Neill [106] states in his criteria list about social games, these games were (1) mostly turn-based, (2) connected to online social networks, and (3) multiplayer, in a sense that there was (4) an awareness of others' actions in games. His four criteria can be summarized as *casual multiplayer*, which means a single-player game play, but multiplayer atmosphere due to asynchronous play and awareness—and thus interplay—of the activities of others. Such awareness of the activities of others fits with the theory that online social networks are virtual third places providing playful experiences [107]. O'Neill [106] even names as a fifth criterion that these games need to be based on social (media) platforms for player identity and basic communication. It is agreed that such a connection is necessary for a social game, but for other reasons.

Such reasons are explained by Järvinen [108] in the design framework for social network games. He describes, how the structure of an online social network can be integrated into gameplay and how a beneficial interdependency with (and impact) the online social network can be achieved (what he describes as four interacting parts). His criteria are summarized as *beneficial social media interaction*.

The computer game magazine PLAYGEN published an article in 2010 discussing and defining the core aspects of interaction that make a social game. Two of the four mentioned aspects are competition and collaboration [109]. Competition is described as achieving goals and measurements of performance in a relative way. Collaboration is described as sharing resources, coordinating activities or simply dividing tasks (cooperation). Competition is meant indirectly here as no direct drawbacks (like loss of resources or end of game) for each player should appear. It is a comparative competition. The social games allow players to keep their achieved status and activities of others do not directly cause disadvantages for one's own game play. This concept is called *coopetition* in business studies [110]. It is a key difference in the comparison of social games to traditional multiplayer games.

By these criteria, the term social game[23] is defined by the author of this thesis as follows (based on Konert et al. [111]):

A social game is a video game satisfying the criteria of *asynchronous play*, *casual multiplayer*, *coopetition*, and *beneficial social media interaction*.

2.3.2 Serious Social Games

Using serious topics as game content and designing a game with the intention that players remember key facts and insights related to the topics, are design aspects to make a social game a serious social game, because these aspects add an additional purpose beside pure entertainment. Indeed, Spiegal and Hoinkes [112, p. 469ff] argue this to be one part. In their deep learning model for the creation of serious social games two conditions of the participants need to be ensured: personal relevance to the topic and stickiness.

Stickiness means continuous engagement with the game. This is quite closely related to the continuous state of game flow [75].

Personal involvement can be supported by (1) non-linear narration, (2) adding game elements for physical interaction with the game environment, and (3) supporting interaction among players. Physical is meant as well as immersion into a virtual world. The deep learning model stresses the non-linearity and interaction aspect, due to the fact that the model evolved from the research on immersive cinema concepts and its use in public places like museums. For games, the interaction is obviously an inherent aspect of the games themselves. The second condition of stickiness is (1) the formation of social networks around topic and participants, (2) the persistence of the user-created creative content, and the support of (3) co-creation.

Inter-dependencies of the factors can be identified, e.g. interaction among players relates to co-creation and formation of social networks. Finally, the model emphasizes the aspects of dialogue among players and co-creation for deep learning.

Among existing social games, some can be considered to be serious social games as they allow dialogue, co-creation, and have a serious topic. Exemplary some examples are described here for a better impression on these games' characteristics.

poweRBrands (category: occupation[24]) It challenges the player, who is a marketing and sales employee, to decide on budgets, make allies with other players for campaigns, and ascent to become the company's boss.[25]

[23] In a broader—and historical—view a social game is in principle every game with a group of participants interacting (like e.g. the olympic games or chess).

[24] Referring to the serious game categories, listed in Sect. 2.2 [67, p. 14].

[25] http://www.rb.com/powerbrands/, last visited on August 17, 2013.

GreenSightCity (category: social change) In the simulation of building up a sustainable city, the player can improve the eco-value of buildings, usage of e-bike stations in the city and modern public transport in order to create a green city that attracts more visitors and thus brings more income. Cooperation is possible for building construction with city neighbors.[26]

Many casual (not necessarily social) games exists that are of game category social change, aiming to rise a player's awareness about a serious topic. Even though these games do not fulfill the criteria mentioned above (e.g. co-creation or beneficial social media interaction) a brief list is given here to underline the difference from the serious social games.

EnerCities (category: social change) The scenario of a world without oil is about to come up for the player, who has to manage a prospering city in this simulation. The main task is to switch to renewable energy resources before the limited amount of available oil is empty. The game is well-balanced, but has no content sharing functionality and is purely single-player[27] [113].

Flutter (category: social change) An adventure game, where the player explores the rainforest and has to care about the collected butterflies. Beside the fact that the logo of the World Wildlife Foundation (WWF) appears in the game, it seeks to sensitize to the beauty and clear that social games addprotection of the rainforest eco-system.[28]

DataDealer (category: social change) Recent scandals concerning the collection, selling, and (ab)use of personal information left and shared by individuals online and while using digital information technology, are the core aspects of the game. The player collects data, "hacks" databases, and sells information to build up his data empire.[29]

FoodForce (category: social change) The farming of crops, preparing humanity help packages and sending food to crisis areas in the world, are some of the tasks a player has to manage when playing this game that tells how the United Nations World Food Programme (WFP) works. Indirectly, each purchase of goods in the game has an impact on real world help visualized by the in-game real-world impact tracker.[30]

WeTopia (category: social change) Like other social games, WeTopia is a city simulation that challenges the player to build up a prospering city, build allies with friends and collect a special currency called Joy. The unique key concept is to spent Joy for real-world non-profit charity projects. The advertisement income

[26] https://www.greensightcity.de/, last visited on August 17, 2013.

[27] http://www.enercities.eu/, last visited on August 17, 2013.

[28] The game was available at https://www.facebook.com/fluttergame/ (discontinued). A new tablet-based version is available, see https://www.facebook.com/flutterbutterflysanctuary/, last visited on August 17, 2013.

[29] http://datadealer.com, last visited on August 17, 2013 (a multiplayer version is in preparation).

[30] http://apps.facebook.com/foodforce/, last visited on August 17, 2013.

of WeTopia is shared with these nonprofit projects and organizations according to the spending of players' Joy in game.[31]

The examples have been chosen thoroughly as representatives of available games, even though it seems impossible to give a broad overview in a few lines. A very well maintained database of games for social change is available online (using peer review for game recommendations).[32]

In conclusion, these examples make clear that social games add the following benefits to gaming and fulfill two of the demanded aspects for deep learning with serious games (as listed in Sect. 2.2.4):

Peer Collaboration by coopetition to accomplish tasks together that are too big for one player alone, and
Social Interaction by beneficial social media interaction enabling sharing and discussing of gameplay experiences.

The currently available social games and models are missing to fulfill the aspects of *peer tutoring* and from a content-perspective as well the provision of *suitable (user-generated) tasks*. The mentioned criteria for social games can be used as mediators for a mapping of social media interactions to the demanded aspects for deep learning in educational games, as proposed later in Chap. 3.

2.3.3 Architectures for Social Media Interaction

While researching existing solutions for interconnection of (serious) games with social media applications, only few scientifically founded architectures could be found. Therefore, best-practice examples from game industry are discussed first, followed by academical solutions.

Game Industry Solutions

Steam Overlay. The online game distribution platform Steam[33] includes the Steam Overlay into games distributed and managed via Steam. Technically the overlay is part of the steam client that runs on the players' machines and contains the games. It offers screenshot functionality (including sharing with Steams own community website[34] or popular social media applications), gifting virtual items, and inviting befriended players for multiplayer games. The overlay provides quick browser and community profile access [52, p. 20].
Steam Workshop. Game developers can create their own modifications or assets for games supporting the content loading via Steam Workshop[35] platform. There

[31] https://apps.facebook.com/wetopia/, last visited on August 17, 2013.
[32] http://www.gamesforchange.org/play/, last visited on August 17, 2013.
[33] http://www.steampowered.com/, last visited on August 17, 2013.
[34] http://www.steamcommunity.com/, last visited on August 17, 2013.
[35] http://steamcommunity.com/workshop/, last visited on August 17, 2013.

is no uniform Application Programming Interface (API) defined, but each game has its own rules and conditions (and possibilities what can and) how to develop content. As operator Valve offers a share of the generated revenue with user-generated content to the contributors, the system contains manifold high-quality extensions. The content needs operator-based approval before being visible for other players. Technically the Steam Workshop works as a central asset repository, accessed by games to load content the player subscribed to. Content creators upload assets to the workshop manually or use their third party editors [52, p. 21].

XFire. Traditionally the XFire client[36] is a versatile messaging client, specialized to the needs of multiplayer gamers communicating within their teams. Additionally, it offers functions to record screenshots and screencast that can be shared on the XFire community site. Social interaction features are also provided for sharing and networking. XFire offers direct in-game browsing, chatting, and game purchasing (like Steam) [52, p. 21].

Still, as it developed recording and sharing functionality independently from the games and decoupled from the own community platform, it appears to be more open to integration and interconnection with third-party social media applications.

Academic Solutions

Community Network Game. The project aims to insert graphical interface elements (overlays) and replace textures in games without necessity of game client code changes. Additionally, it is game independent and uses peer to peer technology to allow overlay-applications to interconnect players independent of the currently played game. Envisioned core functionality consist of live streaming of gameplay video and integration of collaboration tools. The authors speak as well of integration and exchange of user-generated content, but mean exchange of files, votes, chat messages, and screenshots or video [114]. As defined in Sect. 2.1 this does not fulfill the criteria for user-generated content used in this thesis.

Technically the solution consist of an incubating client that starts an embedded game. This client intervenes with the input-output system of the hosting operation system to manipulate graphical elements of the current game and processes inputs meant for currently displayed overlays. All overlays will be realized by browser-technology, rendering HTML-based windows with Adobe Flash and/or JavaScript technology [115].

Virtual Context Based Services. Like the Community Network Game, the *Virtual Context Based Services* framework, proposed by Bergsträßer et al. [116] and Hildebrandt et al. [117] in their coordinated research, offer an infrastructure independent from a specific game and running as an stand-alone client on the player's system. The main focus lies in defining service connectors and virtual contexts that cause a service to be invoked, if specific conditions are met. The service connectors detect running game instances on the client machine and connect to

[36] http://www.xfire.com/, last visited on August 17, 2013.

Table 2.7 Comparison of existing architectures supporting educational game criteria (5–8) and social media interaction functionalities (9–12)

	SteamO	SteamW	Xfire	CNG	VCBS
Design approach	Incubator	Middleware	Incubator	Incubator	Client & Services
Game adaptation needed	Yes	Yes	N.A.	No	No
Reading game data	Yes	No	Yes	Yes	Yes
Writing game data	(Yes)	Yes[a]	No	Yes[b]	Yes
Social community	Yes	Yes	Yes	No	(Yes)
Social interaction	Yes	(Yes)	Yes	Yes	Yes
Peer tutoring	Yes	No	Yes	Yes	Yes
Peer collaboration	No	No	No	No	No
Suitable tasks	No	No	No	No	Yes
Publishing	Yes	Yes	Yes	Yes	Yes
Sharing	Yes	No	Yes	Yes	Yes
Discussing	Yes	Yes	Yes	Yes	Yes
Networking	Yes	Yes	Yes	No	Yes

(SteamO) Stream Overlay, (SteamW) Steam Workshop, (CNG) Community Network Game, and (VCBS) Virtual Context Based Services. [a] pull by game only, [b] visual elements only

the processes by using the game API to read status parameters and manipulate game elements. The services can offer interface elements to the player, allowing the implementation of any service possible (as long as suitable methods can be found in the game internal API). As such, the concept differs significantly from the Community Network Game as the Virtual Context Based Services focus on context detection and need game specific service connectors to work. Contrariwise, this game-specific implementation allows more game element manipulation than pure graphical elements, like game status and object attribute manipulation. In conjunction with Hildebrandt et al. [117] the work allows the extraction of reliable game player profile information, aggregation, and publication on social media platforms maintaining game players' profile information (e.g. hours of gameplay or level of expertise in game) [116, 118].

The proposed solutions differ in focus, scope of supported games, and underlying technology. Therefore a condensed comparison is provided in Table 2.7, focusing on two sets of requirements: First, the criteria derived from the analysis of demands from researchers for deep learning in educational games (based on the core aspects for learning from pedagogy) as described in Sect. 2.2.4 and second, the support for the core concepts of social media applications as they are necessary functionalities to integrate social game functionality into serious games as discussed above (at the beginning of Sect. 2.3.

A detailed description about the assessment of the individual criteria in Table 2.7 is listed in Sect. A.2.1.

2.3.4 Section Summary

The preceding section has outlined, how the key strength of social media (support for creation and content publication, sharing, discussing, and peer networking) can be used to support the desired aspects demanded for educational games to evolve learning with games to deep learning:

- *Social media* can support knowledge transfer and suitable tasks in games with it's created and shared content as learning resources,
- *Peer collaboration and tutoring* in games can be enhanced by adding loose coupling and networking, content discussions and sharing.
- Finally, *social interaction*, as a core functionality of social media (by networking), can be strongly enhanced by creation of learning communities and learning group formation.

2.4 Chapter Summary and Focus of this Work

In Sect. 2.1 this chapter on related work first outlined the fundamentals of learning theory and the importance of observation possibilities, self-practice, and interaction for learning with a focus on peer education, consisting of peer tutoring (low equality, low mutuality) and peer collaboration (high equality, high mutuality).

Social media applications offer possibilities for observation, self-practice, and interaction based on user-generated content that is published, shared, and discussed by individuals on a non-professional basis. It is the inherent ideological foundation behind the usage of social media applications to support active participation in the creation of content by each individual. Interaction is supported by social media applications' social networking support.

In the intersection of both, learning and social media, Massive Open Online Courses (MOOCs) evolved as the Personal Learning Environment (PLE) concept supporting peer education and all social media interaction patterns.

In Sect. 2.2 the concept of game flow explained the necessity to adapt the difficulty of challenges to players' abilities in entertainment games. As not all players are equal, modeling of players' preferences is necessary to adapt difficulty and task type individually. From the intersection with learning, the field of education games evolved, adding the challenge to connect game flow with learn flow. Accordingly, models of learning style preferences are needed as not all learners are equal. It is still a high claim to support deep learning with educational games. Stealth assessment as continuous monitoring of evidence for learning progress and especially the support for problem-based learning have been claimed as requirements.

It is concluded that the discussed research approaches and current status of educational games would especially benefit from support for (a) *social interaction* to allow deep learning and reflection of game experiences, (b) *peer tutoring* to add learning by teaching to games, (c) *peer collaboration* to support creative

problem-based learning, and (d) *suitable tasks* based on player modeling, learner modeling, and continuous stealth assessment.

Finally, in Sect. 2.3, the intersection of serious games and social media has been identified as a research field with limited research results and models available due to the novelty of the field. Based on publications of several game developers and researchers from the field of social and casual games, four core concepts that a social game needs to support were identified: (a) *asynchronous play*, (b) *casual multiplayer*, (c) *coopetition*, and (d) *beneficial social media interaction*. These concepts support the four demanded aspects to be added to educational games.

Game examples were briefly described supporting social interaction and peer collaboration. Further research is required to determine how peer tutoring and suitable task provision can be likewise added to educational games. How the overall depth of the learning experience can be enhanced, similarly necessitates greater study. From a technical point of view, first architectural concepts exist that can add some of these functionalities to existing games.

In conclusion, the intersection of the three research fields (serious games, social media, and peer education) provides the potential to enhance educational games further by combination with social media applications and user-generated content as knowledge media. A content-centered support for peer education concepts is expected to enhance deep learning in educational games and fulfill the requested improvements of open task provision, social interaction, peer tutoring, and peer collaboration in such games.

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Chapter 3
Approach and Concept for Social Serious Games Creation

In this chapter the approach towards the creation of social serious games is outlined based on the findings of the previous chapter.

Therefore, the boundary conditions are primarily set, under which the following proposed concept is designed (Sect. 3.1). As the approach towards social serious games appears to be quite novel, the term is later defined for a more clear understanding (Sect. 3.2). Hypotheses are formulated as a basis for the design (Sect. 3.3). From these hypotheses, it is concluded that the target groups to focus on should be game designers and end users (Sect. 3.4). This conclusion is followed by a discussion of alternatives for the architectural design of the three components of (1) content integration, (2) game adaptation and (3) peer group formation (Sect. 3.5).

Finally the overall architecture is described, followed by a preliminary study evaluating the validity of the approach (Sects. 3.6 and 3.7).

The consecutive Chaps. 4, 5 and 6 then outline the models, solution design, and functionality of the three components of the architecture.

3.1 Boundary Conditions

Prerequisites

Basically, the conceptualization is approached based on the following boundary conditions and prerequisites (BC):

BC1 Most educational games are still single-player and of genre adventure games or simulation games (cf. Sect. 2.2.2, [1, p. 26]).

BC2 Educational games can profit from a support of social interaction for their players (cf. Sect. 2.1.1.3, [2, p. 377]).

BC3 Educational games can strongly benefit from integration of peer education concepts (cf. Sect. 2.1.2, [3, p. 337]).

BC4 Social media interactions are beneficial for learning. They can be used to extend educational games (cf. Sect. 2.3.2, [4, p. 410f]).

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BC5 While making use of social media interactions in educational games, all solutions proposed hereafter take care not to violate the criteria of social games (cf. Sect. 2.3.1, [5]).

Research Focus Exclusion

Based on these conditions and the findings from related work (Chap. 2) the approach and concept to be developed *exclude* the following aspects:

Recommender Systems: As social media interactions are mostly based on user-generated content educational games can as well profit from research results from the field of (content-based) recommender systems to assess the quality of content and highlight the most suitable content for the learner. It is outlined how research results in this field can be added and integrated into the concepts of this thesis, but they are not further investigated in this thesis.
Continuous Adaptation: As educational games need to track the progress of players continuously as described, models of the playing preferences, learning preferences and learning progress are maintained and game flow or learn flow are adapted accordingly. This thesis focuses on the provision of a general solution framework to bring educational games and social media closer together. Adaptation has to take place inside the game engine; using model information. In this thesis the models can be respected for e.g. peer group formation and finding the most suitable collaboration peers, but continuous adaptation is not an aspect here as this thesis is dissociated from aspects of game loop adaptation.
Artificial Intelligence: Machine learning algorithms can contribute to all components of the later proposed model to classify content and players for better structuring of the data. As stated above, the general concept can later on be advanced by adding such aspects, but is not a focus for the first approach.
Game Creation: As described, manifold single-player educational games and concept exists. It is not the aim of this thesis to develop a new game genre concept or one specific game, but to provide general solutions to be used to enhance existing educational games by their developers.

Research Focus and Approach

The approach to supporting the demands of educational games (as stated in Sect. 2.2.4) by using social media is as follows:

Social Interaction: Supported by the functionality of sharing content and discussing it. In order to respect asynchronous play the interaction in a single-player educational game has to be timely decoupled. Content can be used as questions or hints to game scenes or game tasks. Enabling discussions (like bulletin board threads) for the content fosters social interaction (and knowledge transfer).
Peer Tutoring: Supported by re-use of published solutions for game tasks, and the possibility to discuss the approaches taken to the stated game task problem. Such discussion is most effective if provided as peer feedback. Sharing can support peer tutoring if a social media application allows the correlation of published content

to game tasks. From the social game functionality perspective, peer tutoring is mainly added by the concept of beneficial social media interaction.
Peer Collaboration: Even though the games are single-player, collaborative tasks can be added, if interactions among player and other users (in social media applications) are enabled. Respecting asynchronous play and coopetition, these interactions need not to be necessary for the individual progress in the game, but can improve motivation and immersion. Respecting the requirement of casual multiplayer, player and social media participants need to have a chance of perception of each other.
Suitable Tasks: The main factor for the selection of suitable tasks is the proper implementation of progress tracking (player model, learner model) in the game itself. But social media can assist in the availability of suitable content. As budgets for serious games development are usually very tight, the availability of published user-generated content as content for game tasks seems promising. This can be mediated into educational games by the concept of beneficial social media interaction and asynchronous play.

3.2 Defining Social Serious Games

The currently available social games and models are missing to fulfill the aspects of *peer tutoring* and from a content-perspective as well the provision of *suitable (user-generated) tasks*. As described in the preceding section *social interaction* and *peer collaboration* as well benefit from the provision of social media. The author of this thesis suggest a mapping of the core features of social media to demanded

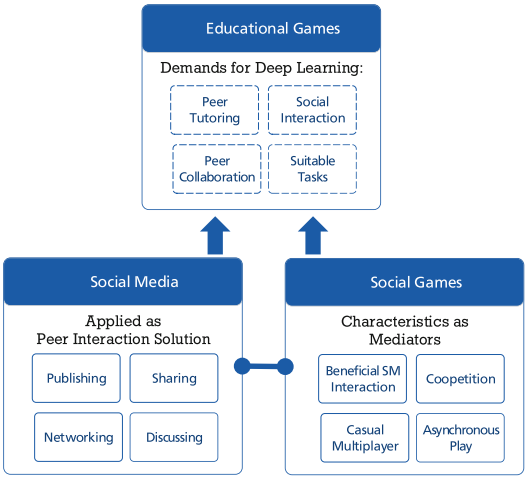

Fig. 3.1 Social serious games—approach by using social game criteria as mediators to apply social media interactions to educational games with the goal to fulfill the demands for deep learning

aspects for deep learning in educational games and proposes to use the social games criteria as mediators as illustrated in Fig. 3.1.

If the criteria of social games are integrated and enabled for a single-player educational game, it can be concluded that all demanded aspects for educational games can be supported. Thus, social media is used beneficially in educational games to allow *social interaction*, *peer tutoring*, *peer collaboration* and provision of *suitable tasks*. The term *social serious game* is defined based on the addition of social game functionality as follows (based on Konert et al. [6]):

A social serious game is a *serious game* satisfying all criteria mandatory for a social game.

To realize the application of social media interactions in educational games and implement the social game characteristics as described above, three components are proposed to be offered to game developers (cf. [7]):

1. **Content Integration**: This component will allow game developers to store user-generated content arising during gameplay into a persistent repository. Amended with metadata describing additional semantic information, the content can be allocated to game scenes, quests, and performance values of the player (model). The content can be displayed in an online-platform for comment-based discussion and rating. Other game instances can fetch suitable content for current game scenes of a player, suggesting such content as hints or best-practice solutions in a sense of peer tutoring and social media interaction. Sharing of such content into social media applications is additionally provided (detailed description in Chap. 4).
2. **Game Adaptation**: Developers can access user profile information from social media applications and adapt the game experience accordingly. Beside information about a player's social graph of befriended users, the *game adaptation* offers the creation and publishing of game influences, a core concept of the proposed solution. A game influence is a *call for action* from the running game instance to currently online acquaintances in connected social media applications. Game developers can use such influences to start a voting, call for content contributions (uploads, text statements), or other forms of interaction. Game adaptation allows peer collaboration (asynchronous) and beneficial social media interaction. If used as an interaction interface to let peers assess a players approaches or solutions it can be used for suitable task presentation (detailed description in Chap. 5).
3. **Peer Group Formation**: As the performance of peer collaboration and peer tutoring can be improved by a proper matching respecting learning style preferences and personality traits as well as other homogeneous and heterogeneous criteria to match, an algorithm can provide game developers with matching suggestions (detailed description in Chap. 6).

3.3 Hypotheses

To allow a focused model design and evaluation of the proposed approach the following hypotheses (H1–H4) are defined as guidelines.

H1 The use of peer education concepts based on user-generated content can positively influence the effectiveness of a serious game.
H2 The use of social media interaction can enhance users' acceptance of a serious game.
H3 Game developers can profit from an architectural solution supporting content exchange and game interaction.
H4 A new algorithm can be found supporting the learning group formation with homogeneous and heterogeneous matching criteria. This algorithm needs to be capable of respecting relevant personal characteristics of the learners and the scenario in order to support an effective peer matching for peer education in educational games. The algorithm is designed to build groups that have a similar group formation quality.

3.4 Target Groups

As main target groups in the process of using the proposed solutions *game developers*, *subject matter experts*, and *end users* can be identified.

An intensive cooperation exists with subject matter experts from the department of didactics in mathematics at Technische Universität Darmstadt for the design of the components and the related suitable evaluation scenarios in this thesis. While these experts are involved in the design process, for evaluation the game developers and the end users are addressed. They are expected to be the main groups using the proposed solutions for the creation of educational games (game developers) and their use for learning (end users).

Game developers: As the proposed solution is primarily to be used by game developers, the APIs is designed with their needs in mind. For evaluation, expert interviews with senior software developers and Chief Executive Officers (CEOs) are conducted to assess the quality of the provided solution and to ask for suggested future improvements (concerning hypothesis H3).
End users: The main focus is to provide new functionality for the intersection of educational games and social media. Thus the evaluation will focus on the impact the use of social media interactions has for end users. Scenarios include a learning-oriented and a gaming-oriented scenario (concerning hypotheses H1 and H2).

Addressing hypothesis H4 can be done by end-user evaluation or simulation-based evaluation. As for group formation a lot of participants are necessary to measure an effect and compare a new developed algorithm against existing solutions, it is

decided to compare the proposed algorithmic solution to the other existing solutions by simulation. It's performance is studied using a new thoroughly developed group formation quality measure.[1]

3.5 Architectural Scenarios

For the architectural design several solutions are possible and outlined here. For the provision of the components *content integration*, *game adaptation* and *peer group formation* to a game instance (from the game developer perspective) two existing systems are involved: game instance(s) and social media application(s).

As social media is used as a medium (or service) to provide the components' functionality and specifically peer education concepts to the game, the two extremes of possible solutions are: a complete implementation in the game(s) on one side or full implementation within social media application(s) on the other. An overview of the possible solutions with benefits and drawbacks is given in Table 3.1. They are described as follows:

In Game: All the components are designed and added by a game developer into the game (or game engine). For the interaction with peers and publishing within

Table 3.1 Alternative solutions for system architecture between game and social media

Scenario	Beneficial	Adverse
In Game	Full game status control	No re-usability
		Social media dependency
		No central repository
Game Library	Re-usability	Social media dependency
		No central repository
Incubator	Re-usability	Social media dependency
	No game programming needed	No central repository
	Difficult game state	
	Manipulation	
Central Middleware	Re-usability	No direct game state access
	Central repository	Extra application
	Social media abstraction	
Social Media Plugin	Seamless social media	Social media mandatory
	Integration	Social media dependency
		Technology restriction

[1] As outlined in the outlook (Sect. 8.3) subject matter experts from pedagogics or pedagogical psychology can then use the algorithm in a next step to evaluate the effects on learning advances and from users' perspective.

social media, the solution directly communicates with the APIs of the social media application(s). This solution provides the benefit of full control by the game developer over system behavior, privacy issues and communication. The architecture components have full local access to game-state and assets. Adversely, the solution is not decoupled from the game and makes re-usability more complicated. Likewise disadvantageous is the direct dependency to social media applications' API functionality and a missing central repository to exchange content among game instances over time (considering asynchronous play).

Game Library or Plugin: A library solution can be developed and added to the game that provides encapsulated functionality via interfaces to the game. As such it is easier to be reused by other games (or developers), but still has the disadvantages of a missing social media API abstraction and no central repository.

Incubator: Wrapping the game instance during run-time by an incubator (cf. Sect. 2.3.3) provides the advantage that no changes must be made to existing game solutions. The incubator uses the game API or at least accessible methods of the game to read and manipulate elements of the game. Even though the solution is more generalizable for several games, the drawbacks mentioned before remain. No repository is provided for content exchange and social media API are not abstracted.

(Central) Middleware: A middleware architecture that is designed as a centrally available service mediating between game instance(s) and social media application(s) can provide a central repository for the game. The middleware can be as simple as a database service, but then abstraction and enrichment of social media application(s) API is not provided. For easier access to the functionality of *game adaptation* an abstraction is desired and the middleware solutions then handles the communication and data transformation for/from social media applications, too. Disadvantageous in this scenario is the necessity of API definition for game instances calling the middleware services, no direct access by middleware components to the game instances inner state for *content integration*, and the need of an extra application beside game(s) and social media application(s).

Social Media Plugin: Some social games, like discussed in Sect. 2.3.1, are designed as plugins to social media applications, running directly within the social media application instance (in the browser of the client). Even though they are called *Social Media Plugins* the games store the players' status on their own central repositories and mainly use the social media applications' environment for messaging, authentication, and publishing of content to the social media application's profile page of the player. Even though most of the game developers provide a second version running without the social media environment, the plugin-based solution cannot run without the environment. As such, the social media interaction is not any more optional, but mandatory. Additionally disadvantageous is the dependency to browser-based technology and the necessity to re-implement (or adjust) existing programming, if several social media applications are desired to be supported by the game.

Even though all of the described solutions are possible to use, it is reasonable to focus on the *Central Middleware* solution as it allows the provision of a central repository for *content integration* respecting *asynchronous play*, still leaves the use of social media applications optional to game developers, and at the same time provides an abstraction and unification for the use of different social media applications for *game adaptation*.

3.6 Architecture

The modularized middleware will consist of the three components with their content-format descriptions and interfaces. The inter-connection and communication of the components is schematically shown in Fig. 3.2. The following sub-chapters will focus on these components in detail.

As illustrated, the architecture connects game instance(s) (on the left) with social media application(s) (on the right). The middleware provides a central API to the games that offers the functionality of the three components of *content integration*, *game adaptation* and *peer group formation*. Technically, this API may be offered by the components directly and grouped (encapsulated) for each component, but conceptually it is seen as one API offered. The middleware core (in Fig. 3.2 named *SoCom.KOM Middleware*) internally forwards the requests to the respective component and returns the result. In more detail the concept for each components functionality is described in the following paragraphs.

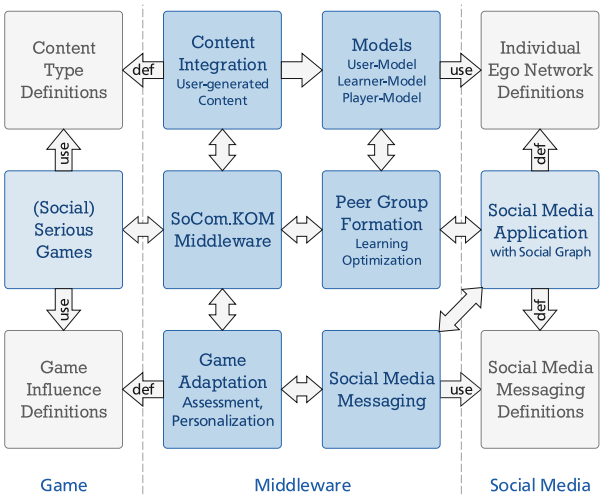

Fig. 3.2 SoCom.KOM middleware architecture—schematic component interconnection (incl. data-formats) ⟨def⟩ for components defining data-formats, ⟨use⟩ for components using the data-formats (positioned in the corners)

Content Integration. This component offers a description to game developers how content can be semantically described when stored to the repository. These metadata can be used to filter and distinguish content when it is requested from the repository. Game developers use this meta-information when adding functionality of content integration to their game (cf. Chap. 4).
Game Adaptation. Beside functions for retrieving an abstraction of a user's social media profile data, this component offers influence type definitions to the game developer to be used for game adaptation. The provided types can be used to define re-usable templates or to start specific influences directly. Such an influence is represented by a *call for action* that asks social media users in connected social media applications to contribute to the game. By this, new content or vote results can be used and added to the game in order to personalize and adapt the game accordingly. To achieve this, the game adaptation component uses the internal social media messaging component which is connected to each supported social media application (Social media messaging definitions). It published the influence availability with a hyperlink that can be used participation (cf. Chap. 5).
Peer Group Formation. By providing a consistent way to define criteria to be used for matching, the component allows to start a group formation process based on criteria from a user-model (personality and preferences), learner-model (proficiency and skills) or player model (playing preferences). Additionally, contextual aspects from the inter-connection of players can be respected (e.g. friendship). These criteria values can be drawn from the ego-network of the player as defined and provided by connected social media applications (cf. Chap. 6).

3.7 Preliminary Expert Requirement Study

After the design and clarification of the approach a preliminary qualitative study was conducted to examine the suitability and acceptance of the new approach to interconnect computer games with social media applications. The study was conduced in April 2012 (between 3rd and 22nd) interviewing CEOs and Lead SoftwareDevelopers of small and medium game developer studios (and one university department) that create serious games. From eight invited interview partners six agreed to give the interview. Among these six half were CEOs and half Lead Software Developers. The companies were all from Germany (Darmstadt, Egelsbach, Frankfurt, Munich, Offenbach, Wiesbaden).

The interview was recorded and afterwards transcribed and answers were categorized. The leading questions were of the following categories:

- overall architecture design and API logic,
- functionality of content integration,
- functionality of game adaptation, and
- social media interaction (data exchange, retrieval of profile information).

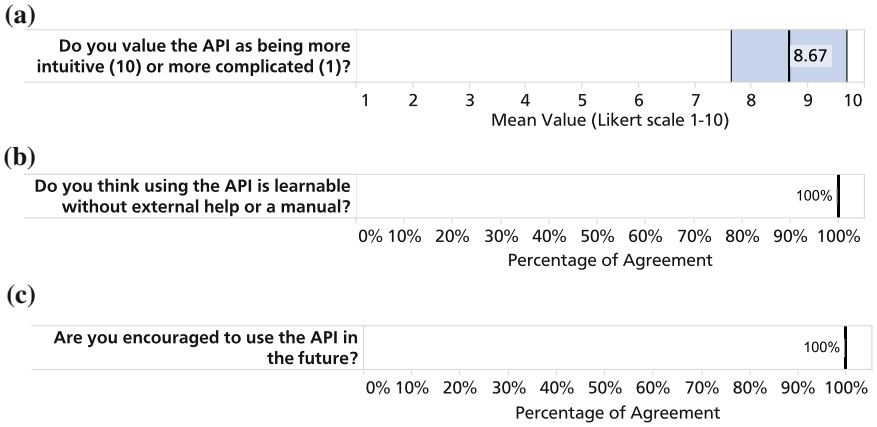

Fig. 3.3 Expert interview answers to acceptance questions (Q1, Q9, Q10). **a** Answers to Q1 on intuitive usage of the API (with 95 % confidence intervals). **b** Answers to Q9 on simplicity to learn the API usage. **c** Answers to Q10 on encouragement for API usage

The interview partners were asked to rate the usefulness of the solution, their interest in using it themselves and most important were encouraged to recommend further improvements or missing functionality they would desire (a full list of the interview questions is listed in Sect. A.2.2).

Results

As visible in Fig. 3.3 the interviewed experts value (a) the intuitive usage of the API ($m = 8.67$, $SD = 1.21$ on 10-point Likert scale) and they agree that (b) it is learnable without intensive training (100 % of all participants agreed). Additionally, all of the partners agreed as well that (c) they like to use it as soon as it is released for public use (100 % of the participants agreed).

The second purpose of the interview was to further improve the current status of the API and thus ideas for improvements where asked in most of the questions (Q1–Q8, see Sect. A.2.2 for details). In general the interviewed experts were enthusiastic about the concept and made manifold suggestions that were partly far beyond the aimed functionality of the middleware (∼39 % of all 72 suggestions). The suggestions in scope were grouped and ranked by frequency of occurrence as shown in Fig. 3.4. The recommended functionality of *statistics*, *automatic mending of the context graph*, *reporting*, *visibility settings*, *filters*, *reading of likes (supporters)* and *requesting only updates (changes)* are added to the concept and implemented in most cases. The suggested extensions of available influence types are as well suitable as the set of supported influence types is extendable by design (see Chap. 5).

In summary, the experts appreciated the approach, expressed their interest in using the solution when available, and made suggestions for enhanced metadata for filtering and search in content integration as well as manifold suggestions to influence types for the game adaptation component. These suggestions help to further improve the concept and are directly integrated in the following chapters.

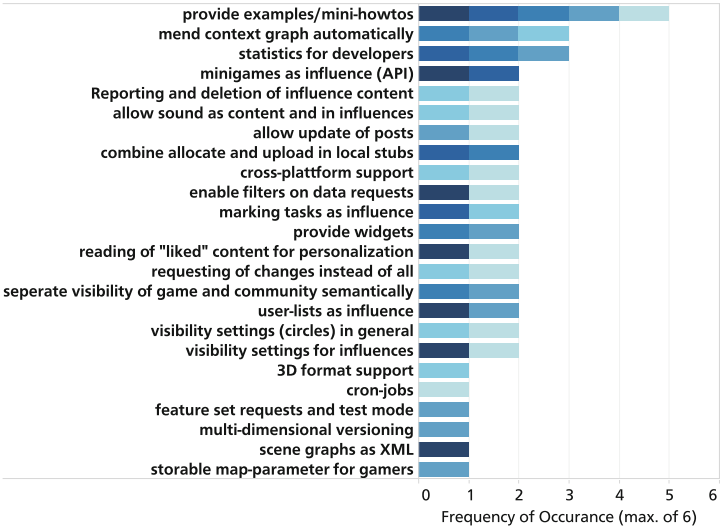

Fig. 3.4 Expert interview improvement recommendations; answers in scope of aimed functionality (from questions Q1–Q8). Same color of the *bar-tiles* indicates the suggestion was made by the same interview partner (total of 6 different colors)

3.8 Chapter Summary

This chapter defined boundary conditions in respect to the approach and concept for the creation of the social serious games architecture. These conditions were derived from the thorough analysis, realized in Chap. 2. As a basis for the following work, the term *social serious game* has been defined along with four hypothesis, which are to be focused on. The discussion of the target groups and alternative technical approaches lead to the design and description of the SoCom.KOM architecture. It's applicability has been evaluated by a preliminary qualitative evaluation with Chief Executive Officers (CEOs) and Lead Software Developers in the serious games field. The study revealed great support and interest of the interview participants and their appreciation of the architectural concept. In more detail, the experts confirmed the importance of the targeted aspects and made even further suggestions of desired functionality extensions. This includes more content types, filter-support based on metadata, and game influence types for social interactions.

The subsequent three chapters will describe in more detail the approach and concept for each of the three architecture components supporting content integration, game adaptation, and peer group formation.

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Chapter 4
Content Integration Model for Peer Tutoring

This chapter describes the use of social media artifacts and user-generated content for peer tutoring and knowledge transfer among players of the same (single-player) educational game. It aims to support the requested aspects of social interaction, peer tutoring, and suitable tasks and respects asynchronous play, as well as beneficial social media interaction.

To achieve this, four major aspects of the content integration model are described here in more detail: *game context mapping*, *content metadata*, *open content type support*, and *semantical content categorization*. To address the issue that only a minority of users is willing to contribute content actively, a dual achievement system is proposed that combines social media achievements and game achievements. Details about the corresponding conceptualized API methods can be found in Sect. A.1.

4.1 Game Context Mapping

As described earlier, Internet users massively consume video, image, and text content on the web (87 %, cf. Sect. 2.1.6). A major problem with user-generated content in discussion forums or as comments to blog posts is the aggregation and classification to a specific semantic meaning to help users find the relevant threads [1, 2]. For the interconnection of game instances and social media applications, as desired in this thesis, the situation is comparatively comfortable. When users create content related to game-issues and even create or post such content from within the game, the context and semantic information about this context is well known (by the game engine). Consequently, it is possible to map created content directly to the game situation it relates to. This has to be done by the game instance when storing the content into the central content repository.

Still, not all computer games are identical and thus have different approaches towards context description and granularity of state changes. As this thesis focuses mainly on single-player educational games that are mostly adventure games (cf. Sect. 2.2.2), the use of specific context identifiers seems to be suitable. Such games

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are structured to levels, stages or scenes a player masters on his way through the game. Game developers can create a directed (not necessarily anti-cyclic) graph of these contexts and name them with a scheme suitable for them and comprehensible by users.

The game context mapping then allows game developers to

- add the context identifier to content stored in the repository,
- create directed vertex connections in a graph of these context identifiers (as edges), and
- fetch content related to such specific context identifiers later on easily to recommend content to users in game.

This concept is enhanced by the later described *Content Metadata* (see Sect. 4.2).

A key benefit of such a context identifier mapping and the graph interdependency is the possibility for linear mapping to existing social media forum or bulletin board structures. The SoCom.KOM architecture component for content integration can deliver a forum-like website providing content, discussion, and rating possibilities to players. On the most abstracted level users can select one of the games[1] they are currently playing or want to play. On the next level the game context identifiers are visualized with an individual picture and description as set by the game developer in the SoCom.KOM content integration repository structure. The order can be generated by calculating the paths from context identifiers with no incoming vertex (starting point sources) to context identifiers with no outgoing vertex (game end destinations). Within this context section the user will see all threads ordered by relevance and filtered by visibility constraints (see Sect. 4.3).

As the mapping is linear between game context and generated forum thread overview, hyperlinks can lead the user directly from game to the content (e.g. in an integrated overlay browser in the game) or the game fetches the relevant content itself via the provided content integration API and visualizes them. The underlying information about the inter-connection of contexts can be used to provide forward and backwards links to users browsing the content.

4.2 Content Metadata for Filtering

To allow more complex filtering of game content and adjust the criteria to the game characteristics, game developers can annotate the submitted game-content with metadata that is not directly bound to the content itself, but stored separately [3, p. 18]. Basic metadata information are the context identifier (as described in the Sect. 4.1 before), creation date (set automatically), visibility (for privacy issues) and a textual description (mainly for end-users if content is of a non-displayable format).

Beside this, game developers can add arbitrary textual key-value pairs to further sub-classify their game-content. Other means of meta-information could have

[1] That are connected and known to the SoCom.KOM middleware.

been provided, such as relating content to other content (a relation-by-example) or letting game developers add context relations to states and characteristics of a semantic ontology unique to their game, but the discussion with game developers in the preliminary study (Sect. 3.7) revealed that the system needs to be as easy to use as possible while still being extendable and adaptable to specific game's needs. As most game developers were familiar with the concept of relations and attributes, the key-value pair paradigm seemed suitable (and was appreciated by the experts in the interview to be flexible enough).

The provided metadata key-value pairs can then be used for filtering and sorting content elements—either on the dynamically generated web frontend of the content integration component or via API by game instances to load the desired content elements.

4.3 Semantic Content Categorization

For *peer tutoring* it is most important from a didactical point of view to provide users only with as much information as they need to solve a problem themselves. When users get stuck in a single-player game they usually tend to pause the game, browse the Internet for a walk through description and try to find the relevant description for the game task at hand. This leads to several problems: First, users interrupt their gameplay and flow experience, spend time-consuming efforts to find relevant information and additionally—maybe accidentally—read more of the walk though description as they need to solve the current problem—which leads to boredom as solutions to coming challenges are already known, too.

To prevent these problems the relation to current game problems is done as already described above by a proper context mapping. Still, for a specific context the content can contain

- questions about the task,
- information not directly related to solving the tasks,
- the complete walk through solution, and
- smaller hints to the solution.

Depending on the gameplay situation and status of a player, he may want to answer questions by his own best-practice experience or—as described above—may need only a hint and not directly the full solution.

Game developers can therefore annotate the content with a category-element a user selected when creating and submitting the content. The categories are as stated above: `question`, `information`, `solution`, `hint`, and can be used as an additional parameter in retrieval, sorting, and filtering.

4.4 Open Content Type Support

Beside addressing the need for proper structuring and attribution of game content, the aspect remains that the content itself exists in several formats. When referring to types, text, audio, video, or complex formats as well as proprietary variation of these are meant. For visualization of submitted content on the website and for exchange among game instances it is necessary to know the format of the transmitted content. Therefore the content integration component provides identifiers to be set as type of content. Directly supported for processing, visualization in the website, and transformation to other formats are:

- Text, e.g. as UTF-8 encoded strings,
- Images, e.g. as jpeg or png binary formats,
- Audio, e.g. as mp3 or ogg byte formats,
- Video, e.g. as mpeg3 or flv formats, and
- Proprietary, e.g. game characters, 3d formats, inventories, and settings.

Game developers can set the type-parameter to any string they wish in order to re-identify their types of content when retrieving search results later on. Reserved parameter values belong to the directly supported formats of `text`, `jpeg`, `png`, `mp3`, `ogg`, `mpeg3` or `flv` which cover all major content types created and consumed in social media environments (cf. Sect. 2.1.6). Other solutions from the field of multimedia learning exist that enable developers to share proprietary software components enhanced with metadata, create the corresponding visualizations (as a set of specific instructions) to allow the integration (and reuse) of the visualizations in several learning contexts [4]. An integration of such extensions can be considered for future versions.

All four concepts of *game context mapping*, *content metadata support*, *semantic content categorization* and *open content type support* are illustrated in Fig. 4.1. The figure uses exemplary content of a fictional game, named *GTB*. The figure illustrated how a user posts an image from game context `F` with an attached question. The game adds two further game specific metadata keys that allow further filtering and stores the content with metadata in the repository (step 1). An aggregated view on the content element uses the underlying metadata to show the created question in a search result only asking for content elements of this category (step 2). Indicated navigation keys use the underlying scene graph of the whole game to suggest preceding and next contexts' content.

It is expected that these four concepts can be transferred and mapped in parts to existing standard metadata formats in E-Learning like the Sharable Content Object Reference Model (SCORM) [5–7]. As no standard is known that supports all aspects, e.g. like proprietary content types to be added dynamically or a context-mapping as described above, the described self-developed format and metadata is used in the course of this thesis.

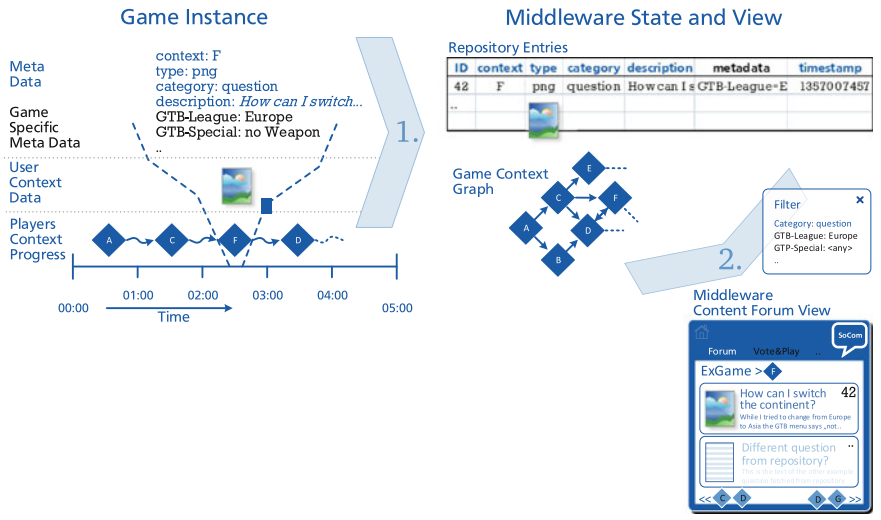

Fig. 4.1 Concept of metadata usage for storage and visualization of game context related content show with exemplary game named *GTB* that adds two own metadata fields. These are stored in the middleware repository (*1*) that results in further filter options as shown in the visualization component drawing (*2*). Graph information about reachable game scenes from current scene helps to provide the user with navigation support (visualized at *bottom* of drawing)

4.5 Dual Achievement System

As the creation of user-generated content is per definition a voluntary and non-professional activity (cf. Sect. 2.1), one major motivation for creating such content is fun and entertainment [8]. Thus, from a player's point of view, the creation of content directly competes with the progress in the corresponding game when comparing the playing of a serious game with the creation of hints or solutions in the social media application related to this game's tasks (contexts).

In more detail, the factors influencing a users will to contribute content are identified by Chen and Hung [9] as:

- Cost/benefit ratio,
- Incentive system,
- Extrinsic/intrinsic motivation,
- Social capital, and
- Social and personal cognition.

All of these factors can be addressed by a dual achievements system. Achievements provide by themselves an incentive system and positively influence the cost/benefit ratio as well as increase the extrinsic motivation. If publicly visible, the received achievements function as a reputation system and can work as social capital [10]. As such, the identification and cognition with a player's community status is given.

It is therefore desirable to provide players with achievements to stimulate content creation and progress in their game. As described in [11] an integrated achievement system that combines achievements of both sides—game and social media—can provide such achievement-based incentives. To the best of the author's knowledge no such combination of achievements in one system exists yet. Therefore a solution with new achievement types is proposed in the following to combine game-based achievements and community-based achievements.

Note: Parts of this section are resulting from the supervision of the master thesis of Nico Gerwien [12] and have been published in [11]. They are repeated here as revision.

4.5.1 Achievement Type Classification for Social Serious Games

Based on the described preceding work and the focus on a combined achievement system for game-based and social media-based achievements, a new classification of types for achievements is suggested, as follows in the next paragraphs. The differentiation is mainly done by focusing on the completion logic part of an achievement. That logic contains the pre-requirements for an achievement to be active, the trigger events watched, and conditions describing when the achievement trigger is accepted. A multiplier (or counter) indicates the amount of times a trigger has to fire while meeting all conditions and pre-requirements before the achievement is completed.

In the following a binary differentiation of achievement types is proposed as *qualitative* or *quantitative* achievements, then whether or not they need *cooperation*, and at last a quaternary division into *static*, *user-generated*, *user-awarded*, or both *user-generated* and *user-awarded* simultaneously.

The classification leads to 16 types as illustrated in Fig. 4.2. The order of the binary splitting can be changed and is exemplary here only.

Two additional types are proposed to support the creation of achievements for the combination of game-based and community-based achievements. *Hybrid* achievements are related to the separation of achievements parts that have to be completed partly in the game and partly in the social media application. *Reversible* achievements are proposed to enable the use of achievement systems as reputation systems in order to discourage undesired behavior in a social media community.

Qualitative and Quantitative Achievements
Traditional achievements in computer games are measured on a scale and can be split up into levels. A group of achievements can share a counter and the progress can be expressed as percentage of completion. As such, these achievements are *quantitative* and neither seldom nor hidden nor invisible. They are common to achieve. Corresponding to [13] they belong to the achievement categories *completion*, *collection* or *veteran*.

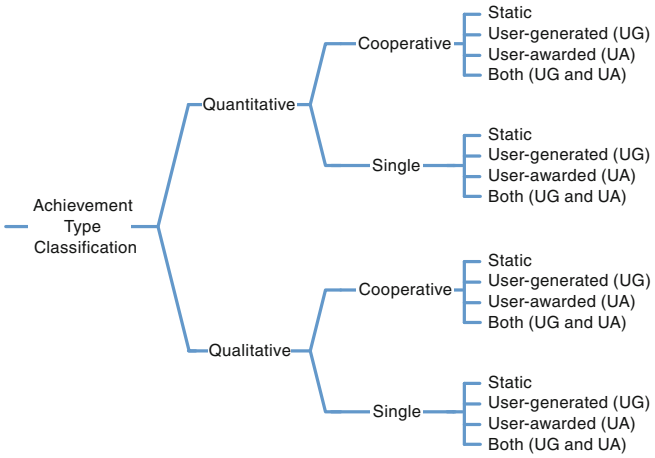

Fig. 4.2 Achievement type classification with two binary and one quaternary layer resulting in 16 different types [11]

In contrast, the *qualitative achievements* may represent rewards of glory or sustenance. They only have a binary status, can be hidden, very seldom, and reward unlikely success or unusual behavior. They belong to the categories of *special play style* and *curiosity* [13].

Cooperative Achievements
If achievements are designed to go beyond pure single-player games, they can be achieved by one player or a group of players together. If the participation of more than one player is required for completion, these are defined as cooperative achievements. A further division can be made depending on synchronicity. If the participation has a time-constraint they are called synchronous cooperative achievements. In the course of this thesis the focus is on asynchronous cooperative achievements in order to respect the criteria of *asynchronous play* and are meant to be useful for *peer collaboration* using the concept of *coopetition*. For example, such an achievement could be the creation of a content-element by one player and the re-use by another.

User-Generated and User-Awarded Achievements
In respect to content creation and social media interactions the achievement system can be designed to allow the creation of achievements by users themselves. Especially when users contribute tasks and challenges as user-generated content to a game concept (e.g. like levels in Sonys LittleBigPlanet game community[2]) it might be most suitable to allow the addition of specific achievements, too. The users define the completion logic with conditions and pre-requisites by writing their own program code or selecting conditions from provided lists. Finally, they decide on the rewards and actions on completion.

[2] http://lbp.me/, last visited on August 30, 2013.

Orthogonally to this, achievements can as well be user-awarded. In this case, the completion logic is not predefined by pre-requisites and conditions, but the community itself votes or awards the achievements to players. These achievements not necessarily need to be user-generated, but can be pre-defined like an achievement in a math task solving game where the task are open problem formats not assessable by computer algorithms. In this case, the community would grant a pre-defined achievement, e.g. a *task solving achievement*, by deciding on the correctness (or curiosity) of a solution.

Hybrid Achievements
When combining game-based and social media-based achievements *hybrid achievements* will require the participants to complete parts in game and parts in the social media applications. By this interdependency, the achievement can encourage the collaboration between game and social media side (e.g. as cooperative achievements). Additionally, experienced players can be motivated to create social media content if parts of quantitative achievements are necessary to be completed in a connected social media application. This appears to be especially valuable for achievements related to game tasks occurring in more advanced phases of the game, where assistance and hints by experienced players is desired (to support peer tutoring). These achievements directly correspond to the functionality of *beneficial social media interaction*.

Reversible Achievements
Likewise, in [11] the relation of reputation systems and achievement system is discussed. The main difference is the usage of reputation systems to reflect the amount of desired and undesired user behavior of a user as a reputation status. In contrast, achievement systems normally only reflect positive development but do not transparently visualize the undesired activity. It can be argued that achievements can be used as reputation indicators without violating the requirement for achievements to be not withdrawn if once completed. The proposed *reversible achievements* are quantitative achievements which reset their counters when an undesired behavior of a user occurs. Moreover, the achievements can be designed as level-based achievements where counters are designed as ratios. In example, the ratio of high quality versus low quality comments in a community can be such a reversible achievement. Each time a comment is reported and needs to be deleted the counter of positive comments for this level is reset. Once a level of this achievement is achieved, it remains completed, but further levels are even harder to complete. This achievement can be suitable addition to *user-created achievements* to avoid spamming and to prevent publishing of too much low-quality content.

If *hybrid* and *reversible* achievements are considered as well for the classification illustrated in Fig. 4.2, the result is a classification type system with 32 different classes, as reversible achievements are necessarily quantitative achievements ($2^2 * 4 * (2 + 1) = 32$).

4.5.2 Achievement Categories

As discussed in [11] the eight reward categories in computer games found by [14] can be connected to the achievement categories found by [13]. They identified 14 categories for games and seven for communities. Based on this, a condensed combination of 16 categories is proposed in this thesis, to be used for a dual achievement system (details are listed as Table A.1 in Sect. A.1.2). Especially the categories *cooperative*, *moderator*, and *instructor* are considered to be valuable for achievements addressing *peer education* concepts.

4.6 Architecture Design

As discussed in Chap. 3, Sect. 3.5, the overall architecture will consist of a middleware providing an API to game instances. For content integration this API provides methods for retrieving and storing content in several formats with metadata. Content can be filtered by category, type, context and arbitrary keys and value-prefixes. Achievements can be created and stored in the central middleware repository to change their status from social media and game instances simultaneously (e.g. for user-awarded, hybrid achievements). The architecture and components are shown in Fig. 4.3 complementary to the overall architecture already illustrated in Fig. 3.2.

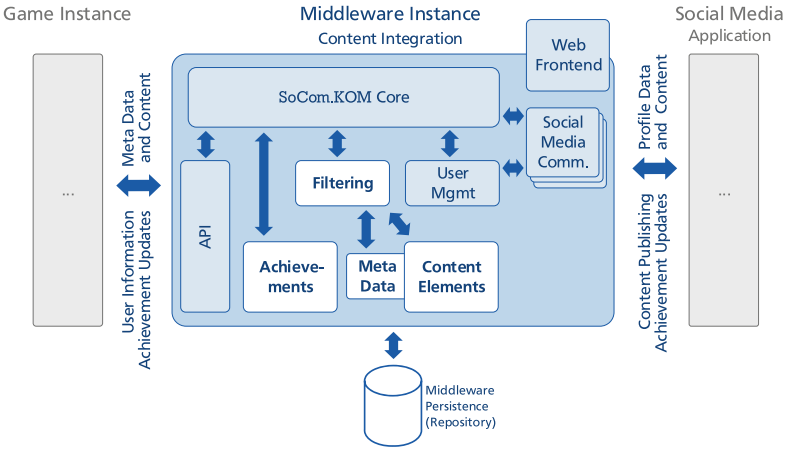

Fig. 4.3 Architecture of content integration component, illustrating the communication between sub-components and among game, middleware and social media applications. The most relevant parts are highlighted (Legend in Sect. A.1.1)

4.7 Chapter Summary

In this chapter, the approach and concept for the SoCom.KOM content integration component has been elucidated. To allow for a more seamless transition and knowledge exchange between game and social media applications, context mapping has been defined to allow a non-linear displaying and navigation through game-related content. Additionally, it supports the semantic relation between game scenes and the related content to be stored for later usage in filter-based access to this content. Furthermore, the filtering and displaying of content items from a didactic perspective is supported by the concept of semantic content categorization that allows the retrieval of questions, hints, information or solutions to game tasks (or contexts) to support deep learning. The concept of content metadata allows the addition of game-dependent additional characteristics to content items for filtering and sorting. As games may differ in genre and content, the concepts for metadata usage and content-type support are both open to extensions by game developers. The suggestion of a corresponding visualization component allows the use of this information to structure the user interface and provide users with a filtered view and navigation concepts related to the game's context transitions.

To assist the game's development and foster content creation, posting, sharing and commenting, a dual achievement system has been proposed extending existing approaches by the concepts and design of intervened achievements. As such, new achievement types for user-generated achievements, user-awarded achievements, and hybrid achievements have been defined. To support reputation systems' functionality of reflecting not only desired but as well undesired user behavior, the concept for reversible achievements has been introduced. As such, achievement systems, adding the functionality suggested in this chapter, can be used as reputation systems simultaneously and support the content creation, the linkage of game-based achievements and social media-based achievements, as well as the avoidance of undesired user behavior.

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Chapter 5
Game Adaptation and Personalization Support

Personalization and individualization of gameplay experience can be done by metrics and data, retrieved from social media platforms. Yet, such attributes can also be realized by interaction and influences directly made by connected individuals not playing at the moment, but whom are notified via social media applications' news feeds (both aspects are visualized in Fig. 5.1). As such, befriended people from the surrounding social network can contribute content to the game-experience of the (known) player. A suitable infrastructure allows the users to be creative and generate new and unique gameplay experiences. Additionally, the infrastructure can be used to integrate an assessment of creative game solutions and solutions to open-format problems by other humans when computer algorithms cannot cope with the degree of freedom for the tasks.

In this chapter game adaptation (Sect. 5.1) by social media metrics is first examined before social game interactions (Sect. 5.2) are subsequently addressed, as they appeared to be of more interest and potential for research. Details about the corresponding designed API methods can be found in Sect. A.1.

Note: Parts of this chapter have been published before [1, 2] and are repeated here as revision.

5.1 Game Adaptation by Social Media Profile Data

A valuable source for personalization and adaptation of gameplay is the information available in user profiles from social media applications. These contain e.g. user name, gender, date of birth, profile picture, city of origin, and the network of friends which can be processed to visualize the network of social ties around the user as a graph. Such a graph is also called ego-centered network or *ego network* [3, p. 8]. It allows calculation of several metrics which can be used as indicators for further adaptation. *Level of trust* among users can be calculated as well as user's key role in interconnecting sub-groups of the user's social network, measured as *betweenness*

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centrality [4]. Such measures of Social Network Analysis (SNA) can help to identify which users or content might be most appropriate to fetch their data and use it in the game. One additionally considerable SNA measure is *tie-strength*. It is known that weakly-tied users are rather a source of new information because their social circle differs compared to the current user's social circle [5, 6]. Consequently, it can be beneficial to facilitate information exchange among user's not closely-tied in order to increase the probability that the current user gets new information that was not known before. Additionally, the level of trust is lower between users with a weak social tie compared to closely-tied users. Consequently, a game could connect users, closely connected and with higher levels of trust, for mutual assistance in the game and on the contrary the game could interconnect only weakly-tied users in case peer tutoring is desired. Such a tutoring could as well consist of information, like hints, approaches, and solutions for specific game tasks that were created and saved by a weakly-tied user before. As mentioned in Sect. 2.1.1.3 other aspects like learning style preferences could be taken into consideration, too.

The *game adaptation* component provides access to the user profile information and the list of friends and their interconnection. As the middleware aims to abstract from implementation details and dependencies of specific social media applications the format is normalized and for each supported social media application a mapping is created converting the retrieved data into the normalized format. Parts of the resulting data structure available to game developers are listed in Sect. A.1 as Table A.11.

As described in Sect. 2.1 Facebook, Google+ and Twitter are the most prevalent social media applications. Without loss of generality the following sections of this chapter refer to these three in case social media applications are mentioned. Still, the concepts described in the following sections are easily applicable to further social

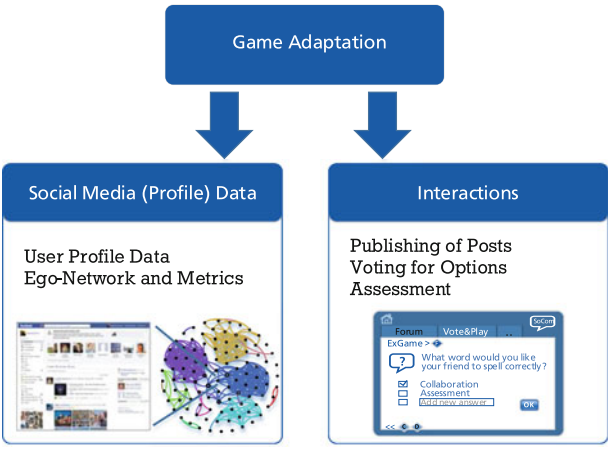

Fig. 5.1 The two aspects of the game adaption component with social media profile data and interactions. Image sources: Facebook (profile page), self preparation

media applications.[1] The architecture components for normalization of fetched data from the social media applications are shown in Fig. 5.2 in Sect. 5.3.

5.2 Social Game Interactions

As described in the introductory paragraph of this chapter, *game adaptation* by interaction with—and influences from—other users promises to be a suitable approach to intensify *peer collaboration* with content or vote contributions, and to support *peer assessment* of a player's solutions and provision of feedback. To the best of the author's knowledge no academically reviewed classification of interactions between a game player and social media users exists. Thus, this research aspect is approached by identifying the relevant interaction patterns in the following. A suggestion of suitable influence types to be used for social game interaction is developed accordingly.

Approach to Social Game Interactions
To enhance the gameplay of a player in a single-player educational game by added content (or influential votes) from outside, three dimensions are identified to be addressed for creating a classification for interactions:

- **Game Situations**
  (distinct contexts in the game a player can be confronted with)
- **Mapping Patterns**
  (one to one, one to many, many to one, many to many)
- **Social Media Interaction Patterns**
  (using interactions from Julien [8])

Each of these dimensions needs to be elaborated as a discrete list of items. The cells of the resulting three-dimensional grid can be filled with specific implementations of interactions in the context of educational games connected to social media applications taking into account the concept of peer education. Such a classification is expected to help developers of educational games to enhance the learning by implementing functionality to support the interactions listed in the classification. Examples of such beneficial functionality can be: players who get assistance from outside the game without pausing (their game), non-players and related users who can contribute to gameplay and influence it or vote on options provides by the game engine or select options made available by other participating users.

5.2.1 Game Situations

The list of game situations has been developed in cooperation with CEOs of two game development studios in the area of Frankfurt, Germany. It focuses on the genre

[1] The social media applications need to be OAuth protocol compatible [7].

Table 5.1 Game situations identified for a single-player educational game (genre: *adventure*)

#	Game situation	Description
1	Game start	Introduction scene, normally without interaction possibilities for the player except a skipping possibility
2	Game scene	A general game scene without any specific situation as listed next
2a	NPC dialog scene	A non-person character is in conversation with the player and waits for the player to answer (e.g. from a given list of dialog options)
2b	New quest scene	The user reads and receives a new quest to solve. Quests can be of type information seek, inventory quest or riddle
2c	Branching scene	The player can decide between several choices (not dialog) for the further development of the game story. Usually these branches in the scene graph of the game are irrevocable
2d	Minigame scene	A game in the game that is in itself enclosed like a memory, puzzle or equation to solve
2e	Conflict scene	A fight or situation demanding a time-critical reaction from the player
2f	Quest solving	The player solves a quest
3	Situation loops	The player reaches no further progress and repeats actions several times or comes along same place without any contextual change (inventory, quests, environment)
4	Savegame	The current game status is saved for later re-loading
5	Game end	The player closes the game application

of adventure games (single-player) as it is the most common genre for educational games (cf. [9, p. 26]). The list is currently neither considered to be completed nor evaluated to be accurate, but is expected to be of value to relate the social media interaction patterns to it. Game situations identified so far are listed in Table 5.1.

5.2.2 Mapping Patterns

It is one of the aims of this thesis to extend the currently mostly one-way connections between (social) games and social media by focusing mainly the other way

Table 5.2 Mapping patterns for player interactions; in italics the last two patterns not applicable for single-player educational games

Mapping type	Description
1:1	One player in game interacts with one specific user in a social media application
1:n	One player in game interacts with many users in a social media application
n:n	*Many players of the game interact with (the same) many other players in social media applications*
n:1	*Many player of the game interact with (the same) one specific user in social media applications*

around: information flow from social media into games and participation possibilities for social media users. Considering both ways between games and social media applications, the mapping patterns listed in Table 5.2 can be identified. The patterns *n:n* and n:1 are listed for consistency reasons (shown italic) and will later on not be considered, as this thesis' approach focuses on single-player games.

5.2.3 Social Media Interaction Patterns

The social media interaction patterns listed in Table 5.3 are structured and described in Julien [8]. Originally they are described for interactions between two users of the (same) social media application. The descriptions here focus on the interaction between game players and users of social media. In this context, from a players perspective, incoming posts or shared content appears quite similar. Thus, posting, sharing and updating are grouped and later on referred to as *post* only. *Buy* and *play* are shown italic as they will later on not be taken into consideration anymore, because

Table 5.3 Social media interaction patterns [8]

#	Pattern	Description
1	Post	A user can store new content
	Share	A user can share content
	Update	A user can quickly share a short piece of information
2	Vote	A user can favor or disfavor a content element
3	Comment	A user can respond to specific content element
4	Chat	A user can communicate directly with another user
5	Tag	A user can enrich content with metadata
6	Invite	A user can ask another user to perform an action
7	Connection	A user can establish a link to another user
8	Join	A user can associate himself with an interest group
	Buy	*A user can directly purchase a product or make a donation*
	Play	*A user can engage with a game*

they do not fulfill the criteria of an interaction (that needs at least two individuals involved). Finally eight interaction patterns are left for the classification.

It is clearly seen that this list of interactions is not identical with the social media interactions identified by Fred Cavazza (Fig. 2.2). For investigation of possible interactions for the game adaptation component the more detailed list from Julien is used. Still a consolidation to match the four interaction patterns of *publishing*, *sharing*, *discussing* and *networking* can be done as described in Sect. 2.1.

5.2.4 Social Interaction Patterns for Educational Games

The mapping pattern as the second dimension of the resulting classification has two characteristics that are taken into account. Thus the three dimensional classification can be listed as two tables; one for each remaining mapping pattern. The tables consist of the eleven game situations as rows and the eight social media interaction patterns as columns. Most of the identified interactions to be listed in these tables are valid for 1:1 and 1:n simultaneously. Interactions incoming to the game player are in some cases only suitable for the 1:1 mapping pattern. There are no interactions only valid for 1:n. A detailed table of all identified interactions is available as Table A.2 in Sect. A.1.3.2.

Interpretation and Conclusion

The interaction classification described above and listed in Table A.2 (Sect. A.1.3.2) is work in progress and not yet evaluated or proven and do not claim to be totally complete. Still, it is valuable to interpret it and draw some intermediate conclusions and discuss it for the development of social serious games. As visible in Table A.2 especially *vote* tends to be a social interaction that suits well both mapping patterns (1:1 and 1:n). The two mappings differ the most for the *post* interaction, as content contributions are made individually and not collective.

The main difference between *vote* and *post* exists for the incoming content (I:) for game situations. *Vote* appears to be suitable for both, 1:n and 1:1 mapping, whereas *post* primarily supports the 1:1 mapping. Additionally, cooperation modes are not applicable in a 1:n matching pattern of single-player educational games. Still, for the embedded mini games a (massive, cooperative) multiplayer mode is imaginable as well as a (massive) sidekick concept for conflict scenes in such games (e.g. a scene with a boss opponent).

For a technical implementation it seems to be reasonable (based on the number of interactions in the table) to focus on the support of *post* and *vote* first, then on *comment*. Concerning the examples, individuals (1:1) might be a most valuable source for creative content, hints, or solutions for game situations as for 1:n most content-related (*post*) incoming (I:) entries are not valid. However, many (1:n) connected users, e.g. the friends connected to the player in an social media application tend to be a valuable source for *vote* results and recommendations. As seen in Table A.2 *vote* is the only column where all items are available for both mapping patterns. Because

more people can possibly contribute in 1:n, the *vote* might be even of more value here compared to 1:1. A combination of both (*post*, *vote*) could be a content contribution of individuals, voted by many others, e.g. to select the most supported contributed content.

In both mapping patterns it seems to be suitable to *post* the status (achievements), *vote* with likes and send invitations from the ongoing game to the connected other users in order to raise awareness and call for participation. It can be assumed that such interactions become more valuable if the recipients are invited to take action, e.g. combining it with a call for a *vote* or content *post* to involve them into ongoing gameplay.

For mini games and conflict scenes (all scenes with time-critical reactions demanded) *chat* and *connection* can be considered to be implemented in the future as they allow a collaborative or competitive interaction scenario in the otherwise single-player gameplay.

5.3 Architecture Design

Game developers use the identified interaction patterns (*post*, *vote*) of the social game interaction classification and invoke concrete influences by selecting an *influence type* and setting parameters like number of answers, timeout and so on. The middleware component for *game adaptation* then instantiates the influence, sends messages to the connected social media applications, collects feedback, and provides the result to the game. Instead of direct invocation, created influences can be saved as *influence templates* to spawn instances later from these templates via API calls.

Aspects of the service design cover abuse protection, data privacy policies and the dynamic rendering of the influence system's web interface for users who respond to messages and follow the invitations (links) embedded in the wall posts (e.g. on Facebook). Considered influence types for first technical support are: single choice, multiple choice, n out of m choices, ordering, text gap, image upload and combination of these, e.g. single-choice with the option to add new options with a text field.

As discussed in Chap. 3, Sect. 3.5, the architecture is designed as a middleware, accessible via web-interface by end-users and via API by game developers. The architecture and components are shown in Fig. 5.2 complementary to the overall architecture illustrated before in Fig. 3.2. Additionally, the components for adaptation based on social media profile data (Sect. 5.1) are illustrated.

5.4 Chapter Summary

In the preceding chapter, game adaptation was discussed and introduced as a two-tier approach to use social media in games for adaptation.

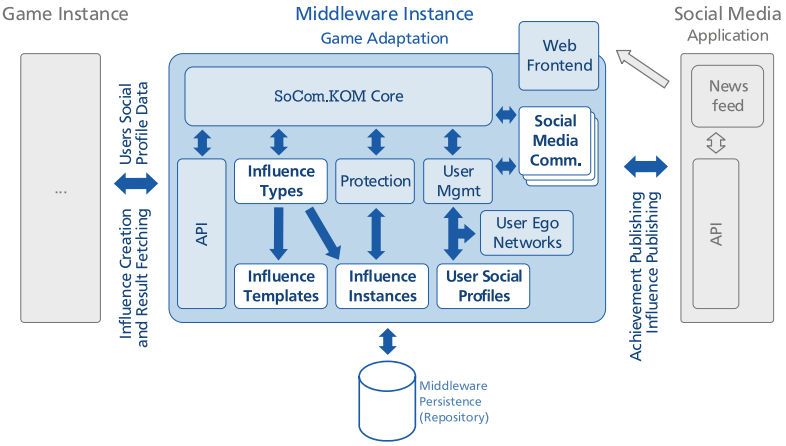

Fig. 5.2 Architecture of game adaptation component, illustrating the communication between sub-components and among game, middleware and social media applications. The most relevant parts are highlighted (Legend in Sect. A.1.1) [1]

First, the concept for adaptation of a game by social media profile information—which can relate to user profile information as well as metrics about the underlying social network (ego-network) of the player—can be used to personalize the game to the player and identify closely related peers. This allows for detection of potential interaction partners (see next paragraph) and adaptation of the game's Non-Player Characters (NPCs) to the current player's ego-network characteristics. As the concept supports the use of several social media applications in conjunction, an abstraction layer and unification of social media profile data is proposed to allow a spanned access to the player's peers and profile information from all connected social media applications for game adaptation on a more comprehensive data basis.

Second, social interaction patterns for educational games were identified based on the thorough analysis of social media interaction patterns, game situations, and the derived classification of interactions that are suitable for educational adventure games. As a result, social media interaction patterns, posting and voting, are identified to be applicable for provision of content and influences by player's peers; respecting the boundary conditions from Sect. 3.1. The concept of game adaptation by social media interactions extends existing solutions from the field of social games and contains the support for content-contributions and participation of peers that are currently not playing but use one of the supported social media applications.

The proposed model for game adaptation is designed to increase user experience (of the player), to activate the player's social environment by published calls for active participation, and to support the provision of more suitable tasks to the player using the contributed content.

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Chapter 6
Peer Group Formation for Learning

To improve the effectiveness of group learning in general, and to address in particular opportunities for educational games, this chapter introduces a technique to match users by considering homogeneous and heterogeneous criteria for matching. Such matching affords the capacity to group users when using a single-player educational game, and thus support content exchange, hints, assistance, and visibility within the group. Additionally, the group formation results can be used to emphasize user-generated content and contributions of group members when formation results are combined with the content integration (Chap. 4) and game adaptation (Chap. 5).

First, the chapter identifies the requirements for the algorithmic design, based on the findings from related work analysis and the *Group Formation Problem* (Sect. 2.1.3). Second, the modeling of matching criteria is derived (Sect. 6.1) and metrics for the group formation algorithm are developed (Sect. 6.2). This includes the proposal of three matching algorithms, and the metrics of *GPI* and *CPI*, which fulfill the defined requirements. Finally, the approach towards optimization is discussed and algorithms are designed to optimize the cohorts and handle incremental updates. Details about the corresponding conceptualized API methods can be found in Sect. A.1.

Note: Parts of this chapter have been published in Konert et al. [1] and are repeated here as revision. As the publication only briefly defines the matching algorithms and completely leaves out the *optimization* aspect, these parts are refined from the supervised master thesis of Burlak [2].

Prerequisites and Requirements

As a basis for the algorithm design some insights and boundary conditions are discussed, based on the related work described in Sects. 2.1.2 and 2.1.3.

Considering these findings, it is clearly seen that some of the relevant criteria for group formation need to be matched optimally homogeneously (e.g. symmetry of knowledge [3, p. 334]) and others heterogeneously (e.g. an individual's group role [4]). Defining the specific criteria and their weights that are essential to improve

J. Konert, *Interactive Multimedia Learning*, Springer Theses,
DOI 10.1007/978-3-319-10256-6_6

learning outcomes of formed groups, is beyond the scope of this thesis. Even though researchers from pedagogical psychology and pedagogy investigate the influences and inter-dependencies, the author doubts that a general list of such criteria and weights can be found as it depends on the learning targets and dynamics of the participants to be grouped. Still, it remains valuable to design an algorithmic approach where domain matter experts and system designers can adjust the criteria and weights to the best of their knowledge. Consequently, a general support for variable criteria and weights is desired. To allow comparison of group formations, built with different parameters of group size and criteria, an assessment and group formation quality measure is needed. In contrast to the approach of existing clustering algorithms the size of each group should be fixed as the optimal group size is expected to be 3–6 members [5]. The optimization problem should respect the need for uniformly well-built groups. As such, the measures calculated should value a minimization of group formation quality differences. The requirements for the algorithmic design (RA) can be concluded as:

RA1 Extendable modeling, exchangeability, and the weighting of criteria;
RA2 Support for building of homogeneous, heterogeneous, and mixed groups;
RA3 Assessment and group formation quality measurement; and
RA4 Minimization of quality differences among groups.

As outlined in Sect. 2.1.3 none of the investigated existing algorithms supports these criteria completely. Therefore, an individually-developed approach, respecting the discussed aspects, is proposed.

6.1 Modeling of Matching Criteria

As a first step for an algorithm design the data representation will be discussed. A unified format for representation of the matching criteria is aimed for easier processing. Thus, users (domain experts, system designers) can adjust and replace criteria, their characteristics, weights and the assignment to the sets of homogeneously or heterogeneously to match criteria. Considering the personality traits of NEO-PI-R, it remains an open question how exactly the personality traits are to match. NEO-PI-R is representable by a 5-dimensional vector, each dimension representing the value for this trait, normed to the interval [0, 1]. If some of these are expected to be matched heterogeneously they are moved to a new criterion of less dimensionality, e.g. extraversion and conscientiousness are expected to be relevant for group formation; the former as heterogeneous, the later as homogeneous criterion [6]. To convey cognitive dissonances and social exchange (Sect. 2.1), learning styles should be matched heterogeneously. All discussed models (Sect. 2.2.3) can be represented as 4-dimensional vectors. Beside this, it is suggested here to additionally match process-based criteria as they are easy to measure in an E-Learning scenario and are expected to increase

the probability that a group formation suits longer the system usage habits of the group members. Such homogeneously to match criteria are, for example, average session length or sliding mean window of time spend per task.

In conclusion, all discussed criteria are representable as vectors of varying dimensionality. The values are normalizable to an interval of [0, 1] which allows an easier weighting.

6.2 The Group Formation Algorithm

6.2.1 Basic Definitions

The following basic definitions are based on [7], leaving out their formation definition and adding this thesis' focus on criteria.

Participants A finite set of participating individuals is defined as $P = \{p_1, p_2, \ldots, p_M\}$, where $M = |P| > 1$ is the amount of all participants. Each participant is represented by a set of criteria $p \subseteq K$. The selected criteria for comparison are equal for all participants.

A criterion is defined as a parameter, variable or characteristic $k \in \mathbb{R}^n$, which is considered to be used as a relevant criterion for group formation. The finite set of possible criteria is defined as $K = \{\{k_1, k_2, \ldots, k_q\} | \forall j = 1, \ldots, q,\ k_j \in \mathbb{R}^n\}$.

Group A group g is defined as a finite set of participants $p \in P$ that has at least 2 elements $|g| > 1$ (minimal group), what means each element $p_i \in g$ is a *member* of the group. The set of all possible groups of group sizes 2 to M is $G = \{g_1, g_2, \ldots, g_o\}$, such that $G = \mathcal{P}(P) \setminus \left(\bigcup_{i=1}^{M} \{p_i\} \cup \emptyset\right)$.

Cohort A cohort C is a set of pairwise disjoint groups $g_1, g_2, \ldots, g_s$ that contains all participants $(\forall p \in P \neg \exists g_1, g_2 \in G : p \in g_1 \wedge p \in g_2)$. $G_x \subseteq G$ is defined as the set of all groups with the fixed size X. In conclusion, each cohort with groups of size $X > 1$, has cardinality $\mathrm{N} = \frac{M}{X}$.

Constraints to Criteria For the group formation two disjunctive sets of criteria exist. A criterion is *homogeneous*, if the occurrence of this criterion in the group should be as similar as possible(K_{hom}). Respectively, for *heterogeneous* criteria contrariwise (K_{het}). They are disjunctive subsets: $K_{hom} \cap K_{het} = \varnothing \wedge K_{hom} \cup K_{het} = K$.

6.2.2 Figure of Merit for Group Formations

The mathematical definition of the *GroupAL* algorithm will be derived here. The algorithm calculates the group formation quality respecting the identified requirements from (Chap. 6) based on the approaches discussed in (Sect. 2.1.3) [8–10]. To allow the comparability of group formations independent of the criteria specifics,

a quality measure is needed for the minimal group of two participants, called PPI. Based on the PPI a quality measure for one whole group is defined as GPI. Finally, a group-spanning measure is needed to calculate the quality of a complete cohort. It will be defined as CPI.

Alternatively to the calculation of exact metrics based on distances in criteria values of pairs and aggregation to a CPI, a different approach could be envisioned based on probability tables, expectancy values, and trained models (by machine learning). This could be an efficient approach if the used criteria are known and widely standardized and no great difference exists between several groups of participants to be matched based on these same criteria. For a large number of participants, calculation effort could thus be narrowed to linear algorithmic complexity. As the underlying prerequisites are different, specifically the amount of participants to be matched is expected to be small and the solution aims to be independent of specific criteria, an exact approach, independent of specific criteria characteristics, appears to be more promising.

Pair Performance Index (PPI)

The *Pair Performance Index* builds on top of a distance function d (metric) as generally defined in Eq. 6.1.

$$\begin{aligned} &d\colon X \times X \to \mathbb{R} \\ &d\,(x, y) = 0 \Leftrightarrow x = y \\ &d\,(x, y) = d(y, x) \\ &d\,(x, y) \leq d(x, z) + d(z, y) \end{aligned} \tag{6.1}$$

To calculate the distance between two participants' criteria vectors several metrics can be considered.

The Euclidean distance is widely known as the shortest distance between the two points in a n-dimensional space. The distance for two orthogonal normed vectors is $d <= \sqrt{n}$ and an unequal distribution over vector dimensions lead to higher values. Thus the coverage of the whole vector space is not linearly represented and the metric tends to give higher values for unequal distribution of differences among dimensions. As all dimensions of a vector should be treated equally, the metric is not suitable here.

The Maximum distance allows the calculation of a shortest path between two points as the maximum of the differences among all dimensions. The maximum for normed vectors is therefore $d <= 1$ as no dimensions difference can be more than the length of the spanning interval [0, 1]. Still, two vectors will have a higher distance if the difference in values is concentrated in one dimension compared to an equally distributed difference over all criterion's dimensions.

Especially suitable for the calculation of the coverage of the whole criteria space is the *Manhattan distance* which sums all dimensions differences linearly (Eq. 6.2). Therefore the same value is calculated for vectors irrespectively of equal or extreme distribution of value difference among the dimensions. The calculation is normalized

with a division by the number of dimensions in order to trade all criteria equally in the following, independent from their dimensionality.

$$\begin{aligned} &d : [0,1]^n \times [0,1]^n \to [0,1], \ \left(k_p^1, k_p^2\right) \mapsto y \\ &d\left(k_p^1, k_p^2\right) = \left|k_p^1 - k_p^2\right| = \frac{\sum_{i=1}^{n} \left|k_{p,i}^1 - k_{p,i}^2\right|}{n}, \\ &k_p^1 = \left(k_{p,1}^1, k_{p,2}^1, \ldots, k_{p,n}^1\right) \text{and} \, k_p^2 = \left(k_{p,1}^2, k_{p,2}^2, \ldots, k_{p,n}^2\right) \ , \end{aligned} \tag{6.2}$$

where k_p^1 and k_p^2 are the same criterion k_p of two different participants and n is the dimensionality of k_p.

To adjust their impact to the result each criterion can have a constant weight w (Eq. 6.3).

$$\left\{ W \in [0,1]^q | \sum_{t=1}^{q} w_t = 1 \right\} \ , \tag{6.3}$$

with q as the number of weights which equals the number of used criteria ($|W| = |K| = q$).

Hence, the weighted normalized distance function to be used can be defined (Eq. 6.4).

$$\begin{aligned} &wd : [0,1]^n \times [0,1]^n \times [0,1] \to \mathbb{P}, \ \left(k_p^1, k_p^2, w\right) \mapsto y \\ &\mathbb{P} = [0, w] \\ &wd\left(k_p^1, k_p^2, w_p\right) = w_p * d\left(k_p^1, k_p^2\right) \ , \end{aligned} \tag{6.4}$$

where k_p^1 and k_p^2 are the same criterion k_p of two different participants, w_p is the weight for this criterion to use, and n is the dimensionality of k_p.

The distance function (wd) can be used equally for homogeneous as well as heterogeneous criteria. As it is the aim of this thesis to form a uniformly usable metric for homogeneous, heterogeneous and mixed groups, the distance function will be signed differently for homogeneous and heterogeneous criteria. The overall quality is expected to be higher if the distance for homogeneous criteria is low (at best zero), therefore the distance of homogeneous matching criteria is given a negative sign: the higher the distance the lower the resulting value.

On the contrary, for heterogeneous matching criteria a high distance value is desired. Thus, the distance will be added with a positive sign. The ratio of impact to the resulting value can be adjusted by choosing the appropriate weights in W.

The Pair Performance Index (PPI) is defined in Eq. 6.7 as the sum of the distances of heterogeneously to match criteria (Eq. 6.5) minus the sum of distances for the

homogeneously to match criteria (Eq. 6.6). It represents the assertion of the calculated pairing quality of two participants in the chosen criteria.

$$
\begin{aligned}
&hetSum : K \times K \times \{0,1\}^n \to \mathbb{P},\ \left(K^1, K^2, \mathrm{W}\right) \mapsto y \\
&\mathbb{P} = \left[0, \sum_{i=1}^{|K_{het}|} w_i\right] \in [0,1] \\
&hetSum\left(K_{het}^1, K_{het}^2, \mathrm{W}\right) = \sum_{i=1}^{|K_{het}|} wd\left(k_i^1, k_i^2, w_i\right) ,
\end{aligned}
\tag{6.5}
$$

where $|K_{het}|$ is the amount of heterogeneous criteria, and K_{het}^1 and K_{het}^2 are the instances of this criterion for two different participants.

$$
\begin{aligned}
&homSum : K \times K \times \{0,1\}^n \to \mathbb{P},\ \left(K^1, K^2, \mathrm{W}\right) \mapsto y \\
&\mathbb{P} = \left[0, \sum_{i=1}^{|K_{hom}|} w_i\right] \in [0,1] \\
&homSum\left(K_{hom}^1, K_{hom}^2, \mathrm{W}\right) = \sum_{i=1}^{|K_{hom}|} wd\left(k_i^1, k_i^2, w_i\right) ,
\end{aligned}
\tag{6.6}
$$

where $|K_{hom}|$ is the amount of homogeneous criteria, and K_{hom}^1 and K_{hom}^2 are the instances of this criterion for two different participants.

$$
\begin{aligned}
&PPI : K \times K \times \{0,1\}^n \to \mathbb{P},\ \left(K^1, K^2, \mathrm{W}\right) \mapsto y \\
&\mathbb{P} = \left[-\sum_{i=1}^{|K_{hom}|} w_i, \sum_{j=1}^{|K_{het}|} w_j\right] \in [-1,1] \\
&PPI\left(K^1, K^2, \mathrm{W}\right) = hetSum\left(K_{het}^1, K_{het}^2, \mathrm{W}\right) - homSum\left(K_{hom}^1, K_{hom}^2, \mathrm{W}\right) .
\end{aligned}
\tag{6.7}
$$

Normalization of the Pair Performance Index (PPI)

The range of values for $PPI\left(K^1, K^2, \mathrm{W}\right)$ is $\mathbb{P} = \left[-\sum_{i=1}^{|K_{hom}|} w_i, \sum_{j=1}^{|K_{het}|} w_j\right]$, where w_i and w_j are the weights of the respective criteria.

To get the *normalized PPI* (*NPPI*) (Eq. 6.8) with values in interval [0, 1] the *PPI* is linearly shifted by $\sum_{i=1}^{|K_{hom}|} w_i$ and would need a division by the maximum possible value $\sum_{i=1}^{|K_{hom}|} w_i + \sum_{j=1}^{|K_{het}|} w_j$ which is equal to $\sum_{k=1}^{|K|} w_k$ which is equal to 1. In this case the interval length is already normed and only needs to be shifted to lie in [0, 1].

Still the division by the length is listed in the formula in case the sum of all weights is not 1 as the algorithm would still work with this liberalization.

$$NPPI : K \times K \times \{0,1\}^n \to [0,1], \ \left(K^1, K^2, \mathrm{W}\right) \mapsto y$$
$$NPPI\left(K^1, K^2, \mathrm{W}\right) = \frac{PPI\left(K^1, K^2, \mathrm{W}\right) + \sum_{i=1}^{|K_{hom}|} w_i}{\sum_{t=1}^{|W|} w_i} \tag{6.8}$$

Group Performance Index (GPI)
To get a measure of the overall quality of a group formation g with X participants the mean of all $\binom{X}{2}$ *NPPI* is calculated (see Eqs. 6.9 and 6.10).

$$\left\{NPPIs \in \mathbb{R}^{\binom{X}{2}} | \ \forall i = 1, \ldots, X-1, \forall j = i+1, \ldots, X, \right.$$
$$\left. NPPIs_i = NPPI\left(K^i, K^j, \mathrm{W}\right), \ \left(K^i, K^j\right) \subseteq g\right\}, \tag{6.9}$$

where *NPPIs* is the set of all *NPPI* of the group g, K^i and K^j are all criteria of participants i and j with X as the number of participants in g.

$$\overline{NPPIs} = \frac{\sum_{i=1}^{\binom{X}{2}} NPPIs_i}{|NPPIs|} \tag{6.10}$$

The value of $\overline{NPPIs}$ expresses how well the participants of a group formation suit the matching criteria in average. The mean value alone is not suitable to express the GPI as it does not respect the constellation within the group. Outliers in values and amount are still disregarded. To countermeasure this, several possible alternative calculations could be used to reflect dispersion in the formula. In general, higher dispersion should lead to lower values of the targeted performance metric.

Beside range or mean difference, which are strongly influenced by single outliers in the data, other measures can be considered. *Interquartile range* and *median absolute deviation* are too robust against outliers and therefore are not suitable. *Quartile coefficient of dispersion* is efficient to calculate, but is not linear in scale. Likewise the variance is not linear, but its square root (*standard deviation*) is, which seem suitable for the targeted solution of this thesis as it is not too strongly affected by single outliers, still gives a good measure of the density of the group, is linear and widely accepted as a measure for dispersion. The standard deviation of all *NPPI* is calculated as listed in Eq. 6.11 and afterwards normalized in Eq. 6.12. By this, outliers and not well suiting participants in a group are respected by multiplying the

calculated mean $\overline{NPPIs}$ with the normalized standard deviation *NSNPPI*. The result is the desired GPI (Eq. 6.13).

$$SNPPIs = \sqrt{\frac{\sum_{i=1}^{\binom{X}{2}} \left(NPPIs_i - \overline{NPPIs}\right)^2}{|NPPIs|}} \tag{6.11}$$

$$NSNPPI = \frac{1}{1 + SNPPIs} \tag{6.12}$$

$$GPI : G \to [0, 1], \; g \mapsto y$$
$$GPI(g) = \overline{NPPIs} * NSNPPI \tag{6.13}$$

6.2.3 Matcher

The preceding pages have outlined how the formation quality can be measured. Based on this, an algorithm can be designed that forms groups and evaluates their formation quality based on the described measure (GPI). A matching algorithm adds participants to the groups until all participants are assigned. To build N groups ofsize X the set of not matched participants ($NMP \subset P$, $|NMP| = M$) is filled with all participants to match and the set of N empty groups G is created. Matched participants are added to the groups and removed from *NMP* until the set is empty and the algorithm stops ($NGP = \emptyset$).

The algorithmic approach,restrictions, and made assumptions can strongly influence the resulting group formation quality. Therefore, several approaches are proposed and discussed here to measure their performance in comparison later on (cf. Sect. 7.3.5). The proposed solutions are inspired by the existing algorithms discussed in Sect. 2.1.3.

Naive Matcher

Before Random Matcher, Group-Centric Matcher, and Participant-Centric Matcher are described in the following, an estimation is given for the Naive Matcher that calculates all possible combinations to find the optimal solution(s). The naive approach is to build all possible group formations for a cohort, calculate for each one the CPI and select the solution with the highest value.

To build the first group of size X, all X members of the group are selected in all possible combinations from the M participants. This means $\binom{M}{X}$ possibilities to fill the first group.

For each of the calculated $\binom{M}{X}$ possible selections of participants for the first group, the members for the second group are selectable in the same way. The members are selected from $M - X$ participants in all possible $\binom{M-X}{X}$ combinations, and so on.

The calculation of subsequent groups continues until only $M - (N-1) \cdot X = X$ participants remain in *NMP*, which allow exactly one variation for the last group to build, i.e. $\binom{X}{X} = 1$ possibility.

Finally, all N terms (each calculating the number of possibilities *within* an individual group) are multiplied, but have to be divided by the number of possible permutations among the resulting N groups, because order of drawing of the groups is not relevant in the resulting cohort. Thus, the factor $\frac{1}{N!}$ is added to the product. The number of possible combinations $C_{NM}(M)$, to be calculated by the Naive Matcher (NM), is illustrated in Eq. 6.14.

$$C_{NM(M)} = \frac{1}{N!} \cdot \prod_{i=0}^{N-1} \binom{M - (X \cdot i)}{X} \tag{6.14}$$

To estimate the applicability of the Naive Matcher to real calculation of cohorts, it is suitable to estimate the lower boundary of runtime complexity to know by which means the runtime increases at least, depending on the number of participants M to match. As stated above, depending on the desired fixed group size X, the number of groups N to build for a cohort varies, but increases linear with M $\left(N = \frac{M}{X}\right)$. Without loss of generality, we can assume that M is a multiple of X to be able to fill all groups perfectly. Additionally, without loss of generality, for estimation of the lower boundary, it is assumed that the algorithm needs (at least) one calculation step to build one variation of a group within the cohort. Thus, number of calculation steps to build all groups can be expressed as the number of possible group variations. May $f_{NM}(M)$ be the function that represents the number of calculation steps the Naive Matcher needs in dependency of the number of participants M to be matched. A factorization of $C_{NM}(M)$ is used to express f under the made assumptions in Eq. 6.15.

$$\begin{aligned}
f_{NM}(M) &= \frac{1}{N!} \cdot \prod_{i=0}^{N-1} \binom{M - (X \cdot i)}{X} \\
\Leftrightarrow f_{NM}(M) &= \frac{1}{N!} \cdot \binom{M}{X} \cdot \binom{M - X}{X} \cdot \binom{M - 2 \cdot X}{X} \cdots \binom{M - (N-2) \cdot X}{X} \\
&\quad \cdot \binom{M - (N-1) \cdot X}{X} \\
\Leftrightarrow f_{NM}(M) &= \frac{1}{N} \cdot \binom{M}{X} \cdot \frac{1}{N-1} \cdot \binom{M - X}{X} \cdot \frac{1}{N-2} \binom{M - 2 \cdot X}{X} \cdots \frac{1}{2} \\
&\quad \cdot \binom{2 \cdot X}{X} \cdot \frac{1}{1} \cdot 1
\end{aligned} \tag{6.15}$$

In the trivial case of $N = 1$, the one group to build simply consists of all M participants and only one possible combination exists. The focus in the following is on

the cases for $N > 1$. For estimation of the boundary, the calculation can be simplified by replacing all factor terms by a constant representing the lower bound estimation that is valid for all factors. To find this replacement for the factors, first, all factors are combined in pairs, resulting in one factor from the $\frac{1}{N!}$ expressed as $\frac{1}{N} \cdot \frac{1}{(N-1)} \cdots \frac{1}{1}$, and the other factor from the bionominal coefficient product. As described above, the last term, estimating the number of possibilities to build the last group, results always in exactly one possible selection of X members from X remaining participants. But for the other $N-1$ terms the value of $\frac{1}{N-i} \cdot \binom{M-(i \cdot X)}{X} \forall\, i \in [0, 1, \ldots, N-2]$ is at least as big as the value of the smallest element $\frac{1}{2} \cdot \binom{M-((N-2) \cdot X)}{X} = \frac{1}{2} \cdot \binom{2 \cdot X}{X} = \alpha$, with $\alpha > 1$. Thus, the number of possible combinations to create the desired cohort of groups is at least α^{N-1} for a certain $\alpha > 1$, as formally derived in Eq. 6.16.

$$
\begin{aligned}
& f_{NM}(M) \geq \frac{1}{2} \cdot \binom{2 \cdot X}{X} \cdot \frac{1}{2} \cdot \binom{2 \cdot X}{X} \cdots \frac{1}{2} \cdot \binom{2 \cdot X}{X} \\
\Leftrightarrow \quad & f_{NM}(M) \geq \left(\frac{1}{2} \cdot \binom{2 \cdot X}{X} \right)^{N-1} \\
\Leftrightarrow \quad & f_{NM}(M) \geq \alpha^{N-1}, \text{ with } \alpha = \frac{1}{2} \cdot \binom{2 \cdot X}{X} > 1 \; \forall \, X > 1
\end{aligned}
\tag{6.16}
$$

Due to $N = \frac{M}{X}$, the estimation can be expressed as $f_{NM}(M) \geq \alpha^{\frac{M}{X}-1}$. As the constants X and -1 are ignorable for calculation of complexity class boundaries, the estimate for a lower bound of runtime complexity of the Naive Matcher can be simplified as: $f_{NM}(M) \in \Omega(\alpha^M)$, with $\alpha > 1$.

Consequently, this *exponential complexity* of calculating all possible cohorts shows that the naive approach is not efficient. Thus, there is an interest in investigating other approaches that are able to find (nearly) optimal solutions with less necessary computational steps.

Random Matcher (RM)

The *Random Matcher* represents the most simple approach and groups all participants by random order. No measurement of formation quality or optimization is done. The runtime estimation of algorithmic complexity leads to $f_{RM}(M) \in \mathcal{O}(M)$ as each participant has to be accessed only once to be added to the corresponding group.

Participant-Centric Matcher (PCM)

The *Participant-Centric Matcher* advances from the perspective of the unmatched participants in the set *NMP*. First it assigns to each group a random participant as pivot element. Then for each next participant, taken from set *NMP*, the matcher searches for the group whose GPI raises most on a percentage basis among all not yet full groups (formally defined in Eq. 6.17). The algorithm is shown in Listing 1 [10].

The runtime estimation of algorithmic complexity leads to $f_{PCM}(M) \in \mathcal{O}\left(M^2\right)$ as there are two nested loops. The outer runs for all participants (M), the inner for all groups (N). In worst case the number of groups is $\frac{M}{2}$.

$$\left\{ g \cup p_{fix} \mid p_{fix} \in NMP, \forall g \in G_x : |g| < X \wedge max\left(\frac{GPI\left(g \cup p_{fix}\right)}{GPI(g)} \right) \right\} \tag{6.17}$$

Listing 1 Participant-Centric Matcher

```
Require: G, NMP                          ▷ G are all groups, NMP are all participants to match
  for all p ∈ NMP do
    Δ_Max ← 0
    bestGroupIndex ← −1
    for all g ∈ G do
      GPI ← GPI(g)
      GPI_tmp ← GPI (g ∪ p)
      Δ ← GPI_tmp / GPI
      if Δ_Max < Δ then
        Δ_Max ← Δ
        bestGroupIndex ← G.index(g)
      end if
    end for
    if bestGroupIndex > −1 then
      G[bestGroupIndex] ← G[bestGroupIndex] ∪ p
    end if
  end for

  return G                               ▷ NMP = ∅
```

Group-Centric Matcher (GCM)

From the perspective of all not yet completely filled groups the *Group-Centric Matcher* fills each group before it continues with the next group until all groups are filled with participants. GCM adds the participant to the group that increased the groups GPI the most on a percentage basis, then searches for the next most suitable participant until the group has all X participants needed (formally defined in Eq. 6.18). The algorithm is listed in Listing 2.

$$\left\{ g_{fix} \cup p | \; \forall p \in NMP, g_{fix} \in G_x : |g_{fix}| < X \wedge max\left(\frac{GPI\left(g_{fix} \cup t\right)}{GPI\left(g_{fix}\right)} \right) \right\} \tag{6.18}$$

Identically to the *PCM*, runtime estimation of algorithmic complexity here leads to $f_{GCM}(M) \in \mathcal{O}\left(M^2\right)$ as GCM has two nested loops as well. The outer runs for all groups (N), the inner for all participants not yet matched (M). In worst case the number of groups is $\frac{M}{2}$.

More matching approaches could be defined and investigated. In this thesis, the approaches from the participants' and groups' perspective are favored, as they are promising to deliver reasonable results without anticipating any order or dependencies in the given criteria. As Ounnas et al. [9] describe, a matcher can also group participants based on rules and constraints to fulfill a specific *pattern*. This implies the knowledge of the underlying criteria to formulate the rules or the rules need to

be given explicitly by the user of the algorithm. As it is considered in this thesis that providing such dependency rules is much more workload for instructors or system designers when using the algorithm, this approach is omitted here (see discussion on semantic group formation algorithms in Sect. 2.1.3).

Listing 2 Group-Centric Matcher

```
Require: G, NMP                          ▷ G are all groups, NMP are all participants to match
  for all g ∈ G do
    while |g| ≠ N do
      Δ_Max ← 0
      bestParticipant ← 0
      GPI ← GPI(g)
      for all p ∈ NMP do
        GPI_tmp ← GPI (g ∪ p)
        Δ ← GPI_tmp / GPI
        if Δ_Max < Δ then
          Δ_Max ← Δ
          bestParticipant ← p
        end if
      end for
      if NMP ≠ ∅ then
        g ← g ∪ bestParticipant
        NMP ← NMP \ bestParticipant
      end if
    end while
  end for

  return G                               ▷ NMP = ∅
```

6.2.4 Evaluation of Group Formation Quality

When matching algorithms successfully added all participants to groups, the overall formation quality of the cohort must be evaluated to compare several cohort qualities.

Cohort Performance Index (CPI)
As stated before, a measure calculating the group formation quality needs to value a uniform distribution of the GPI and should be normalized to be able to compare group formation qualities among different cohorts even if number or kind of criteria differs. In the evaluation it will allow the comparison of the different matchers' quality and can be used to calculate the formation quality of other algorithms' group formation results.

Similar to the calculation of the GPI, the *CPI* calculates the formation quality as a measure in the interval [0, 1]. To detect outliers (groups with extreme low or high GPI) the CPI is designed similar to the GPI by using the mean value of all GPI

($\overline{GPIs}$ in Eq. 6.19) and multiply it with the normalized standard deviation of all GPI ($NSGPI$ defined via Eqs. 6.20 and 6.21). This results in the CPI, listed in Eq. 6.22.

$$\overline{GPIs} = \frac{\sum_{i=0}^{|GPIs|} GPI_i}{|GPIs|} \tag{6.19}$$

$$SGPI = \sqrt{\frac{\sum_{i=0}^{N} \left(GPIs_i - \overline{GPIs}\right)^2}{|GPIs|}} \tag{6.20}$$

$$NSGPI = \frac{1}{1 + SGPI} \tag{6.21}$$

$$\begin{aligned} CPI &: C \rightarrow (0, 1), \ C \mapsto y \\ CPI(C) &= \overline{GPIs} \cdot NSGPI \end{aligned} \tag{6.22}$$

6.2.5 Optimization

Due to the fact that the suggested matching algorithms do not evaluate all possible matching combinations to find the best possible solution guaranteed, an optimization method for the group formation algorithm can be defined to improve the intermediate resulting cohort.

As the CPI is defined based on the mean value of GPI and the standard deviation of all GPI to create a more uniformly cohort, the optimizer focuses on the two groups with the lowest and the highest GPI as it conflicts with the aim of the algorithm to have not more than necessary formation quality differences among the groups. Thus, it tries to minimize the standard deviation ($SGPI$) and consequently maximizes the CPI.

From both selected groups all participant members are added to the set of unmatched participants NMP. Then the matching is applied to NMP to form two new groups. If the CPI increases with the newly formed groups, they are saved permanently, otherwise they are discarded and the old groups are kept. The optimization then continues with the next optimization cycle until a maximum of R optimization cycles is reached as shown in Listing 3.

The number of rounds R, the optimizer should try to find two groups for optimization, can not clearly be calculated as it depends on the criteria value distribution and the number of participants per group. A reasonable value of 2–3 cycles is concluded and discussed in Sect. 7.3.5. As the results without optimization are already very good, it is reasonable to call the optimization algorithm only if the standard deviation of GPI is above a certain threshold. Additionally the reached overall CPI can be

an indicator. To estimate the degree of possible optimization the maximum possible value of GPI and CPI for the current participants needs to be known as deducted hereafter.

6.2.6 Maximum Value Calculation for Cohort Performance Index

To allow the calculation of a GPI and CPI not only independently of criteria amount, type, and dimensions but also provide a using instructor with a percentage of how close the current GPI or CPI is at the maximum possible value, induction can proof

Listing 3 Optimization Algorithm

Require: G, R ▷ G contains all groups sorted by GPI value, R is the number of cycles
$r \Leftarrow 0$
while $r < \frac{|G|}{2} \wedge r < R$ **do**
$g_a \leftarrow G.popFirstElement()$
$g_b \leftarrow G.popLastElement()$
$g_{a,tmp} \leftarrow \emptyset$
$g_{b,tmp} \leftarrow \emptyset$
for all $p \in g_a$ **do**
$NMP \leftarrow NMP \cup p$
end for
for all $p \in g_b$ **do**
$NMP \leftarrow NMP \cup p$
end for
$[g_{a,tmp}, g_{b,tmp}] \leftarrow matcher.matchToGroups([g_{a,tmp}, g_{b,tmp}], NMP)$
$CPI_{tmp} \leftarrow CPI(G \cup g_{a,tmp} \cup g_{b,tmp})$
if $CPI_{tmp} > CPI$ **then**
$G \leftarrow G \cup g_{a,tmp} \cup g_{b,tmp}$
else
$G \leftarrow G \cup g_a \cup g_b$
end if
$r \leftarrow r + 1$
end while

return G

that—depending on the number of group members X—the upper bound $max(GPI_X)$ can be calculated as shown in Eq. 6.23

$$GPI_X \leq max(GPI_X) = \begin{cases} \sum_{i=1}^{|K_{het}|} w_i \cdot \frac{\frac{X}{2} \cdot \frac{X}{2}}{\binom{X}{2}} + \sum_{j=1}^{|K_{hom}|} w_j, & \text{if } X \bmod 2 = 0 \\ \sum_{i=1}^{|K_{het}|} w_i \cdot \frac{\lfloor \frac{X}{2} \rfloor \cdot \lceil \frac{X}{2} \rceil}{\binom{X}{2}} + \sum_{j=1}^{|K_{hom}|} w_j, & \text{if } X \bmod 2 = 1 \end{cases} \tag{6.23}$$

Case 1: (*Only homogeneous criteria*) When only homogeneous criteria exist or the weights for all heterogeneous criteria are zero, then $max(GPI_X) = 1$ which is a trivial proof as the *PPI* for all pairs is then maximal, if all homogeneous criteria dimension values are identical for all participants.

Case 2: (*Mixed homogeneous and heterogeneous criteria*) As the sum of all criteria weights is defined to be 1, $max(GPI_X)$ will be maximized as along as all homogeneous criteria are in all dimensions identically for all participants. As such the critical part to focus on is the approximation of the maximum value for the heterogeneous criteria. Thus, the induction proof will focus on this (Case 3).

Case 3: (*Only heterogeneous criteria*) The critical aspect to calculate a $max(GPI_X)$ is to determine how well could (at max) participants of a group be matched in heterogeneous criteria of n dimensions. As such the following induction sets the sum of weights completely on heterogeneous criteria. Without loss of generality the sum of weights for heterogeneous criteria can be assumed to be 1 in this case ($\sum_{j=1}^{|K_{het}|} w_j = 1$).

The *induction start* will begin with $X = 2$ (see Eq. A.24 in Sect. A.1) as this is the minimal group size. As differences exists for even and uneven number of group members, the *induction start* proves the equation additionally for $X = 3$. The *induction step* will likewise be split, depending on $X + 1$, with $3 \leq X$, being even or uneven (in Eqs. A.26, A.27 and A.28). For better readability of this chapter the induction proof has been moved to Sect. A.1.4.1 in Sec A.1.

In conclusion, the upper bounds of the *group formation algorithm* depend on the number of participants in the groups and not on dimensionality or amount of criteria. Consequently, the metric can than as well be used to express the quality of the group formation by dividing the GPI or CPI results by the maximum possible value and express it as a percent value. The induction proof as well showed the comparability of the values if the amount of participants grow, the criteria change in numbers and/or dimensions.

6.2.7 Updating

Over time the criteria values of participants will change, especially if process-based and skill-based criteria are taken into account. Consequently, the GPI and probably the whole CPI will decrease significantly and it can be considered to re-match certain participants, if they do not fit to their current group any more. Still, a re-matching of all participants is impracticable as it would interrupt the learning process of all other groups, too.

Thus the problem arises to decide (a) when such an update should be performed and (b) which scope this update should have. Concerning this, two approaches can be considered: a Timer-based Update or an Event-based Update.

Timer-based Update. After a fixed, preset time the suitability of calculating an update of the group formation is checked. Between two checks participants can be sure to remain in their groups which is expected to lead to better group results due to the group formation processes each group moves through and may increase group learning aspects of positive interdependence, individual accountability, promoting interaction, social skills and group processing in general [11, p. 49, 203f]. On the contrary a long time period can lead to unsatisfactory group experiences due to the mismatching. The optimal time period to choose must be decided by the domain matter expert as it depends on learning targets, expected mean time the participants are expected to work together in the group, and the criteria stability, to name a few.
Event-based Update. Each time the values of one participant change the necessity for an update of the group formation is checked. With this approach, the time to re-matching can be minimized. As soon as two participants with changed values should be exchanged among their groups as the corresponding GPI and CPI increase by such a switch, it will be performed. It brings the positive effect of accurate reaction to changes in participants' profile values which are relevant for the group formation and group fitness. Still, it brings the challenge to decide when this will happen. Most importantly it raises the issue how to communicate to the group and the moved participant when this will happen, why and how the work flow is to be expected to continue. Especially as the new group of the moved member already has an internal structure, which raises the risk that new members will not be integrated into the work progress as much as in the beginning of the group work (see phases of group formation and allocation of roles in Haake et al. [11, p.43, 212]).

Due to the argumentation above, it can be concluded that the Timer-based reorganization of groups is more suitable for the purpose of the algorithm in this thesis. A corresponding algorithm for Time-based Update is suggested in Listing 4.

Listing 4 Timer-based Update Algorithm

```
Require: G, time_0      ▷ G are the existing groups, time_0 is the period between two update checks
  time ← System.currentTime
  nextTime ← time + time_0
  while true do                                          ▷ Endlessly perform update checks
    if time ≥ nextTime then
      CPI ← CPI(G)
      NMP_tmp ← P                                        ▷ P contains all participants
      G_tmp ← matching (NMP_tmp)
      CPI_tmp ← CPI (G_tmp)
      Δ ← CPI_tmp / CPI
      if Δ ≥ ϵ then
        G ← G_tmp                                        ▷ G needs to be accessible by other application parts
      end if
    end if
    time ← System.currentTime
  end while
```

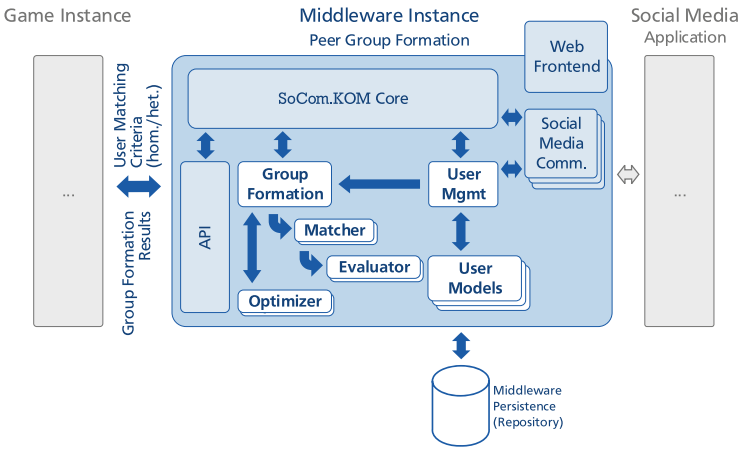

Fig. 6.1 Architecture of peer group formation component, illustrating the communication between sub-components and the input of criteria by the game. The most relevant parts are highlighted (Legend in Sect. A.1.1)

6.3 Architecture Design

The algorithm described above results in an interface (API) that allows the definition and weighting of the matching criteria as K_{hom} and K_{het}. The available criteria can be asked by the game instance in advance. This causes the group formation sub-component in the SoCom.KOM middleware to access the stored user-profiles (e.g. learner profile, player profile, and personality profile) to fetch the necessary participant criteria vector data that can be used as input for the chosen matching algorithm. The matcher then uses a specific evaluator and after cohort formation finished, the group formation may eventually use an optimizer before returning the resulting cohort to the caller.

As discussed in Chap. 3, Sect. 3.5 the overall SoCom.KOM architecture is designed as a middleware architecture. The extensions, specifically for peer group formation, are shown in Fig. 6.1 complementary to the overall architecture illustrated before in Fig. 3.2.

6.4 Chapter Summary

In this chapter the peer group formation approach has been outlined on a mathematical basis. The requirements for the algorithmic design respect the desired improvements necessary for educational games (cf. Sect. 2.2.4).

Criteria for the group formation algorithm are modeled as n-dimensional vectors in disjoint sets of homogeneous and heterogeneous matching criteria. Overall, the

design of the algorithm and fitness metrics (GPI and CPI) were closely aligned to the findings on group formation from related work and the identified missing functionality (cf. Sects. 2.1.2 and 2.1.3).

The developed metrics respect not only both types of criteria simultaneously, but also allow for the calculation of a formation quality, independent of criteria amount, weighting, and dimensions. This enables comparability of the CPI across several cohorts, even if an individual cohort is built with a different matching algorithm.

Additionally, this chapter defined two targeted matching algorithms. The Group-Centric Matcher approaches the *Group Formation Problem* (cf. Sect. 2.1.3) by selecting for each group the most suitable among all unmatched participants until the group is filled or no further unmatched participants remain. Thus, the algorithm aims for completing group by group while maximizing each groups GPI. The second matcher, called Participant-Centric Matcher, approaches the problem from the perspective of unmatched participants. Each one is added to the group, whose GPI increases the most on a percentage basis (and has not yet reached the maximum number of group members). Additionally, a random matching algorithm has been defined for comparison of group formation results as it is expected that the two targeted matching algorithms deliver better results (cf. evaluation in Sect. 7.3.5).

For performance reasons the proposed matchers do not calculate all possible combinations. Therefore, this chapter provided approaches towards optimization cycles that allow re-combination of group formations in case only low local maxima have been reached by the used matching algorithm. Additionally, conceptual approaches for incremental updates of group formations have been designed to allow re-formation of learning groups in case individual participants drop out or in case the GPI of specific groups drop below a certain threshold due to changes in the participants' values of the used matching criteria.

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Chapter 7
Implemented Scenarios and Evaluation Results

The components derived and designed in the preceding Chaps. 4, 5, and 6 have been implemented as prototypical applications in the three scenarios described below. The implementation was realized to investigate the acceptance of the conceptualized components by end-users, evaluate their impact on knowledge exchange and user experience, and finally, in the case of the group formation algorithm, to conduct a comparison with algorithms from related work.

Therefore this chapter describes the implemented aspects, underlying research questions, evaluation, and findings of the following proof-of-concept applications:

PEDALE (Sect. 7.1) The Peer Education Diagnostic and Learning Environment—the first implementation of the SoCom.KOM architecture component for content integration—delivered insight into how well the technical components for peer tutoring, assessment, and content exchange were accepted and furthermore has the capacity to determine which criteria might be important for matching of learners for peer education.

Genius (Sect. 7.2) The SoCom.KOM middleware implementation and integration into a prototype of a single-player educational adventure game enabling network interaction of users with social media, using the game adaptation component.

GroupAL (Sect. 7.3) The SoCom.KOM peer group formation algorithm is an implementation to match users based on homogenous and heterogeneous criteria. It provides insight into the algorithms absolute performance and achieved improvements in comparison to other related algorithms.

7.1 PEDALE

The motivation for the design, implementation and evaluation of PEDALE is to investigate the applicability of the social game criteria and the social media interactions for peer education in an educational context. Thus, the focus is primarily on

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educational aspects and less on gaming. Equally, the focus is more on peer tutoring as peer collaboration. This implementation works as a proof-of-concept for the SoCom.KOM *content integration* component.

For peer tutoring the exchange of user-generated content among school pupils is used. Their solutions to mathematical problems are send to peers who have the chance to assess the approach, rate the solution, give feedback and thus learn by reflection, judgment over some others' solutions, and discovering mistakes. By writing feedback they articulate their approach and explain the identified mistakes [1, 2, p. 45]. Because recipients can rate the applicability of the feedback, the interaction can later be evaluated concerning the feedback quality and the impact on peers' math performance improvements, depending on the characteristics of the interacting peers.

The network of class mates is considered here as the underlying social network of peers. The supported social media interactions are publishing and discussing. Considered social game criteria are

- beneficial social media interaction (publishing, discussing),
- casual multiplayer (awareness of each others approaches and tasks solutions),
- coopetition (giving feedback and the desire to receive good feedback while at the same time compete for best results), and
- asynchronous play (timely decoupled peer tutoring based on the task solutions).

Problems, addressed during approach and design, are the *Group Formation Problem*[1] (cf. Sect. 2.1.3) and the *Individual Group Assessment Problem*.[2]

Note: Parts o f this section have been published before in Konert et al. [4] and are repeated here as revision.

Individual Group Assessment Problem Most precise diagnosis is conducted on on an individual level. Thus, during assessment students are not allowed to work collaboratively, give hints, and share their ideas even though group learning has been reported beneficial in several studies [6, 7]. Moreover it is advantageous for students when feedback is given not only by teachers, but as well by their peers [6]. As peers share the same background and use the same language they can understand misconceptions better when explaining to each other [8]. The fact that diagnosis and assessment need to be individually, but for learning progress the exchange among the peers is favorable, is called the *Individual Group Assessment Problem*.

[1] Referred to as *Peer Matching Problem* in Konert et al. [3], but renamed here for consistency reasons.

[2] Additionally, the *Diagnosis Adaption Problem* and the *Teacher's Supervision Problem* are addressed and explained in the PEDALE-related publications, but will not be discussed here as they are not necessary for comprehension of the following explanations [3–5].

7.1.1 Approach and Scenario

The proposed system, PEDALE, aims to address the above-mentioned problems by combining diagnosis and learning together with social networking principles for peer assessment and knowledge sharing between students. The system will use a carefully reviewed and empirically validated didactic model of competence development and diagnosis from Bayrhuber et al. [9], based on findings from Leighton and Gierl [10]. Hence, PEDALE aims to be highly valuable for diagnosis (teacher's perspective) and understanding the own learning progress (students' perspective).

The pedagogical conception and didactic design of the PEDALE software and evaluation scenario has been developed in a research tandem with Kristina Richter from the department of didactics in mathematics at Technische Universität Darmstadt. Like the author of this thesis, she held a scholarship of the German Research Foundation (DFG) and was member of the graduate school of E-Learning. The research tandem is supporting this thesis' interdisciplinary entitlement. The approach and results of PEDALE are discussed in Richter [11] with a pedagogical and media-didactical focus.

From a technical perspective, PEDALE allows insight into the users' acceptance of the concept of peer education in an E-Learning scenario. Moreover, the evaluation delivers insight about the matching characteristics that lead to better feedback and an increase in users' performance.

The proposed system is used by teachers during classroom instruction to get a detailed diagnosis about their students' competencies. The students are instructed to use the software within a fixed time period (e.g. 40 min, depending on test configuration) to solve the diagnostic tasks. Each student uses an individual computer. While the students are working with the software, the teacher can monitor the progress and participate in the process. With the help of a specific control panel that is activated if a teacher uses the software, the teacher can get an overview about the whole class' progress and can access information about certain events (e. g. given feedback of specific students or task solutions to a specific task).

Beside other application areas, the design of educational software faces the problem that the main experts for the content (e.g. teachers) are not programmers and vice versa. To decouple the dependencies during development a feasible approach is to provide authoring software for teachers to create content and configure the application behavior independently from programmers. A second component is a player tool that displays the configured test interface and content to the students. The authoring tool will be used for the setup of diagnostic tests and the input of test questions fitting the used diagnostic model. The corresponding player tool has to be capable of displaying the new interface elements and will adapt the test course [12, 13].

A diagram of the software components with their key functionality and the data flow are displayed in Fig. 7.1. The work with the software is arranged in three stages:

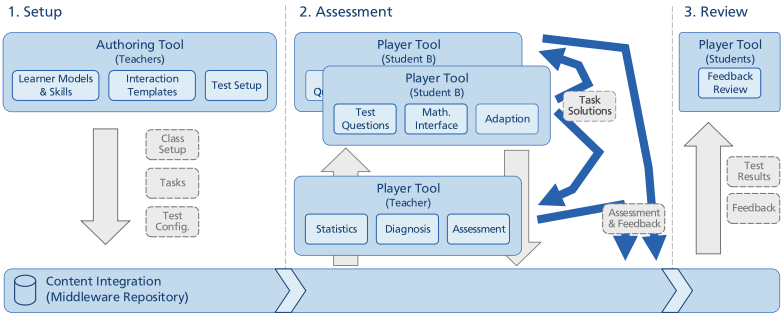

Fig. 7.1 Stages (1–3) of diagnostics and learning with peer tutoring and peer assessment

Stage 1: The assessment is configured by teachers who create or select the desired test questions and set the characteristics like duration, amount of peer assessment and the class setup (students' login accounts).
Stage 2: For the assessment students load the configured test via their player tool and work through the diagnostic assessment in the classroom (displayed as Student A in Fig. 7.1). In the first phase of the assessment the students solve machine-analyzable tasks. On the base of these tasks a first diagnosis is generated automatically and directly displayed to the students after they went through the tasks of the first part. The second part of the assessment asks the students to solve open-format problems. They can use a digital pen to write down their solution approach and result. The written solutions to the problems are displayed to peer students (e.g. student B gets a solved problem of student A and vice versa). They are asked for assessment regarding the correctness and the solution process. The solved problems are retrieved from the tool's data repository and the player tool decides which of the related solved problems matches best to be displayed.
Stage 3: The given peer feedback is stored for later review. In a final *feedback phase* the students are provided with all their assessment results and peer feedback, as well as a feedback from the teacher.

PEDALE is designed to distribute the matching among all peers randomly to achieve an equal distribution of peer interactions with the aim that each student gives and receives an equal amount of feedback. By matching the students automatically, PEDALE helps solving the *Group Formation Problem* as teachers do not need to match the students manually. The analysis of the randomly matched pairings and their performance as well as the perceived feedback quality can give insight into which criteria can be considered to be important for a group formation algorithm. Future work is expected to integrate the findings for peer matching optimization (cf. Chap. 6 and Sect. 7.3).

7.1.2 Research Questions

Based on hypotheses H1 and H2 (Sect. 3.3) the following research questions are specified for PEDALE:

RQ1 To which extend will students value the peer tutoring and assessment in an educational software positively?
RQ2 To which extend will students' performance change due to peer tutoring and assessment?
RQ3 What is the influence of anonymity, users' math proficiency, personality, and learning style preferences on peer interactions?

Answering the first research question will help to understand the value of peer tutoring for users. If a positive attitude can be shown in the classroom scenario, it can be assumed that a similar or even more supportive attitude can be shown in more relaxed (and more game-oriented) scenarios.

The second question will assess the effect in task-solving performance based on peer tutoring and assessment to find out the impact such knowledge exchange can induce.

The investigation of the last research question will provide insight into parameters that might be considerable for optimization of peer matching beyond the provision of equally distributed peer matching. Expected effects of anonymity and personality traits or learning style preferences can then be used to calculate a more precise matching based on these criteria. This aims for a better suitability of the matched individuals for peer learning.

7.1.3 Architecture

As PEDALE uses the architectural solution of the SoCom.KOM *content integration* component the architecture is based on this as shown in Fig. 7.2. The player tool of one student in the classroom plays the current scene-based test that has been stored and distributed before with the authoring tool (for details refer to Mehm [12, p. 19, 119ff]. When the user creates task solutions, these solutions are stored in the content repository. They are annotated with metadata like time needed or graphical solutions attached (i. e. digital pen support).

When the player tool reaches a situation where other peers' solutions to tasks should be loaded it accesses the middleware repository and loads suitable task solutions to display, asks the user for feedback and stores this afterwards as new content to the repository to be available for other player tool instances.

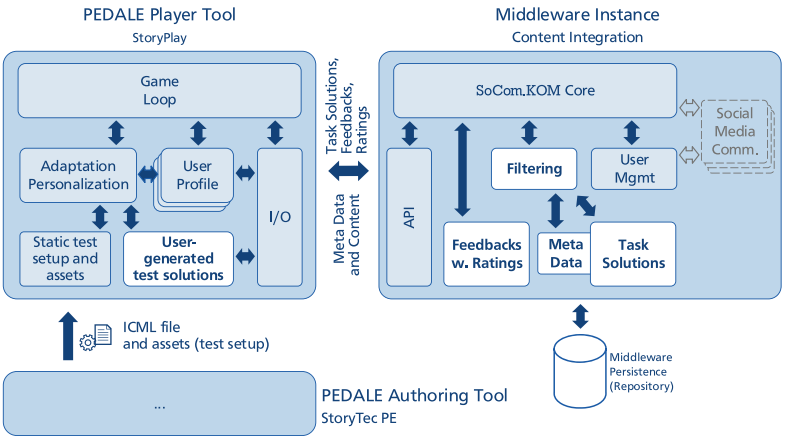

Fig. 7.2 Architecture of PEDALE with authoring tool, player tool, and SoCom.KOM middleware. The most relevant parts are highlighted (Legend in A.1.1)

7.1.4 Implementation

The author of this thesis decided to build on two software components developed in the serious games research group at Multimedia Communication Lab (KOM). Both components, authoring tool StoryTec and player tool StoryPlay, use the (XML)-based format for narrative game-based learning objects to exchange all dependencies and rules of the classroom scenario elements (for details see [14]). Both software components are flexibly extendible and proved their validity as authoring and player tools already for learning scenarios in the research field of serious games [12, 15–17].

In the PEDALE context, StoryTec allows teachers to set up the classroom characteristics and select, change, or create the tasks and their order in the scenario setup without requiring programming skills [12]. More precisely, StoryTec visualizes the flow of activities that later occur in the player tool and provides for editing a graph of connected elements called scenes (see Fig. 7.3) that can be manipulated. The appearance of scenes can be set up in a WYSIWYG[3]-like editor. Beside video, sound, text-explanations, and images, interactive elements like text-inputs, multiple-choice, and handwriting support can be used for the scene design. Flow characteristics, like time restrictions for single scenes or for a groups of scenes, can be set. Teachers can configure which task scenes should be automatically assessed and specify the conditions. For task scenes that are not automatically assessed, teachers can configure the conditions for peer review (which of the open-format tasks are used to be assessed by users).

By manipulating the properties of scenes in several provided text fields, checkboxes and dropdown menus the parameters are set to define whether a scene is an

[3] What You See Is What You Get, used to describe visual authoring tools that provide a continuous preview of the final result during preparation.

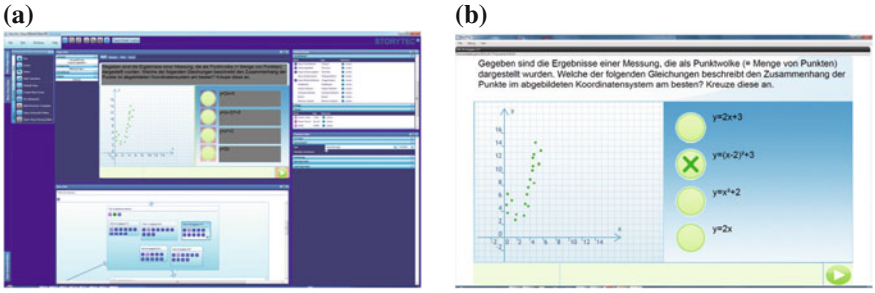

Fig. 7.3 Example of a math task creation with authoring tool StoryTec, displayed afterwards in StoryPlay. **a** Authoring with StoryTec. **b** Displayed in StoryPlay

instructional one, contains a math task to be solved and stored to the database, or contains the requesting or displaying of feedback. Teachers can easily arrange the scenes, connect them as well as create and group tasks to be solved. The scenes can be cascaded to group elements and inherit properties from others. For the PEDALE scenarios the scene types for task result storage, task containers, giving feedback, and displaying feedback have been added.

The corresponding player tool, StoryPlay (formerly known as BatCave [13]), is used by the students and loads all the data for the configured scenario. StoryPlay is capable of displaying the tasks, connecting with the database to read and write the task answers, and can control the flow of the scenario as configured. It has been extended to display the dialog that requests or displays feedback. Additionally, the player tool has been extended by a user login and repository connection module to store as well as receive written solutions, handwriting notes and feedback elements to and from the middleware repository.

All extensions described in this section (*Implementation*) are bundled as the software product StoryTec PE as described in Sect. 1.2.

7.1.4.1 Flexible Task Selection

For the grouping of several scenes that contain math tasks of the same type, StoryTec has been extended by the scene type *container*. If several sub-scenes are created within a container scene and the sub-scenes are not connected by any static transitions, the player tool can interpret this as a free choice to select the next most suitable scene. The implementation has been extended by support for recursively cascaded scenes and special scene types. One type, called *free choice container*, can be set in StoryTec's *property editor* to activate the behavior as described above. If this type is set, in a second drop-down property, the author selects an algorithm that is used for the selection of the next scene from all available sub-tasks in the container. For PEDALE, an algorithm has been implemented that is suitable for the selection of the next math task. Beside other aspects, the algorithm considers math tasks already

displayed, type of tasks the current user gave already feedback for and the amount of feedback already stored to a specific task type in the repository.

With the container solution, task prototypes can be once created and be stored as interaction templates to be re-used by authors to create several tasks of the same type quickly by drag and drop of interaction templates to container scenes. For PEDALE, such interaction templates were created and provided for the math tasks of *graphical algebraic realization* and *graphical algebraic identification* as used in the evaluation setup (cf. [3–5]).

7.1.4.2 Task Solving

Additional task types where created to indicate whether or not a task scene should be automatically interpreted by algorithm for correctness (suitable for multiple choice tasks, i. e. closed problems). In this case, the player tool directly provides feedback about the correctness to the user. Likewise the author can select a task scene to be of type *result storage*. Then the scene's current status is stored to the content repository when unloaded (i. e. when the player tool switches to the next scene). All state changes, manipulations and added content (like drawings or calculations) are attached.

Calculations to open-format problems (math tasks that ask for an approach towards the stated problem) can be done via digital pen. The writing on normal paper is recorded and in real-time transferred to the screen. When users finish their writing, the result is attached as an JPEG compressed file to the current scene (and a zoomable preview is provided), can be deleted, replaced, or more pages can be added. Implementation of support for digital camera pictures and digital drawing tablets was considered during system design. Due to the heterogeneity in computer labs of the schools where the evaluation was planned to be conducted, first choice was the digital pen support.

To track the performance and assign the solutions to the corresponding users, the SoCom.KOM middleware provides a central management of user accounts. The player tool asks the user in the beginning for a login and stores all created tasks solutions and feedback with the corresponding user id in the repository.

7.1.4.3 Feedback Provision and Listing

To allow teachers an easy arrangement of the test setup, the scene type can be configured to be *result display and feedback* or *feedback display*.

When the player tool reaches such a task scene of type *result display and feedback*, it's implementation has been extended to load from the repository all task solutions to tasks of the current setup that are not yet solved by the current user. The player tool sorts them ascending by already received feedback. As a result, the student gives feedback to a solution of a task that the user has not solved before and where the

creator of the solution is one of the peers who received the least feedback by now. This approach allows an equable distribution of feedback.

The student can examine the task and the attached previews of the attached JPEG files containing the calculations of the peer who created the task solution. The calculations can be opened in an extra window and zoomed for better readability. On the left side a feedback form is permanently displayed asking for assessment of the task solution's completeness and correctness, self-confidence of the assessor about his assessment, and estimated helpfulness of the provided feedback. The feedback elements are developed in cooperation with the experts from the department of didactics in mathematics. Details can be found in Konert et al. [3].

The scene type *feedback display* can as well be added to the order of scenes and loads all feedback currently stored in the repository for the current users' solutions to tasks of the current setup. The users can scroll the list of feedback, see their own task and solution as previously stored, and they can inspect the filled feedback form on the left side. They are asked to rate the feedback usability on a Likert scale of zero to 5 stars. The rating is one factor to be analyzed later in evaluation to find indicators which matching of assessor and assessment receiver lead to better rating results.

7.1.5 Session Management, Class Separation, and Variations

To support easy evaluation with several setups, the authoring and player tool were extended to divide the visibility of existing solutions in the repository by equality of the setup name. The authoring tool allows to set a *story name* which is used as the setup name in PEDALE and is applicable to filter all stored content in the repository by this name. Hence, several classes can use the same repository and not see each other's solutions in case different *story names* for the setups are used.

Moreover, different software versions can be tracked by the file names of the setup. This orthogonal naming scheme allows to know which version of setup (and software) a student uses. The file name of the used setup is stored in the repository after successful login.

For evaluation reasons the authoring tool was extended to allow the configuration of the database connection and a check box to set whether or not the player tool should anonymize the displaying of task solutions and provided feedback. Both settings are stored in the setup file.

7.1.6 Evaluation

Design

To answer RQ1 an online questionnaire has been designed to be answered directly after using the software. The questionnaire contains items about attitudes, impressions, favored peer feedback partners, and suggestions for improvement. For control

reasons computer usage, software usage experience, math grade in last term, and prior experience with peer feedback are asked.

For RQ2 the diagnostic test is split in two different groups. The experimental group gives feedback and receives feedback in the middle of the test. The control group gives feedback in the end and can review feedback in the end. Thus, the control group is having no intervention by feedback giving or receiving during the full test.

The setup for research question RQ3 requires more extensive setup design. The groups of participants will be further divided orthogonally into one anonymous group with a software version displaying no names at all, and a group with a software version that displays the names of participants which gave feedback and for whom feedback is asked to give. By this design, it is evaluated what influence social bindings have to feedback quality and rating.

Personality traits are not suitable to be split in advance into groups, as there are too many variances and continuous scales in the personality traits values, learning style preferences, and player type preferences. Therefore it is reasonable to randomly mix the participants and let each individual answer a questionnaire to get profile information for NEO-PI-R [18], Kolb's LSI [19], and BPT [20]. Investigation of learning style preferences and their correlations with feedback quality and peer's characteristics is of great value as related work states the benefit of matching heterogeneous approaches to problems for group learning. Kolb's LSI has been chosen instead of ILS from [21], as it has an absolute measurement (each question contains all axis directions as choice) whereas ILS compares pairings of two of four possible preferences per questions. Consequently, ILS seems to be better for knowing in which category a participant has the strongest value, but for a difficile characteristic of all four possible dimensions as a participants profile in learning preferences, the LSI seems to be more appropriate.

To add more information about the participants personality, the questionnaire for Bartle's playing style preferences were added to investigate correlations among these preferences and the impact on peer feedback quality. Finally, the questionnaire for NEO-PI-R was additionally used as it is one of the most sophisticated and reliable personality trait measurements and insight into the influence of these values to quality of peer feedback is equally valuable.

Setup

For evaluation teachers visiting postgraduate training for math teaching and didactics at Technische Universität Darmstadt were informed about the PEDALE software. They were invited to take part in the evaluation with their school classes of grade 9 (fifth year of secondary school, aged ~14). Seven school classes on three different schools in the state of Hesse (in Germany) finally participated in the evaluation with 183 pupils. Details on the distribution of participants can be found in Sect. A.2.3.1.

The evaluation of the computer-supported diagnostic instrument is designed to last 1.5 h with following 5 PHASES:

1. Introduction to the tool with a video and oral presentation to the class (20 min)
2. Testing round with one closed-format (multiple-choice) task and one open-format task to give pupils the chance to become familiar with the digital pens and task

types as well as check their login and network connection to work. After settling all questions and issues the next step was started. (10 min)
3. **Diagnostic test** with peer tutoring and assessment (20 min, details below)
4. Online questionnaire about learning preferences and usability of the PEDALE system (10 min)
5. Paper-based questionnaire containing the standardized questions on Bartle playing preferences, Kolb learning style preferences and the short-version to measure personality traits based on NEO-PI-R. This questionnaire was taken home and returned the next math class to the teacher (20 min).

The remaining 30 min of the 1.5 h time-slot are used asbuffer time in case of delays. Details about the questionnaires can be found in Sect. A.2.3.1.

Based on the research questions the following setup has been designed for the PHASE 3 diagnostic test:

3a Solving two closed-format tasks on a comparably easy level, followed by automated diagnosis of the performance,
3b (pre-test) Solving two open-format tasks and sending them to the system,
3c Writing up to four times feedback to such open-format tasks' solutions of peers (depending on the time spent in the previous steps. The less time was spent in step 1 and 2, the more often feedback should be given),
3d Reviewing received feedback,
3e Equally to step 1. (solving two closed-format tasks),
3f (post-test) Equally to step 2. (solving two open-format tasks),
3g Provision of feedback at the end, equally to step 3c, and
3h Finally, a feedback review including all received feedback (from 3c to 3g).

PHASE 3, with the diagnostic test, was split into different group setups to evaluate later the difference in questionnaire answers, feedback quality, and performance impact. The variations are visualized in Fig. 7.4.

Setup α: A PEDALE-based test with no intermediate feedback function (omitting steps 3c and 3d of PHASE 3) as a control group for feedback and social tie influence

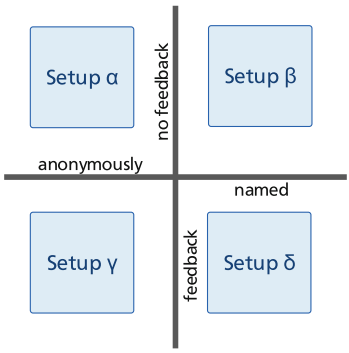

Fig. 7.4 Setup variations α–δ on axes *anonymity* and *feedback*

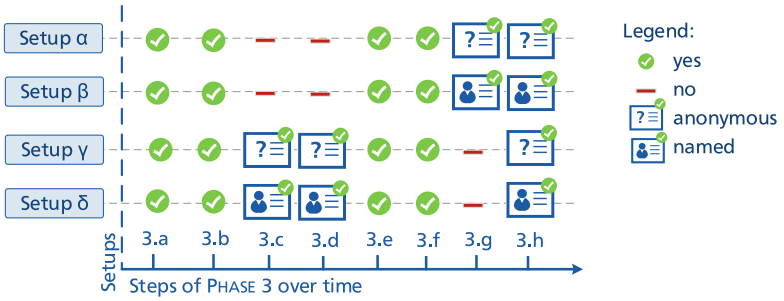

Fig. 7.5 Schedule for evaluation PHASE 3 using setups α and β as control group and setups γ and δ as experimental group

(The control group gives and receives feedback only at the end of the course after all the tasks solving is over.) The tasks are solved without any name recorded or displayed with the task solution. In short, this setup variant is called *no feedback, anonymously*.
Setup β: A PEDALE-based test with no intermediate feedback function (omitting steps 3c and 3d of PHASE 3) but name recording and displaying with the task solution as a control group for impact of feedback. In short: *no feedback, named*.
Setup γ: A PEDALE-based test with intermediate feedback to and from peers without displaying names in the task solutions and the feedback as an indicator of the influence by assessment and feedback functionality. In short: *feedback, anonymously*.
Setup δ: A PEDALE-based test with intermediate feedback to and from peers with displaying names in the task solutions and the feedback as an indicator of the influence by social ties between students and anticipated competition. In short: *feedback, named*.

Together with the 8 steps (3a–3g) PHASE 3 is scheduled as visualized in Fig. 7.5.

7.1.7 Results

7.1.7.1 Descriptive Statistics

Overall, 183 school class students attended the evaluation (106 f/77 m) that was conducted between 21st March and 3rd of May in 2012. As all seven classes were secondary school classes of German school grade 9, participants' age was between 13 and 14 years. In Setup α and Setup β were equally 41, in Setup γ 49 and in Setup δ 52 of the participants. Mean of marks as an indicator of level of proficiency was $m \approx 4.0$ (67 %) on a scale from 1–6 (6 as best, $N = 176$). Beside one, all other 182 students filled in the online questionnaire. The paper survey was returned by 74 of

152 participants (from first and last school only, as the teacher of the second participating school did not permit the distribution of the paper survey). Further details about the evaluation's participants are listed in Sect. A.2.3.1 in Sect. A.2. There are as well tabular representations of the results described in the following.

7.1.7.2 RQ1 Participants' Assessment of PEDALE and the use of Peer Education

The participants were asked to give school marks to their overall impression of working with the digital environment. With an overall mean mark of 4.52 ($SD = 1.18$) on a scale from 1 to 6 this means a rating > 75 %. A little lower are the ratings for writing feedback ($m = 4.33$, $SD = 1.31$) and receiving feedback ($m = 4.26$, $SD = 1.35$). The highest value is gained for using the digital pen interface for writing their calculations and drawings ($m = 4.57$, $SD = 1.50$). An overview is given in Fig. 7.6 (illustrating Table. A.17).

The values are independent (no significant correlations) of amount or quality of received or given feedback as well as personality characteristics, learning style preferences or level of proficiency. There is a positive significant correlation of the overall score ($m = 4.52$) with the achieved score in pre-test ($r = 0.205$, $p < 0.006$) and post-test ($r = 0.197$, $p < 0.01$).

A more detailed question about satisfaction aspects (illustrated in Fig. 7.7) revealed that students are above average have the feeling they learned something especially by giving and/or receiving feedback ($m_{give} = 1.71$, $m_{rec} = 1.66$). This opinion is independent of their level of proficiency, but both aspects inter-correlate with each other ($r = 0.315$, $p < 0.001$) and positively correlate with the expression that it was fun to work with PEDALE ($r = 0.203$, $p < 0.01$ for feedback writing and $r = 0.299$, $p < 0.001$ for feedback receiving). On the contrary, both correlate negatively with level of expertise in computer usage ($r = -0.161$, $p < 0.05$ for writing and $r = -0.200$, $p < 0.05$ for receiving). Of both, only the expression of having learned something by receiving feedback correlates positively with the user's

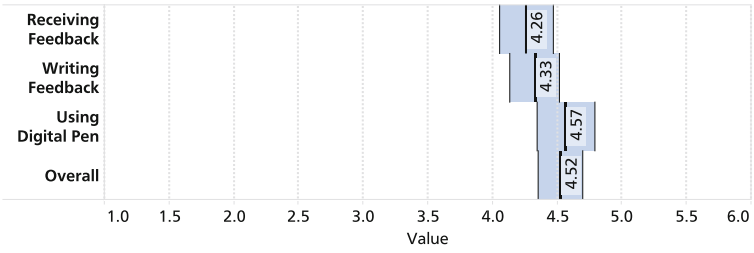

Fig. 7.6 Mean results to item group *How did you like the digital learning environment?* (1 worst, 6 best) including 95 % confidence intervals

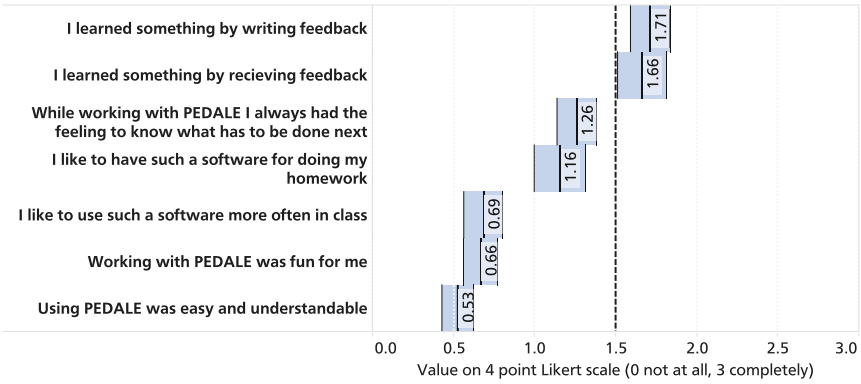

Fig. 7.7 Mean results to item group *How much do you agree to the following statements?* (0 worst, 3 best) including 95 % confidence intervals

own level of proficiency ($r = 0.196$, $p < 0.05$). A detailed correlation table can be found in Sect. A.2 as Table. A.18.

Contrariwise, the participants did not agree that they always knew how to use the software ($m = 1.26$) and do not necessarily want to use the software for homework ($m = 1.16$). Together with the will to use of such software in class ($m = 0.69$), this correlates negatively with reported computer skill level ($r = -0.197$, $p < 0.05$ for homework usage and $r = -0.196$, $p < 0.05$ for usage in class). Score values for overall fun with PEDALE and the easiness of use were the lowest in this category ($m_{fun} = 0.66$ and $m_{ease} = 0.53$).

7.1.7.3 RQ2 Performance Measurement

For RQ2 the influence of high quality feedback (received and sent) is investigated by comparing the mean improvement of scores from pre- to post-test of the experimental group (Setups γ and δ, abreviated as EG) with the mean improvement of the control group (Setups α and β, abbreviated as CG). As a complete comparison of pre- and post-test results for control group and experimental group did not reveal any interpretative data, the comparison was split by proficiency level and students were grouped with high level of proficiency (German marks 1 and 2; inverted scale scores 6 and 5), average level of proficiency (German mark 3, inverted value 4) and low level (German marks 4 and 5, inverted to 3 and 2[4]). The result is shown in Fig. 7.8.

As easily to see, none of the differences between pre- and post-test for any of the groups is significant as confidence intervals overlap. Still the trend shows that the experimental group has a higher improvement in scores after treatment compared to the control group—at least for the students with high and average levels (improvement from $m_{high,pre} = 7.93$ to $m_{high,post} = 8.59$ and from $m_{avg,pre} = 7.26$ to

[4] No participant had the lowest possible German mark of 6, inverted 1.

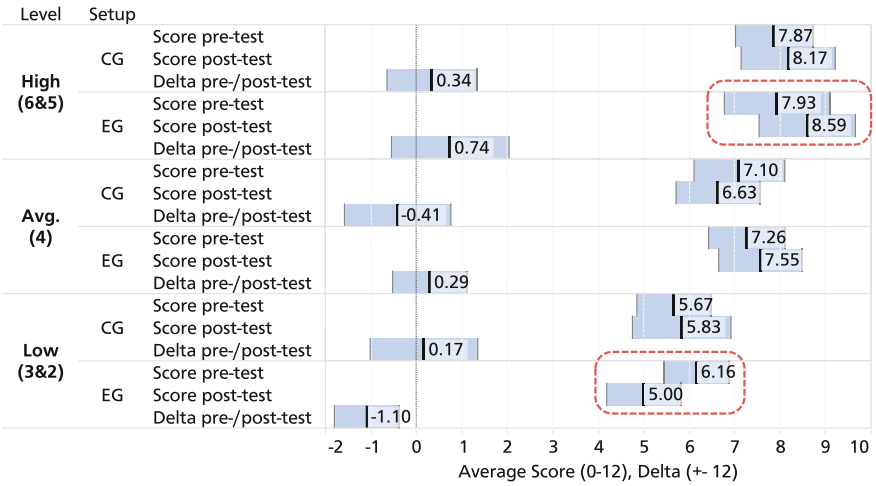

Fig. 7.8 Comparison of performance depending on setup, $N = 172$ (Scores with 3 points maximum on each task per test leads to 12 points at maximum) including 95 % confidence intervals

$m_{avg,post} = 7.55$). The students with low level of proficiency in math had a drop in test results from pre- to post-test (from $m_{low,pre} = 6.16$ to $m_{low,post} = 5.00$).

7.1.7.4 RQ3 Influence of Social Bonds and Personality to Peer Interactions

Beside the focus on system acceptance, peer education acceptance and improvement effects on students' test result, the influence of pairing characteristics to the quality of peer education is of interest to conclude indicators to be used for a group formation algorithm matching peers for peer education. Beside the findings from related work (cf. Sect. 2.13), the results from PEDALE were investigated to find indicators of further relevant matching criteria especially for the content exchange in a peer education context. During investigation the three used models (Kolb's Learning Style Inventory, Bartle Player Types, and NEO-PI-R) proved to be of little inter-correlation in this study, cf. [22].

To achieve an insight, two dependent variables were investigated: the improvement of achievement level of students (similar to Sect. 7.1.7.3) and the quality of the produced content itself (feedback quality) which is measurable as subjective rating by feedback recipients and objective rating by a subject matter expert. The expert rated the created feedback and underlying task solutions on several didactic criteria. Details about the rating calculation can be found in Sect. A.2.3.2.

Additionally, the influences of social bonds (friendship, peer matching) and personal characteristics of sender and receiver to the interactions (personality traits, learning style preferences) were of interest.

All findings related to RQ3 are based on investigation of peer interactions during the evaluation. The underlying data was transformed to represent one interaction (task solving, feedback provision, and feedback rating) as one case in the underlying calculation of correlations.

The results are listed in two sets: First, the influence on objective improvements in achievements (delta between pre- and post-test) and second, the influence on objective and subjective quality of feedback (peer interaction).

Influence on performance. Correlations are calculated between the improvement value (delta between pre- and post-test) and personality traits, learning style preferences, and player type preferences as well as evaluation process data (like amount of feedback written).

Influence on feedback quality. For the judged subjective feedback quality (by receiver) and the objective feedback quality (judged by subject matter expert) correlations are calculated with personality traits, learning style preferences and player type preferences of sender and receiver of feedback. Additionally, a focus is laid on investigation of the differences and similarities of the sender-receiver combination and its correlations with the feedback quality (objective and subjective).

Influence on Performance

To investigate the influence on performance caused by feedback sender's personality traits and the differences among sender and receiver, only interactions among participants were analyzed where the receiver got a feedback in-between (experimental group). Several significant correlations with the increase in performance (delta pre-post-test) could be found. For better readability the positive correlating and negative correlating aspects are listed separately. When listing *delta* it means differences in values of sender and receiver. Positive correlation means that the value increases, if the underlying measure has a higher value for the receiver. When listing *difference* it means the absolute value of *delta*. A positive correlation of *difference* means that a higher value of difference leads to higher value of the correlating variable (higher increase in performance). In combination, any significant positive correlation of *delta* in combination with a negative correlation in *difference* means the *difference* is not independent of direction. If the *difference* correlates as well positive, the *delta* can be interpreted as being symmetric.

Positive correlation to delta pre-post-test
Difference in score pre-test ($r = 0.123$, $p < 0.021$), difference in openness ($r = 0.233$, $p < 0.05$), and concrete experience learning style of sender ($r = 0.219$, $p < 0.01$).

Negative correlation to delta pre-post-test
Delta in score pre-test ($r = -0.378$, $p < 0.000$), difference in conscientiousness ($r = -0.281$, $p < 0.011$), delta in neuroticism ($r = -0.311$, $p < 0.01$), difference in concrete experience learning style ($r = -0.249$, $p < 0.05$), difference in active experimentation learning style ($r = -0.224$, $p < 0.05$), and delta in socializer player type preference ($r = -0.232$, $p < 0.05$).

Influence on Feedback Quality

As the objective or subjective feedback quality is not depending on experimental or control group, all interactions are analyzed in the following.[5] For interpretation, it needs to be considered that both, objective and subjective feedback rating, correlate with each other ($r = 0.372, p < 0.001$). In the following section, the subjective rating by receivers is further differentiated between anonymous and named version of the receiver's software (comparing setups α and γ as *anonymous* with setups β and δ as *named*). In the following list, all correlations that can be re-verified, if only interactions from anonymous or named versions are correlated, are marked additionally with ∘ (anonymous), or • (named). The lists are sorted by naming first correlations with both feedback ratings (objective and subjective), followed by the correlations only with subjective rating and finally listing the correlations with objective feedback rating.

Positive correlation to subjective (S) and objective rating (O)
Both ratings have a positive correlation with sender's and receiver's pre-test score (sender: $r = 0.330$ (O)$^{\circ\bullet}$, $r = 0.187$ (S)$^{\bullet}$, receiver: $r = 0.213$ (O)$^{\circ\bullet}$, $r = 0.111$, $p < 0.05$ (S)$^{\bullet}$, all first three with $p < 0.001$). Additionally, the neuroticism of receiver ($r = 0.170, p < 0.05$ (S)$^{\bullet}$, $r = 0.215, p < 0.001$ (O)$^{\circ\bullet}$) and the difference in level of proficiency ($r = 0.128, p < 0.01$ (S)$^{\circ\bullet}$ and $r = 0.320, p < 0.001$ (O)$^{\bullet}$) correlate positively for both ratings.

Correlating positively with subjective rating are sender's learning style of reflexive observation ($r = 0.246, p < 0.01^{\circ}$), abstract conceptualization ($r = 0.193, p < 0.05$) and active experimentation ($r = 0.199, p < 0.05$) as well as the sender's conscientiousness ($r = 0.180, p < 0.05^{\circ}$).

With objective rating positive correlations exists for openness of receiver ($r = 0.219, p < 0.001^{\circ\bullet}$), difference in conscientiousness ($r = 0.180, p < 0.05^{\circ}$), delta in neuroticism ($r = 0.212, p < 0.01^{\bullet}$), delta in openness ($r = 0.181, p < 0.05$) and delta in socializer player type ($r = 0.174, p < 0.05^{\bullet}$).

Negative correlations to subjective (S) and objective rating (O)
None of the items correlates with both ratings.

Correlating negatively with subjective rating are socializer player type of receiver ($r = -0.199, p < 0.05^{\circ}$), receiver's learning styles of reflexive observation ($r = -0.163, p < 0.05^{\bullet}$) and active experimentation ($r = -0.225, p < 0.01^{\circ}$) as well as receiver's extroversion ($r = -0.209, p < 0.05^{\circ}$), and killer player type preferences of sender ($r = -0.223, p < 0.01^{\circ}$). Concerning dependencies of both individuals, negative correlations exist for the delta in reflexive observation learning style ($r = -0.246, p < 0.05^{\bullet}$[6]), delta in active experimentation learning style ($r = -0.282, p < 0.05^{\bullet}$), and the delta in level of proficiency ($r = -0.097, p < 0.05$).

[5] However, nearly all correlations are found to be higher (with slightly lower significances) if only calculated for the experimental group.

[6] The named setups show as well a negative correlation with the objective rating ($r = -0, 256, p < 0.05$).

With objective rating only the learning style of concrete experience of receiver ($r = -0.149$, $p < 0.05°$) correlates negatively.

Difference in subjective rating for anonymous and named setups
If only correlating the items for receivers of feedback who had a anonymous software version not displaying the senders name, the correlation of the subjective feedback quality rating with pre-test scores of sender and receiver vanishes, but the correlation with the objective feedback quality remains. The subjective rating correlates positively in the anonymous setups with receivers player types killer ($r = 0.212$, $p < 0.05$).

If only the interactions with receivers having a named setup is analyzed, the subjective rating correlates negatively with difference in explorer player type ($r = -0.414$, $p < 0.05$).

As anonymity is an independent variable varied in the evaluation design, a t-test could be conducted comparing the differences between the groups. The t-test proves that the subjective ratings given by receivers are significantly higher in the named version as in the anonymized (the test can be found in Sect. A.2.3.6). Additionally, the correlation among subjective rating with the objective feedback quality is higher in the anonymized version ($r = 0.343$, $p < 0.001$ in named setups, $r = 0.411$, $p < 0.001$ in anonymous setups).

7.1.8 Interpretation and Limitations

RQ1 Acceptance by participants
As the participants assessed the overall system usage with a mean value of 4.52 (on the 6-point Likert scale) and especially gave similar ratings to the capacity to give and receive feedback ($m_w = 4.33$ and $m_r = 4.26$) it can be interpreted that the concept of user-generated content as the base for peer education was accepted. This is supported by the fact that the values representative of users' opinions regarding whether or not they learned something by writing or receiving feedback, were above average on the 0-to-3-point Likert scale ($m_w = 1.71$ and $m_r = 1.66$) even though the users did not have fun while using the learning environment ($m_{fun} = 0.66$).

RQ2 Influence on performance
Even though the results show a clear benefit of intermediate peer feedback and assessment to the improvement between pre- and post-test (difference between control group and experimental group), the difference between the groups is not of significance and thus can only be interpreted as a tendency. As only about one third of all task solutions where solved correctly, it is assumed that the selected tasks were not appropriate and thus the learning effect (improvement) was lower than expected on study design. In general, the used set of math problems is highly suitable for the targeted participants of 9th grade in secondary school [9]. Still, the specific subject matter, needed to solve the problems, was thought about nine month earlier to the participants of the PEDALE study. Consequently, most of them might have had difficulties in recalling what they have learned. Additionally, only working on four tasks

in each test (pre- and post test) seemed to be insufficient when trying to determine a significant impact of the feedback (in average for two task solutions) received by each participant. As the proper formulation of feedback is itself a skill that students have to learn and practice, it is reasonable to assume that here more prior training and teaching can assists the goals of a subsequent study. Likewise, from a media-didactic point of view, additional overlay effects can be considered as reasons for the low quality of task solutions. Media competency cannot be assumed to be existing abundantly as up to date only a few schools and their teachers actively teach the handling of media. Especially, deficits in problem solving competency seem to be a major issue and need to be considered more thoroughly in future studies [1]. Abstraction and generalization of the problem at hand, decision making, targeted approaching of the problem, and critical reflection of the result are needed as prerequisites in order to study the effects of peer education by assessment and feedback. In the following paragraphs, the main focus is on the characteristics of the pairing of sender and receiver and the influence on performance increase, due to intermediate feedback. The results will be interpreted in order to determine a classification of criteria to be matched more homogeneously or heterogeneously in future peer matching. Such work is proposed to be done by algorithms selecting a peer education partner (cf. Sect. 7.3.5). A simplified overview concerning these recommendations for applicable matching criteria is shown in Table 7.1 for the findings related to RQ2 and RQ3.

As there is a positive correlation of the performance increase with the difference in pre-test score and at the same time a negative correlation with the delta of this score among sender and receiver, this means users benefit more from feedback (concerning their post-test improvement) when the feedback sender has significantly better test results than the receiver (heterogeneous matching). This seems self-evident when corresponding to the asymmetry of knowledge mentioned by Damon [8] as a characteristic for effective peer tutoring (cf. Sect. 2.1.2).

Table 7.1 Matching criteria recommendations based on the interpretations of the evaluation results for RQ2 and RQ3

	Homogeneous	Heterogeneous
Matching criteria for performance increase		
Stronger indicators	LSI: Concrete experience (CE)	Level of proficiency
Weaker indicators	NEO-PI-R: Openness	BPT: Socializer
	LSI: Active experimentation (AE)	
Matching criteria for feedback quality increase		
Stronger indicators		Level of proficiency
		LSI: Reflexive observation (RO)
Weaker indicators	NEO-PI-R: Neuroticism	NEO-PI-R: Conscientiousness
	NEO-PI-R: Openness	
	BPT: Achiever	

The recommendations are grouped by the strength of indicators found in the underlying data (stronger indicators, weaker indicators)

The *concrete experience* learning style of the sender correlates positively with the receiver's performance increase, but a difference of this learning style correlates negatively with that increase. This can be interpreted as matching this learning style homogeneously for a positive impact on performance.

Weaker indicators exists for homogeneous matching of the openness personality trait. The values correlate positively with the reciever's performance improvement. Likewise weak indication exists for homogeneous matching of the active experimentation learning style. The difference in this style among sender and receiver correlates negatively with performance improvement. As the delta in socialiser player type preferences correlates negatively with the receiver's performance improvement, it might be an indicator for better performance increase if the feedback senders have high(er) socialiser values than the receivers.

RQ3 Influence on feedback quality

One of the main impacts on feedback quality is the presence of anonymity in peer interaction. Participants rate feedback higher and less accurate (resulting in a lower correlation with the objective feedback quality) when the name of their classmates were displayed. This is corroborated by the fact that the correlation of the subjective rating with the pre-test score of the feedback sender vanishes if only the anonymized pairings are analyzed.

Thus, it can be interpreted that the displaying of a sender's name results in assumptions about the sender's proficiency level by the receiver. Consequently, a bias can exist resulting in systematically higher ratings for peers of whom the receiver assumes they are good in the topic. Then it is coherent that the positive correlation of the subjective rating with the pre-test score of the feedback sender vanishes when only anonymized pairings are analyzed. This is supported by the fact that the correlation between the objective feedback quality rating and the pre-test scores remains, even if only anonymized pairings are investigated. Moreover, in the anonymized pairings the receivers rate feedback significantly lower when they have high values for player type *socialiser* or have an more extroverted personality than the sender. As these correlations do not occur in the pairings with displayed names it can be concluded that the value of feedback drops for a receiving *socialiser* and extroverted individual when feedback is anonymized. In brief, anonymized pairing leads to more objective ratings by receivers. Therefore, it can be argued that peer assessment should be anonymized in future systems of similar setup.

In order to sufficiently interpret homogeneous or heterogeneous characteristics and thus optimize feedback ratings, the correlations between differences of personality traits, learning style preferences, and player types are focused in the next three paragraphs. A condensed overview over the concluded recommendations for matching criteria is listed in Table. 7.1.

First, for peer tutoring, the learning style of *reflexive observation* appears to be significant and is therefore recommended to match *heterogeneous* as subjective rating correlates negatively with delta of this learning style among sender and receiver, which also appears for objective feedback quality rating in the setups that displayed names. As this correlation is only with the delta among sender and receiver in this

learning style, but not with the difference in this learning style preference, the sender of the feedback should have a high *reflective observation* style of learning.

Second, the subjective rating correlates negatively with the receiver's socialiser player type; the objective rating correlates negatively with the sender's socialiser player type (in the anonymized setups); and delta in this player type correlates positively with objective feedback quality. As such, socialiser type seems to be an aspect generally contra-productive for good (focused, relevant) feedback, but if the sender has at least a lower socialiser score than the receiver, it seems to be suitable. This is contrary to the indication for improvement in performance mentioned above. Consequently, general advise for matching criteria cannot be deduced. To prevent socialisers from being all together in learning groups, heterogeneous matching might be the most appropriate.

Third, the difference in the level of proficiency (pre-test scores) leads to better feedback results (objective and subjective). Yet in the case of subjective ratings, the delta of the level of proficiency correlates negatively with these subjective ratings, which means that the receiver of the feedback should have a lower level of proficiency for a subjectively better rated feedback (by this receiver). It seems reasonable to argue that the matching of peer should be heterogeneous and optimally with a higher level of proficiency from the sender. This suits the aspect of knowledge transfer and asymmetry of knowledge mentioned above.

For further, marginally supported interpretations, it seems reasonable to refer only to the correlations with the objective feedback score, as they have a better linkage to the desired feedback quality in future peer matching. Based on this, the objective feedback rating positively correlated with the delta values in the personality traits of neuroticism and openness indicate that these criteria should be matched heterogeneously, but the receiver should have higher values of these criteria than the feedback sender. A positive correlation exists between the difference in *conscientiousness*, meaning the criterion to be *heterogeneously* matched for good feedback results. As the receiver rates the feedback better if senders have higher values of conscientiousness (positive correlation) this personality trait seems to be an indicator for good peer feedback. Even less generalizable, but still significant, are the indications for the homogeneous matching of the achiever player type (as there is a negative correlation between delta achiever and objective feedback quality in the anonymous setups) and the heterogeneous matching of extroverts (as there is a significant correlation between delta extroversion and objective feedback quality in setups with displayed names).

7.2 GENIUS

With GENIUS the *game adaptation* component of the SOCOM.KOM middleware is analyzed on its acceptance beyond the results from the expert interview (cf. Sect. 3.7). Opposite to the PEDALE scenario, in GENIUS the focus is on the entertainment aspect

of the social media interaction to be integrated into the gameplay. Consequently, the focus is on peer collaboration.

Game adaptation by profile data is used to personalize the gameplay by using the profile information from the social media profile and adapt the game accordingly.

Social game interactions are used to support peer collaboration which allows peers to contribute own content to game situations of a befriended peer. The peers are informed about the possibility to contribute their own creative content to the game situations of the currently playing acquaintance. The published *call for action* contains a forwarding to the website generated by the middleware component providing the options to select existing content or contribute new, self-created content (for details see concept in Chap. 5).

7.2.1 Approach and Scenario

To investigate the effects of the game adaptation by social media metrics and the impact of contributions by peers from outside the gameplay, a solution is proposed which allows character personalization based on the social media profile information of the player and integrates content into the game play, contributed by peers that are currently online.

Therefore, an existing educational game is extended to connect to the SoCom.KOM middleware component for *game adaptation* and fetch the available profile information of the player to adapt the game parameters accordingly. Then the game will post achievements of the player to the user's profile pages in the supported social media platforms. This allows acquaintances to comment and vote these achievement posts. The support from outside by comments and votes will influence the gameplay in a consistent way suiting the game story (game dependent influence). Additionally, the game will use the social influence types and publish the *calls for action* on the news feeds in the social media platforms to allow acquaintances to contribute their opinion or content to specific game scenes.

With Genius, the prototype of a commercial serious game, called BizConsulter,[7] was connected with the online social media application Facebook. The SoCom.KOM middleware works as an abstraction layer and handles the storing of player-/profile information and ego-network information, and provides the web-interface to contributing users.

The game BizConsulter was selected due to the following reasons:

- The game is of the genre adventure game which is one of the main game genres of single-player educational games and thus suits the game-type this thesis focuses on.

[7] In attribution to the cooperation with game creation company DECK13 from Frankfurt, Germany, the prototype of the BizConsulter adventure game was provided for integration into the Genius scenario.

Fig. 7.9 Game scene from BizConsulter game. All texts are in German (as the game is only available in one language)

- The contributions of this thesis are focusing on support for game developers to create (and enhance existing) serious games by the SoCom.KOM functionality. Therefore, the designed API supports the connection and extension of an existing game with reasonable effort.
- An existing game, created by a professional game studio, is expected to better fulfill the user experience expectations of the players.

Target group of the game are bachelor and master students who are potentially interested to start a career in the consulting business after they finished their degree. The game sets the player into the role of a trainee who stands in for his mentor in a client project.

There the player is confronted with real world problems typical for the consulting business and has to solve several tasks related to communication issues and social conflicts in the client company in order to gather relevant information and help the client company to get an essential loan from its bank to save the future of the company. As typical for adventure games the player has to interact with objects, find items and talk to several NPCs to get the necessary information (for impressions of a game scene see Fig. 7.9).

7.2.2 Research Questions

Based on hypothesis H2 (Sect. 3.3) the following research questions are specified for GENIUS:

RQ1 How will participants value the technical implementation of the concept? (functionality)

RQ2 Will game experience increase due to personalization of gameplay by social media profile data? (social media personalization)

RQ3 Will gameplay experience increase due to active participation and content contribution by peers? (influence-based adaptation)

RQ4 How will participants value the possibility to influence the gameplay by reacting to social media posts? (social media awareness)

Answering the first research question will help to understand the technical acceptance of the overall concept by users. As the contribution of content to a currently active gameplay is new compared to related work discussed in this thesis, it will provide findings on the design of content contribution.

The second and third questions investigate the effect the game adaptation has to players' gameplay experience. It is expected that personalization and adaptation are increasing the user experience.

The fourth question will assess the perception by peer users outside the current gameplay. It is expected to bring insight into the acceptance and perception of active participation.

7.2.3 Architecture

With GENIUS the *game adaptation* component of the SOCOM.KOM middleware is used as shown in Fig. 7.10. A local client representation of the SOCOM.KOM API allows the game instance to call methods locally, abstracted from the communication channel used between client an middleware. The implementation is using the architectural design as described in Chap. 5. Precisely, it only used the Facebook connection implementation even though several social media applications could be supported. As Facebook is currently the most public social media application the system

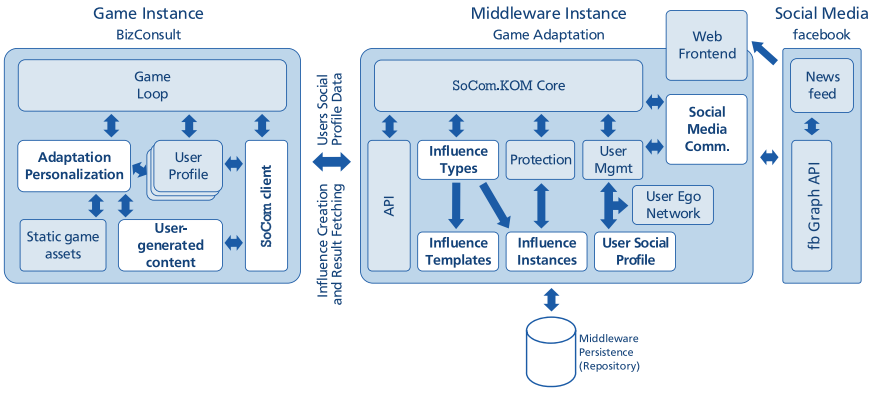

Fig. 7.10 Architecture of GENIUS with BizConsulter game instance, SOCOM.KOM middleware and facebook. The most relevant parts are highlighted (Legend in Sect. A.1.1)

design focuses on this social media news feed for publication without loss of generality.

The game instance uses the player's profile information provided by SoCom.KOM to configure the name of the protagonist in the game accordingly. Likewise, the game adjusts the city in which the game story is taking place to the user's city of origin. Depending on the gender of the user a new influence instance is created using the influence type of *single choice* with activated option for provision of own free text answers. This influence is used to ask peers (on Facebook) to contribute a name for a NPC in the game. If the player is female, the users are asked to name the grumpy character of the male senior accountant in the game. If the player is male, peers contribute name ideas for the female assistant of the senior accountant. In the influence web interface, peers can post own proposals or vote on names already proposed by others. Additionally, the game posts intermediate achievements of the player to the social media application and reads the number of supportive reactions on it. In the case of Facebook, these reactions are called *likes* that are given by peers to the news feed posts. Depending on the number of these likes, the dialogue of the protagonist with the female assistant of the senior accountant will be more or less complicated. In other words, if the player is popular and his news feeds are liked, the assistant will be more open to helping him. More details about the implemented game adaptation and game characteristics can be found in Sect. A.2.4.2.

In summary, three aspects of using social media metrics and interactions to adapt the gameplay are used in BizConsulter:

1. a personalization by user profile information,
2. a game flow adaptation by Facebook *likes*, and
3. the integration of contributed names into the game's dialogues.

7.2.4 Implementation

For better usability and extensibility a client side stub was implemented which can be provided to game developers later on. This stub allows local method calls and hides the communication channel implementation between client and SoCom.KOM middleware server.[8] Currently, clients are available for C++, C#, the game engine Unity 3D (via C#), and PHP5. The server-side APIs expect HTTP GET or HTTP POST requests with the parameters as documented. All methods return JSONs for results that may contain additional error codes and messages (e.g. for missing or invalid parameters). Void methods return at least error code 0 (for no error = OK). The BizConsulter is implemented in C++ and thus the corresponding SoCom.KOM game client is used.

[8] Even though the server-side API is completely documented and condensed in public interface definitions (cf. Sect. A.1.5).

Middleware Instance

The SoCom.KOM middleware and its modules are implemented using Java 1.6 SE Servlets[9] running on a Jetty v8.0.3 servlet container[10] and web server [23]. For persistency the abstraction layer interface to the databases is currently implemented for the relational database HyperSQL.[11] For the extensibility the implemented component for *game adaptation* registers its own namespace for the URL scheme. All sub-paths of the registered patterns (and HTTP parameters attached) are managed by the component itself.

Facebook Connection

To allow the connection of SoCom.KOM middleware with Facebook and publish news feed messages in the name of the player, a Facebook application was created and is used for the OAuth protocol-based access [24].

The middleware-side plugin (Facebook connector) implements the necessary SoCom.KOM interface to allow calls by SoCom.KOM core in order to

- Publish announcements for (new) participation possibilities in the name of the player (cf. Fig. 7.11a)
- Post content (e.g. achievements or photos for album) related to a game scene (cf. Fig. 7.11b)
- Retrieve the (URL) for login and access provision (e. g. for the OAuth protocol)
- Retrieve (and cache) profile information about the player
- Retrieve information and metrics concerning the ego-network (e. g. friend-list)
- Manipulate or remove formerly published content
- Deactivate the access rights of SoCom.KOM for this specific social media application for the current user

The plugin (Facebook connector) provides a list of supported methods to allow game developers to disable game functionality depending on the (missing) support for specific features of the social media application a player has granted access to. For example, if Twitter is the only application the player has granted SoCom.KOM access to, the game developers may decide not to publish temporarily available hyperlinks in the case it is not possible to remove such published hyperlinks from the Twitter feed of the player after a while.

Web Frontend

To keep dependencies from functionality provided by social media applications as small as possible, participating users are redirected to the SoCom.KOM specific web application via published hyperlinks as described in the concept (cf. Chap. 5) .

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[9] cf. Oracle Java 1.6 SE Documentation, http://docs.oracle.com/cd/E17802_01/webservices/webservices/docs/1.6/api/overview-summary.html last visited on September 19, 2013.

[10] cf. Eclipse Foundation Jetty 8.x Documentation, http://download.eclipse.org/jetty/stable-8/apidocs/ last visited on September 19, 2013.

[11] cf. HyperSQL Documentation, http://hsqldb.org/web/hsqlDocsFrame.html last visited on September 19, 2013.

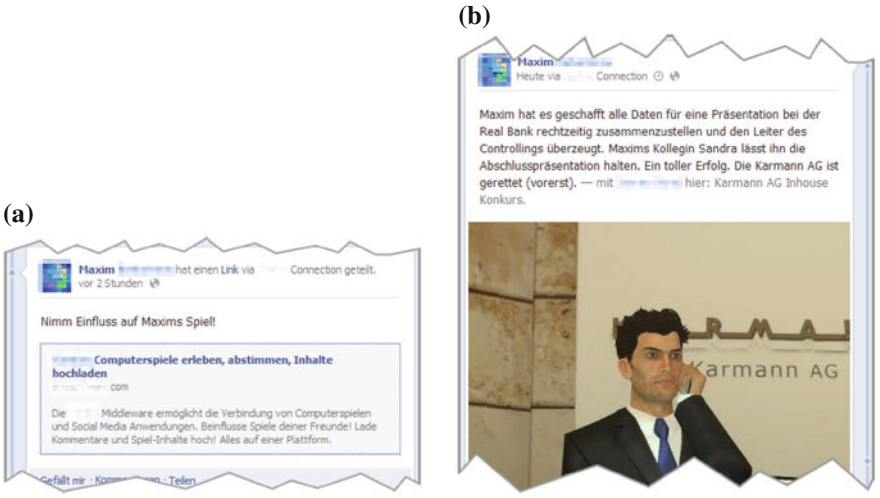

Fig. 7.11 Post examples promoting a new influence participation (*call for action*) for peers and a new achievement on facebook. All texts are in German (due to game language dependencies). Image sources: Facebook, BizConsulter game. **a** News post announcing an influence. **b** News post with new achievement

The user front end is implemented as a Google Web Toolkit v2.5 (GWT)[12] application running on the same Jetty instance as the SoCom.KOM middleware itself. If the user opens a URL pointing to a SoCom.KOM participation, the GWT client-side code extracts the participation ID from the URL and fetches the participation data in JSON format from the server-side methods and renders the Graphical User Interface elements in the user's browser. Currently, the user front end can display all combinations of selectable pre-defined options for text, audio, and images as well as the corresponding previews and upload components. For user-provided options the name and time of upload is displayed for others and a hyperlink is set to the SoCom.KOM player profile of this user (indicated in Fig. 7.12a by the small text lines).

If the timeout is within the next five minutes, a countdown is displayed. After timeout the view switches to displaying the results of the participation with some statistical information. Thus, the user frontend provides valuable information even if someone follows a published URL after the timeout (as shown in Fig. 7.12b).

[12] cf. GWT Documentation, http://www.gwtproject.org/doc/latest/DevGuide.html last visited on September 19, 2013.

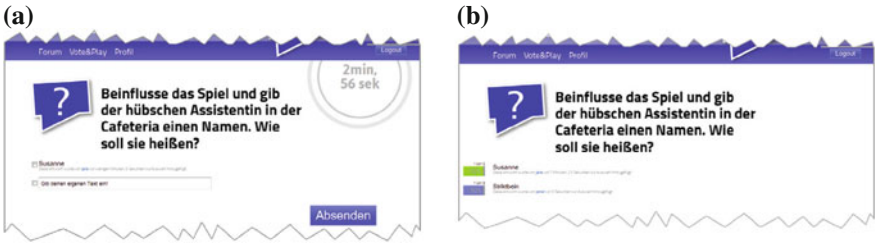

Fig. 7.12 Example screens of a influence with free text options before and after timeout (two contributions, each voted once). All texts are in German (due to evaluation scenario). **a** Participation of type *text*. **b** Participation results after timeout

7.2.5 Evaluation

Design

For all GENIUS-related research questions online questionnaire items were designed. Is aimed to cover both sides of the resulting interactions by the questionnaire: the perception in the game on one side and outside of the game (on Facebook and via web interface) on the other. This results in seven questionnaire items:

1. Player's attitude towards personalization via social media profile information[13]
2. Player's attitude towards posting of achievements and messages on Facebook
3. Player's attitude towards content-contribution and influence by peers
4. Player's assessment of technical functionality
5. Peer's attitude towards posts of achievements (consistent with 2.)
6. Peer's attitude towards content-contribution and influences (consistent with 3.)
7. Peers's assessment of technical functionality (consistent with 4.)

Each item was encoded by three statements to be agreed or disagreed on a 10-point Likert scale. One of the three statements was an inverted for reliability reasons. This results in 12 statements for the game player perspective and 9 statements for the peer perspective (A detailed list of the questionnaire statements can be found in Sect. A.2.4.1).

Beside the questionnaire items asking the participants about their attitude towards the social media interactions and profile information usage, the difference in game experience is of interest in research questions R2 and R3. For these research questions, it is necessary to design the evaluation with different groups of participants to compare the user experience of game version with the game adaptation and without. A standardized user experience questionnaire exists from Nacke [25]. It has been used as a base to develop a User Experience Questionnaire (UXQ) that suits the evaluation of serious games experience. The reliability of the resulting (UXQ) has

[13] There is no questionnaire item corresponding to the personalization (1.) from the peer's perspective as the social media profile information are used for personalization without any interaction by peers.

been shown before by evaluation in cognitive psychology with other game prototypes [26]. In summary, the UXQ measures 7 aspects[14] with 3 statements each to calculate from overall 21 statements the scores for a User Experience score. All statements are rated by participants on a 10-point Likert scale (consistent with the setup of the questionnaire items 1–7 described above).

Setup

The evaluation was conducted between 17th and 20th June 2013 with students enrolled in the master's degree for computer science at the Technische Universität Darmstadt. All participants were attending the serious games course in summer term 2013. Due to privacy protection each participant was given a new Facebook test account. The participants enrolled to time slots of 1 h for attendance and where assigned to groups of up to 8 members depending on the selected time slots. All test accounts of the members of the same group have been made Facebook-friends among each other before and their social media profiles are left clean. At the beginning of the evaluation with each group, the participants are instructed to set their first name and an individual profile picture to allow some identification with their profile. They are divided randomly into two groups to allow an A–B-test setup. While Group A is expected to play the game first, group B is instructed to fill out the provided Facebook profile with further information, upload pictures and be aware of the events in their surrounding social network as they would usually do when using Facebook. Afterwards the tasks between the groups are switched.

The evaluation is divided into four phases:

1. *Phase (15 min):* Members of group A play a simplified subset of the gameplay that can be finished within the provided time. Members of group B use their Facebook profile, add more information, and react to events they may be aware of. During the gameplay of test persons from group A, the game instances create and publish via the SoCom.KOM game adaptation component new participation possibilities on Facebook that can be seen and activated by members of group B. Additionally, the game publishes success messages of gathered achievements with screenshots from the game on the players' Facebook wall that can be as well liked and commented by the members of group B. This influences the gameplay of the players as described above in Sect. 7.2.3.
2. *Phase (10 min):* Members of both groups fill out the corresponding parts of the questionnaire (group A questionnaire parts 1–4, group B 5–7). Members of group A fill as well the UXQ to assess their gameplay experience.
3. *Phase (15 min):* Roles are switched. Now members of group B play the game and members of group A are advised to use the provided Facebook profile, add information and react on events.
4. *Phase (10 min):* The remaining questions of the UXQ are completed by both groups (group A now answers questionnaire parts 5–7 and group B answers

[14] The seven aspects are: negative emotion, positive emotion, cognitive load, motivation, immersion, flow and arousal.

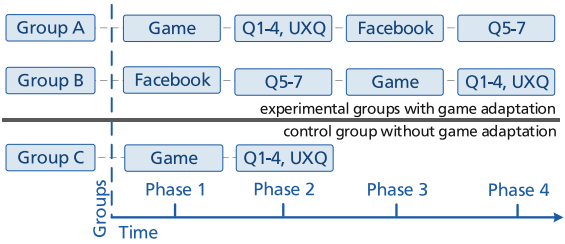

Fig. 7.13 Evaluation setup variations A–C

parts 1–4). Additionally, members of group B fill the UXQ for their gameplay experience.

To investigate the effects of the game adaptation aspects (RQ2, RQ3) to the user experience and attitude , about one third (∼33 %) of the participants is selected to become members of a control group. This control group (Group C) is playing the bare version of the BizConsulter game without the game adaptation (only phases one and two of the evaluation). The corresponding questionnaire is filled after the 15 min of gameplay and contained the UXQ and all questions statements (1–7), but these were rephrased to hypothetical statements.[15] Thereby, the answers can be compared with answers of users playing a version of the game with the game adaptation (Groups A and B together). The unchanged statements of the UXQ allow the comparison and investigation of significant differences between control group and experimental group. The different group setups are illustrated in Fig. 7.13.

In brief, independent variables are the belonging of participants to one of the groups (A, B or C) resulting in existence or absence of the game adaptation. Dependent variables are the questionnaire items (1–7) and the 7 UXQ's aspects. Control variables are the intensity of game usage, scenes reached in game, intensity of contributed participation content, and demographic data about the participants.

7.2.6 Results

Descriptive Statistics

Overall 70 students enrolled in the evaluation (10 f/60 m, aged 20–34), divided into 7 groups used for the experimental setups (A/B). They had between 5 and 8 members ($m = 6.857$) and in sum 48 participants in the experimental group (∼69 %, 5 f/43 m). The control group had 22 members (∼31 %, 5 f/17 m). All participants completed the questionnaire.

[15] e. g. whether they would have liked a posting of game achievements to a social media application like Facebook; a detailed list of the rephrased statements can be found in Sect. A.2.4.1.

RQ1 Participants Assessment of the Technical Implementation

Overall users rate the technical functionality with a mean value of $m_g = 6.233$ for the game and $m_s = 6.326$ for the social media interactions on the 10-point Likert scale. No significant differences exist, as illustrated in Fig. 7.14. The control group could not rate the technical functionality of the Facebook integration and dynamic web frontend as they solely used the bare version of the game and had no Facebook interaction.

RQ2, RQ3 Change of Game Experience by Game Adaptation Functionality

Findings for research questions RQ2 and RQ3 are established by comparing the overall user experience values of the members from experimental groups (N 48) and the control group (N 22). The two-sided t-test is not significant for the seven aspects of user experience or the mean user experience value of the UXQ. A comparison of the mean values is shown in Fig. 7.15. All aspects of user experience and the total mean over all aspects are higher for the experimental group. Only the aspect of negative emotion prevention is lower for the experimental group. In general, beside the emotional aspects all user experience values are below the center value of the Likert scale and thus are not agreed by the participants.

If the groups are compared after filtering out the 15 participants who did not receive any content contribution (in experimental group) to their game, then the value differences increases, but still the significance is not given. Nevertheless, this leads to an alignment of the aspect of negative emotion prevention which is then likewise higher for experimental group ($m_{EG} = 6.293$, $m_{CG} = 6.045$).

Investigation of the acceptance of social media personalization and influences from outside the game, reveals significant differences between experimental and control group ($m_{EG,1} = 6.639$, $m_{CG,1} = 3.046$ with $p < 0.001$, shown in Fig. 7.16). It can be seen that the control group declines this aspect with a value below the average value of 5.5 and the experimental group has a positive attitude towards it. An additional significant effect exists for the attitude towards posting of achievements to social media even though both mean values are below the Likert-scale average value ($m_{EG,2} = 4.799$, $m_{CG,2} = 3.758$ with $p < 0.05$). Details about the corresponding t-test can be found in Sect. A.2.4.3.

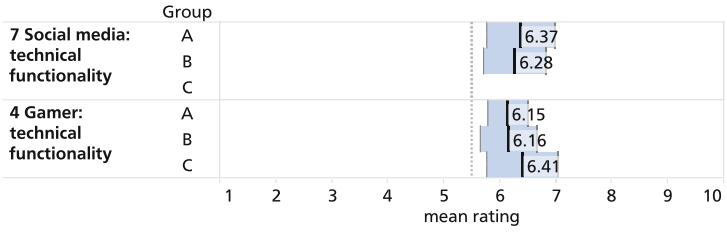

Fig. 7.14 Rating results for technical functionality on a 10-point Likert scale (with 95 % confidence intervals)

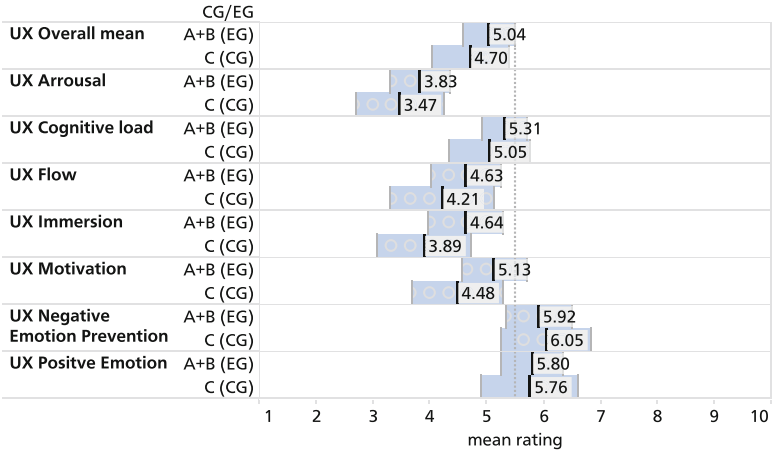

Fig. 7.15 Mean user experience values of control group and experimental group on a 10-point Likert scale (with 95 % confidence intervals)

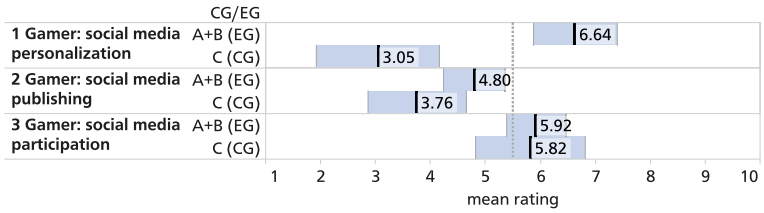

Fig. 7.16 Mean gamer acceptance values of control group and experimental group on a 10-point Likert scale (with 95 % confidence intervals)

All users value the aspect of influence on gameplay from outside slightly positive ($m_3 = 5.89$) but with no significant difference between both groups (in Fig. 7.16 listed as *3 Gamer: social media participation*).

RQ4 Participants Assessment of the Social Media Interaction Possibilities

In the questionnaire the acceptance of the publication of achievements, calls for participation and the possibility to influence the game, is only assessed by members of the experimental groups (A and B) as the control group played the bare game only and cannot assess the Facebook aspects. Among the experimental groups no significant difference exists between setup A and B. The participants rate the perception of the achievement publications of the player and the possibility to contribute likes and comments to it with $m = 6.28$ ($m_A = 6.27$, $m_B = 6.29$). They rate the possibility to influence the game and the related content-contribution possibilities with a higher mean value of $m = 7.10$ ($m_A = 7.03$, $m_B = 7.19$). The results are displayed in Fig. 7.17. Both items receive a value higher than average.

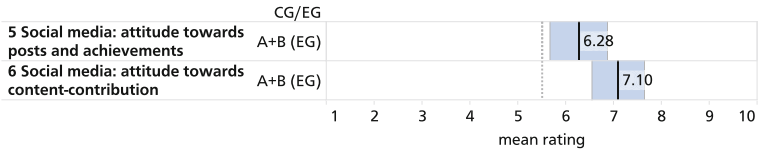

Fig. 7.17 Mean social media acceptance values of experimental group on a 10-point Likert scale (with 95 % confidence intervals)

7.2.7 Interpretation and Limitations

RQ1 Acceptance of the technical implementation for game adaptation
The technical extension by social media profile personalization and participation did not lead to a significant difference in the technical assessment of the game. Both, experimental and control group assess the technical game implementation with values between $m_A = 6.15$ and $m_C = 6.14$ (cf. Fig. 7.14). Thus, the technical implementation is rated a bit above average (5.5). The result can be interpreted as a more satisfactory than unsatisfactory solution, but participants see room for further improvement.

The social media functionality is rated, on average, better than the game functionality ($m_A = 6.37$ and $m_B = 6.28$). As the control group could not use the social media components, no rating of this group exists.

It is reasonable to conclude that the technical implementation on both game and social media is satisfactorily assessed above average, but this leaves aspects open for improvement. No significant difference exists between the groups. Especially the order of game and social media usage made no significant difference to the assessment.

RQ2 Gamer experience improvement by social media personalization, and RQ3 Gamer experience improvement by participation and content-contribution
For both research questions, the resulting values in user experience of the experimental group do not significantly differ from the control group's results, but at least all user experience measures have higher values for the experimental group (cf. Fig. 7.15). Thus, only a tendency can be shown. In general the values are mostly below average rating value[16] which seems to show the overall low acceptance of the game itself. It can be argued that a unsatisfactory game, which is not able to satisfy any of the user experience expectations, may as well lead to an ignorance and dissatisfaction of the extending functionality given by game adaptation. In this case, the results may not be significant due to the chosen game.

Nevertheless, the differences in the assessment of the functionality itself (independent of the user experience) are quite clear (cf. Fig. 7.16). The significant higher scores for social media personalization (item 1) and the social media publishing (item 2) clearly show acceptance by the experimental group whereas the control group declines these aspects. A valid interpretation could be that a general skepticism towards game adaptation by social media results in the low values of the control

[16] The average is 5.5.

group, but the experience is very positive for participants in experimental groups. From the game player's point of view (experimental group), the game adaptation via content-contribution and participation (item 3) is not significantly better rated compared to the control group. Both, control and experimental group, value this slightly positive ($m_{CG} = 5.82$, $m_{EG} = 5.92$). Investigating this further, it can be seen that the rating values given for participation and content-contribution from the social media perspective are relatively high. Additionally, there is a significant correlation between item 6 and item 3 ($r = 0.319$, $p < 0.05$). Consequently, a higher acceptance value of content-contribution from a social media perspective leads to a higher acceptance value of such content in one's own gameplay.

In brief, for RQ2 it can be concluded that the acceptance of such social media personalization and publishing to social media news feeds significantly increases when implemented as given in the GENIUS scenario. The rating for the aspect of personalization change from strong disagreement to agreement. From a social media user's perspective, the posts and achievements are accepted.

RQ3 cannot be answered with the same definiteness, because no significant improvement of acceptance could be shown between control group and experimental group. Still, from gamer's perspective and social media user's perspective, the functionality of content-contribution and participation is accepted with rating values above average.

RQ4 Acceptance of the possibility of social media interaction functionality
Figure 7.17 illustrates a general acceptance of the conceptual functionality given to game adaptation by social media profile data (item 5), content contributions, and participation (item 6). The values for the more creative and open aspects of content-contribution are more than 10 percent higher than the pure adaptation via social media achievement posts, commenting, or voting ($m_{item5} = 6.28$, $m_{item6} = 7.10$). In conjunction with the results interpreted for RQ2 and RQ3, it can be concluded that game adaptation that allows for more content-contribution (social media interactions of posting and sharing instead of voting and commenting) is generally more appreciated and even accepted if only assessed in hypothetical item questions (as seen in the similar and common positive attitude to autoeditedtem 3 in Fig. 7.16).

7.3 GroupAL

The quality of the group formation algorithm is evaluated by comparison with existing algorithms from related work (cf. Sect. 2.1.3). Even though for evaluation of effectiveness this thesis could focus on the improvement of social media content recommendation (via content integration component, cf. Chap. 4) or to match the most suitable peers for game adaptation via participation (cf. Chap. 5), it seems to be more reliable to evaluate the algorithm as a general solution to the group formation problem.

Group Formation Problem As outlined in learning group performance depends on the suitable matching of group members. In E-Learning scenarios, where peers may not know each other in advance, at best these group formations tend to be randomized. The problem to form appropriate groups, respecting simultaneously homogeneous and heterogeneous matching criteria, has been identified as the *group formation problem* in Sect. 2.1.3.

Accordingly, the algorithm and evaluation is focusing on E-Learning scenarios and refers to the four algorithm requirements from the analysis in Chap. 6. These are characterized by a greater amount of users or be matched into learning groups and in unsupervised applications the group formation process cannot be moderated by instructors. The algorithm GROUPAL, as defined in Chap. 6, is a contribution towards a qualitative matching of peers respecting n-dimensional criteria (homogeneous and heterogeneous) while forming equally good groups of a fixed size from the set of participants to match.

7.3.1 Approach and Scenario

In the evaluation approach the focus lies on E-Learning scenarios where online course systems are used (e. g. Moodle[17]). These scenarios are characterized by a variable number of students attending one course. In the following the number is expected to be up to 500 participants, as sometimes possible for first term lectures (e. g. in computer science). It is inherent that especially here students are unable to select a good set of fellow students to form a learning group; first, because in first term no friendships are yet established and fellow students are mostly unknown; second, because the support function of a course system leads to more unpersonalized information exchange online makes effective group formation even harder. A more detailed discussion on the group formation problem can be found in Sects. 2.1.2 and 2.1.3).

7.3.2 Research Questions

Based on hypothesis H4 (Sect. 3.3) the following research questions are specified for the evaluation of the GROUPAL algorithm: the scenario to support a more effective peer matching for peer education in educational games.

RQ1 Are there differences of the defined GROUPAL matchers concerning group formation quality?

RQ2 How robust is the algorithm towards not uniformly distributed criteria values among the participants?

[17] Moodle Course Management System, https://moodle.org/ last visited on August 30, 2013.

RQ3 How much improvement brings optimization by permutation?
RQ4 How will the GROUPAL formation results differ from results created by related work algorithms?

The hypothesis aims for an algorithm respecting only the relevant criteria of learners to support effective peer matching for peer education. As manifold side-effects can occur when the algorithm is purely evaluated based on effectiveness of the matched groups (e. g. compared to randomly matched groups) in learning scenarios, it is more suitable to evaluate the group formation results itself first and show here their suitability concerning the group performance index metric (as defined in Sect. 6.2.2).

Thus, RQ1 will investigate how the characteristics of the different defined matching approaches can be compared and whether there exist scenarios in which one matcher might be more suitable than the other. A primary focus lies on the Group-Centric Matcher and Participant-Centric Matcher as these are most promising candidates for research results.

In RQ2 it is shown how the group formation quality of GROUPAL changes when participants matching criteria characteristics change and are not uniformly distributed. This will deliver insight into algorithmic robustness.

RQ3 focuses on the effectivity of optimization cycles (as described in Sect. 6.2.5) and under which conditions optimization seems suitable.

Finally, RQ4 will relate the formation results of GROUPAL with the existing related work approaches. As the abilities of the related algorithms differ, two scenarios will be used for comparison as described below in Sect. 7.3.5 to prove the benefits of GROUPAL.

7.3.3 Architecture

Due to the fact that the implementation for evaluation has not been done for an application scenario with end-user evaluation in the case of GROUPAL, the implementation's architecture is identical with the architectural model described in Sect. 6.3 (see Fig. 6.1).

7.3.4 Implementation

The implementation was realized with the language C# [27] as it combines the runtime performance of C++ [28] and the ease of use of object-oriented paradigms from Java [23]. Additionally useful is the support of functional programming and data querying for effective list-manipulation [29].

For evaluation, the matcher interface was implemented for the Group-Centric Matcher, the Participant-Centric Matcher and the Random Matcher. The naive

matcher was omitted to implement as the combinations to calculate would be beyond reasonable effort, but the Random Matcher serves as the lower-bound solution.

The evaluators implemented for evaluation of RQ4 are

- GROUPAL evaluator using the Cohort Performance Indexs and Group Performance Index (cf. Sect. 6.2.2) for evaluating the performance quality of a cohort and contianing group formations,
- TeamMaker evaluator using the metric *choose-any-of* for homogeneous criteria and the metric *multiple choice* for heterogeneous criteria as defined in Cavanaugh and Ellis [30],
- OmadoGenesis evaluator using the randomizer-based metrics as defined in Gogoulou et al. [31], and
- GroupFormationTool evaluator based on the definitions in Christodoulopoulos and Papanikolaou [32].

Finally, the optimizer for re-matching the participants of the two groups with the highest and lowest group performance index has been implemented (cf. Sect. 6.2.5).

Data Generator

For evaluation it is necessary to have different sets of participant data concerning the amount of criteria to compare GROUPAL with the related work algorithms and to evaluate the behavior under different pre-conditions. Based on the underlying research for this thesis and referring to an interview with E-Learning expert Dr. Rensing[18] no data corpus exists to evaluate the matching appropriateness of group formation algorithms. As such, a randomizer based data generator has been written which generates a number of M participants with q criteria of a selected dimensionality n. The generator can be configured with a rule implementation that ensures the data generated to follow certain dependency rules. For example a dependency of specific criteria peculiarities or occurrence of values for the criteria dimension can be implemented to pe respected. By default all values are spread to be equally distributed.

The data generator implements several input and output interfaces to read and write data about participants in an XML-based format (for an example see Sect. A.1.4.2).

7.3.5 Evaluation

Design

For all research questions data about participants is needed. To suit the restrictions of the related work for comparison, two different sets of participant data have been generated:

[18] Head of Knowledge Media Group at Multimedia Communication Lab, Technische Universität Darmstadt, Germany; interview conducted on April 24, 2013.

Set1 $M = 500$ participants, each with 1 criterion $k_{het,1} \in K_{\text{het}} \mid dim(k_{\text{het},1}) = dim(k_{\text{het},2}) = 4$. Thus the algorithms only suitable to process one criterion with maximum of 4 dimensions can be compared with GROUPAL on this dataset.

Set2 $M = 500$ participants, each with 4 criteria $k_{\text{het},1}, k_{\text{het},2} \in K_{\text{het}} \wedge k_{\text{hom},1}, k_{\text{hom},2} \in K_{\text{hom}} \mid dim(k_i) = 4 \, \forall i \in [0, 1, \ldots, 4] \wedge k_i \in K$. This set is suitable for the comparison of group formations from algorithms capable of respecting several heterogeneous and homogeneous criteria simultaneously.

Orthogonally, for both sets the following variations have been generated:

V1 Uniformly distributed values for all generated criteria dimensions' values.
V2 Normal distribution of values for all generated criteria dimensions' values.
V3 Uniformly distributed extreme values of 0 (not at all) and 1 (full value) for all generated criteria dimensions' values.

This results in six data sets available for evaluation. Each set has been generated 100 times to eliminate random effects in the generated data. If in the following referring to a set, it is always meant to run the evaluation 100 times with each generated instance of the set. For easier readability the data sets will be referenced as Set1V1, Set1V2, Set1V3, Set2V1, Set2V2, and Set2V3.

For RQ1 and RQ2 a comparison of results from all four matchers is made for the three more complex data sets of Set2 (Set2V1–V3). RQ3 can be answered by comparing the results of the matcher comparison for RQ1 and RQ2 to identify the closeness to the maximum value of formation quality results of the Group-Centric Matcher or Participant-Centric Matcher. Based on this, a comparison can be conducted using the matcher result with and without several cycles of optimization to identify the effectiveness and suitability of optimization cycles. For RQ4 GROUPAL will be compared in two different setups (see below) with the related work algorithms.

Setup

For RQ1 and RQ2 (as well as basis for RQ3) the following Setup α is used. Based on the results, Setup β investigates the optimization cycles aspect.

The focus of the evaluation is the comparison of the GROUPAL algorithm group formation results with the group formation of existing algorithms of related work. To account for the different abilities of the algorithms the last two setups γ and δ were used for RQ4:

Setup α (RQ1, RQ2, RQ3): Using the more comprehensive Set2 in all variations (Set2V1–V3) to compare the three implemented matching algorithms of GROUPAL.
Setup β (RQ3): As a successive comparison to Setup α the same set and variations are used (Set2V1–V3) to compare the improvement of the randomized matcher, Group-Centric Matcher and Participant-Centric Matcher for up to three optimization runs (each with the maximum value of cycles $R = 50$).
Setup γ (RQ4): Using Set1V1–V3 to compare GROUPAL in these three variations with the algorithms of GroupFormationTool and Together as both allow only one heterogeneous criterion at the same time (with several dimensions). As

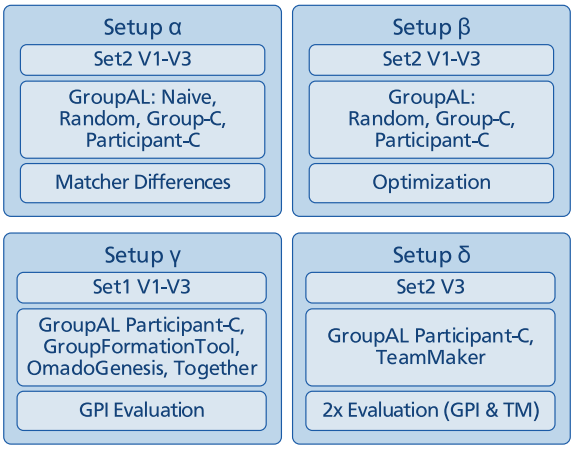

Fig. 7.18 Evaluation setup variations α–δ, each evaluated three times for matching 2, 3, and 6 group members

OmadoGenesis supports solely heterogeneous criteria for the analytic matching and otherwise uses a genetic algorithm to approximate a result when homogeneous and heterogeneous criteria are used combined, OmadoGenesis will as well be compared in this setup.
Setup δ (RQ4): As TeamMaker allows the usage of several homogeneous and heterogeneous criteria simultaneously like GROUPAL, both are compared based on Set2 to have a closer and more realistic comparison of these algorithms. In Set2 variation V3 is used (Set2V3) as TeamMaker expects criteria dimensions to have only values 0 and 1. Additionally, in this setup two evaluation variations will be done: Setup δ_1 will use both algorithms with their implemented evaluators and compare the resulting group formation quality based on the Group Performance Index defined in this thesis (cf. Sect. 6.2.2). To investigate the formation quality of GROUPAL further, in Setup δ_2 the resulting group formation quality is then assessed based on the evaluator for group formation quality (and cohort formation quality) of TeamMaker to investigate whether or not GROUPAL creates results only better for the own metric or likewise better if evaluated by the related work algorithm's metric.

In all runs of the comparisons the matchers have been configured to create groups of 2, 3, and 6 members [33]. Criteria have been weighted equally as some of the related work algorithms do not allow the weighting of criteria [31, 32, 34]. The resulting setup variations and runs are illustrated in Fig. 7.18.

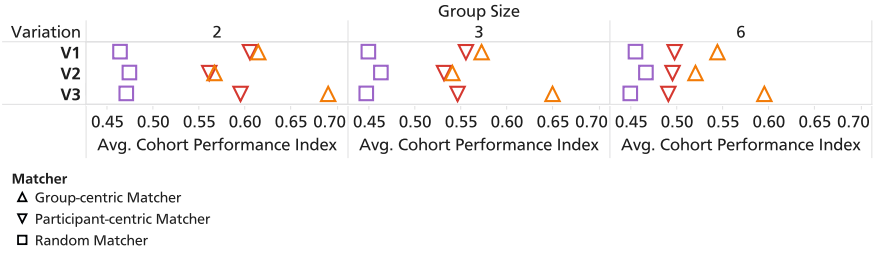

Fig. 7.19 Matcher differences in setup α

7.3.6 Results

Descriptive statistics are omitted here as the participant's characteristics are algorithmically generated. Additionally, standard deviations are all very small ($SD < 0.01$) and therefore not listed here.

RQ1 GROUPAL *Matchers' Differences in Group Formation Quality*

The average Cohort Performance Indexs is used as measure to compare the formation quality. In all variations the Group-Centric Matcher attains the highest results that is closely followed by the Participant-Centric Matcher (e. g. $m_{GCM_{G3}} = 0.59$[19], $m_{PCM_{G3}} = 0.55$, $m_{RND_{G3}} = 0.45$). A synoptic overview on the differences per variation is displayed in Fig. 7.19. It shows higher differences on variation 3, where Group-Centric Matcher reaches about 15–20 % higher values than Participant-Centric Matcher (e. g. $m_{GCM_{V3,G2}} = 0.69$, $m_{PCM_{V3,G2}} = 0.60$). The Random Matcher attains the lowest CPI values in all variations and group sizes ($\sim m_{RND_{all}} = 0.46$).

A closer look to all 100 cohorts of some of the 9 combinations (3 group sizes, 3 setup variations) reveal specific characteristics and robustness of the matchers. In variation 1 (V1) with uniform value distribution the Random Matcher performs better for group size 2 than for the bigger groups ($m_{RND_{V1,G2}} = 0.50$, $m_{RND_{V1,G3}} = 0.47$, $m_{RND_{V1,G6}} = 0.47$). With increasing group-size the difference between the values for participant-centric and Group-Centric Matcher increase and for all matchers the standard deviation decreases. Two of the nine diagrams are shown in Fig. 7.20 for comparison of results. It contains the uniform extreme value distribution (V3) for small groups (G2) on one side and the normal distribution variant (V2) for bigger groups (G6) on the other. The remaining seven diagrams as well as plots of runtime characteristics can be found in Sect. A.2.5.1.

The diagram trend lines indicate the ratio between Cohort Performance Indexs and average Group Performance Index for the respective cohort of groups. A steeper trend line indicates a higher gain in mean of all Group Performance

[19] Indices: G for group size, V for variation.

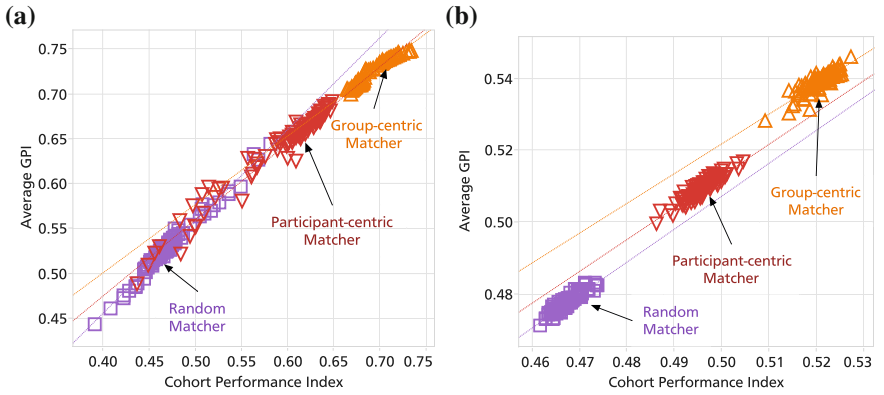

Fig. 7.20 Matcher differences in setup α, comparing variation 3, group size 2 with variation 2, group size 6. **a** Results on V3, group size 2. **b** Results on V2, group size 6

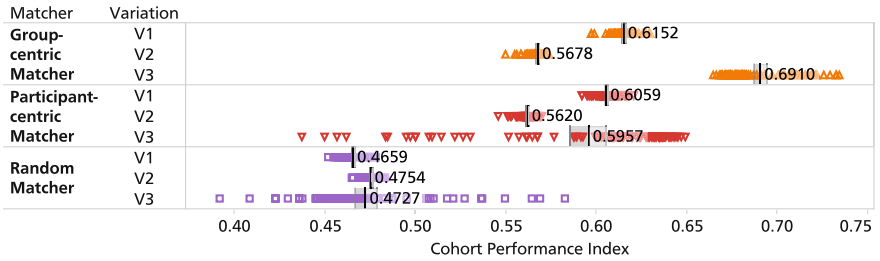

Fig. 7.21 Matcher robustness to distribution variances in setup α (with mean CPI value and 95 % confidence intervals)

Indexes when a more uniform cohort (with a higher Cohort Performance Indexs was found.

RQ2 GROUPAL *Matchers' Robustness Towards Different Value Distributions*

As shown in Fig. 7.19 before, the comparison between the uniformly distributed and normal distributed values results in the same order of matchers' quality. The Group-Centric Matcher remains as the best of the three investigated matchers in all variations. Still, the highest values are observable in variation 3 (extreme values) for the Group-Centric Matcher, whereas the Participant-Centric Matcher performs best on variation 1 (uniform distribution) and the Random Matcher performs best for variation 2 (normal distribution). For both non-Random Matchers, the differences in results within one matchers results for all three variations becomes smaller when group sizes increase.

As shown in Fig. 7.21, the mean values of the Cohort Performance Indexs for each matcher vary the least for the Random Matcher among the three different value distributions (V1–V3), followed by Participant-Centric Matcher and then Group-Centric Matcher. The variance and thus the confidence interval increases for all

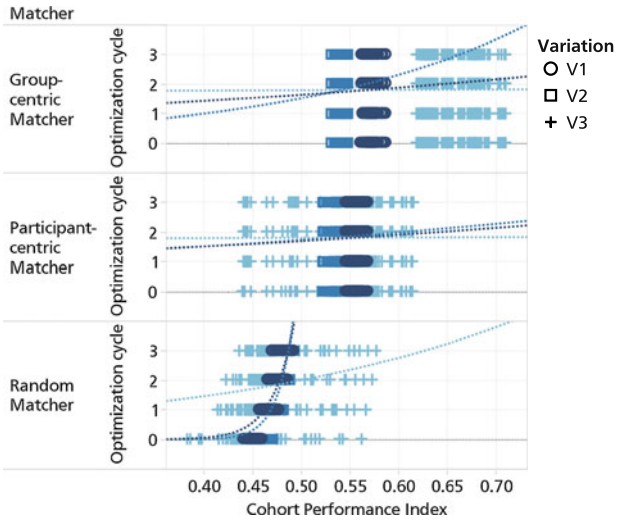

Fig. 7.22 Matcher's optimization improvement in setup β with 0–3 optimization cycles, using a group size of 3 members

matchers on the extreme value distribution (V3). A diversified investigation of the variations for each group size has similar characteristics.

RQ3 GROUPAL *Improvement by Optimization*

As the results of cohort formation is not guaranteed to be the optimal solution achievable with the given participants and their criteria values, the optimization as defined in Sect. 6.2.5 will be used up to 3 times (each with $R = 50$ maximal rounds per optimization) to improve the created cohort. The results, shown in Fig. 7.22 for group size of 3 members, indicate that the logarithmic approximation to a local optimum over all cohorts per algorithm has more impact for the Random Matcher than the others.

The trend lines indicate the logarithmic approximation of the improvement made over the optimization cycles. Each variation is shown by an own trend line. This illustrates that the most improvement for all matching algorithms can be achieved for the normal distribution variation (V2). The trend-line for the Random Matcher becomes as well quite flat when extreme values (V3) are used as a basis for optimization. A table with the improvement value percentages, as well as the figures for the other group size variations, can be found in Sect. A.2.5.2.

RQ4 GROUPAL *Comparison to Related Work Algorithms*

Comparison with Together, OmadoGenesis and GroupFormationTool
For setup γ the GROUPAL matchers were compared to the matchers Together, Omado Genesis and GroupFormationTool. As the later does match a heterogeneous criterion by randomizer only, in the following the Random Matcher is listed likewise for the GroupFormationTool. The comparison of the mean CPIs of all 100 cohort

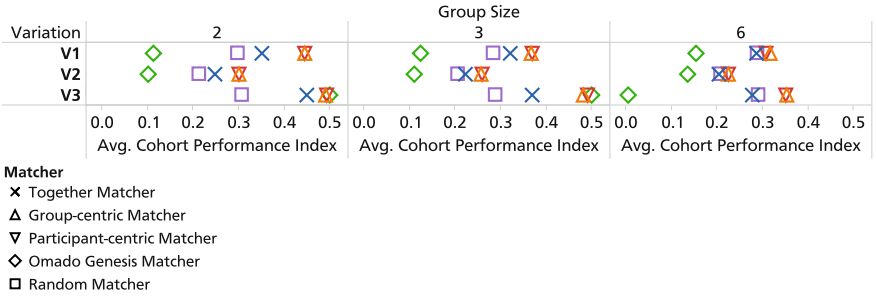

Fig. 7.23 Matcher differences in setup γ

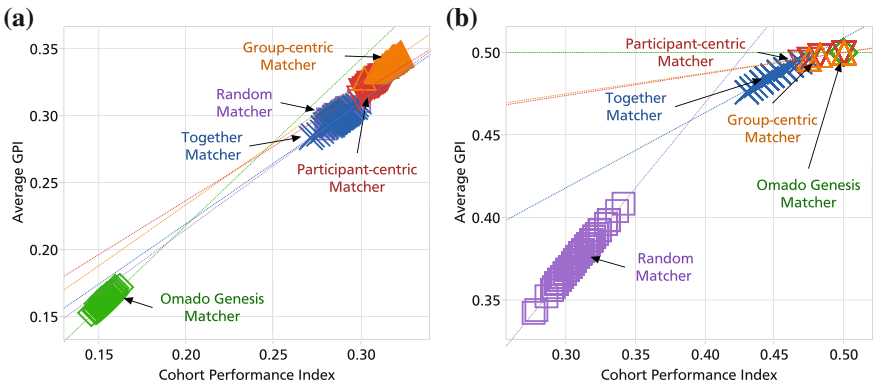

Fig. 7.24 Matcher differences in setup γ, comparing variation 1, group size 6 with variation 3, group size 2. **a** Results on V1, group size 6. **b** Results on V3, group size 2

computations in each variant and group size combination of data in Set 1 reveals some specifics of the algorithm implementations as illustrated in Fig. 7.23.

For the smaller group sizes (G2, G3) OmadoGenesis produces the highest values for the Cohort Performance Indexes for uniformly distributed extreme values (V3), but has the lowest values for group-size 6 there. In the other variations and group-sizes OmadoGenesis performs under the RandomMatcher (GroupFormationTool). In all these runs the Group-Centric Matcher and Participant-Centric Matchers return the cohorts with the highest Cohort Performance Indexs. When group-size increases Together's better results compared to the Random Matcher (GroupFormationTool) vanish.

A closer look to uniform value distribution (V1) with group sizes of 6 members compared to uniformly distributed extreme values (V3) with 2 group members to match is displayed in Fig. 7.24.

The comparison reveals the difference in results for OmadoGenesis which creates constantly equal cohorts with maximum values on extreme values (V3) as documented by the vertical trend line. Together is better as the Random Matcher (GroupFormationTool) for small group sizes and returns lower Cohort Performance Indices

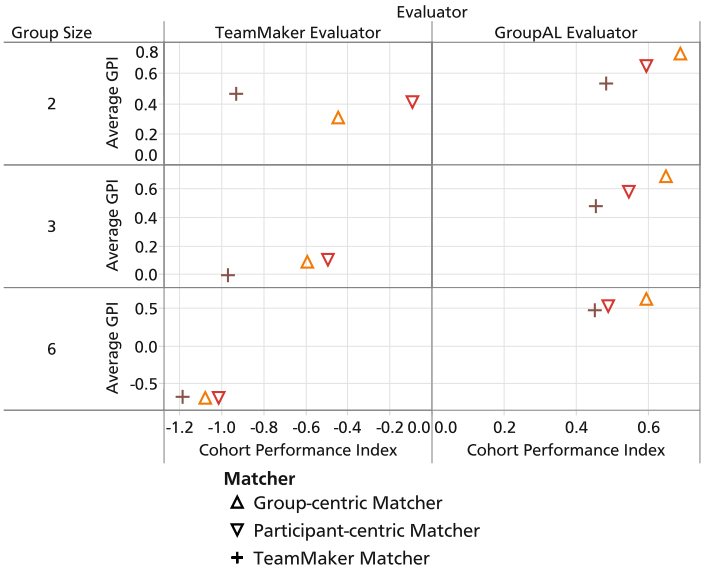

Fig. 7.25 Matcher differences in setups δ_1 and δ_2

than this on group size of 6 members. More diagrams for comparison can be found in Sect. A.2.5.3.

Comparison with TeamMaker

In Setup δ two different metrics were used to compare the results of the algorithm from TeamMaker with GROUPAL. An overview over the results for all group sizes for the used variation with uniform extreme values (V3) is given in Fig. 7.25. As TeamMaker does not normalize it's own Group Performance Index and Cohort Performance Indexs calculations the values can be negative depending on the criteria and weights [30, p.8].

As visible, the Cohort Performance Indexes of TeamMaker remain under the values of GROUPAL's Group-Centric Matcher and the Participant-Centric Matcher; even if the performance indexes are calculated based on TeamMaker's metrics after cohort construction. The average Group Performance Index is higher for TeamMaker results in the smallest group-size and when TeamMakers own evaluator is used ($m_{GPI_{TM,G2}} = 0.461$, $m_{GPI_{GCM,G2}} = 0.407$, $m_{GPI_{PCM,G2}} = 0.303$). If the TeamMaker evaluator is used among GROUPAL's matchers the values of the Participant-Centric Matcher are higher, if the GROUPAL owns evaluator is used, the Group-Centric Matcher has higher values.

A closer look at two extreme values of the 6 combinatorial plots from Fig. 7.25 will be shown for the performance indexes calculated by TeamMaker evaluator at group-size of 2, compared to the results calculated by the GROUPAL evaluator for group-size 6 (see Fig. 7.26). The remaining variations' plots can be found in Sect. A.2.5.4.

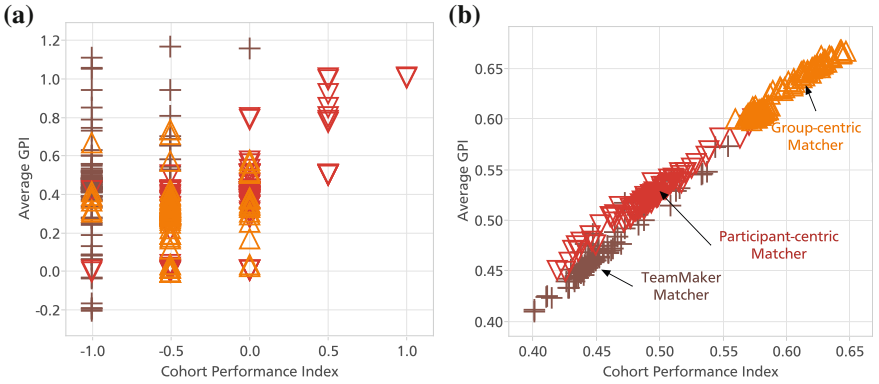

Fig. 7.26 Matcher differences in setup γ, comparing group size 2, evaluated by TeamMaker metrics, with group size 6, evaluated by GROUPAL metrics. **a** Results for group size 2 (TeamMaker evaluator) **b** Results for group size 6 (GROUPAL evaluator)

7.3.7 Interpretation and Limitations

RQ1 GROUPAL matchers' differences in group formation quality
The results show the existing differences of the three matching algorithms implemented. The Random Matcher can be considered as a lower-bound reference whose results should at least be outperformed. The higher the number of members to match the closer the achieved performance indexes of the groups are. This is a reasonable result, as the likelihood to randomly match participants so that at least one other participant's skills cover all skills needed in the group, increases with the number of group members—as long as a distribution of values among participants is given. Therefore it is more important which matching algorithm is used if only extreme values exist (V3). In this case the Group-Centric Matcher performs best as it selects the participant most likely to improve the Group Performance Index (cf. Fig. 7.20). It could be concluded that for both optimized matchers (group-centric and participant-centric) the results are similar as long as the group-size remains small and the values to match are normally or uniformly distributed. On extreme values (like binary criteria), the Group-Centric Matcher performs better. For high numbers of participants with continuous criteria value, the Random Matcher could deliver good results if computation power is an issue to consider (e. g. in environments with higher numbers of participants).

Taking into account the run-time performance of the algorithms, for smaller group-sizes (2,3) on continuous data values (V1,V2) the Participant-Centric Matcher could be considered as it computes comparatively good results (in relation to the Group-Centric Matcher) in half the time.

RQ2 GROUPAL matchers' robustness towards different value distributions
Among the three matchers, the Random Matcher appears to be the most robust matcher. It returns similar results for all variations. Among these the best results are returned if the criteria values are normally distributed (V2). Among the other

two matching algorithms, the Group-Centric Matcher has the strongest dependency on the underlying data values and distribution. Especially for discrete values, like binary criteria, this matcher outperforms the others with better cohort results. In none of the investigated cases did the participant-centric or Group-Centric Matcher deliver results below the results of the Random Matcher (when comparing the average Group Performance Index and Cohort Performance Indexs of all built cohorts). Still, especially for small group-sizes the Participant-Centric Matcher has it's limitations and returned results with lower performance values than the Random Matcher (cf. Fig. 7.21). Due to the higher standard deviations of participant-centric and Random Matcher on binary values (V3), these two matchers can be considered less stable on such values. The Group-Centric Matcher has as well a higher standard deviation on binary values, but the effect is less distinctive.

RQ3 GROUPAL improvement by optimization
Among all matchers the optimization has the highest impact for the Random Matcher. This seems reasonable, as group formation was not done considering the underlying performance metrics. It can be argued that one, maximum two, optimizations are suitable for the Random Matcher. Still, the resulting Cohort Performance Indexs does not reach the values of the other matchers. Additionally, on the extreme values, optimization for the Random Matcher and for all other matchers is less effective, as the number of participants with more suitable values are limited (by design). Optimization should then be omitted.

The Participant-Centric Matcher is, in general, not suitable for the evaluated optimization algorithm. The increase of the CPIs is low. It seems reasonable to investigate a different optimizer for the groups built by the Participant-Centric Matcher or omit optimization entirely.

The Group-Centric Matcher can optimize its results, especially for matching based on normally distributed criteria data. One cycle of optimization appears to be enough.

In general, for all matchers, variation V3 is the least suitable data basis for optimization after cohort formation, followed by variation V1, with uniformly distributed values. The best base is normal distribution based data, as this provides the most continuous criteria concerning personality traits, learning style preferences, and player type preferences, and therefore affords optimization in cases when the Group-Centric Matcher is used.

RQ4 GROUPAL comparison to related work algorithms
Surprisingly, in setup γ, OmadoGenesis seems to have a computational logic that counteracts the measures important for a high Group Performance Index. Still, for the discrete values, the algorithm finds the most suitable cohorts (V3), but only for up to 3 group members. As the next step of group-size investigated was 6 members, it cannot be exactly concluded at which point between 3 and 6 members OmadoGenesis stops finding a suitable match.

The high values for Cohort Performance Indexs and Group Performance Index are likewise reached by GROUPAL group-centric and Participant-Centric Matchers, with only small deviations in the combinations of binary data distribution (V3) where OmadaGenesis performs well. Overall, the GROUPAL matchers perform better, on

average, than all other related work algorithms (based on the underlying research and data of this thesis). A closer look at the distribution of cohorts in each of the computed variations revealed that the matcher of Together delivers as well good results, especially if group-sizes increase (3 and 6 members). Overall it can be concluded that the investigated aspects and defined metrics of GROUPAL matchers perform better, or at least as good as the related work algorithms, in setup γ. The findings need to be related to the following investigation in setup δ, as in setup γ only one heterogeneous criterion was used.

In setup δ, the four criteria (2 homogeneously matched, 2 heterogeneously matched) were used by TeamMaker and the GROUPAL matchers. Based on the findings illustrated in Fig. 7.25 it can be said that GROUPAL calculates, on average, better group formations than TeamMaker, even when measured by TeamMaker metrics. This is valid for the conditions and underlying data used for this evaluation. As TeamMaker considers other aspects like e. g. a time schedule and solely focuses on answers to multiple choice or choose-any-of questions, there might be scenarios where GROUPAL—in comparison with TeamMaker—delivers less optimal results. Due to these limitations, the comparison was only possible for the binary distributed data, as TeamMaker expects criteria dimension values of 1 (yes) or 0 (no) [30, p. 8–10].

The intervals covered by Cohort Performance Indexs values of GROUPAL and TeamMaker are overlapping in some variations' results (cf. Sect. A.2.5.3). This indicates that not always one or the other is better on a specific set of data (only on average). This effect becomes stronger when relying on the TeamMaker evaluation metric, as it sets the Cohort Performance Indexs of a cohort to the lowest Group Performance Index of all groups within the cohort. Thus, the existence of one group with a low performance index is sufficient to lower the Cohort Performance Indexs to this value. Consequently, the areas overlap more in the diagrams based on the TeamMaker evaluation metric. Here, the GROUPAL matchers can calculate cohorts of a higher overall Cohort Performance Indexs as TeamMaker, and thus manage to build cohorts where even the least suitable group created is better than in the cohorts built by TeamMaker.

In summary, the matcher and metrics defined in GROUPAL appear to be most suitable for calculating group formations based in homogeneous and heterogeneous criteria. In comparison with related work algorithms, the results of GROUPAL are more stable, of higher value, or at least adequately good in certain situations (like binary distributed data in V3 with small group-size of 2, where OmadoGenesis performs equally good).

7.4 Chapter Summary

In this chapter three prototypical implementations of the concepts of the SOCOM.KOM middleware architecture model were presented, focusing on the implemented functionality, research questions, evaluation design, and findings. In summary, the interpretation of the results reveals the acceptance of the content

integration and game adaptation by end-users. The simulative evaluation of peer group formation points out the benefits of the joint consideration of homogeneous and heterogeneous criteria for peer matching.

In PEDALE the content exchange was implemented for peer tutoring and peer assessment in a classroom setup. To allow for easier updating and customization by domain experts, an underlying authoring environment has been developed (StoryTec PE). The PEDALE functionality and usefulness was positively rated by the 183 participants, who subjectively rated both the peer feedback provision and reception of data via content-exchange as "helpful". Tendencies in the resulting data indicate the improvement in proficiency, as well. Significant impact of several attributes of the content sender-receiver matching were found and can be used as a basis for further improvement of the peer group formation algorithm.

With Genius, mainly the SoCom.KOM game adaptation was implemented and connected to an existing educational adventure game prototype. The evaluation study, with 80 participants, showed the acceptance of the concept. Furthermore the evaluation revealed a significant change in attitude towards adaptation by social media adaptation and social media publishing between control and experimental group. Presumably, due to overall low user experience values for the chosen game, only positive tendencies, with no significant impact of game adaptation to user experience values, could be shown. Still, the participants positively value the functionality of content-contribution and participation.

The GroupAL implementation was evaluated based on two sets of generated data, each with different matching criteria value distribution (uniform distribution, normal distribution and a uniform distribution with only boolean discrete values). The robustness and performance of the algorithm was investigated compared to the related work algorithms: the investigation focused on the performance and resulting Group and Cohort Performance Indices of heterogeneously matched criteria, and compared these indices with algorithms only capable of matching one criterion (OmadoGenesis [31], GroupFormationTool [32] and Together [34]). For a comparison with TeamMaker [30], a set of 2 heterogeneously and 2 homogeneously matched criteria was used. In all setups and variations the matching algorithms were used to group 500 participants in groups of 2, 3, or 6 members. The interpretation of results clearly shows the benefits of GroupAL for the overall group formation quality. However, the results are based on generated participant attributes. The acceptance by end-users and the impact on knowledge exchange or participants' performance improvements still must be shown.

Overall the concepts of content integration for peer tutoring (PEDALE) and the concept of game adaptation based on social media interactions (Genius) have been accepted by the participants. The implementation feasibility has been demonstrated by these first prototypes. Significant improvement of proficiency or user experience were not found, but tendencies are identifiable in the results.

The most clear results could be found for the peer group formation implementation (GroupAL). The algorithm provides better group formations and respects the pedagogical requirements identified from related work. It even gains

higher group formation quality values if resulting cohorts are assessed by metrics of the TeamMaker algorithm.

The findings can be interpreted as a sound first step towards the use of social media for peer education in educational games.

The following final chapter will conclude the thesis and critically assess the approaches, prototypes and results.

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Chapter 8
Conclusions and Outlook

Learn from yesterday, live for today, hope for tomorrow.
The important thing is not to stop questioning.
Albert Einstein

This thesis presented the three-tier approach towards the use of social media interactions for peer education in serious games. Major results include the SoCom.KOM middleware concept, including the components for content integration, game adaptation and peer group formation. In evaluation studies with implemented prototypes for three scenarios the applicability of the approach and concepts behind SoKom.KOM has been shown.

Before concluding and summarizing the thesis contributions in Sects. 8.2, 8.1 will critically reflect on the initial thesis objectives. Finally, the outlook in Sect. 8.3 will give a brief overview of potential future aspects for research, based on the knowledge generated from thesis.

8.1 Critical Reflection on Thesis' Aim

In Sect. 1.1 this thesis claimed to bring the fields of serious games and social media closer together. From a technical perspective the thesis focused on the provision of definitions, architectural frameworks, and algorithmic solutions. To investigate the suitability of the three components (1) content integration, (2) game adaptation, and (3) peer group formation of the defined SoCom.KOM framework, four hypotheses were defined (Sect. 3.3). To which extend these hypotheses are proven to be true, is reflected critically in the following.

H1 The use of peer education concepts based on user-generated content can positively influence the effectiveness of a serious game.

J. Konert, *Interactive Multimedia Learning*, Springer Theses,
DOI 10.1007/978-3-319-10256-6_8

The defined aspects of peer education (Sect. 2.1.2) were implemented and evaluated with the rapid prototyping environment StoryTec PE in the PEDALE application scenario (Sect. 7.1). Even though the conceptual approach and design was honored,[1] not all research questions could be fully answered and supported by significant evaluation data (Sect. 7.1.7). It has been shown that the concept has been accepted by the participants. No significant proof was found that the peer education concept lead to better effectiveness (better performance) of participants. Still, tendencies were clearly visible in the evaluation results. In addition, it can be critically questioned how many aspects of gaming were evident in the PEDALE scenario to allow a generalization of the findings for serious games. Nevertheless, PEDALE delivered insight into dependency of peer feedback's effectiveness and perception by receivers depending on combinatorial aspects of the sender-receiver matching. This supported the design of the peer group formation component and the resulting GroupAL algorithm (Chap. 6).

H2 The use of social media interaction can enhance users' acceptance of a serious game.

The game adaptation component was designed to support the use of social media profile data in the game and furthermore allow the publication of game participation in order for peers to contribute content and influence the game (social posting and voting, cf. Chap. 5). The resulting software solution and scenario, Genius (Sect. 7.2), showed a significant shift from denial of such functionality to acceptance between the evaluation groups playing with or without the extensions (see RQ2, RQ3 in Sect. 7.2.6). Still, for user-experience measures, the tendency towards a higher user experience with game adaptation was shown in the results, but no significant difference could be proven. This was interpreted as being partly caused by very low experience values for the underlying serious game prototype. Nonetheless, from both perspectives (participants using the game and participants using the social media components) the provided functionality of content-contribution and participation was rated above average and can be interpreted as being accepted. In the end, the hypothesis could not be proven or supported by significant results, but the functionality of the game adaptation component itself has been shown to be functional and accepted by participants.

H3 Game developers can profit from an architectural solution supporting content exchange and game interaction.

Based on the SoCom.KOM architectural design (Sect. 3.6) a qualitative study was employed through the use of expert interviews, which afforded the capacity to ask game developers for assessment of the functionality, conceptualization, and interest in using such a solution. The results indicate the acceptance, strong support, and interest in using such a solution. Still, the interviewed game developers did not use the architecture itself and thus, the expression of interest has to be questioned critically. A profit was not measured in figures. Still, the hypothesis is supported by

[1] Best Paper Award for the publication in [1].

the results of the study. A field study with architecture usage by game developers could follow.

H4 A new algorithm can be found supporting the group formation with homogeneous and heterogeneous matching criteria. This algorithm should be capable of respecting relevant personal characteristics of the learners and the scenario in order to support an effective peer matching for peer education in educational games.

Based on the findings from related work on the group formation problem (Sect. 2.1.3) and the importance for peer education to build suitable peer groups for content exchange and game interaction, the indicators for matching criteria as identified in PEDALE (Sect. 7.1) were used as a basis to define the peer group formation (Chap. 6) and the GROUPAL algorithm (Sect. 7.3).[2] The evaluation results show strong benefits of the algorithm for the investigated scenario. Still, the results are based on simulation and generated data and should be valued only critically. The support for the hypothesis based on these findings appears to be quite strong.

8.2 Concluding Summary

Due to the interdisciplinary nature of this work, a thorough introduction to related work has been provided in Chap. 2 including the findings this work is based on and the used nomenclature in the fields of peer education, social media, and serious games. As one major result, the limitations in educational games and the four needs to be fulfilled by the usage of social media interactions, have been identified (Sect. 2.2.4).

As the research field of social serious games appears to be not widely addressed, boundary conditions (Sect. 3.1) and a definition of social serious games was developed (Sect. 3.2). As a result, the architecture of SOCOM.KOM was proposed (Sect. 3.6) to support (1) content integration and exchange of user-generated content, (2) game adaptation by social media profile information and the new concept of game participation based on social interactions, and (3) the peer group formation to support the creation of effective peer groups. This was proposed for (1) content integration and exchange as well as (2) game adaptation by participation. The components are designed to support the identified needs of social interaction, peer tutoring, peer collaboration, and suitable tasks.

For content integration, a model has been developed with the four elements of game context mapping, content metadata, semantic content categorization, and open content type support (Chap. 4). Furthermore, a dual achievement system was proposed, combining game-based and community-based achievements, to increase the incentives that facilitate the creation and contribution of content (Sect. 4.5).

[2] Honored with a Best Paper Award for the publication in [2].

The analysis for game adaptation lead to the support for adaptation by social media profile information and metrics (Sect. 5.1) and the social interaction patterns for educational games (Sect. 5.2.4).

As the peer group formation component primarily addresses an optimization problem, it first defines the modeling of matching criteria and how n-dimensional homogeneous and heterogeneous criteria can be respected with weights simultaneously (Sect. 6.1). As a consequence of the identified requirements, classical clustering might not be sufficient, as fixed group sizes are requested and the difference in formation quality of all groups is desired to be as small as possible. The proposed metric Group Performance Index (Sect. 6.2.2) was deduced from the requirements and lead to the definition of several matching algorithms (Sect. 6.2.3). Based on this, the quality of the group formation process is measured with the deduced Cohort Performance Index (Sect. 6.2.4). This allows for the comparison of formation qualities among different matcher algorithms and is independent of criteria exchange or changes in criteria weights.

Finally, the implementations of the concepts and their evaluation have been presented (Chap. 7). With PEDALE (Sect. 7.1) the peer tutoring and peer assessment based on content exchange has been investigated in a classroom scenario. Results show the acceptance of the technical functionality and the concept. Likewise tendencies for performance improvement based on peer tutoring and assessment could be shown, but not significantly. Several dependencies and significant correlations could be found, influencing the quality of peer feedback and it's perception. These findings were used as a basis for the design of the peer group formation component.

With GENIUS (Sect. 7.2), elements of game adaptation were implemented to connect an existing educational adventure game prototype with the social media platform Facebook and evaluate the functionality, acceptance, and impact of game adaptation. Acceptance has been shown, as well as the change in attitude from decline towards acceptance between control group (not using the game adaptation) and the experimental group. Presumably, due to the low user experience values for the game, the user experience did not increase significantly with the game adaptation component. The functionality of content-contribution and participation was valued positively by the participants.

The implementation of GROUPAL (Sect. 7.3) reflects the mathematical definitions of the peer group formation component. The two implemented matchers proved to achieve significantly better results than the algorithms from related work (Omado-Genesis, Together, GroupFormationTool and TeamMaker), even if compared to the related work algorithms' metric (only suitable and done for TeamMaker). As such, based on the different generated data sets and data distributions used, the GROUPAL evaluation proved the benefit of the approach.

8.3 Outlook

The findings of this thesis are expected to be the first step for improvement and future research on social serious games. Likewise the presented concepts, implementations and solutions cover a broad and interdisciplinary field with manifold promising open aspect to further investigate.

Variations of Evaluation Studies

The evaluation studies were of a certain scale, but some expected findings could only be shown by tendencies and not with significant differences in the data. It seems promising to repeatedly conduct the GENIUS evaluation with a competitive game prototype and more game adaptation aspects offered. As social media-based influencing and adaptation appears to be a quite new field of research, aspects that investigate the most suitable game types, interactions, and impact on learning with educational games are open to further study.

The study on the impact of content-exchange in the classroom scenario, as done with PEDALE, could be conducted with an adapted setup. Using a longitudinal study that allows peers to give and receive more feedback is expected to deliver better insight into the impact of peer feedback. Manifold side-effects can exist that otherwise overlay the intended knowledge-transfer by peer education and thus lead to insignificant differences between experimental and control group.

Specifically, based on the insights won from the first study, the pairings of feedback sender and receiver should not be randomly chosen any more, but based on the gained insight into the relevance of several matching criteria, the GROUPAL algorithm could be used to match selective. Thereby the impact of specific matching criteria on feedback quality could be investigated.

The findings from the study with GROUPAL are a promising base to conduct user studies designed by domain matter experts from pedagogics and pedagogical psychology using the algorithm to evaluate the impact on learner's advancements in a game-based learning scenario or E-Learning environment. Ideally, such a study compares different configurations and assesses the effectiveness compared to the solutions from related work.

Extension of Matching Conditions

After the proof of the peer group formation algorithm's performance with GROUPAL, the system should be further extended to take into account more side-conditions like triadic peer dependencies, metrics from social network analysis about tie-strength, and metrics on community-clusters [3–5]. Especially in E-Learning scenarios, the effectiveness of learning groups might benefit from such continuation. Beside homogeneous and heterogeneous criteria it is considerable to allow hybrid criteria, e.g. criteria like extroversion should be matched heterogeneous, but with a maximum

difference value for each pair (or additionally a maximum targeted mean of all group members values on extroversion). Such extensions allow more complex conditions that can be important to allow the group formation with heterogeneous criteria, while at the same time avoiding too diverse matching results. Moreover, the weights of criteria to be used for matching, could be drawn from the findings in PEDALE concerning the impact on feedback in the peer tutoring scenario.

Handling Missing Data and Big Data

At the moment the peer group formation does not address the missing data problem. Robustness for sparse and missing data is an important aspect for practical use of the matching algorithm, especially if personal information (like personality traits) is used as criteria for matching [6]. In this case, the algorithm could be extended to use probability tables or machine learning algorithms, used to guess the most likely value depending on correlations within the criteria values. The main challenge to address with such an approach is the correct clustering and detection of similarities among individuals and groups of individuals between several scenarios in which the algorithm is used, even though differences between the scenarios may exist due to target group variations, different cultural backgrounds or variations in criteria value measurement.

Likewise, handling huge groups of participants to match is a challenge in itself. Run-time optimization of the algorithm might be considerable if peer group formation is desired for huge E-Learning courses like some of the currently popular Massive Open Online Courses. Parallelization, caching and pre-calculation could be considered then.

Content Recommendation

The research on resource based learning and recommender systems, as well as data mining, can be used to extend the content exchange component [7–9]. Such extensions may be adaptable to select the most appropriate content elements that can be rated and assessed by peers in order to maximize the assessor's learning effects (e.g. as intended in PEDALE). If a corpus for evaluation of recommender quality for group formation would be available, a precise evaluation could deliver further insight into the quality of the GROUPAL algorithm. Such research on the matching of peers should not focus on standard metrics from traditional recommender systems, like precision and recall, but should use metrics considering benefits for the users like user satisfaction [10, p. 428]. It seems reasonable to create a corpus in future joint research projects to compare group formation algorithms that use several personality-oriented, skill-oriented, user-preferences, learning targets, and for games even player-style preferences for simultaneously homogeneous and heterogeneous matching.

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Appendix A

A.1 Architecture Details

This appendix contains detailed aspects of the architecture removed from the chapters. This includes a detailed description of symbols used in architectural diagrams, as well as listings and data format descriptions.

A.1.1 Legend of Symbols

The symbols, explained in Fig. A.1, are used for architecture components, communication flow, and data storage in Figs. 3.2, 4.3, 5.2, 6.1, 7.2, and 7.10.

A.1.2 Content Integration

Achievement Categories for the Dual Achievement System

As described in Sect. 4.5.2 a combined version of the achievement categories from [8] has been defined. In Table A.1 the categories are listed and annotated whether or not they contain quantitative or qualitative achievements (or both). The categories are explained with examples from the game and the social media perspective. Beside two, all other categories can be applied to both.

A.1.3 Game Adaptation

A.1.3.1 Educational Game Social Interactions

As described in Sect. 5.2.4, a classification of possible interaction patterns depending on gameplay scene and mapping patterns was created, respecting the interaction patterns of [4]. Table A.2 contains the data for both mapping patterns; the ones only

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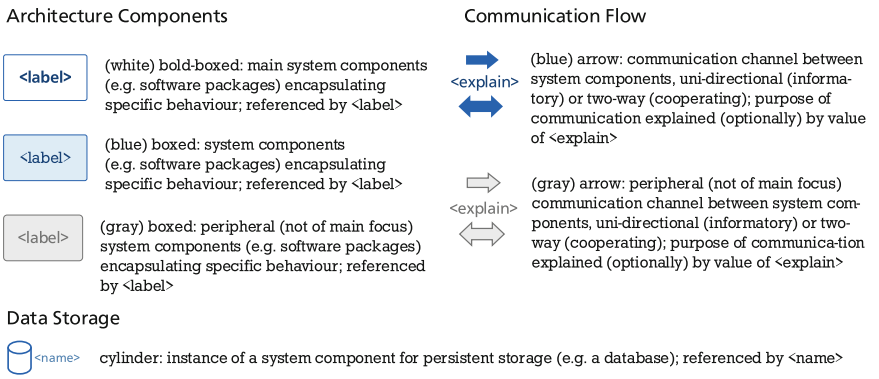

Fig. A.1 Legend of symbols used in diagrams of system architecture (SoCom.KOM), explaining architecture components, communication flow, and data storage

Table A.1 Achievement categories for the dual achievement system [6, p. 7]

Category	Description for game	Description for social media
Tutorial (qualitative)	Trying and learning features of the game	Visit and read parts of the community-stored content
Veteran (quantitative)	Accumulation of game items like currency	Participating a lot in community activities
Collection (quantitative)	Complete a collection of game items	Take part in discussions, collect votes, collect answered questions (or best answers)
Completion (quantitative)	Finish a sequence of the game (or everything)	Complete all community achievements or a specified collection
Curiosity (qualitative)	Discovering unexpected secrets or master unlikely situations	Contribute content about a game curiosity. (community feature: curiosity votes)
Cooperative (both)	Outstanding performance in multiplayer scenarios	Solve a crowd-sourcing task, e.g. participate in a survey or tag community elements
Virtuosity (qualitative)	Play sequences perfectly	Be a community role model; e.g. always get a high rating for content.
Fandom (neither)	Attend out of game activities, like purchasing merchandise articles	Attend out of community fan activities; e.g. fanfests
Loyalty (neither)	Playing regularly	Contribute to the community regularly
Luck (neither)	Getting a rare item	Perform an unlikely activity (e.g. the first post of the day)
Mini-game (neither)	Succeed in mini-games	Succeed in mini-games
Paragon (qualitative)	Being rewarded for pioneer activities	Being rewarded for pioneer activities

(continued)

Table A.1 (continued)

Category	Description for game	Description for social media
Special play style (qualitative)	Master parts of the game with even more restrictions; like fast-running	Master activities in the community with more restrictions; like answering a question within 30 s (with good rating)
Hard mode (qualitative)	Succeed on high difficulty level	–
Moderator (qualitative)	–	Administer content and like/dislike elements
Instructor (qualitative)	Assist other players in the game (side-kick or follow-mode)	Provide hints, solutions, guidelines

valid for 1:1 are printed italic and the ones for 1:n are left normal. A detailed explanation of the interactions can be found in the following Sect. A.1.3.2 as Table A.3.

A.1.3.2 Educational Game Social Interactions

The social interaction classification for single-player educational games of genre adventure games has been described in Sect. 5.2.4. A detailed explanation of the interactions listed Table A.2 of the preceeding section is described in Table A.3.

A.1.4 Group Formation Details

As the Chap. 6 on the *peer group formation* algorithm is quite formal, the induction proof of the boundaries for the maximum value of the *group performance index* as introduced in Sect. 6.2.6 has been moved here.

Table A.2 Interactions for educational game situations using social media (incoming interactions to the game marked as I:, outgoing as O:, items only for 1:1 are italic)

#	Game situation	Post	Vote	Comment	Chat	Tag	Invite	Connection	Join
1	Game start	*I: inventory equipment O: status*	I: inventory equipment, scene selection				O: rec., streaming	*I/O: cooperation*	I: cooperation, streaming
2	Game scene	*I: solution, question, pers. content O: status, screen, solution, question*	I: scene selection, assessment O: content rating	I: solution O: solution	I/O: consultation	*I: content location O: content location*	O: rec.	*I/O: cooperation*	*I: cooperation*
2a	NPC dialog scene	I: dialog option, names O: dialog decision	I: dialog option, traits	*I: dialog answer*	*I: dialog takeover*			*I: dialog takeover*	O: join decision (indirect)
2b	New quest scene	I: tasks, rewards, item donation, item repairing, params O: quest decision, question	I: available quests, tasks, rewards, quest parameters O: quest likes	I: banter O: notes, restrictions		I/O: categorization	O: rec.	*I/O: cooperation*	*I: cooperation*

(continued)

Table A.2 (continued)

#	Game situation	Post	Vote	Comment	Chat	Tag	Invite	Connection	Join
2c	Branching scene	*I: false decision items* *O: branch decision*	I: branch options O: branch likes	I: banter					
2d	Minigame scene	I: game content	I: minigame options O: minigame likes				I: content rec. O: rec.	I/O: cooperation, competition	I: cooperation, competition
2e	Conflict Sc.		I: traits, difficulty, tactics, inventory		I: barter, acclamation		O: sidekick	I: sidekick	I: sidekick
2f	Quest Solving	*I: rewards* *O: rewards*	I: assessment O: quest likes	I: shouts of victory, questions, remarks O: remarks		I/O: categorization	O: rec.		
3	Situation Loops	*I: assistance* *O: assistance request*			I/O: consultation	*I: content location*	*O: assistance request*	*I/O: cooperation*	

(continued)

Table A.2 (continued)

#	Game situation	Post	Vote	Comment	Chat	Tag	Invite	Connection	Join
4	Savegame	O: savegame, status	I: likes, usages	I: likes O: remarks		I/O: categorization	O: rec.	I/O: affiliation	I: usage
5	Game End	*I: questions* *O: status, solutions, question*	I: assessment O: likes	I: barter, acclamation (at stream)					I: rec.

Table A.3 Description of interactions used in Table A.2

Interaction	Description
Acclamation (at stream)	Sympathy or antipathy concerning the consumed (live) screencast video stream of the game played
Affiliation	Dynamic membership in an ad-hoc group of interest of all users connected or liking the same content, e.g. savegame
Available quests	Influencing the availability of quests a player can choose
Branch options	Influence on the available game branches a player can choose
Branch likes	Players and/or users can express their (dis)favor
Categorization	Players and/or users can edit or add metadata
Content location	Placing items in the game context, map or area
Dialog takeover	The dialog is not any more answered by a NPC, but by humans
False decision items	Contribution of (creative) but wrong answers to a question or decision to make
Item donation/repair	Other players/users owning items can help by donation or repair
Join decision (indirect)	NPC dialogs can ask players for favorites or memberships resulting in joins e.g. of affiliated interest groups in OSNs
Params	Abbreviation for parameters, e.g. difficulty, time restrictions
Rec	Abbreviation for recommendations, e.g. recommending a quest
Restrictions	Players/users can express (by text) self-imposed restrictions making the game e.g. more fun or harder
Sidekick	Assistance player restricted to competition support, not capable of interacting with story pacing (e.g. co-fighters)
Usages	Who/how many other used this item

A.1.4.1 Inductive Proof for the Maximum Value of Group Performance Index

Induction Start (Part 1)

$$
\begin{aligned}
GPI_2 &= \overline{NPPIs} * NSNPPI = \overline{NPPIs} * \frac{1}{1 + SNPPIs} \\
&\leq \overline{NPPIs}, && \text{because } SNPPIs \in [0, 1] \\
&\leq \frac{\sum_{i=1}^{\binom{2}{2}} \frac{PPI(K^1, K^2, W)}{\sum_{t=1}^{|W|} w_t}}{|NPPIs|}
\end{aligned}
$$

$$
\begin{aligned}
&\leq \frac{PPI(K^1, K^2, W)}{\sum_{t=1}^{|W|} w_t}, && \text{because } |NPPIs| = \binom{X}{2} = \binom{2}{2} = 1 \\
&\leq PPI(K^1, K^2, W), && \text{because } \sum_{t=1}^{|W|} w_t = 1 \\
&\leq \sum_{i=1}^{|K_{het}|} wd\left(k_i^1, k_i^2, w_i\right) \\
&\leq \sum_{i=1}^{|K_{het}|} w_i, && \text{because } wd\left(k_i^1, k_i^2, w_i\right) \leq 1 \\
&\overset{\text{Ind.}}{\leq} \sum_{i=1}^{|K_{het}|} w_i * \frac{\frac{2}{2} * \frac{2}{2}}{\binom{2}{2}} = \sum_{i=1}^{|K_{het}|} w_i * 1 && \text{(A.1)}
\end{aligned}
$$

Similarly, the equation for GPI_3 is proven:

$$
\begin{aligned}
GPI_3 &\leq \frac{\sum_{i=1}^{\binom{3}{2}} PPI(K^1, K^2, W)}{|NPPIs|} && \text{because } \sum_{t=1}^{|W|} w_t = 1 \\
&\leq \frac{\sum_{i=1}^{\binom{3}{2}} PPI(K^1, K^2, W)}{3}, && \text{because } |NPPIs| = \tbinom{3}{2} = 3 \\
&\leq \frac{3 * \sum_{j=1}^{|K_{het}|} w_j * \frac{2}{3}}{3}, && \text{because } PPI\left(K^1, K^2, W\right) \leq \tfrac{2}{3} \text{ for } X \geq 3 \\
&\overset{\text{Ind.}}{\leq} \sum_{i=1}^{|K_{het}|} w_i * \frac{\lfloor \frac{3}{2} \rfloor * \lceil \frac{3}{2} \rceil}{\binom{3}{2}} = \sum_{i=1}^{|K_{het}|} w_i * \tfrac{2}{3} && \text{(A.2)}
\end{aligned}
$$

Induction Step (Part 2)

$$
\begin{aligned}
GPI_{X+1} &= \overline{NPPIs} * NSNPPI = \overline{NPPIs} * \frac{1}{1 + SNPPIs} \\
&= \left(\sum_{i=1}^{\binom{X+1}{2}} \frac{PPI(K^1, K^2, W)}{\sum_{t=1}^{|W|} w_t} \right) * \frac{1}{|NPPIs|}, \text{ with } |NPPIS| = \binom{X}{2} \\
&\leq \left(\sum_{i=1}^{\binom{X+1}{2}} PPI(K^1, K^2, W) \right) * \frac{1}{\binom{X}{2}}, \text{ because } \sum_{t=1}^{|W|} w_t = 1 \\
&\leq \left(\left(\sum_{i=1}^{\binom{X}{2}} PPI(K^1, K^2, W) \right) * \frac{1}{\binom{X}{2}} * \frac{x-1}{x+1} \right) \\
&\quad + \left(\sum_{i=1}^{\frac{X+1}{X-1}} PPI(K^1, K^2, W) \right) * \frac{1}{\binom{X+1}{2}} \qquad \text{(A.3)}
\end{aligned}
$$

If $X \bmod 2 = 0$ ($X \geq 4$) the induction step can be continued as shown in Eq. A.4. For uneven values of X the induction step continuation is shown in Eq. A.5.

$$
\begin{aligned}
GPI_{X+1} &\overset{\text{Ind.Pre.}}{\leq} \frac{\frac{X}{2} * \frac{X}{2}}{\binom{X}{2}} * \frac{X-1}{X+1} + \frac{\sum_{i=1}^{\frac{X+1}{X-1}} PPI(K_i^1, K_{X+1}^2, W)}{\binom{X+1}{2}}, && \text{if } X \bmod 2 = 0 \\
&\leq \frac{\frac{X}{2} * \frac{X}{2}}{\binom{X+1}{2}} + \frac{\frac{X+1}{X-1}}{\binom{X+1}{2}}, && \text{because } max(PPI) = 1 \\
&\leq \frac{\frac{X^2}{4} + \frac{X+1}{X-1}}{\binom{X+1}{2}} \\
&\leq \frac{\frac{X^2}{4} + \frac{X}{2}}{\binom{X+1}{2}}, && \text{because } \frac{X+1}{X-1} < \frac{X}{2} \; \forall \; X \geq 4 \\
&\leq \frac{\frac{X}{2} * \left(\frac{X}{2} + 1\right)}{\binom{X+1}{2}} \\
&\leq \frac{\lfloor \frac{X+1}{2} \rfloor * \lceil \frac{X+1}{2} \rceil}{\binom{X+1}{2}}, && \text{because } X \bmod 2 = 0 \\
& && \text{(A.4)}
\end{aligned}
$$

$$
\begin{aligned}
GPI_{X+1} &\overset{\text{Ind.Pre.}}{\leq} \frac{\lfloor \frac{X}{2} \rfloor * \lceil \frac{X}{2} \rceil}{\binom{X}{2}} * \frac{X-1}{X+1} + \frac{\sum_{i=1}^{\frac{X+1}{X-1}} PPI(K_i^1, K_{X+1}^2, W)}{\binom{X+1}{2}}, && \text{if } X \bmod 2 = 1 \\
&\leq \frac{\frac{X-1}{2} * \frac{X+1}{2}}{\binom{X+1}{2}} + \frac{\frac{X+1}{X-1}}{\binom{X+1}{2}}, && \text{because } max(PPI) = 1 \\
&\leq \frac{\frac{X^2-1}{4} + \frac{X}{2}}{\binom{X+1}{2}}, && \text{because } \frac{X+1}{X-1} < \frac{X}{2} \; \forall \; X > 4 \\
&\leq \frac{\frac{X^2+2X-1}{4}}{\binom{X+1}{2}} \leq \frac{\frac{X^2+2X+1}{4}}{\binom{X+1}{2}} \\
&\leq \frac{\frac{(X+1)^2}{4}}{\binom{X+1}{2}} \leq \frac{(\frac{X+1}{2})^2}{\binom{X+1}{2}}
\end{aligned}
\tag{A.5}
$$

As shown the upper bounds of the *group formation algorithm* depend on the number of participants in the groups and not on dimensionality or amount of criteria.

A.1.4.2 Participant XML-Based Storage Format

To illustrate the data basis, GROUPAL is using for calculating group formations, a short extract from the generated data from set 2 variation 1 is given in Listing 5 (extraction of the first four participants from the first of 100 generated sets of 500 participants each).

Listing A.1 Extract from GROUPAL data file of Set 2, Variation 1, Run 1

```
<?xml version="1.0" encoding="utf-8"?>
<Participants version="1">
  <UsedCriteria>
    <Criterion name="Khet1" minValue="0" maxValue=
        "1" isHomogeneous="false" weight="1"
        valueCount="4" />
    <Criterion name="Khet2" minValue="0" maxValue=
        "1" isHomogeneous="false" weight="1"
        valueCount="4" />
    <Criterion name="Khom1" minValue="0" maxValue=
        "1" isHomogeneous="true" weight="1"
        valueCount="4" />
    <Criterion name="Khom2" minValue="0" maxValue=
        "1" isHomogeneous="true" weight="1"
        valueCount="4" />
  </UsedCriteria>
  <participant id="1">
    <Criterion name="Khet1" minValue="0" maxValue=
        "1" isHomogeneous="false" weight="1">
      <Value name="value0" value="0.5701112" />
      <Value name="value1" value="0.3749264" />
      <Value name="value2" value="0.9372103" />
      <Value name="value3" value="0.7470176" />
    </Criterion>
    <Criterion name="Khet2" minValue="0" maxValue=
        "1" isHomogeneous="false" weight="1">
      <Value name="value0" value="0.3749264" />
      <Value name="value1" value="0.7470176" />
      <Value name="value2" value="0.6099697" />
      <Value name="value3" value="0.9554885" />
    </Criterion>
    <Criterion name="Khom1" minValue="0" maxValue=
        "1" isHomogeneous="true" weight="1">
      <Value name="value0" value="0.9554885" />
      <Value name="value1" value="0.8159446" />
      <Value name="value2" value="0.702167" />
      <Value name="value3" value="0.1664555" />
    </Criterion>
    <Criterion name="Khom2" minValue="0" maxValue=
        "1" isHomogeneous="true" weight="1">
      <Value name="value0" value="0.8159446" />
      <Value name="value1" value="0.1664555" />
      <Value name="value2" value="0.05847595" />
      <Value name="value3" value="0.3383698" />
    </Criterion>
  </participant>
  <participant id="2">
    <Criterion name="Khet1" minValue="0" maxValue=
        "1" isHomogeneous="false" weight="1">
      <Value name="value0" value="0.1957468" />
      <Value name="value1" value="0.09976961" />
      <Value name="value2" value="0.6619307" />
```

```
          <Value name="value3" value="0.8840483" />
41      </Criterion>
        <Criterion name="Khet2" minValue="0" maxValue=
            "1" isHomogeneous="false" weight="1">
          <Value name="value0" value="0.09976961" />
          <Value name="value1" value="0.8840483" />
          <Value name="value2" value="0.4644893" />
46        <Value name="value3" value="0.06960629" />
        </Criterion>
        <Criterion name="Khom1" minValue="0" maxValue=
            "1" isHomogeneous="true" weight="1">
          <Value name="value0" value="0.06960629" />
          <Value name="value1" value="0.9909998" />
51        <Value name="value2" value="0.2972111" />
          <Value name="value3" value="0.9142116" />
        </Criterion>
        <Criterion name="Khom2" minValue="0" maxValue=
            "1" isHomogeneous="true" weight="1">
          <Value name="value0" value="0.9909998" />
56        <Value name="value1" value="0.9142116" />
          <Value name="value2" value="0.3328616" />
          <Value name="value3" value="0.2844184" />
        </Criterion>
      </participant>
61    <!-- continued for participants 3 to 500 -->
    </participant>
  </Participants>
```

A.1.5 SoCom.KOM Application Programming Interface (API)

The designed API for SoCom.KOM middleware as described in Chaps. 4, 5, and 6 is listed here in more detail with parameters for each method.

Legend
Italic parameters are optional.
URL Patterns refer to the REST-API. The patterns are appended to the base URL of the application, e.g. a URL pattern of `game` results in http://socom.example.com/game in case http://socom.example.com/ is the application's base URL.

A.1.5.1 Game API

URL Pattern: `game`
Class: `de.tud.kom.socom.components.game.GameManager`
The API to create, read, change, and delete the game instances, registered in the SoCom.KOM middleware, is listed in Table A.4.

Table A.4 API methods designed for game and context management (method parameters are omitted)

API method	I/O	Functionality	Parameter
`addGame`	I	Creates a new game	Name, genre, password, masterpassword
`removeGame`	–	Removes a game	Game, mastersecret
`getGame`	O	Shows information about an existing game, including all instances	Game, password
`addGame Instance`	I	Creates an game instance	Game, password, version, *description*
`setGameInstance Description`	I	Sets the description for a gameinstance	Cookies: game, password, gameversion; Stream: description
`removeGame Instance`	–	Removes a game instance	Game, password, version
`addGameContext`	I	Creates a new context (e.g. game scene)	Game, password, version, contextid, name
`setGameContext Description`	I	Sets the description of a context	Cookies: game, password, gameversion, contextid; Stream: description
`removeGame Context`	–	Removes a game context	Game, password, version, contextid
`getGameContexts`	O	Shows all contexts with their relations for a gameinstance	Game, password, version
`getGameContext`	O	Shows a context with its relations	Game, password, version, contextid
`addGameContext Relation`	I	Adds a relation between existing contexts	Game, password, version, parent, child
`removeGameContext Relation`	I	Removes a relation	Game, password, version, parent, child
`getGameContext Relations`	O	Shows the context relations of a gameinstance	Game, password, version
`setGameInstance Image`	I	Set the image for a gameinstance	Cookies: game, password, gameversion, extension; Stream: data
`setGameContext Image`	I	Set the image for a context	Cookies: game, password, gameversion, extension; Stream: data

A.1.5.2 User API

URL Pattern: `user`
Class: `de.tud.kom.socom.components.user.UserManager`

The API to create, read, change, and delete the registered users, known by SoCom.KOM middleware, is listed in Table A.5.

Table A.5 API methods designed for user and user information management (method parameters are omitted)

API method	I/O	Functionality	Parameter
`getUser`	O	Shows general information about a user	*Id*
`loginUser`	–	Performs a login (linking a user to this session)	Game, version, gamepassword, username, password
`logout`	–	Performs a logout	–
`createUser`	I	Creates a user and logs in	Username, password, game, version, gamepassword, visibility
`createUserWith SocialNetwork`	I	Creates a user and generates a social network login url	Game, version, gamepassword, visibility, network
`deleteUser`	–	Deletes a user account	Password
`becomeAdmin`	–	Let the current user become administrator	Mastersecret, password
`getUsersGames`	O	Shows a list of game instances a user is playing	–
`setCurrent Context`	I	Sets the currently playing context (scenes, level, mappart, …)	Context
`getVisited Contexts`	O	Shows all contexts the user ever visited	–
`addLog`	I	Creates a game log (e.g. debug messages, errors, …)	Type, message
`addJournalEntry`	I	Creates a journal entry (user ingame logs)	*Visibility*, type, message
`getJournal Entries`	O	Shows all visible journal entries	*Limit*, *offset*, *type*
`getLogs`	O	Shows all game logs	Gamepassword, *limit*, *offset*, *type*
`addTimePlayed`	I	Adds time to the time played in the current context	Time
`resetTimePlayed`	I	Resets the time played in the current context	–
`setTimePlayed`	I	Overwrites the time played in the current context	Time

(continued)

Table A.5 (continued)

API method	I/O	Functionality	Parameter
`getTimePlayed`	O	Shows the time played in the current context	–
`createMetadata`	I	Creates a key-value datapair for the user	Key, value, *visibility*
`updateMetadata`	I	Changes a key-value datapair for the user	Key, value, *visibility*
`deleteMetadata`	–	Removes a key-value datapair for the user	Key, *deleted*
`getMetadata`	O	Shows existing, visible key-value datapairs for the current user	*Of*
`changeUsername`	–	Changes the username	Username, password
`changeUser Password`	–	Changes the password	Password, newpassword

A.1.5.3 Game Influence API

URL Pattern: `influence`
Class: `de.tud.kom.socom.components.influence.InfluenceManager`
The API to create, read, change, and delete the influence instances or their templates, is listed in Table A.6. The influence types can be instantiated by game developers as new calls for participation (which are then published and spread via connected social media applications).

Table A.6 API methods designed for influence preparation, starting, and result fetching (method parameters are omitted)

API method	I/O	Functionality	Parameter
`createInfluence Template`	I	Creates a template for influences	Visibility, question, type, *minchoices*, *maxchoices*, *contextid*, allowfreeanswers, freeanswersvotable, *maxlines*, *maxdigits*, *maxbytes*
`createInfluence (template)`	I	Clones an influence template as new influence instance	Templateid
`createInfluence`	I	Creates a new influence instance	Visibility, question, type, *minchoices*, *maxchoices*, *contextid*, allowfreeanswers, freeanswersvotable, *maxlines*, *maxdigits*, *maxbytes*, *publish*, *message*, *time*

(continued)

Table A.6 (continued)

API method	I/O	Functionality	Parameter
`addPredefined Answer`	I	Adds a predefined answer	Id, answer
`addPredefined AnswerWithData`	I	Adds a predefined answer with data like images, audio, …	Cookies: id, answer, fileextension; Stream: data
`startInfluence`	–	Starts an influence and sets a timeout	Id, time
`stopInflunce`	–	Immediately stops an influence (timeout = now)	Id
`fetchResult`	O	Shows the result of an influence	Id
`getInfluence`	O	Shows the properties of an influence and Its result	Id
`changeInfluence`	–	Changes the properties of an influence	Id, *question*, *type*, *minchoices*, *maxchoices*, *maxdigits*, *maxlines*, *maxbytes*, *visibility*, *allowfreeanswers*, *freeanswersvotable*

A.1.5.4 Content API

URL Pattern: `content`
Class: `de.tud.kom.socom.components.content.ContentManager`
The API to create, read, change, and delete the content elements, stored in SoCom.KOM middleware, is listed in Table A.7.

Table A.7 API methods designed for influence preparation, uploading, fetching, rating and discussing (method parameters are omitted)

API method	I/O	Functionality	Parameter
`createUserContent`	I	Prepares a user content	Visibility, contextit, title, description, type, category, *further params as metadata*
`createGameContent`	I	Prepares a game content	Contextit, title, description, type, category, *further*
`uploadContent`	I	Adds the data to a content	Cookies: contentident; Stream: data
`getContentInfo ForContext`	O	Shows available contents for a given context	Context
`getContentInfo`	O	Shows available contents for given criteria	*Contexts*, *since*, *type*, *title*, *keywords*, *metadata*
`downloadContent`	O	Sends the binary data of a content	Contentid
`rateContent`	I	Rates a content	Contentid, rating
`addComment`	I	Comments a content	Contentid, message
`deleteComment`	–	Deletes a coment to a content	Commentid, delete

A.1.5.5 Achievements API

URL Pattern: `achievements`
Class: `de.tud.kom.socom.components.achievements.AchievementsManager`
The API to create, read, change, and delete achievements and achievement progress of players, stored in SoCom.KOM middleware, is listed in Table A.8.

A.1.5.6 Group Formation API

URL Pattern: `matching`
Class: `de.tud.kom.socom.components.content.GroupFormationManager`
The API to create, read, and delete peer group formations, based on user-profiles stored in SoCom.KOM middleware, is listed in Table A.9. The designed update-methods from Sect. 6.2.7 are not yet available in the API.

Table A.8 API methods designed for achievement creation, update and retrieval (method parameters are omitted)

API Method	I/O	Functionality	Parameter
`addAchievement`	I	Adds a new achievement	Achievementname, description, category, image, countermax, rewardpoints, game, password
`getAchievement`	O	Get an achievement with all its rewards	Achievementname, game, password
`removeAchievement`	–	Delete achievement and all its relations	Achievementname, game, password
`addAchievement Level`	I	Adds an achievement level	Achievementname, countermax, rewardpoints, game, password
`updateAchievement Process`	I	Update the achievement progress	Achievementname, counter, game, password
`resetAchievement Process`	–	Resets the achievement progress of the current achievement level	Achievementname, game, password
`getAchievement Process`	O	Get the achievements process	Achievementname, game, password
`addAchievement Reward`	I	Adds a new achievement reward	Name, description, value, game, password
`setAchievement Reward`	I	Relates a reward with an achievement	Achievementname, rewardname, achievementlevel, game, password

Table A.9 API methods designed for peer group formation based on GROUPAL algorithm (method parameters are omitted)

API method	I/O	Functionality	Parameter
`createFormation`	–	Starts a new run of the matching algorithm	Ids, groupsize, homcriteria, hetcriteria, *optimization*, *matcher*, *evaluator*
`getFormation`	O	Shows the whole cohort with CPI, split into groups, containing userids and GPIs	Matchingid
`getCriteriaInfo`	O	Shows available user criteria stored in the profiles	Game, password, version
`deleteFormation`	–	Deletes a formation result	Matchingid, delete

A.1.5.7 Social Networks API

URL-Pattern: `social`
Class: `de.tud.kom.socom.components.social.SocialMedia Manager`
The API to access the underlying social media applications, known and supported by SOCOM.KOM middleware, is listed in Table A.10. It allows to fetch the list of supported social media applications, access their news feeds, create or delete posts, and fetch profile information of a specific user.

Table A.10 API methods designed for social media profile reading and writing (method parameters are omitted)

API method	I/O	Functionality	Parameter
`loginURL`	O	Returns the URL for OAuth authentification with desired network	Network
`logout`	–	Deletes required information for social network interaction	Network
`isLoggedIn`	O	Whether a user is logged in to a social network	Network
`getNetworkFriends`	O	Lists all friends of all connected social media applications	–
`getSupported Networks`	O	Lists all available (implemented) social media applications with name and ID	–
`getProfileData`	O	Lists the profile information as described in Table A.11	–
`getProfileDataOf`	O	Returns profile data of a different person (identified by parameters)	Usersnid, network
`getSupporter`	O	lists the supporter of a post (e.g. *likes*)	Post, network

(continued)

Table A.10 (continued)

API method	I/O	Functionality	Parameter
`publishOnFeed`	I	Publishes the given text message on compatible social media feeds of the user	Message
`publishInfluence OnFeed`	I	Posts the text message and a link to the given influence on the social media feeds	Message, influence
`publishMedia OnFeed`	I	Like `publishOnFeed` but with binary data (image, video, …)	Message, type, extension
`deletePost`	–	Deletes a post preliminarily made	Post, network
`readPost`	O	Returns a post including comments	Post, network
`comment`	I	Adds a comment to a specific post	Post, network, message
`getSocomId`	O	SoCom.KOM user lookup using his social network identity	Network, snuid
`getPicture Thumbnail`	O	Link to a thumbnail photo	Network, usersnid

A.1.5.8 Profile Information

The attribute keys of the normalized profile information are listed in Table A.11. If no information for an attribute is available, its value is returned as `null`.

Table A.11 Normalized key-value pairs for users' social media profile information

Keyword (A-Z)	Description
`about`	Self description
`birthday`	Date of birth
`education`	Educational degree designation
`email`	Email address
`first_name`	First name
`gender`	m or f for male/female
`hometown`	City of residence (as zip, name)
`last_name`	Sir name
`languages`	Comma-seperated list of languages
`locale`	Current place of residence (as zip, name)
`name`	Composed name
`relationship_status`	One of: single, relation, engaged, married, widowed
`website`	URL of users own website (externally)
`work`	Current employer name (usually a company name)

A.1.5.9 Parameters

In case of sending binary data via HTTP-POST, cookie-parameters are expected to be in the cookie-header, while the stream should only contain the binary data. If data is fetched via the API (output requests), the parameters can as well be part of the HTTP-GET request URL. A list of the parameters is given in Table A.12.

Table A.12 Parameter used in SoCom.KOM API methods

Name (A–Z)	Type	Range/Values	Description
`allowfreeanswers`	Boolean	True/false	Enables free answers for influences
`achievementname`	String	–	Display name for achievement
`answer`	String	–	Answer to an influence
`category (content)`	String	'Hint', 'information', 'question', 'solution'	Category for contents
`category (achievement)`	String	–	Category for achievement
`child`	String	Valid context ID	Reference to the child context of a relation (to)
`contentid`	Long	≥0	References a content
`contentident`	String	Valid content ID	Uniquely identifies the currently uploading content
`contextid` or `context`	String	Valid content-ID	References a context
`contextids`	String	–	Commaseperated list of context-IDs to references them
`countermax`	Int	≥0	Max value of achievement's points
`delete/deleted`	Int	0–3	Values bigger than 0 hide something: '0': visible (not deleted), '1': hide only, '2': abuse, '3': offense
`description`	String	–	Description of any entity
`evaluator`	String	de, tme	Selection of evaluator to use (default evaluator using GPI and CPI, or TeamMaker evaluator [2])
`extension` or `fileextension`	String	'png', 'mp3', 'ogg', … (depends on function)	File extension of the currently uploading data
`freeanswersvotable`	Boolean	True/false	If free answers should be allowed to be voted
`game`	String	–	Public name of the game
`genre`	String	–	Game genre
`groupsize`	Int	≥2	Size of matching groups

(continued)

Table A.12 (continued)

Name (A–Z)	Type	Range/Values	Description
`homcriteria` or `hetcriteria`	String	Valid attribute keys	Comma separated list of profile attribute names (keys) to use; each followed by an optional float value for weighting
`id (user)`	Long	≥0	References a user
`image`	String	URL	URL to image displayed for achievement
`influenceid` or `influence`	Int	≥0	References an influence
`key`	String	–	Any keyword specifying a metadata
`keywords`	String	–	Comma seperated list of words which must be in the description
`limit`	Int	≥0	Limits the amount of output data
`mastersecret`	String	–	Secret (passphrase) needed for administrative functions
`matcher`	String	gcm, pcm, rdm	Selection of matcher to use (group-centric, participant-centric, random)
`matchingid` or `matching`	Int	≥0	References a group formation
`maxbytes`	Long	≥1	Maximal size (in bytes) of influence free answers which binary data
`maxchoices`	Int	≥ minchoices	Maximal allowed answers to an influence
`maxdigits`	Int	≥1	Maximal allowed digits for a free text answer
`maxlines`	Int	≥1	Maximal allowed lines for a free text answer
`message (log/journal entry)`	String	–	Message stored to a log
`message (social networks)`	String	–	Message which should be posted in a social network
`metadata`	String	–	Metadata which must be contained and be equal. Format: 'key1:value1, key2:value2,…'
`minchoices`	Int	≥1	Minimal allowed answers to an influence
`name`	String	–	Name of any entity
`network`	String	'Facebook', 'Google+'	Selects a social network
`of`	long	Valid User ID	References a user id
`offset`	Int	≥0	Offset to any output data (allows paging)
`optimization`	Boolean	–	If true, optimization cycles will be run
`parent`	String	Valid context ID	Reference to the parent context of a relation (from)

(continued)

Table A.12 (continued)

Name (A–Z)	Type	Range/Values	Description
password (game)	String	–	Game specific password
password (user)	String	–	Users private password for logins
post	String	Valid social network post id	References a social network post
publish	Boolean	True/false	Whether it should be published in the social networks
question	String	–	The question of an influence
rating	Float	0–1	Rating between 0 and 1
rewardpoints	Float	$0 \leq x \leq$ countermax	Points to trigger reward
since	Long/String	≥0 / 'yyyy-MM-dd HH:mm:ss'	Selects only content which is newer than specified date. Either time in ms since 01.01.1970 00:00:00 or as date format 'yyyy-MM-dd HH:mm:ss'
templateid	Int	Valid influence template id	References an influence remplate
time (influence)	Long	≥0	Time in ms which an influence should be active
time (playtime)	Long	≥0	Amount of time to be added/setted
title	String	–	Title of a game content
type (content)	String	'Text', 'audio', 'image', 'binary'	Type of a game content
type (influence)	String	'text', 'audio', 'image', …	Type of influence answers
type (log/journal Entry)	String	–	Any type for logs (Keyword 'all' inclose all types)
username String	–	Public name of a user	
usersnid/snuid	String	–	Social network internal id of a user
value	String	–	Value for a metadata
version or gameversion	String	–	Version of a game instance
visibility	Int	0–4	'0': private, '1': friends-only, '2': public, '3': only SoCom.KOM users, '4': only socom users playing the same game

A.2 Evaluation Details

This appendix contains details about setup, assessment criteria, and conditions of the conducted evaluations.

A.2.1 Assessment of Related Work Architectures

The assessment of the individual criteria in Table. 2.7 is described here for confirmability reasons.

Design approach means the technological architectural design elected. Considerable are *game-integrated library* as a service library game developers integrate to communicate with the provided service, *service* describes an independently running process that docks onto the running game instance at client-side to extract and insert data, *incubator* means a client binary that hosts the game application and mediates all input and output, *plugin* is a third-party plugin written for a provided game API to read and write data from the game, *middleware* describes an application (not running on the client machine) providing services (or APIs) to game instances running on the client to intermediate between the client and other server applications.
Game Adaption assesses whether or not the game code itself needs to be changed or prepared in order to work with the architecture.
Reading game data/Writing game data describes the ability of the architecture to access and transmit the status of game data (reading) or manipulate existing objects. If the functionality is quite limited (e.g. only text or only graphics parentheses are used)
Social Community judges the existence of an own social media application supported by the architecture. Thus it is *no* if third-party product are supported only.
Social Interaction interpreted as the ability to exchange free text-messages or voice-chat among players.
Peer Tutoring states the support for tutoring other players on basis of 1:1 communication and the exchange of video-files or chat-messages. As it depends on Social Interaction, these are mostly equally.
Peer Collaboration describes the possibility to work collaboratively on one task. Thus the application needs to be able to support conditional change of the game environment objects' attributes depending on player status. This depends on the ability to write and manipulate game data.
Suitable Tasks assesses the support for task definition by players to be worked on by other players.
Publishing describes the support for publishing new content (like text-messages, video, screenshots).
Sharing means the ability of players to share existing content (e.g. a file or formerly taken screenshot) with other players
Discussing refers to the support for content-related discussion threads (attached to the content).
Networking means social networking support that allows players to connect with other players, view profiles and browse the community. This depends on social community criterion and is always true for architectures providing their own social community.

A.2.2 SoCom.KOM Architecture Preliminary Expert Interview

As described in Sect. 3.7 an interview with 6 educational game experts was conducted between 03 and 24 April 2012. The questions of the qualitative individual interview are listed here (translated from German to English).

1. Is the API of the Middleware more intuitive or more complicated? Why?
2. Are there procedures you would automatize or where you think they are obsolete?
3. Are there terms, nomenclature or symbols you did not directly understand?
4. Are there steps that are needed to follow in a too strict order? Which?
5. Are there return values you would prefer in a different type?
6. Did you recognize inconsistent API methods?
7. Does the API provide in your opinion all functionality needed for a game designer, …
   (a) For social messaging?
   (b) To use social media data for game personalization?
   (c) To store and fetch user-generated content?
   (d) To fetch game influence metrics?
8. Where could problems arise from a game designers point of view?
9. Do you think using the API is learnable without external help or a manual?
10. Are you encouraged to use the API in the future and try the functionality? Why?

A.2.3 PEDALE Evaluation

A.2.3.1 Particpant Distribution

The descriptive data of the participants from the seven school classes of three schools is listed in Tables A.13, A.14 and A.15. Corresponding evaluation results and key findings are described in Sect. 7.1.7.

Table A.13 Descriptive data about the 183 participants and their distribution to the four setup variations

		Is female	Version with anonymity	Version with feedback in-between	Mark (1–6)
N	Valid	183	183	183	176
	Missing	0	0	0	7
Value true (1)		106	93	82	–
Value false (0)		77	90	101	–
Mean (*m*)		0.579	–	–	2.966
Std. Deviation (*SD*)		0.495	–	–	1.047

Table A.14 Distribution of marks (1 best to 6 worst)

		Frequency	Percent	Valid percent	Cumulative percent
Valid	1	13	7.1	7.4	7.4
	2	45	24.6	25.6	33.0
	3	68	37.2	38.6	71.6
	4	35	19.1	19.9	91.5
	5	15	8.2	8.5	100.0
	Total	176	96.2	100.0	
Missing	System	7	3.8		
Total		183	100.0		

Table A.15 Distribution participants to schools and classes

	Class no.	School no.	Date of evaluation	Mean mark	Frequency	Percent	Valid	Cumulative
Valid	1	1	21.03.2012	2.65	23	12.6	12.6	12.6
	2	1	21.03.2012	3.28	27	14.8	14.8	27.3
	3	1	21.03.2012	2.74	19	10.4	10.4	37.7
	4	2	29.03.2012	2.59	31	16.9	16.9	54.6
	5	3	03.05.2012	3.37	27	14.8	14.8	69.4
	6	3	03.05.2012	3.30	27	14.8	14.8	84.2
	7	3	03.05.2012	2.75	29	15.8	15.8	100.0
	Total				183	100.0	100.0	

A.2.3.2 Calculations and Measurements

The evaluation test setup consisted of tasks automatically solvable by computer algorithms as they were closed-format tasks (multiple-choice). Half of the tasks were as well open-format tasks where students were asked to deduce a solution from their own approach by using digital pens. These solutions were the focus of the evaluation and were assessed by peers as well as the basis for feedback of these peers to the solution creator. A subject matter expert, not involved in the evaluation process and unaware of the research questions, rated the solutions and provided feedback in several categories as a basis to calculate a pre-test and post-test score for each student as well as to calculate a feedback score for the provided feedback. With these measures a comparison and correlation of pre-test and post-test score is possible as well as investigations on which factors influence this objectively calculated feedback quality compared to the subjective rating of the receiver as well as it allows to see what influences the improvements or decline of accomplishments between pre-test and post-test. In Table A.16 the rating criteria for task solutions and feedback used by the subject matter expert are shown. The criteria have been developed in cooperation with the department of didactics in mathematics and are discussed in more detail in [10].

Table A.16 Subject matter expert boolean criteria for rating task solutions and feedback

Criteria	Description
Task Worked	
TaskSolutionExists	
TaskSolutionCorrect	
TaskIntermediateStepsExistMinimal	(Not used)
TaskIntermediateStepsExistComplete	(Not used)
TaskGraphicalAlgebraicApproach	(Not used)
TaskGraphicalNumericalAlgebraicApproach	(Not used)
TaskGraphicalSituativeAlgebraicApproach	(Not used)
TaskNoAnsatz	If no approach has been found/written
TaskCalcError	If calculation errors exist
TaskReadingError	If student seems to have made a reading mistake
TaskComprehensionError	If student seems to have misunderstood task
TaskOtherError	If another error exists (only set if the others are not)
TaskIndicatorsForMisconception	If student seems to have misconceptions about the topic (not used)
TaskIndicatorsForDigPenProblems	If written solution seems to be incomplete due to problems with digital pen (not used)
TaskReadabilityDifficulties	If written solutions are hard to read (not used)
FbSolutionExists	
FbSolutionCorrect	
FbDecisionOnCorrectnessExists	
FbDecisionOnCorrectnessCorrect	
FbTextualFeedbackExists	
FbTextualFeedbackCorrect	
FbTextualFeedbackWrong	
FbTextualFeedbackPartlyWrong	If neither completely wrong nor right
FbVeryDetailed	If text is very long (not used)
FbConstructiveAspectsExist	
FbMotivatingAspectsExist	
FbDemotivatingAspectsExist	
FbOfftopicPrivateCommunication	If all text is off-topic (e.g. chatting, cheering)
FbPartyOfftopicPrivateCommunication	If only parts are off-topic (not used)
FbMisconceptionIndication	If feedback provider seems to have a misconception about the topic (not used)
FbErrorNamed	If the made mistake is named (not used)
FbHintToApproachExists	If a hint is given (not used)
FbCorrectionExists	If the made mistake is corrected (not used)
FbSolutionProvided	If the solution is given (not used)
FbConfessionLackOfKnowledge	If feedback provider admits his own lack of knowledge (not used)
FbSuitableLanguageChoice	If choice of language/words is appropriate (not used)
FbVeryHumorousAspects	(Not used)

The following scores were calculated, based on these measures:

Task score: For each task the task score $\text{Score}_T \in \{0, 1, 2, 3\}$ was calculated as $\text{Score}_T = \min(0, \text{TaskWorked} + \text{TaskSolutionExists} + \text{TaskSolutionCorrect} - \text{TaskNoAnsatz} - \text{TaskCalcError} - \text{TaskReadingError} - \text{Task Comprehension Error} - \text{TaskOtherError})$. The values could have been weighted each, but as no reliable base exists to justify specific weights this measure is assumed to be accuratley enough without adding additional bias due to chosen weights. It is expected to represent a good performance measure of the tasks. As only 151 of 452 task solutions in the interactions (∼33.4 %) were correct, the measure provides a good distribution ($m = 1.56$, $SD = 1.073$ with N 428 due to some missing data in score values).
Feedback score: For each feedback the score $\text{Score}_{Fb} \in \{0, 8\}$ was calculated as $\text{Score}_{Fb} = 2 + \min(0, \text{FbDecisionOnCorrectnessExists} + \text{FbDecisionOnCorrectnessCorrect} + \text{FbTextualFeedbackExists} + \text{FbTextualFeedback Correct} - \text{FbTextualFeddbackWrong} - \text{FbTextualFeedbackPartly Wrong}) + \text{FbConstructiveAspectsExist} + \text{FbMotivatingAspectsExist} - \text{FbDemotivatingAspects Exist} - \text{FbOfftopicPrivateCommunication}$. Similar to task score no weights have been used. This score consists of two parts: first the score of the peer assessment aspects with lower boundary of zero [$min(0, ..)$] and the textual aspects of the peer tutoring with no lower boundary. Thus the value of 2 is added to get values between 0 and 8 (253 of 718 (35.2 %) correctly decided, $m = 8.11$, $SD = 2.116$).
Task sum score: For pre-test the sum score was build for solutions 3–6, for post-test for 7–10 (see setup of evaluation in Sect. 7.1.6).
Feedback sum score: The mean of all feedback provided by user and/or received by an user was calculated.

A.2.3.3 Questionnaire Items and Results

Three questionnaires were filled by the participants during the PEDALE evaluation (Sect. 7.1.6). First, the online questionnaire concerning the perception of the PEDALE learning environment and the attitudes towards peer learning. Items from this questionnaire will be marked wit OQ. Second, the paper-based questionnaire, which contained the items for the Bartle player type preferences,[1] the questions from the Kolb Learning Style Inventory,[2] and the questions for the Neuroticism Extraversion Openess (NEO)-Personality Inventory Revised[3] personality traits.

The questionnaire items are listed in Table A.17 and will be marked with the prefixes PQ for Bartle test, LQ for the aggregated values of Kolb's LSI, and TQ for NEO-PI-R. The used German translation is listed in *italics*, if only a English version

[1] Reprinted here with permission from Bartle Test author [1], supplemented with German translations.

[2] Not reprinted here as no permission from Hay Group [5] is granted. The copyright prohibits as well publication of the translated questions.

[3] Reprinted here from [9], supplemented with English translations.

Table A.17 All questionnaire items with mean and SD values

	Question (English/German) or (German/English)	Scale	*N*	*m*	*SD*
OQ1	Wie hat dir die Lernumgebung gefallen? Bitte beurteile folgende Aspekte auf dem Schieberegler mit einer Schulnote *How did you like the learning environment? Please assess the following aspects with a school grade using the slider*	1 (best) to 6 (worst)			
OQ1.1	die digitale Lernumgebung insgesamt *the digital learning environment overall*		181	2.48	1.176
OQ1.2	das Arbeiten mit dem digitalen Stift *working with the digital pen*		178	2.43	1.503
OQ1.3	das Schreiben von Feedback *writing feedback*		180	2.67	1.307
OQ1.3	das Erhalten von Feedback *receiving feedback*		167	2.74	1.350
OQ2	Wie sehr stimmst du folgenden Aussagen zu? *How much do you agree with the following statements?*	1 (completely agree) to 4 (completely disagree)			
OQ2.1	Ich würde gerne so eine Software öfter im Unterricht einsetzen *I like to use such a software more often in class*		181	2.31	0.813
OQ2.2	Ich habe durch das Schreiben von Feedback etwas gelernt *I leaned something by writing feedback*		175	1.29	0.823
OQ2.3	Ich habe durch das Erhalten von Feedback etwas gelernt *I learned something by receiving feedback*		155	1.34	0.942
OQ2.4	Das Arbeiten mit der Lernumgebung hat Spaß gemacht *Working with the learning environment was fun for me*		176	2.34	0.698
OQ2.5	Ich hatte beim Arbeiten mit der Lernumgebung jederzeit das Gefühl, dass ich weiss, was als Nächstes zu tun ist. While working with the learning environment, I always had the *feeling to know what has to be done next*		173	1.74	0.812
OQ2.6	Die Bedienung der Lernumgebung war leicht verständlich *Using the learning environment was easy and understandable*		180	2.47	0.655
OQ2.7	Ich hätte so eine Software auch gerne zur Bearbeitung von Hausaufgaben *I like to have such a software for doing my homework*		179	1.84	1.080
OQ3	Wie sehr trifft das für dich zu? *How much does this apply to you?*	1 (completely agree) to 4 (completely disagree)			
OQ3.1	Es fiel mir leicht meinen Mitschülern Feedback zu schreiben *It was easy for me to write feedback for my classmates*		176	1.79	0.898
OQ3.2	Ich habe das Feedback meiner Mitschüler aufmerksam gelesen *I read the feedback from my classmates intently*		154	2.44	0.731

(continued)

Table A.17 (continued)

	Question (English/German) or (German/English)	scale	*N*	*m*	*SD*
OQ4	Welche Mathematiknote hattest du im letzten Zeugnis? *What was your school grade in math in the last school certificate?*	1 (best) to 6 (worst)	176	2.97	1.047
OQ5	Für wen würdest Du am liebsten Feedback schreiben? *For whom do you prever to write feedback?*	multiple-choice 0 (no) or 1 (yes)			
OQ5.1	Schüler, die meine Freunde sind *Classmates which are my friends*		182	0.52	0.501
OQ5.2	Schüler, die nicht meine Freunde sind *Classmates which are not my friends*		182	0.31	0.463
OQ5.3	Schüler, die besser in Mathe sind als ich *Classmates which are better in math than I am*		182	0.19	0.395
OQ5.4	Schüler, die ähnlich gut in Mathe sind wie ich *Classmates which are as good in math as I am*		182	0.69	0.463
OQ5.5	Schüler, die schlechter in Mathe sind als ich *Classmates which are less good in math as I am*		182	0.57	0.496
OQ6	Von wem würdest Du am liebsten Feedback erhalten? *From whom do you prefer to recieve feedback?*	multiple-choice 0 (no) or 1 (yes)			
OQ6.1	Schüler, die meine Freunde sind *Classmates which are my friends*		182	0.35	0.479
OQ6.2	Schüler, die nicht meine Freunde sind *Classmates which are not my friends*		182	0.25	0.433
OQ6.3	Schüler, die besser in Mathe sind als ich *Classmates which are better in math than I am*		182	0.86	0.351
OQ6.4	Schüler, die ähnlich gut in Mathe sind wie ich *Classmates which are as good in math as I am*		182	0.48	0.501
OQ6.5	Schüler, die schlechter in Mathe sind als ich *Classmates which are less good in math as I am*		182	0.09	0.284
OQ6.6	unserer Lehrerin/unserem Lehrer *Our teacher*		182	0.53	0.501
OQ7	Wie löst du Mathematikaufgaben? Bitte entscheide, wie sehr folgende Aussagen für dich zutreffen *How do you solve math assignments? Please decide, how much the following statements apply to you*	1 (completely agree) to 4 (completely disagree)			
OQ7.1	Wenn ich eine Aufgabe bearbeitet habe, kontrolliere ich nochmal, ob das Ergebnis richtig sein kann *When I work on an assignment, I reexamine whether or not the result can be correct*		178	1.90	0.858
OQ7.2	Ich traue mir schwierige Aufgaben zu, auch wenn nicht immer alles gleich richtig ist *I trust myself to do difficult assignments, even though not everything is correct instantly*		177	1.76	0.931

(continued)

Table A.17 (continued)

	Question (English/German) or (German/English)	scale	*N*	*m*	*SD*
OQ7.3	Ich arbeite gerne mit anderen Schülern zusammen *I like to work together with other classmates*		179	2.32	0.811
OQ7.4	Ich spreche meine Mitschüler an, wenn ich Hilfe in Mathe brauche *I talk to my classmates, when I need assistance with math*		179	2.22	0.830
OQ7.5	Meine Mitschüler kommen zu mir, wenn sie Hilfe in Mathe brauchen *My classmates come to me, when they need assistance with math*		173	1.43	0.960
OQ8	Wie stehst du zum Fehlermachen im Mathematikunterricht? Bitte entscheide, wie sehr die folgenden Aussagen für dich zutreffen *How do you adhere to making mistakes in math class? Please decide, how much the following statements apply to you*	1 (completely agree) to 4 (completely disagree)			
OQ8.1	Meine Fehler helfen mir mich zu verbessern *My mistakes help me to improve*		178	2.00	0.752
OQ8.2	Ich mache lieber einen Fehler, als gar nicht anzufangen *I prefer to make a mistake than not to start at all*		178	2.11	0.895
OQ8.3	Im Mathematikunterricht habe ich Angst etwas falsch zu machen *In math class I am afraid to make a mistake*		173	0.97	0.961
OQ8.4	Ich würde meine Fehler lieber für mich behalten *I prefer to keep my mistakes to myself*		177	1.19	0.962
OQ8.5	Wenn ich einen Fehler gemacht habe, frage ich andere, wie ich die Aufgabe besser lösen kann *When I make a mistake, I ask others, how I can solve the assignment better*		179	2.04	0.810
OQ9	Bitte entscheide, wie sehr die folgenden Aussagen für dich zutreffen, wenn Du mit anderen zusammenarbeitest *Please decide, how much the following statements apply to you, when you work together with others*	1 (completely agree) to 4 (completely disagree)			
OQ9.1	Ich traue mich zu sagen was ich denke, auch wenn die anderen nicht meiner Meinung sind *I have the courage to express my thoughts, even when others are not of my opinionv*		182	2.28	0.803
OQ9.2	Wenn mich jemand ungerecht behandelt, wehre ich mich dagegen *If someone treats me unjustly, I react against it*		179	2.45	0.743
OQ10	Welche dieser Aussagen trifft auf dich zu? *Which of the following statements apply to you?*	multiple-choice, 0 (no) or 1 (yes)			

(continued)

Table A.17 (continued)

	Question (English/German) or (German/English)	scale	*N*	*m*	*SD*
OQ10.1	Ich lerne etwas, wenn ich mir Aufgaben und Lösungen von meinen Mitschülern ansehe *I learn something, when I look at the asisgnements and solutions of my classmates*		182	0.63	0.484
OQ10.2	Ich lerne etwas, wenn ich anderen helfe, ihre Fehler zu finden *I learn something, when I assist others to find mistakes*		182	0.46	0.499
OQ10.3	Das Ansehen fehlerhafter Lösungen finde ich lehrreich *Looking at incorrect solutions is instructive for me*		182	0.23	0.419
OQ10.4	Das Ansehen richtiger Lösungen finde ich lehrreich *Looking at correct solutions is instructive for me*		182	0.82	0.386
OQ11	Wie sehr trifft das für euren Mathematikunterricht zu? *How much applies the following to your math class?*	1 (completely agree) to 4 (completely disagree)			
OQ11.1	Der/die Lehrer/in und die Klasse diskutieren gemeinsam *Teacher and class discuss together*		178	1.89	0.823
OQ11.2	Die Schüler bearbeiten Arbeitsblätter *Classmates work on assignment papers*		179	1.94	0.869
OQ11.3	Wir sprechen im Mathematikunterricht über das Vorgehen beim Lösen von Aufgaben *We talk about ways to approach solutions of assignements during class*		181	2.30	0.776
OQ11.4	Wir stellen im Unterricht Fragen, bevor wir etwas rechnen *We ask questions in class, before we start calculations*		175	1.61	0.837
OQ11.5	Im Unterricht vergleichen und bewerten wir unterschiedliche Lösungswege von Aufgaben *In class we compare and assess different solution approaches to assignments*		179	2.03	0.817
OQ12	Wie sehr treffen die folgenden Aussagen für dich zu? *How much apply the following statements to you?*	1 (completely agree) to 4 (completely disagree)			
OQ12.1	Mit den meisten meiner Mitschüler verstehe ich mich gut *With most of my classmates I get along well*		180	2.52	0.593
OQ12.2	Wenn wir morgen wegziehen müssten, würde ich meine Mitschüler vermissen *If we would need to move away tomorrow, I would miss my classmates*		175	2.47	0.850
OQ13	Wie viel Zeit verbringst du mit Computern? *How my time do you spend using computers?*	1 (not at all), 2 (less than 2h/week), 3 (less than 4h/week), 4 (more than 4h/week)			
OQ13.1	zu Hause *at home*		177	2.54	0.805

(continued)

Table A.17 (continued)

	Question (English/German) or (German/English)	scale	*N*	*m*	*SD*
OQ13.2	in der Schule *at school*		177	0.51	0.595
OQ13.3	im Mathematikunterricht *in math class*		178	0.27	0.458
OQ13.4	zum Lernen von Mathematik *to learn math*		175	0.35	0.536
OQ14	Wie schätzt du dich ein? *How do you evaluate your computer expertise?*	1 (Dummy) to 4 (Expert)	170	1.94	0.751
OQ15	Was möchtest Du uns noch sagen, was wir jetzt nicht gefragt haben? *What do you want to tell as that we did not ask?*	free text	–	–	–
OQ16	Bitte sage uns noch, was du gut und was du schlecht an der vergangenen Stunde fandest *Finally, please tell us what you liked and disliked of the preceeding math class*	free text			
OQ16.1	Ich fand schlecht, dass… *I disliked that…*		–	–	–
OQ16.2	Ich fand gut, dass… *I liked that…*		–	–	–
BQ1	Are you more comfortable, as a player on a MUD: *Wobei fühlst Du Dich als Spieler eines Rollenspiels wohler?*	1 or 2	74	1.46	0.502
BQ1.1 (S)	Talking with friends in a tavern? *Reden mit Freunden in einem virtuellen Café*				
BQ1.2 (A)	Out hunting orcs by yourself for experience? *Draußen sein und Monster jagen, um eigene Erfahrungen zu sammeln*				
BQ2	Which is more enjoyable to you? *Was macht Dir als Spieler eines Rollenspiels mehr Spaß?*		74	1.24	0.432
BQ2.1 (A)	Killing A big monster *Große Monster bekämpfen*				
BQ2.2 (S)	Bragging about it to your friends? *Bei Freunden damit angeben*				
BQ3	Which do you enjoy more in MUD quests: *Was macht Dir mehr Freude bei Quests (Aufgaben) in Rollenspielen?*		73	1.64	0.482
BQ3.1 (S)	Getting involved in the storyline *Teil der Geschichte zu sein*				

(continued)

Table A.17 (continued)

	Question (English/German) or (German/English)	scale	*N*	*m*	*SD*
BQ3.2 (A)	Getting the rewards at the end? *Die Belohnung am Ende zu erhalten*				
BQ4	Which would you rather be noticed for on a MUD?: *Wodurch würdest Du in einem Rollenspiel eher auffallen?*		73	1.68	0.468
BQ4.1 (A)	Your equipment *Deine Ausrüstung*				
BQ4.2 (S)	Your personality *Deine Persönlichkeit*				
BQ5	Would you rather be: *Was wärst Du lieber in einem Rollenspiel?*		74	1.58	0.497
BQ5.1 (S)	Popular *Berühmt*				
BQ5.2 (A)	Wealthy *Reich*				
BQ6	Which do you enjoy more on a MUD?: *Was macht Dir beim Spielen eines Rollenspiels mehr Spaß?*		74	1.46	0.502
BQ6.1 (S)	Getting the latest gossip *Die neuesten Dinge und Geschichten zu erfahren*				
BQ6.2 (A)	Getting A new item *Einen neuen Gegenstand zu erhalten*				
BQ7	Which would you rather have, as a player on a MUD?: *Was würdest Du eher haben wollen als Spieler eines Rollenspiels?*		72	1.40	0.494
BQ7.1 (S)	A private channel, over which you and your friends can communicate *Einen eigenen Chatraum über den Du mit deinen Freunden kommunizieren kannst*				
BQ7.2 (A)	Your own house, worth millions of gold coins *Ein eigenes Haus, dass Millionen von Gold-Münzen wert ist*				
BQ8	Which would you enjoy more as a MUD player? *Was würde Dir als Spieler eines Rollenspiels mehr Spaß machen?*		73	1.41	0.495
BQ8.1 (S)	Running your own tavern? *Ein eigenes virtuelles Café aufmachen*				
BQ8.2 (E)	Making your own maps of the world, then selling them? *Deine eigenen Karten der virtuellen Welt erstellen und verkaufen*				
BQ9	What's more important in a MUD to you? *Was ist Dir bei einem Rollenspiel wichtiger?*		73	1.62	0.490
BQ9.1 (S)	The number of people *Die Anzahl an Spielern*				

(continued)

Table A.17 (continued)

	Question (English/German) or (German/English)	scale	*N*	*m*	*SD*
BQ9.2 (E)	the number of areas to explore *Die Anzahl an Gebieten zum Erkunden*				
BQ10	What's more important to you: *Was ist Dir wichtiger?*		74	1.43	0.499
BQ10.1 (S)	The quality of roleplaying in a mud *Das die Rolle, in die Du schlüpfen kannst, vielfältig ist*				
BQ10.2 (E)	The uniqueness of the features, and game mechanic *Die Einzigartigkeit der Features (Funktionen) und der Spiel-Logik*				
BQ11	You are being chased by a monster on a MUD. Do you: *Du wirst in dem Spiel von einem Monster verfolgt. Was tust du?*		74	1.42	0.497
BQ11.1 (S)	Ask a friend for help in killing it *Du fragst einen Freund um Hilfe beim Bekämpfen*				
BQ11.2 (E)	Hide somewhere you know the monster won't follow *Du versteckst dich an einem Ort von dem Du weißt, dass das Monster dir nicht folgen kann*				
BQ12	You're a player on a mud, and you want to fight a really tough dragon. How would you approach this problem? *Du möchtest im Spiel einen wirklich starken Drachen bekämpfen. Wie gehst du mit dem Problem um?*		74	1.43	0.499
BQ12.1 (S)	Get a big group of players to kill it *Du rufst eine große Gruppe Leute zusammen, um es gemeinsam zu bekämpfen*				
BQ12.2 (E)	Try a variety of weapons and magic against it, until you find its weakness *Du probierst einige Waffen und Zaubersprüche aus, bis Du weißt, was bei dem Drachen funktioniert*				
BQ13	You're a player on a mud, and about to go into an unknown dungeon. You have your choice of one more person for your party. Do you bring: *Du willst in einem Rollenspiel in eine unbekannte Höhle gehen. Wen nimmst Du mit?*		73	1.67	0.473
BQ13.1 (S)	A bard, who's a good friend of yours and who's great for entertaining you and your friends *Einen Barden (Sänger), der ein guter Freund von Dir ist und der dich und deine Freunde gut unterhalten kann*				
BQ13.2 (E)	A wizard, to identify the items that you find there *Einen Zauberer, der unbekannte Gegenstände in der Höhle identifizieren kann*				
BQ14	Is it better to be: *Was ist besser?*		74	1.81	0.394

(continued)

Table A.17 (continued)

	Question (English/German) or (German/English)	scale	*N*	*m*	*SD*
BQ14.1 (K)	Feared *Wenn sich andere im Spiel vor Dir fürchten*				
BQ14.2 (S)	Loved *Wenn Dich andere im Spiel lieben*				
BQ15	Someone has PK'ed you. Do you want to: *Jemand hat Dich im Spiel verletzt. Was tust Du?*		74	1.66	0.476
BQ15.1 (S)	Find out why, and try to convince them not to do it again *Du findest heraus warum und versuchst ihn zu überzeugen, das nicht wieder zu tun*				
BQ15.2 (K)	Plot Your revenge *Du planst Deine Rache*				
BQ16	Which is more exciting? *Was ist aufregender für Dich?*		74	1.31	0.466
BQ16.1 (S)	A well-roleplayed scenario *Eine tolle Rollenspiel-Szene*				
BQ16.2 (K)	A deadly battle *Ein toller, heftiger Kampf*				
BQ17	Which would you enjoy more? *Was würde dir im Spiel mehr Spaß machen?*		74	1.62	0.488
BQ17.1 (K)	Winning A duel with another player *Ein Duell gegen einen anderen Spieler gewinnen*				
BQ17.2 (S)	Getting accepted by a clan *Als neues Mitglied eines Clans (Gruppe) aufgenommen zu werden*				
BQ18	Would you rather *Was würdest Du eher tun?*		74	1.49	0.503
BQ18.1 (K)	Vanquish Your enemies *Deine Gegner besiegen*				
BQ18.2 (S)	Convince your enemies to work for you, not against you				
BQ19	What's worse: *Was ist schlimmer?*		73	1.73	0.449
BQ19.1 (K)	to be without power *Keine Stärke zu haben*				
BQ19.2 (S)	To be without friends *Keine Freunde zu haben*				
BQ20	Would you rather: *Was würdest Du eher tun?*		73	1.23	0.426
BQ20.1 (S)	Hear what someone has to say *Dir anhören, was ein Charakter im Spiel zu sagen hat*				

(continued)

Table A.17 (continued)

	Question (English/German) or (German/English)	scale	*N*	*m*	*SD*
BQ20.2 (K)	Show them the sharp blade of Your axe *Einem anderen Charakter im Spiel die scharfe Klinge Deiner Axt zeigen*				
BQ21	On a MUD, a new area opens up. Which do you look forward to more? *Eine neue Karten-Gegend im Spiel wird eröffnet. Worauf freust Du Dich eher?*		70	1.17	0.380
BQ21.1 (E)	Exploring the new area, and finding out its history *Die neue Gegend zu entdecken und herauszufinden, was es damit auf sich hat*				
BQ21.2 (A)	Being the first to get the new equipment from the area *Der erste zu sein, der die neuen Ausrüstungsgegenstände der Gegend hat*				
BQ22	On a MUD, would you rather be known as: *Als was für ein Spieler wärst du gerne bekannt?*		72	1.28	0.451
BQ22.1 (E)	Someone who can run from any two points in the world, and really knows their way around *Jemand, der immer den Weg kennt, wenn er von einem Punkt der Spielewelt zum anderen läuft*				
BQ22.2 (A)	The person with the best, most unique equipment in the game *Jemand, der die beste, seltenste Ausrüstung im ganzen Spiel hat*				
BQ23	Would you rather: *Was würdest Du eher wollen?*		72	1.67	0.475
BQ23.1 (A)	Become A hero faster than Your friends *Schneller ein Held werden wollen, als Deine Freunde*				
BQ23.2 (E)	know more secrets than Your friends? *Mehr Geheimnisse kennen als Deine Freunde*				
BQ24	Would you rather: *Was würdest Du eher wollen?*		72	1.57	0.499
BQ24.1 (E)	know where to find things *Wissen, wo man Gegegnstände findet*				
BQ24.2 (A)	know how to get things? *Wissen, wie man Gegenstände bekommt*				
BQ25	Which would you rather do: *Was würdest Du eher tun?*		72	1.22	0.419
BQ25.1 (E)	Solve A riddle no one else has gotten *Ein Rätsel lösen, das niemand zuvor gelöst hat*				
BQ25.2 (A)	Getting to A certain experience level faster than anyone else *Ein bestimmtes Level an Erfahrung schneller errreichen als jemand anderes*				

(continued)

Table A.17 (continued)

	Question (English/German) or (German/English)	scale	*N*	*m*	*SD*
BQ26	Do you tend to: *Was trifft eher auf Dich als Spieler eines Rollenspiels zu?*		72	1.25	0.436
BQ26.1 (E)	know things no one else does *Du weißt Dinge, die sonst keiner weiß*				
BQ26.2 (A)	Have items no one else does *Du hast Gegenstände, die sonst keiner hat*				
BQ27	On a MUD, would rather join a clan of: *Welchem Clan (Gruppe) eines Rollenspiels würdest Du eher beitreten?*		72	1.38	0.488
BQ27.1 (E)	Scholars *Die Gelehrten*				
BQ27.2 (K)	Assassins *Die Attentäter*				
BQ28	Would you rather win: *Was möchtest Du lieber in einem Rollenspiel gewinnen?*		72	1.58	0.496
BQ28.1 (E)	A trivia contest *Einen Wissens-Quiz*				
BQ28.2 (K)	An arena battle *Eine Gebiets-Schlacht*				
BQ29	If you're alone in an area, do you think: *Wenn Du alleine in einem Gebiet des Spiels bist, was denkst Du?*		71	1.23	0.421
BQ29.1 (E)	It's safe to explore *Es ist sicher, die Gegend zu erkunden*				
BQ29.2 (K)	You'll have to look elsewhere for prey *Du mußt woanders nach Beute suchen*				
BQ30	On a MUD, would rather be known for *Für was wärst Du lieber bekannt in einem Rollenspiel?*		71	1.39	0.492
BQ30.1 (E)	Knowledge *Dein Wissen*				
BQ30.2 (K)	power *Deine Stärke*				
BQ31	Would you rather: *Was würdest Du in einem Rollenspiel lieber tun?*		71	1.73	0.446
BQ31.1 (K)	Defeat An enemy *Einen Gegner bekämpfen*				
BQ31.2 (E)	explore A new area *Eine neue Gegend erkunden*				

(continued)

Table A.17 (continued)

	Question (English/German) or (German/English)	scale	*N*	*m*	*SD*
BQ32	You learn that another player is planning your demise. Do you: *Du erfährst, dass ein anderer Spieler deinen Untergang plant. Was tust Du?*		72	1.25	0.436
BQ32.1 (E)	Go to An area Your opponent is unfamiliar with and prepare there *Du gehst in ein Gebiet, in dem sich dein Gegner nicht so gut auskennt und bereitest Dich dort vor*				
BQ32.2 (K)	Attack him before he attacks you *Du greifst ihn an, bevor er Dich angreift*				
BQ33	You meet a new player. Do you think of him as: *Du triffst einen neuen Spieler. Was denkst Du spontan über ihn?*		72	1.39	0.491
BQ33.1 (E)	Someone who can appreciate Your Knowledge of the game *Er ist vielleicht jemand, der Dein Wissen über das Spiel schätzen wird*				
BQ33.2 (K)	As potential prey *Er ist vielleicht ein potentieller Gegner*				
BQ34	On a mud, would you rather: *Was würde in einem Rollenspiel eher zu Dir passen?*		73	1.27	0.449
BQ34.1 (A)	Have A sword twice As powerful As any other in the game *Du besitzt ein Schwert, das doppelt so stark ist, wie jedes andere im Spiel*				
BQ34.2 (K)	be the most Feared person in the game *Du bist die am meisten gefürchtete Person im Spiel*				
BQ35	On a mud, would you be more prone to brag about: *über was wärst Du in einem Rollenspiel stolzer?*		74	1.57	0.499
BQ35.1 (K)	How may other players you've killed *über die Anzahl an anderen Spielern, die Du besiegst hast*				
BQ35.2 (A)	Your equipment *über die Ausrüstung, die Du hast*				
BQ36	Would you rather have: *Was hättest Du lieber?*		74	1.55	0.500
BQ36.1 (K)	A spell to damage other players *Einen Magierspruch, mit dem ich andere Spieler bekämpfen kann*				
BQ36.2 (A)	A spell that increases the rate at which you gain experience points? *Einen Magierspurch, der die Vermehrung Deiner Erfahrungspunkte schneller macht*				

(continued)

Table A.17 (continued)

	Question (English/German) or (German/English)	scale	*N*	*m*	*SD*
BQ37	Would you rather have: *Was hättest Du lieber?*		74	1.38	0.488
BQ37.1 (A)	two levels of experience *Mehr Erfahrungspunkte*				
BQ37.2 (K)	An amulet that increases the damage you do against other players by 10 % *Ein Amulett, dass Deinen Schaden gegenüber anderen Spielern erhöht*				
BQ38	Would you rather receive as a quest reward: *Was würdest Du lieber als Belohnung für gelöste Quests (Aufgaben) haben wollen?*		73	1.40	0.493
BQ38.1 (A)	experience points *Erfahrungspunkte und Wissen*				
BQ38.2 (K)	A wand with 3 charges of a spell that lets you control other players, against their will. (charm person) *Einen Zauberstab mit dem Du dreimal andere Spieler kontrollieren kannst (Bann)*				
BQ39	When playing a video game, is it more fun to: *Wenn Du ein Computerspiel spielst, was findest Du besser?*		74	1.35	0.481
BQ39.1 (A)	Have the highest score on the list? *Den höchsten Highscore (Punkte) in der Liste zu haben*				
BQ39.2 (K)	Beat Your best friend one-on-one? *Deinen besten Freund/Freundin in einem 1:1 Spiel zu besiegen*				
BQ_A	Bartle Achiever normalized	0–1	74	0.48	0.149
BQ_E	Bartle Explorer normalized	0–1	74	0.60	0.158
BQ_K	Bartle Killer normalized	0–1	74	0.37	0.188
BQ_S	Bartle Socializer normalized	0–1	74	0.52	0.181
Kolb's LSI items are left out due to publication prohibition [5]					
LQ_CE	Kolb LSI CE normalized	0–1	74	0.52	0.186
LQ_RO	Kolb LSI RO normalized	0–1	74	0.45	0.138
LQ_AC	Kolb LSI AC normalized	0–1	74	0.47	0.150
LQ_AE	Kolb LSI AE normalized	0–1	74	0.45	0.128
TQ1 (E-R)	Ich bin eher zurückhaltend, reserviert *I am rather conservative, reserved*	1 (very inapp.) to	74	2.64	1.117
TQ2 (V-R)	Ich neige dazu, andere zu kritisieren *I have a tendency to criticise others*	5 (very applicable)	74	2.92	1.132
TQ3 (G)	Ich erledige Aufgaben gründlich *I complete tasks thoroughly*		74	3.89	0.769

(continued)

Table A.17 (continued)

	Question (English/German) or (German/English)	scale	*N*	*m*	*SD*
TQ4 (N)	Ich werde leicht deprimiert, niedergeschlagen *I become depressed or feel low easily*		73	2.33	1.248
TQ5 (O)	Ich bin vielseitig interessiert *I am interested in miscellaneous things*		72	4.17	0.671
TQ6 (E)	Ich bin begeisterungsfähig und kann andere leicht mitreißen *I am enthusiastic and can carry others along*		73	3.78	0.932
TQ7 (V)	Ich schenke anderen leicht Vertrauen, glaube an das Gute im Menschen *I can easily place my trust on others and believe in the good in man*		74	3.51	1.024
TQ8 (G-R)	Ich bin bequem, neige zur Faulheit *I am easy-going, tend to laziness*		74	3.26	1.147
TQ9 (N-R)	Ich bin entspannt, lasse mich durch Stress nicht aus der Ruhe bringen *I am laid-back, don't let myself get worked up by stress*		74	3.12	1.170
TQ10 (O)	Ich bin tiefsinnig, denke gerne über Sachen nach *I am profound, like to reflect about things*		74	3.91	0.953
TQ11 (E-R)	Ich bin eher der "stille Typ", wortkarg *I am more the silent one, reticent*		74	2.65	1.409
TQ12 (V-R)	Ich kann mich kalt und distanziert verhalten *I can be distanced and react cold*		74	3.45	1.195
TQ13 (G)	Ich bin tüchtig und arbeite flott *I am proficiently and work briskly*		74	3.59	0.792
TQ14 (N)	Ich mache mir viele Sorgen *I am worrying about a lot of things*		74	3.15	1.143
TQ15 (O)	Ich habe eine aktive Vorstellungskraft, bin fantasievoll *I have an active imagination; I am fancifull*		74	3.92	0.840
TQ16 (E)	Ich gehe aus mir heraus, bin gesellig *I can let myself go and mix well*		74	3.59	0.935
TQ17 (V-R)	Ich kann mich schroff und abweisend anderen gegenüber verhalten *I can be harsh and dismissive with others*		72	3.29	1.192
TQ18 (G)	Ich mache Pläne und führe sie auch durch *I make plans and carry them out afterwards*		74	3.62	0.902
TQ19 (N)	Ich werde leicht nervös und unsicher *I become nervous and feel unconfident easily*		73	2.79	1.013
TQ20 (O)	Ich schätze künstlerische und ästhetische Eindrücke *I appreciate artistic and aesthetic impressions*		73	3.44	1.167

(continued)

Table A.17 (continued)

	Question (English/German) or (German/English)	scale	*N*	*m*	*SD*
TQ21 (O-R)	Ich habe nur wenig künstlerisches Interesse *I have only little artistry interest*		74	2.49	1.327
TQ_E	NEO-PI-R E normalized	0–1	74	0.63	0.224
TQ_V	NEO-PI-R V normalized	0–1	74	0.51	0.210
TQ_G	NEO-PI-R G normalized	0–1	74	0.62	0.152
TQ_N	NEO-PI-R N normalized	0–1	74	0.45	0.198
TQ_O	NEO-PI-R O normalized	0–1	74	0.70	0.164

was available from the referenced literature. In case, only the German version was available, an English translation is provided and marked in *italics*.

Where applicable, the question identifiers are complemented with the questionnaire item in parentheses to an allocation to the measured dimensions, e.g. for Bartle Player type preferences (A) stands for Achiever player type preference. Additionally, for inverse encoded questions -R is appended.

A.2.3.4 Evaluation Results for Questionnaire Item on Acceptance

The measure, used as a basis for the illustration in Fig. 7.6 (Sect. 7.1.7), are listed in Table A.18.

A.2.3.5 Correlation of Questionnaire Items with Pre-test and Post-test Measures

For all correlations the *Pearson correlation* for interval scales was used instead of *Spearman-Rho correlation* as the scales in the questionnaire where only labeled at the extreme values and thus a linear distribution can be justified. Correlations between satisfactory values of the questionnaire with the proficiency level and performance characteristics of the participants are correlated in Table A.19.

Table A.18 Mean results to item group 'How did you like the digital learning environment?'

Aspect	*N*	*m*	*SD*
Overall	181	4.52	1.18
Using digital pen	178	4.57	1.50
Writing feedback	180	4.33	1.31
Receiving feedback	167	4.26	1.35
Overall valid values in list: 162			

Table A.19 Correlations between satisfaction values of questionnaire and performance measures

		PEDALE Overall score (1–6)	Working with the digital pen (1–6)	Writing feedback (1–6)	Receiving Feedback (1–6)	I like use such software more often in class (0–3)	I learned something by by receiving feedback (0–3)	I learned something by sending feedback (0–3)	Working with PEDALE was fun for me (0–3)	…I always had the feeling to to know what has to be done next (0–3)	Using PEDALE was easily and understandable (0–3)	I like to have such a software for doing my homework (0–3)
My computer skills are (1 = dummy, 4 = expert)	Pearson Correlation	0.096	0.044	0.136	0.105	−0.197*	−0.183*	−0.224**	−0.227**	−0.128	−0.118	−0.196*
	Sig. (2-tailed)	0.221	0.578	0.082	0.200	0.011	0.021	0.008	0.004	0.110	0.132	0.012
	N	165	163	164	152	165	159	141	161	158	164	163
Level of proficiency (school marks normed to interval [0,1])	Pearson Correlation	0.073	0.081	0.035	−0.131	0.128	0.075	0.199*	0.085	−0.123	−0.053	0.033
	Sig. (2-tailed)	0.343	0.297	0.653	0.101	0.094	0.336	0.016	0.276	0.114	0.493	0.674
	N	171	169	170	157	171	167	145	167	165	170	169
Delta pre-test score to post-test score	Pearson Correlation	0.012	0.007	−0.058	−0.076	0.091	0.096	0.016	0.070	−0.055	−0.172*	0.041
	Sig. (2-tailed)	0.877	0.930	0.445	0.335	0.228	0.210	0.848	0.360	0.478	0.023	0.590
	N	177	175	176	163	177	171	151	173	170	176	175
Score pre-test	Pearson Correlation	0.205**	0.111	0.196**	0.178*	−0.029	−0.046	0.028	−0.164*	−0.147	0.031	−0.105
	Sig. (2-tailed)	0.006	0.144	0.009	0.023	0.704	0.554	0.729	0.031	0.057	0.682	0.166
	N	177	175	176	163	177	171	151	173	170	176	175
Score post-test	Pearson Correlation	0.197**	0.107	0.122	0.086	0.062	0.049	0.040	−0.078	−0.184*	−0.137	−0.055
	Sig. (2-tailed)	0.009	0.158	0.107	0.277	0.413	0.525	0.628	0.308	0.016	0.069	0.472
	N	177	175	176	163	177	171	151	173	170	176	175

**Correlation is significant at the 0.01 level (2-tailed). * Correlation is significant at the 0.05 level (2-tailed)

Table A.20 Group statistics for t-test of differences in rating scores (subjective and objective) depending on anonymity in the software setup

Measure	Anonymity	N	Mean	SD	Std. error mean
Subj. rating	0	246	**0.6455**	0.3138	0.0200
	1	207	**0.5614**	0.3203	0.0223
Obj. rating	0	374	8.1203	2.2780	0.1178
	1	335	8.1552	1.8859	0.1030

Table A.21 T-test of differences in rating scores (subjective and objective) depending on anonymity in the software setup

		Levene's Test for Equality of Variances		t-test for Equality of Means						
		F	Sig.	t	df	Sig., 2-tailed	Mean difference	Std. error difference	95 % Confidence interval of the difference	
									Lower	Upper
Subj. rating	EVA	0.275	**0.600**	2.817	451	**0.005**	0.084	0.030	0.025	0.143
	EVNA			2.812	434.734	**0.005**	0.084	0.030	0.025	0.143
Obj. rating	EVA	4.668	0.031	−0.221	707	0.825	−0.035	0.158	−0.345	0.276
	EVNA			−0.223	702.727	0.824	−0.035	0.156	−0.342	0.272

EVNA for *Equal variances not assumed*, EVA for *Equal variances assumed*

A.2.3.6 t-test for Rating Differences in Dependency of Anonymity

As the correlations between personality aspects, differences and deltas between sender and receiver of feedback showed some differences for the anonymous and named setups of the evaluation, a t-test was conducted to prove the difference of subjective ratings depending on this anonymity aspect. The results can be found in Tables A.20 and A.21. The subjective rating by the receiver was done on a 5-scale Likert scale, represented as stars in the interface. The objective feedback rating (feedback score) was calculated by the formula explained in Sect. A.2.3.2.

A.2.4 Genius Evaluation

A.2.4.1 Questionnaire Items and Results

The questionnaire items were split into three groups of questionnaires. First a questionnaire the player of the BizConsulter game filled after playing (Game User Questionnaire EG), second the questionnaire the Facebook users (peers) filled after using the social media interactions (Social Media User Questionnaire EG), and third the questionnaire for the control group only playing the game without any additional

game adaptation functionality (Game User Questionnaire CG). This last questionnaire contains all questions of the first, but slightly rephrased as hypothetical questions. Originally the questions where in German, but translations to English listed here in italics for consistency and readability reasons. All questionnaires, items and descriptive data can be found in the following Table A.22.

The questions for measuring user experience are derived from Göbel et al. [3]. Their translation to English was provided by Mehm from his work on the Ph.D. thesis [7].

A.2.4.2 BizConsulter Implemented SoCom.KOM Game Adaptation Functionality

The simplified gameplay of BizConsulter can be divided into 8 scenes the player plays in a more or less sequential order: Mission-Takeover, Retrieval-of-Presentation-File, Call-for-Action-Accountant, Assistant-Convincing, Progress-Report, Retrieval-of-Archive-File, Delivery-of-Files, Mission-Success.

As it is not essential to know the scene details here only the occurrence of participations and usage of social media profile data is described. When reaching the first scene (Mission-Takeover) the game instance requests the players name, gender and city of residence and replaces all naming of the player's avatar in dialogues by her real name. Additionally, the location of the customer's headquarter the player has to assist in BizConsulter is set to the hometown of the player. Depending on the gender of the player different participations are created and send via SoCom.KOM to Facebook. If the player is male, the OSN friends are offered to contribute a name suggestion for the female assistant of the male senior accountant (mainly used for scene Assistant-Convincing). If the player is female the peers in the social media application are asked to name the male senior accountant (mainly used for scene Call-for-Action-Accountant).

When the user selects the dialog option "Yes, let's do it" to take over the job (cf. Fig. 7.9), the game publishes an achievement message on the wall with a screenshot. In the following scenes the provided names are used within dialogs to name the NPCs accordingly. More achievements are posted during further progress through the game. Briefly, social media users can create name suggestions or vote for answers submitted by others before. The name with the most votes is used in the game scenes in all NPC dialogs (if several names have the same number of most votes, it is chosen randomly). The published screenshots and achievement messages can be 'liked' and commented. Depending on the likes, the dialogue with the female assistant NPC in the game is more or less difficult. When players receive more than two likes or comments he is considered to be popular and liked. Consequently it will be easier in the NPC dialog to convince the assistant to help with getting some information needed for further gameplay.

In the end a success story is published as the last achievement as e.g. shown in Fig. 7.11b.

Table A.22 All questionnaire items with mean and SD values

	Question (German/English)	scale	*N*	*m*	*SD*
Game User Questionnaire (experimental group)					
Age	Wie alt sind Sie? *How old are you?*	0–127	48	24.46	2.492
Gender	Geschlecht *gender*	1f or 2m	48	1.90	0.309
Shours	Stunden pro Woche an Nutzung von Computerspielen/Konsolenspielen: *hours a week using computer games/console games:*	0–168	46	10.22	17.296
Gamer	Bitte geben Sie eine Einschätzung zwischen 1 (trifft überhaupt nicht zu) und 10 (trifft voll zu) zu den folgenden Aussagen. *Please assess between 1 (does not apply at all) to 10 (applies completely)*	0–10			
SA1	Ich fand es positiv, dass die Spiel-Inhalte sich automatisch an meinen Facebook-Namen, Geschlecht und Ort angepasst haben *I percieved it as positive that game content automatically adjusted to my Facebook name, gender and city of origin*		48	6.79	2.813
SA2	Dass ich mit meinem Facebook-Namen im Spiel angesprochen wurde, hat positiv zum Spielerlebnis beigetragen *That I was addressed with my Facebook name in the game, has positively supported game experience*		48	6.33	3.171
SA3	Ich empfand es als störend, dass meine Facebook-Angaben, wie Name und Ort, vom Spiel verwendet wurden *I percieved it as incommoding that my Facebook details, like name and city, were used by the game*		48	4.21	3.182
SB1	Dass außerhalb des Spiels andere Personen Statusmeldungen zu meinem Spielverlauf lesen, hat die Spielspannung erhöht *That other people could read status messages outside the game, increased game tension*		48	3.85	2.370
SB2	Ich finde es motivierend, dass das Spiel Screenshots von erreichten Zwischenzielen mit einer Erfolgsmeldung auf Facebook veröffentlicht *It was motivating that the game published screenshots of achieved intermediate goals together with success messages on Facebook*		48	4.27	2.456
SB3	Ich fand es nicht gut, dass andere Personen außerhalb meinen Spielverlauf erfahren *I was not overly excited that other, exteriorly people get to know my course of the game*		48	4.73	2.930

(continued)

Table A.22 (continued)

	Question (German/English)	scale	*N*	*m*	*SD*
SC1	Die Beeinflussung des Spielverlaufs von außen hat positiv zu meinem Spielerlebnis beigetragen *The influencing of the cource of game, has positively added to my game experience*		48	4.15	2.475
SC2	Das Inhalte (Text, Likes) von anderen zum Spiel beigesteuert werden können, hat das Spiel persönlicher gemacht *That content (text, likes) could be contributed by others for the game, has made the game more personal*		48	5.38	2.915
SC3	Ich habe es als störend empfunden, dass einzelne Inhalte (Texte, Audio) durch andere Personen via Facebook hinzugefügt wurden *I percieved it as disturbing that individual content (text, audio) has been added by other people via Facebook*		48	2.75	2.217
SD1	Ich hätte mir für besseres Erreichen des Spielziels weitere Spielfunktionen gewünscht *I wished there would have been additional game functionalities for better achievement of game goals*		48	6.83	2.652
SD2	Ich fand die Oberfläche des Spiels leicht zu bedienen *I percieved the interface of the game as easy to use*		48	6.81	2.490
SD3	Die technische Umsetzung des Spiels ist gut gelungen *The technical realization leaves a good impression*		48	6.19	2.447
Sgood	Was hat Dir/Ihnen besonders gefallen an der Personalisierung/Adaption des Spiels mittels Social Media (Facebook)? *What in particular did you like, concerning the personalization/adaption of the game via social media (Facebook)?*	text			
Sbad	Was hat Dir/Ihnen nicht gefallen? *What aspects did not please you?*	text			
Sideas	Welche Dinge würdest Du/würden Sie? anders machen/verbessern? *What aspects would you change/improve?*	text			
SA	Gamer: social media personalization (aggregated)	1–10	48	6.64	2.655
SB	Gamer: social media publishing (aggregated)	1–10	48	4.80	1.913
SC	Gamer: social media participation (aggregated)	1–10	48	5.92	1.829
SD	Gamer: technical functionality (aggregated)	1–10	48	6.15	1.008
UX	Bitte wählen Sie für die folgenden Aussagen jeweils einen Wert zwischen 1 (trifft überhaupt nicht zu) und 10 (trifft völlig zu) *Please assess for the following statements between 1 (does not apply at all) to 10 (applies completely)*	1–10			

(continued)

Table A.22 (continued)

	Question (German/English)	scale	*N*	*m*	*SD*
UX01LA	Was Spiel hat Langeweile vermieden *The game avoided boredom*		48	5.58	2.360
UX02FR	Das Spiel hat Frustration vermieden *The game avoided frustration*		48	5.63	2.710
UX03kAE	Ich habe mich nur selten über das Spiel geärgert *The game only seldomly made me angry*		48	6.56	2.431
UX04FOR	Das Spiel hat mich angenehm gefordert *The game challenged me in a pleasant way*		48	4.67	2.444
UX05FAN	Die Geschichte hat meine Fantasie angeregt *The story engaged my fantasy*		48	4.25	2.497
UX06kUE	Ich konnte den Aufgaben, Eindrücken, Informationen und Möglichkeiten im Spiel gut folgen und war nicht überfordert oder überlastet *I was able to keep track of tasks, impressions, information and possibilities of the game and was not overstrained nor overloaded*		48	7.00	2.288
UX07FUN	Das Spiel hat Spaß gemacht *The game was fun*		48	5.38	2.385
UX08KOM	Das Spiel gab mir das Gefühl eigenbestimmt und kompetent zu sein *The game made me feel self-determined and competent*		48	5.17	2.529
UX09AES	Ich fand das Spiel ästhetisch/ ansprechend gestaltet *I found the game's design to be asthetically pleasing*		48	6.85	2.083
UX10EIN	Das Spiel war mitunter so einnehmend, dass ich unbedingt wissen wollte, wie es weiter geht *The game was at times so engaging that I had the need to know how it continued*		48	4.94	2.794
UX11MOT	Einen Entwicklungsprozess festzustellen motivierte mich stark weiter zu machen *Realizing a process of progression strongly motivated me to continue playing*		48	5.56	2.576
UX12SBE	Teilweise spielte ich nur noch um des Spieles willen *At times I played only fort the sake of playing*		48	4.90	2.434
UX13WOR	Teilweise fühlte ich mich wie ein Teil der Spielwelt *At times I felt like a part of the game world*		48	4.52	2.325
UX14CHA	Ich hatte während des Spiels das Gefühl die Spiel-Figur zu sein *I felt like I was the game's protagonist while playing*		48	4.69	2.969

(continued)

Table A.22 (continued)

	Question (German/English)	scale	*N*	*m*	*SD*
UX15SCO	Das Spiel bot die Möglichkeit ein eigenständiges Selbstkonzept zu entwickeln, dem es Spaß machte zu folgen *The game offered the possibility of developing an individual concept that was fun to follow*		48	4.71	2.405
UX16ATT	Das Spiel war so spannend, dass es meine ganze Aufmerksamkeit beim Spielen auf sich zog *The game was so exciting that it captured my whole attention during play*		48	4.63	2.498
UX17ZEI	Das Spiel war so interessant, dass ich gar nicht merkte, wie schnell die Zeit vergeht *The game was so interesting that I lost all track of time*		48	5.46	2.593
UX18FES	An manchen Stellen war das Spiel so, dass ich vollkommen vom Spiel eingenommen wurde *At times the game was so enthralling that I was completely engaged in the game*		48	3.81	2.209
UX19ERL	Manchmal war ich im Nachhinein sehr erleichtert, da ich ein Scheitern befürchtete *After some points of the game I was very relieved since I had expected a failure*		48	3.35	2.329
UX20EMO	Ich merkte, dass ich teilweise stark emotional beteiligt war (Spannung, Trauer, Erleichterung, Freude, Wut) *I noticed that I was at times strongly emotionally involved (excitement, sadness, relief, joy, anger)*		48	3.02	2.410
UX21ANG	Ich fühlte mich durch das Spiel in einen angenehmen Zustand versetzt *I was in a pleasant state due to playing the game*		48	5.10	2.425
UXNegEmo	Gamer: UX negative emotions (aggregated)	1–10	48	5.92	1.999
UXCogLoad	Gamer: UX cognitive load (aggregated)	1–10	48	5.31	1.358
UXPosEmo	Gamer: UX positive emotions (aggregated)	1–10	48	5.80	1.893
UXMoti	Gamer: UX motivation (aggregated)	1–10	48	5.13	1.972
UXImm	Gamer: UX immersion (aggregated)	1–10	48	4.64	2.260
UXArr	Gamer: UX arrousal (aggregated)	1–10	48	3.83	1.824
UXFlow	Gamer: UX flow (aggregated)	1–10	48	4.63	2.132
UXSum	Gamer: UX (aggregated)	1–10	48	5.04	1.575

(continued)

Table A.22 (continued)

	Question (German/English)	scale	*N*	*m*	*SD*
Social Media User Questionnaire (experimental group)					
Age	Wie alt sind Sie? *How old are you?*	0–127	48	24.46	2.492
Gender	Geschlecht *gender*	1f or 2m	48	1.90	0.309
Fhours	Stunden pro Woche an Nutzung von Facebook/ Social Media: *hours a week using Facebook/social media:*	0–168	48	12.83	30.172
Facebooker	Bitte geben Sie eine Einschätzung zwischen 1 (trifft überhaupt nicht zu) und 10 (trifft voll zu) zu den folgenden Aussagen *Please assess between 1 (does not apply at all) to 10 (applies completely)*	0–10			
FE1	Durch Möglichkeit auf Facebook mit Likes und Abstimmungen das Spiel anderer zu beeinflussen, habe ich die Meldungen aktiver gelesen *I read the posts more actively due to the possibility to influence the game of others with Likes and participation possibilities on Facebook*		48	6.00	2.910
FE2	Die Einflussnahme auf das Spiel anderer mittels Facebook hat mein Interesse an solchen Spielen erhöht *The exertion of influence on the game of others via Facebook participations has increased my interest in such games*		48	5.75	2.825
FE3	Die veröffentlichten Erfolgsmeldungen auf Facebook und Möglichkeiten zum Mitgestalten des Spielverlaufes befreundeter Personen führen eher dazu, dass mich ein solches Spiel weniger interessiert *The published success messages and possibilities to influence the game course of befriended people, tends to decrease my interest in such a game*		48	3.92	2.305
FF1	Ich habe gerne mit Likes unterstützt sowie individuelle Inhalte ausgewählt und beigetragen zum Spiel einer befreundeten Person *I liked to support with Likes, as well as selecting individual content and contributing to the game experience of a befriended person*		48	7.27	2.386

(continued)

Table A.22 (continued)

	Question (German/English)	scale	*N*	*m*	*SD*
FF2	Ich vergebe eher ein *Like*, wenn ich anderen im Spiel damit helfen kann *I give more likely a Like when I can help others in their game by this*		48	7.58	2.600
FF3	Ich habe es als langweilig empfunden, Inhalte auszuwählen und mit beizutragen/abzustimmen für das Spiel einer befreundeten Person *I percieved it as boring to choose content and contribute/vote to the gameplay of a befrieded person*		48	4.54	2.775
FG1	Ich hätte mir für die bessere Erledigung der Aufgaben weitere Funktionen auf der Website gewünscht *I wished there would have been additional website functionalities for better execution of tasks*		48	6.92	2.648
FG2	Ich fand die Oberfläche der Webseite leicht zu bedienen *The interface of the website was easy to use*		48	7.63	2.256
FG3	Die technische Umsetzung der Beeinflussung von Spielen über eine mit Facebook verbundene Webseite ist gut gelungen *The technical connection for participating in games via a website connected to Facebook leaves a good impression*		48	6.56	2.351
Fgood	Was hat Dir/Ihnen besonders gefallen an der Verbindung von Spiel und Social Media (Facebook)? *What in particular did you like, concerning the connection of game and social media (Facebook)?*				
Fbad	Was hat Dir/Ihnen nicht gefallen? *What aspects did not please you?*				
Fideas	Welche Dinge würdest Du/würden Sie? anders machen/verbessern? *What aspects would you change/improve?*				
FE	Social media: attitiude towards posts and achievements (aggregated)	1–10	48	6.28	2.074
FF	Social media: attitude towards content-contribution (aggregated)	1–10	48	7.10	1.918
FG	Social media: technical functionality (aggregated)	1–10	48	6.33	1.367
Game User Questionnaire (control group)					
Age	Wie alt sind Sie? *How old are you?*	0–127	22	23.59	1.652
Gender	Geschlecht *gender*	1f or 2m	22	1.77	0.429
Shours	Stunden pro Woche an Nutzung von Computerspielen/Konsolenspielen: *hours a week using computer games/console games:*	0–168	22	8.18	7.657

(continued)

Table A.22 (continued)

	Question (German/English)	scale	*N*	*m*	*SD*
Gamer	Bitte geben Sie eine Einschätzung zwischen 1 (trifft überhaupt nicht zu) und 10 (trifft voll zu) zu den folgenden Aussagen *Please assess between 1 (does not apply at all) to 10 (applies completely)*	0–10			
SA1	Ich fände es positiv, wenn die Spiel-Inhalte sich automatisch an meinen Facebook-Namen, Geschlecht und Ort angepasst hätten *I would appreciate it, if game content automatically adjusts to my Facebook name, gender and city of origin*		22	3.09	2.653
SA2	Es hätte positiv zum Spielerlebnis beigetragen, wenn ich mit meinem Facebook-Namen im Spiel angesprochen worden wäre *It would have had positively supported my game experience, if the game addresses me with my Facebook name*		22	3.14	2.916
SA3	Ich empfinde es als störend, wenn meine Facebook-Angaben, wie Name und Ort, vom Spiel verwendet werden *I percieve it as incommoding when my Facebook details, like name and city, are used by a game*		22	8.09	2.877
SB1	Wenn außerhalb des Spiels andere Personen Statusmeldungen zu meinem Spielverlauf lesen könnten, erhöht das die Spielspannung *When other people can read status messages outside of the game, it increases game tension*		22	3.64	2.629
SB2	Ich fände es motivierend, wenn das Spiel Screenshots von erreichten Zwischenzielen mit einer Erfolgsmeldung auf Facebook veröffentlichen würde *It would be motivating, if the game publishes screenshots of achieved intermediate goals together with success messages on Facebook*		22	2.32	2.079
SB3	Ich fände es nicht gut, wenn andere Personen meinen Spielverlauf erfahren *I would not be overly excited in case other, exteriorly people get to know my course of the game*		22	5.68	3.107
SC1	Eine Beeinflussung des Spielverlaufs von außen hätte ich positiv für mein Spielerlebnis gefunden *I suppose, an influencing of the cource of game from outside, would have positively added to my game experience*		22	6.50	2.521

(continued)

Table A.22 (continued)

	Question (German/English)	scale	*N*	*m*	*SD*
SC2	Falls Inhalte (Text, Likes) von anderen (Freunden) zum Spiel beigesteuert werden könnten, würde es das Spiel persönlicher machen *If content (text, likes) could be contributed by others for the game, it would make the game more personal*		22	5.55	2.502
SC3	Ich würde es als störend empfinden, wenn einzelne Inhalte (Texte, Audio) durch andere Personen via Facebook hinzugefügt werden würden *I would percieve it as distrubing, if individual content (text, audio) is added to the game by other people via Facebook*		22	5.59	2.873
SD1	Ich hätte mir für besseres Erreichen des Spielziels weitere Spielfunktionen gewünscht *I wished there would have been additional game functionalities for better achievement of game goals*		22	7.00	2.370
SD2	Ich fand die Oberfläche des Spiels leicht zu bedienen *I percieved the interface of the game as easy to use*		22	8.00	1.574
SD3	Die technische Umsetzung des Spiels ist gut gelungen *The technical realization leaves a good impression*		22	6.77	2.137
Sgood	Was hat Dir/Ihnen besonders gefallen an dem Spiel? *What in particular did you like of the game?*				
Sbad	Was hat Dir/Ihnen nicht gefallen? *What aspects did not please you?*				
Sideas	Welche Dinge würdest Du/würden Sie? anders machen/verbessern? *What aspects would you change/improve?*				
SA	Gamer: social media personalization (aggregated)	1–10	22	3.05	2.514
SB	Gamer: social media publishing (aggregated)	1–10	22	3.76	2.022
SC	Gamer: social media participation (aggregated)	1–10	22	5.82	2.262
SD	Gamer: technical functionality (aggregated)	1–10	22	6.41	1.425
(Followed by all items from UX Questionnaire, identically to experimental group)					
UXNegEmo	Gamer: UX negative emotions (aggregated)	1–10	22	6.05	1.777
UXCogLoad	Gamer: UX cognitive load (aggregated)	1–10	22	5.05	1.611
UXPosEmo	Gamer: UX positive emotions (aggregated)	1–10	22	5.76	1.919
UXMoti	Gamer: UX motivation (aggregated)	1–10	22	4.48	1.802
UXImm	Gamer: UX immersion (aggregated)	1–10	22	3.89	1.861
UXArr	Gamer: UX arrousal (aggregated)	1–10	22	3.47	1.757
UXFlow	Gamer: UX flow (aggregated)	1–10	22	4.21	2.066
UXSum	Gamer: UX (aggregated)	1–10	22	4.70	1.527

A.2.4.3 t-test for Attitudes Towards Game Adaptation

A t-test was conducted comparing experimental and control group concerning all User Experience Questionnaire items and all aggregated measures for attitude of player towards social media personalization, postings, influencing, and the technical functionality of the game interface. Two items (attitude towards social media-based personalization and attitude towards social media postings) were significant. These items are marked bold in Table A.23.

A.2.5 GroupAL Evaluation

A.2.5.1 Results to Setup Alpha

In Setup α data from Set 2 in all three variations has been used to evaluate the different matchers of GROUPAL: Random Matcher, Group-Centric Matcher, and Participant-Centric Matcher. All three data variations were run three times with targeted group sizes of 2, 3, and 6 members. The nine resulting plots of Cohort Performance Indexs and corresponding average Group Performance Indexs per cohort is shown in Fig. A.2.

Additionally, the needed runtimes of the three different matchers were recorded to compare the speed in dependency of group size as shown in Fig. A.3. As illustrated, the better group formation quality results achieved by the Group-centric Matcher (as shown above in Fig. A.2) are gained by the drawback of longer computation runtime.

A.2.5.2 Results to Setup Beta

The optimization runs on the different data variations and group-size calculations brought the improvements on optimization as shown in Fig. A.4. An overview with the percentages of improvement achieved for group-size of 3 members is given in Table A.24.

A.2.5.3 Results to Setup Gamma

In Setup γ data from Set 1 in all three variations has been used to evaluate GROUPAL versus GroupFormationTool, OmadoGenesis and Together. All these three data set variations were run three times with targeted group sizes of 2, 3, and 6 members. The nine resulting plots of Cohort Perormance Indices and corresponding average Group Performance Indices per cohort are shown in Fig. A.5.

Table A.23 T-test comparing experimental and control group

		Levene's Test for Equality of Variances		t-test for Equality of Means						
		F	Sig.	t	df	Sig., 2-tailed	Mean difference	Std. error difference	95% Confidence interval of the difference	
									Lower	Upper
Gamer UX negative emotions prevented	EVA	0.261	0.611	0.245	68	0.807	0.122	0.498	−0.871	1.115
	EVNA			0.256	45.585	0.799	0.122	0.476	−0.837	1.081
Gamer UX cognitive load	EVA	0.200	0.656	−0.701	68	0.486	−0.260	0.371	−1.000	0.480
	EVNA			−0.658	35.226	0.515	−0.260	0.395	−1.063	0.543
Gamer UX positive emotions	EVA	0.028	0.867	−0.084	68	0.933	−0.041	0.489	−1.018	0.936
	EVNA			−0.083	40.312	0.934	−0.041	0.492	−1.035	0.953
Gamer UX motivation	EVA	0.913	0.343	−1.308	68	0.195	−0.647	0.495	−1.634	0.340
	EVNA			−1.353	44.419	0.183	−0.647	0.478	−1.610	0.316
Gamer UX immersion	EVA	3.020	0.087	−1.349	68	0.182	−0.745	0.552	−1.847	0.357
	EVNA			−1.450	48.968	0.153	−0.745	0.514	−1.777	0.287
Gamer UX arrousal	EVA	0.226	0.636	−0.768	68	0.445	−0.357	0.464	−1.283	0.570
	EVNA			−0.779	42.276	0.440	−0.357	0.458	−1.281	0.567
Gamer UX flow	EVA	0.095	0.759	−0.772	68	0.443	−0.420	0.544	−1.505	0.665
	EVNA			−0.781	42.017	0.439	−0.420	0.537	−1.504	0.665

(continued)

Table A.23 (continued)

		Levene's Test for Equality of Variances		t-test for Equality of Means						
		F	Sig.	t	df	Sig., 2-tailed	Mean difference	Std. error difference	95 % Confidence interval of the difference	
									Lower	Upper
Gamer UX	EVA	0.349	0.557	−0.835	68	0.407	−0.335	0.402	−1.137	0.466
UserExperience	EVNA			−0.845	41.991	0.403	−0.335	0.397	−1.137	0.466
Gamers attitude	EVA	0.116	0.735	−5.343	68	**0.000**	−3.593	0.673	−4.936	−2.251
SM personalization	EVNA			−5.454	42.942	**0.000**	−3.593	0.659	−4.922	−2.265
Gamers attitude	EVA	0.004	0.947	−2.077	68	**0.042**	−1.041	0.501	−2.041	−0.041
SM posting out	EVNA			−2.034	38.846	**0.049**	−1.041	0.512	−2.076	−0.006
Gamers attitude	EVA	1.662	0.202	−0.208	68	0.836	−0.105	0.508	−1.119	0.908
SM influences	EVNA			−0.192	34.092	0.849	−0.105	0.550	−1.223	1.012
Gamers attitude	EVA	5.215	0.026	0.863	68	0.391	0.256	0.297	−0.336	0.849
game interface	EVNA			0.761	31.009	0.453	0.256	0.337	−0.431	0.943

EVNA for *Equal variances not assumed*, EVA for *Equal variances assumed*

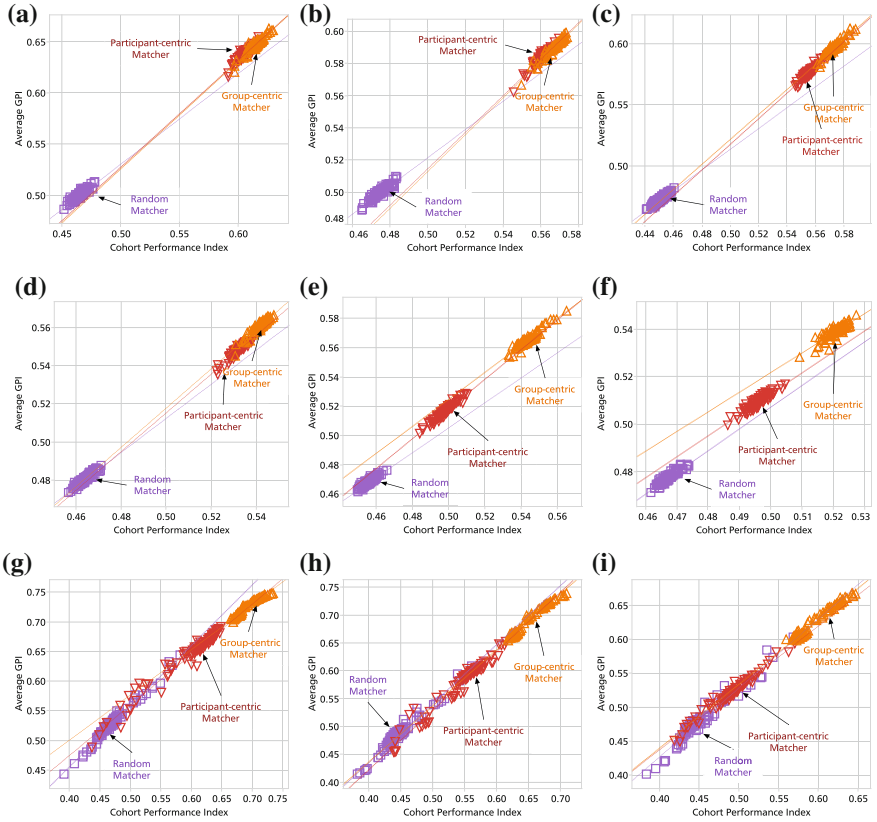

Fig. A.2 Matcher differences in Setup α based on data from Set 2. **a** Results on V1, group size 2. **b** Results on V2, group size 2. **c** Results on V1, group size 3. **d** Results on V2, group size 3. **e** Results on V1, group size 6. **f** Results on V2, group size 6. **g** Results on V3, group size 2. **h** Results on V3, group size 3. **i** Results on V3, group size 6

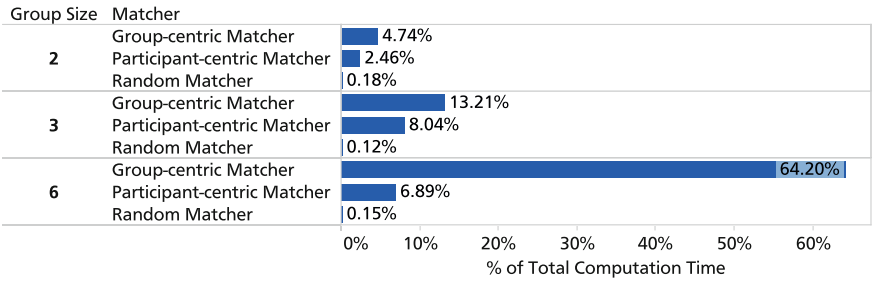

Fig. A.3 Matcher's runtime differences in Setup α based on data from Set 2

Table A.24 Optimization Cycles Improvement in Setup β for group size of 3 members

Matcher	Variation	Optimization cycles improvement				
		1 (%)	Gain (%)	2 (%)	Gain (%)	3 (%)
Group-centric matcher	V1	0.02	0.02	0.03	0.02	0.05
	V2	0.04	0.03	0.06	0.02	0.08
	V3	0.00	0.03	0.03	0.02	0.05
Participant-centric matcher	V1	0.04	0.00	0.04	0.02	0.05
	V2	0.02	0.01	0.03	0.01	0.04
	V3	0.11	0.04	0.15	0.05	0.20
Random matcher	V1	3.50	2.04	5.54	1.40	6.94
	V2	1.87	1.18	3.05	0.88	3.93
	V3	2.72	1.74	4.46	1.36	5.82

The columns list percent improvement compared to average CPI without optimization; between optimization cylce columns is the gain from one cycle to the next calculated

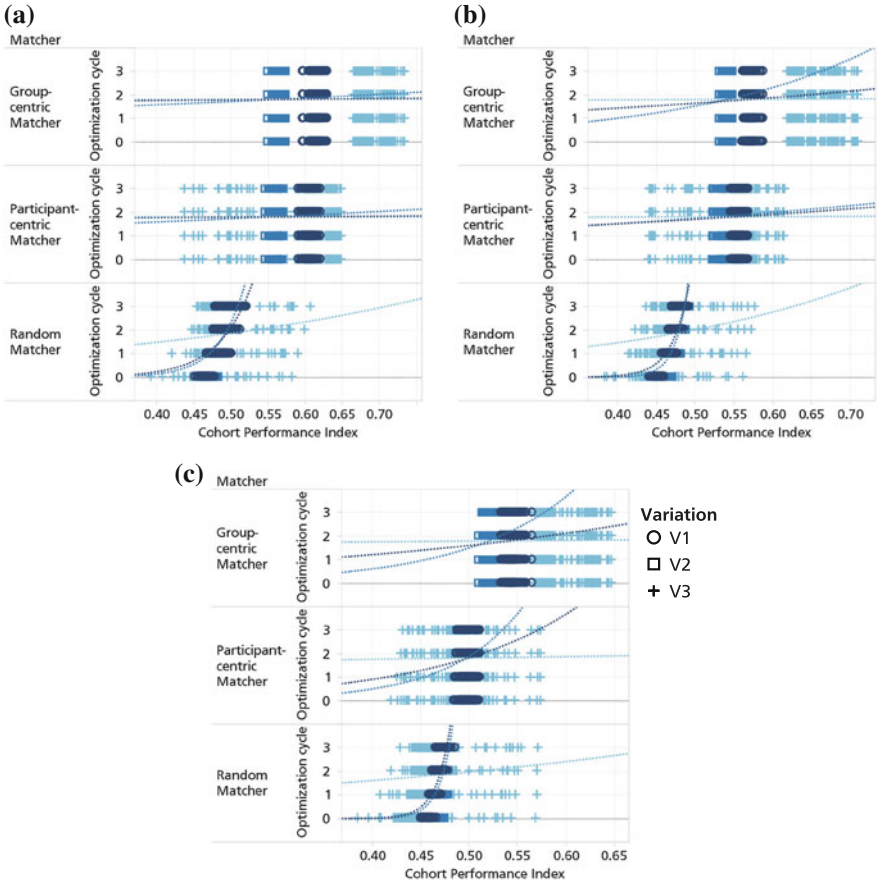

Fig. A.4 Matcher differences in Setup β based on data from Set 2. **a** Optimization results on group size 2. **b** Optimization results on group size 3. **c** Optimization results on group size 6

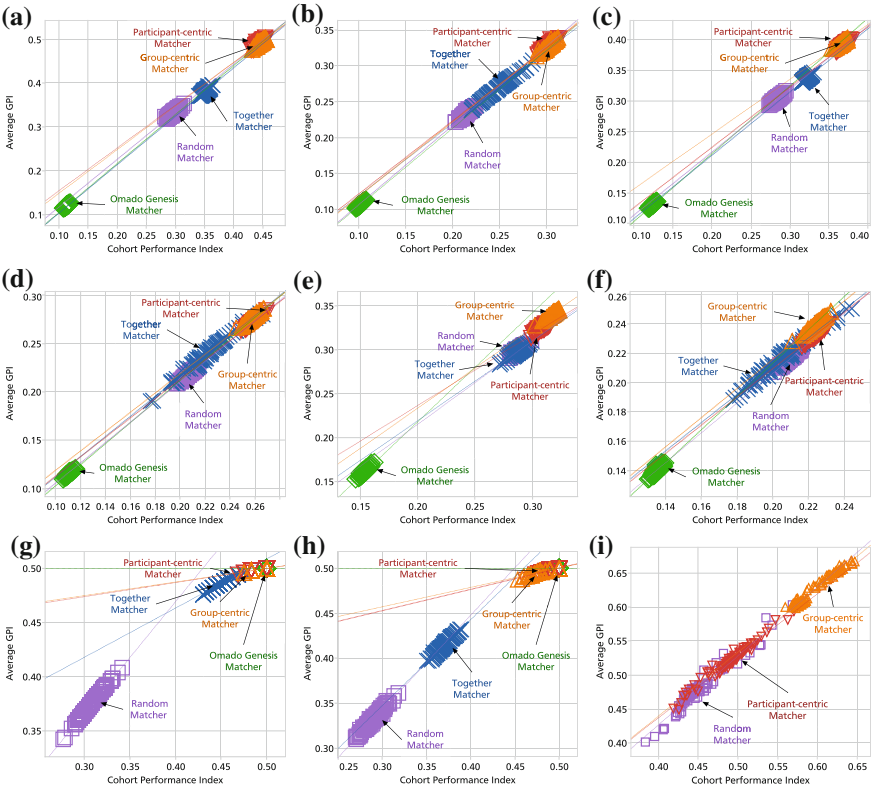

Fig. A.5 Matcher differences in Setup γ based on data from Set 1. **a** Results on V1, group size 2. **b** Results on V2, group size 2. **c** Results on V1, group size 3. **d** Results on V2, group size 3. **e** Results on V1, group size 6. **f** Results on V2, group size 6. **g** Results on V3, group size 2. **h** Results on V3, group size 3. **i** Results on V3, group size 6

A.2.5.4 Results to Setup Delta

In Setup δ data from Set 2 variation 3 (extreme values) was used to compare GROUPAL's Group-Centric Matcher with TeamMaker's matcher. The calculation with the data set was run three times with targeted group sizes of 2, 3, and 6 members. This was then repeated again with evaluating the resulting cohorts by TEAMMAKER's evaluation metrics for Group Performance Index and Cohort Performance Index. The six resulting plots of CPIs and corresponding average GPIs per cohort is shown in Fig. A.6.

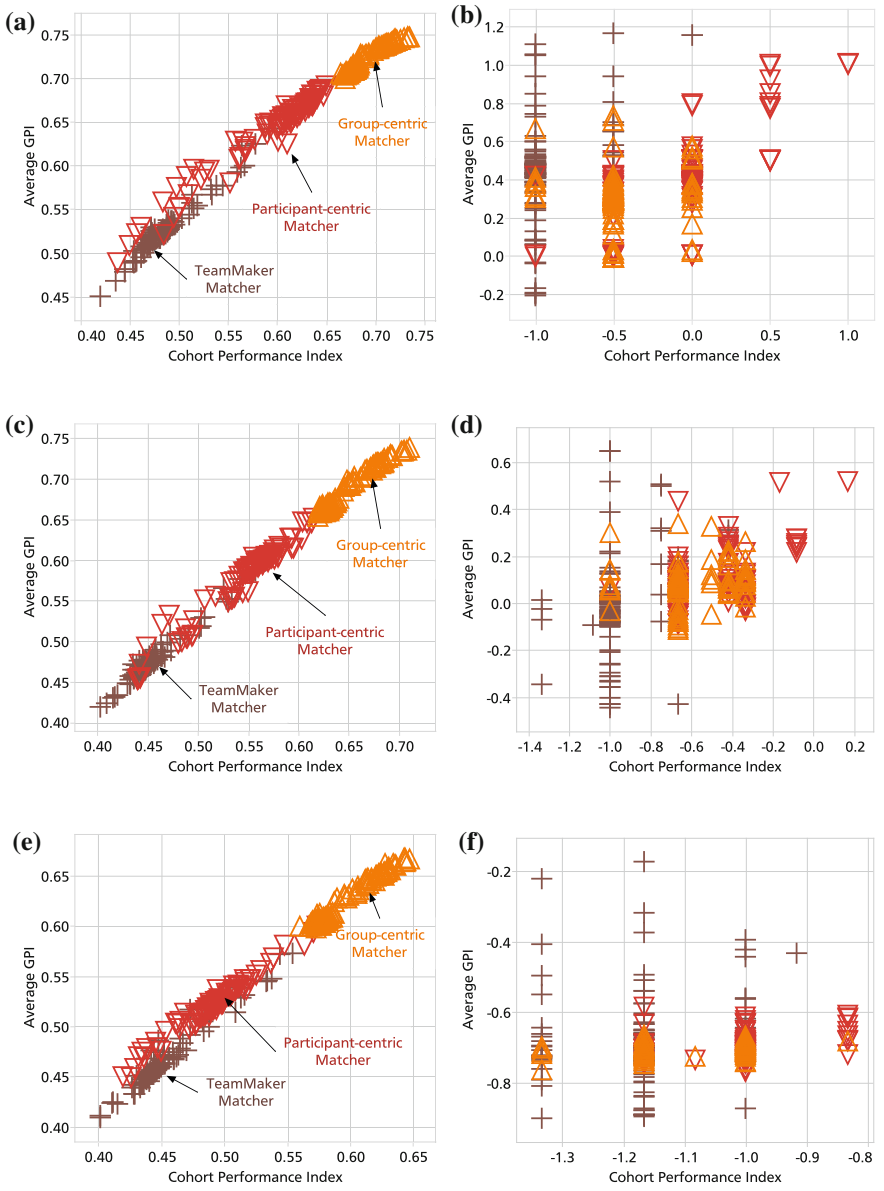

Fig. A.6 Matcher differences in Setup δ based on data variation 3 from Set 1. **a** Results on group size 2, GROUPAL metrics. **b** Results on group size 2, TeamMaker metrics. **c** Results on group size 3, GROUPAL metrics. **d** Results on group size 3, TeamMaker metrics. **e** Results on group size 6, GROUPAL metrics. **f** Results on group size 6, TeamMaker metrics

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