Effectivity of Affine Transformation Knowledge Training Using Game Mechanics

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***Abstract*—The Gamified Training Environment for Affine Transformation (GEtiT) was developed as a demonstrator for the Gamified Knowledge Encoding model (GKE). The GKE is a novel framework that defines knowledge training using game mechanics (GMs). It describes the process of directly encoding learning contents in GMs to allow for an engaging and effective transfer-oriented knowledge training. Overall, GEtiT is developed to facilitate the training process of the complex and abstract Affine Transformation (AT) knowledge. The complexity of the AT makes it hard to demonstrate this learning content thus learners frequently experience issues when trying to develop an understanding for its application. During the gameplay, the application of the AT's mathematical grounded aspects is required and information about the underlying principles are provided. In this article, a short overview over GEtiT's structure and the knowledge encoding process is given. Also, this article presents the results of a study measuring the training effectivity and motivational aspects of GEtiT. The results indicate a training outcome similar to a traditional paper-based training method but a higher motivation of the GEtiT players. Hence, GEtiT yields a higher learning quality.**

I. Introduction

The ultimate goal of using gamified training environments for knowledge training is to achieve a training transfer from the simulation to a real world context [1], [2]. *Transfer* is the application of knowledge learned or trained in one context to a different context, e.g., transferring the training outcome from a computer game to a real world context [3]. For the purpose of facilitating the training transfer, the gamified training environment has to create similar requirements to the targeted real world context [4], [5]. This can be achieved by using game mechanics (GMs) to encode the knowledge by *moderating*, i.e., scaling its level of abstraction, and *mediating* it, i.e., demonstrating and requiring its application. GMs can be distinguished in *player-bound* and *game-bound* GMs [6], [7]. While game-bound GMs are used to create the game world and the game's challenges, player-bound GMs are executed by the players to interact with the game. The *interaction* between the two GM types creates a game's gameplay thus leading to a knowledge application and demonstration. In general, GMs are the underlying rules of a computer game as they define what is possible and how actions can be performed [7]. Thus, gamified training environments include any knowledge training application that utilizes GMs to implement a knowledge application and demonstration, such as regular computer games [8], serious games [9] or, to a certain extend, gamified e-learning systems [10].

So far, the actual process of encoding learning contents in gamified training environments is still unclear. One approach suggests the *Learning Mechanics-Game Mechanics* model combining pedagogy, learning and entertainment [11], [12]. However, this model still has a lot of uncertainties about the actual training effects of GMs and the process of encoding the learning content in them. Therefore, we propose the *Gamified Knowledge Encoding* model (*GKE*) [13] that maps knowledge rules to interacting GMs to create *learning affordances* [14]. The mapping process transforms the learning content into knowledge rules that are subsequently used as a GM's internal game knowledge rules. Learning affordances require the application of the encoded knowledge and inform about the underlying principles. This is achieved by utilizing player-bound GMs to periodically require the application of the knowledge inside of a gamified training environment. The resulting interaction with the game-bound GMs provides learners with feedback about the underlying principles and the correctness of their inputs. This repetitive training process achieves a compilation of *mental models* for the learning content and its application [15]. Mental models are mental representations of a particular knowledge that allow for an internal visualization, problem solving, and knowledge transfer [16], [17]. Also, GMs present the encoded knowledge in an audiovisual way that supports the compilation of mental models [18], [19].

Our contribution: The *Gamified Training Environment for Affine Transformation* (*GEtiT*) [20], [21] was developed as a demonstrator for the GKE (see Figure 1). It encodes the Affine Transformation (AT) knowledge in its GMs to allow for an effective training of this complex and abstract knowledge. Being part of linear algebra, ATs are a sub-field of mathematics. From a theoretical standpoint, they are specialized functions that map between affine spaces. Commonly, they are expressed as matrices, usually of dimensionality 4×4, and their operations as matrix-matrix multiplications, each matrix representing one desired mapping. ATs have pervasive applications in applied geometry where they are commonly used, e.g., in the field of robotics to realize kinematic controls [22], or in

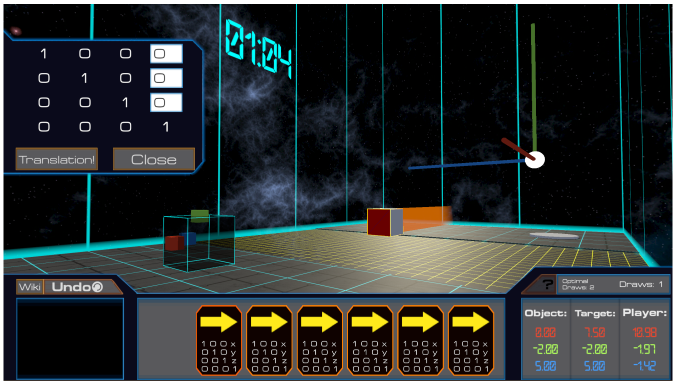

Fig. 1. GEtiT challenges learners with spatial puzzles that can be solved using AT operations. Their main goal is to transform the object (solid cube) in such a way that it matches a level's victory conditions (transparent cube). AT operations can be applied and defined using the cards and the direct value configuration screen. The object immediately gets transformed according to the values and casts a trail to provide visual feedback.

computer graphics to display and position objects [23]. Due to their complexity, ATs cannot easily be demonstrated and hence learners often encounter issues when trying to develop an understanding of this learning content. Hence, they represent an ideal knowledge for a demonstration of the GKE. Working with the GKE, the AT learning content was segmented into rules that subsequently were mapped to interacting GMs. By moderating the knowledge, i.e., reducing its level of abstraction by only encoding a subset of the total rules, an intuitive training and scaling of GEtiT's complexity is achieved. In this article, a study measuring the training environment's training effect and motivational effects is presented.

In particular, the study is guided by the following hypotheses: (H1) GEtiT causes a similar training outcome in comparison to traditional training methods. (H2) GEtiT causes a higher motivation to solve the training tasks, although the same amount of time has to be invested. (H3) Adjusting the knowledge moderation is crucial for the training outcome.

This paper begins with an analysis of the current state of research and describes our method how GMs can be used to encode specific knowledge in a computer game. Subsequently, the structure of GEtiT is examined and the design of the study is explained. Finally, this article presents and discusses the results of the study and hence provides first insights about the effectivity of the GKE.

II. Related Work

A. Game-based Training

Amongst other things, computer games have already been implemented to train complex sets of human skills such as surgery skills [24], leadership styles [25], [26], and skills of communication [27], [28] and cooperation [29], [30]. Also, video games were used to train human abilities such as the cognitive flexibility trait [31], spatial visual attention [32], and spatial resolution [33]. In general, computer games encode specific knowledge that can be learned and mastered during the gameplay [34], [35] as players periodically discover new challenges and multiple ways to solve them [36]. The immersive effect of playing a computer game can be used to introduce players to ethical questions [37] and moral problems thus achieving a training of moral decision making [38].

Well designed computer games automatically fulfill the conditions for *optimal learning* [39]. Due to their flow-inducing capabilities [40], they present the encoded game knowledge in a highly engaging and immersive way thus achieving a high player *motivation* to tackle a game's tasks. Also, computer games periodically increase the game goals' difficulty to compensate the training effect and to continuously provide players with new challenges [41]. In this way, a computer game requires *pre-existing* knowledge and even requires the knowledge learned during the gameplay. Computer games provide players with *immediate feedback* about the effects and correctness of their actions and their progress towards solving a challenge. Lastly, a game's general gameplay requires a *repetitive* application of the encoded knowledge thus ultimately achieving a training effect due to repetition [8].

The implementation of an AT training game requires an environment that allows for the presentation and training of geometry. The gameplay of adventure and strategy games provides players with clear objectives and puzzles they need to solve to proceed with the game [41]. Solving the game objectives challenges the players' skills of logic, memory, visualization, and problem-solving [42] which also are crucial for solving training exercises. The gameplay of action-based computer games results in a training of spatial abilities such as the mental rotation skill [43], spatial visual attention [32], spatial resolution of vision [33], and spatial navigation [44]. Playing action-based video games can also improve cognitive abilities [5], such as the working memory capacity, and hence enhance the players' ability to monitor task relevant information [45]. The improvement of the spatial abilities by playing action-based games can even have a positive impact on the understanding of geometry. It was shown that an improvement in spatial abilities can improve 3D geometry thinking [46]. Furthermore, research has shown that descriptive geometry instructions stimulate the development of spatial abilities [47]. Hence, designing GEtiT's GMs in a way that they challenge the cognitive spatial abilities of a player should support its training effect.

B. Construct 3D

Using virtual environments for the teaching of geometry was already approached with *Construct3D*, an Augmented Reality (AR) application to teach mathematics and geometry, which is based on the AR framework *Studierstube* [48]. Construct3D allows students to create geometrical objects from a selection of basic object types and to explore these new objects in detail by manipulating them.

The application's key feature is the strength to display abstract geometrical problems and to visualize geometrical objects almost haptically. Students can explore the geometrical objects by walking around them, hence developing a spatial understanding of the geometry.

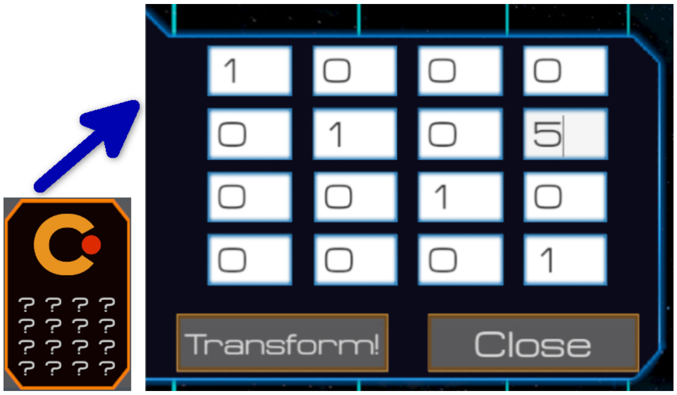

Fig. 2. By activating an AT card, the direct value configuration screen is opened to allow for an input of self-obtained values.

In contrast to GEtiT discussed in this paper, Construct3D is not a gamified training environment and hence is not implementing GMs to present and require the knowledge. Although the users of the AR application can perform playful experiments with geometry [49], the main focus lies on the visual presentation of geometry with the aid of AR. Moreover, Construct3D is used for a more general education in geometry and does not only focus on a specific branch of it. Construct3D also does not provide the users with clear goals they need to achieve to proceed.

III. Gamified Training Environment for Affine Transformation

Aside from encoding the AT knowledge in its GMs, GEtiT must fulfill three additional requirements to achieve an effective knowledge training. 1) Clear and well defined goals are needed that require learners to apply their AT knowledge to proceed with the game. 2) A manipulable object is required to give the users a concrete target for the AT operations and to provide them with immediate feedback about the effects and correctness of the applied AT operations. 3) Lastly, an input GM is needed that allows for the configuration and application of individual AT operations. Also, one of the GMs needs to scale the level of abstraction of the AT knowledge.

The manipulable object and the input GM represent the core GMs for the gamified knowledge encoding of the AT. A manipulable object is a commonly used GM. It is often implemented as a means to solve puzzles in an action or adventure game. Working with the GKE, the object GM is used to encode the knowledge rules that determine the effects of individual AT operations thus mediating them. As a result, the object changes its status when an AT operation is applied to it thus demonstrating and visualizing its effects. The object is implemented as a cube featuring three differently colored sides to allow for a visualization of the object's orientation.

The AT input GM, on the other hand, encodes the theoretically grounded mathematical aspects of the AT knowledge. In particular, this GM allows for a definition and application of an AT operation to transform the object. This input GM is implemented with the player's ability to select and play cards that open a direct value configuration screen resembling the structure of a 4×4 matrix (see Figure 2). This direct value configuration screen provides an interface for the configuration of an AT operation by using self-obtained values as inputs. After confirmation, the entered values are propagated to the object that immediately gets transformed thus demonstrating the AT's underlying principles. The cards and the configuration screen are not only visually representing, i.e., mediating, the knowledge rules, but also are moderating them. Depending on the selected difficulty level, i.e., the moderation of the abstraction, the cards display a symbol indicating the provided AT type and a symbolized vector or matrix representation. Cards can even be fully defined thus immediately applying an AT operation without requiring additional value inputs. Also, the direct value configuration screen gets adjusted and either displays an empty vector, a reduced 4×4 matrix giving only access to the fields relevant for a particular AT type, or the full matrix. Ultimately, the interaction between the game-bound object and the player-bound AT input GM requires the application of the learning content and demonstrates its underlying principles.

The game goals are implemented following the concept of an escape scenario [50]. At the start of each training level, the players find themselves trapped in a sealed room. They can only escape by solving spatial puzzles that ultimately unlock the level's exit. The spatial puzzles are created with the level design, i.e., the position of obstacles blocking the object's path and a switch GM. The switch displays a level's victory conditions in the form of a semi-transparent version of the object and simultaneously checks if these conditions are met to finally unlock the exit. As a result, GEtiT challenges the learners to analyze a spatial puzzle and to subsequently transform the object in such a way that it matches the victory conditions using the AT cards.

Ultimately, the mapping process of the AT knowledge rules to the two core GMs and the level design creates a gamification metaphor. A gamification metaphor represents and requires the learning content inside of a particular training environment. Thus, a gamification metaphor creates a knowledge's gamified meta-model that can fully be internalized in the form of mental models. In this way, the AT gamification metaphor achieves the compilation of mental models during the gameplay and is responsible for the training transfer to a different context.

GEtiT also features additional GMs to enhance its accessibility and usability. In order to successfully transform an object, four positions in a particular level must be known: the position of the object, the player, the origin, and the target. The origin's position is needed to correctly perform an AT operations when the object is not located directly inside of the origin as this will result in the object's translation. The indication of the player's position can be used to determine a specific position in the room whereas the object's position is required to correctly calculate a transformation. In addition, the indication of the object's position helps the learners to compile a mental model for the relation between the matrix representation and the actual transformation of the object.

Finally, the position of the target is shown to help the users to plan their steps ahead and to allow them to focus on the application of the AT knowledge instead of being required to determine the target's position by walking to it first.

Apart from the indication of these different positions, GEtiT displays the direction of the room's three axes to visually assist learners with the determination of the correct transformation. In order to immediately display the path on which the object has moved, the object casts a trail each time it gets transformed. This indication is implemented to visually support the compilation of a mental model for the effects of sequencing different AT operations and the individual operations' effects in general. Also, this GM is introduced to allow students to learn from wrong inputs as it provides a means to analyze own mistakes [51]. This feature is combined with an undo-function that allows the learners to revert their last action.

Finally, GEtiT provides learners with a clear bonus objective by providing an optimum amount of transformations for a particular level and keeping track of the amount of transformations a player needed. Based on the ratio between both variables, players are rewarded with highscore points that reflect a player's performance throughout the game. Furthermore, the game displays the time a player needed to solve a level to encourage the players to retry a level and to beat their own time.

In the end, GEtiT purely implements GMs relevant for the AT knowledge encoding and training. Therefore, the structure of GEtiT represents a direct implementation of the GKE. Thus, the GEtiT acts as a demonstrator for a transfer-oriented knowledge training using GMs and can be used to validate the GKE.

GEtiT is developed with *unity* in the version 5.5.2p1 [52] for PC and Mac. It runs without any performance issues on all current machines.

IV. Methods

A. Measures

1) Training Outcome: The training outcome of GEtiT was measured with an exam assessing the AT knowledge of the participants. The exam consisted of 15 multiple choice assignments that were designed to be of equal difficulty to the assignments normally used in the final exam of an Interactive Computer Graphics lecture.

2) Gameplay Progress: In order to analyze the training progress and effectivity, a player's amount of successfully solved levels, amount of highscore points earned, and the time spent in each individual level was measured.

3) Joy of Use: For the purpose of comparing the joy of use of both training methods, a questionnaire (1 = disagree, 5 = agree) consisting of nine questions (Q1 - Q9) was designed. The questionnaire for GEtiT players also included further questions about GEtiT's motivational effects (Q10 - Q14).

- Q1 Have you enjoyed playing GEtiT / solving the paper-based assignments?
- Q2 Have GEtiT's puzzles / the assignments helped you to develop a better understanding of the AT?
- Q3 Have you noticed a knowledge gain while you were solving the GEtiT puzzles / the assignments?
- Q4 Has the raise in the difficulty matched your knowledge gain?
- Q5 Were the tasks of the GEtiT puzzles / the assignments easy to understand?
- Q6 Was the difficulty of the GEtiT puzzles / the assignments well adjusted?
- Q7 Were you motivated by new challenges due to a raise in the difficulty?
- Q8 Have you enjoyed the class that was based on GEtiT / the paper-based assignments?
- Q9 Was it interesting to solve the GEtiT puzzles / the assignments by using AT operations?
- Q10 Was the computer game-based training method more enjoyable than traditional training methods (e.g. paper-based assignments)?
- Q11 Would you prefer to utilize a training game instead of visiting a regular class?
- Q12 Have you noticed a higher motivation to play GEtiT to train your knowledge in contrast to other training methods?
- Q13 Were you motivated by the additional feedback mechanisms, such as highscores and the amount of used operations?
- Q14 Have the feedback mechanisms motivated you to try a particular level again to improve your performance?

B. Participants

All participants of a lecture on Interactive Computer Graphics at the University of Würzburg were invited to take part in the study. The students were rewarded with credits mandatory for obtaining their Bachelor's degrees. The group of participants who completed the study consisted of 64 students (16 females, 48 males), 21 of which were between 19 and 21, 24 between 22 and 24, nine between 25 and 27, one between 28 and 30, and two above 30 years old ($M_{age} = 20.61$, $SD_{age} = 7.66$). The remaining seven participants never reported their age. Except for two female participants, all other participants had previous experience with playing computer games, 17 of which played less than 1 hour, eleven between 1 and 5 hours, eleven between 5 and 10 hours, six between 10 and 15 hours, twelve between 15 and 20 hours, and seven more than 20 hours computer games per week.

C. Experimental Design

The study consisted of four weekly 90-minute training sessions and a final knowledge assessment test. The training began in the same week in which the first part of the AT learning content was presented in the lecture thus simulating a regular class-based training that aligns with a lecture's progress. For the purpose of analyzing the training outcome of playing GEtiT, the participants were randomly assigned to three different groups. The *paper group* ($n = 25$) trained their AT knowledge with traditional paper-based assignments, the *game group* ($n = 24$) and the *home group* ($n = 15$) played

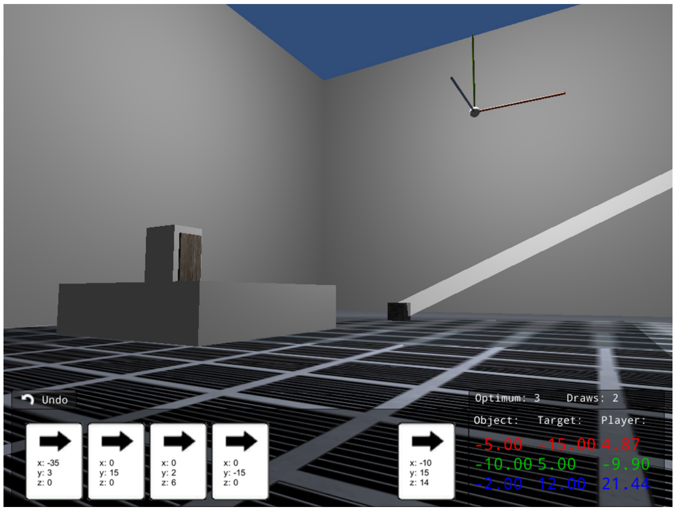

Fig. 3. GEtiT was played in its prototype status during the study. Although it lacks the current futuristic style and overall appearance of a regular game, it implements all GMs encoding the AT knowledge.

Fig. 4. Students playing GEtiT in the lab. The class-based training allows for a comparability with the traditional paper-based training method.

GEtiT. The game was used in its prototype version as Figure 3 displays. In contrast to the game group who played GEtiT on the computers in the lab (see Figure 4), the home group had no fixed appointments and was allowed to play the game as much as they liked. The paper group gathered in a class room and received a new set of paper-based training assignments they had to solve to foster their AT knowledge each week.

One week after the end of the training period, the exam was written. Also, the participants were asked to rate the joy of use of their training method by filling out the questionnaire.

V. Results

A. Training Effects

Over the course of the training period, the game group solved $M_{game} = 72.58$ levels and the home group $M_{home} = 65.87$ levels on average.

TABLE I
Overview of the test results in the final exam.

Group	n	mean result in %	sd	min	max
All	64	65.52	20.49	15	97
Paper	25	68.00	19.17	31	96
Game	24	64.33	23.09	15	97
Home	15	63.27	19.10	34	96

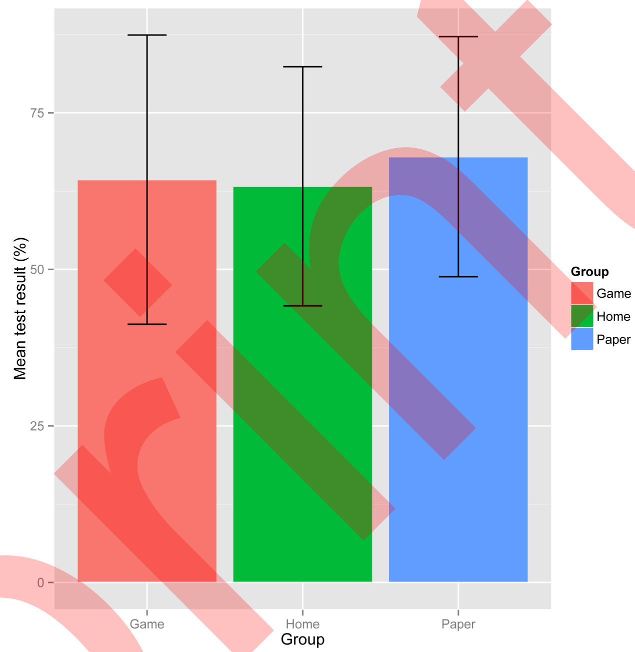

Fig. 5. Comparison of the mean results in the final exam in percent. The error bar indicates the standard deviation.

In the final exam, as shown in Figure 5 and Table I, the paper group achieved 68%, the game group 64.33%, and the home group 63.27% of the total amount of points on average. A one-way ANOVA test was applied to compare all three groups and revealed no significant difference in the test results between the groups ($F(62) = 0.469$, $p = 0.496$). Furthermore, no correlation could be found (Pearson's $cor = -0.087$, $t(62) = -0.68$, $p = 0.496$) between the test results and the groups.

A more in-depth analysis of the test results of the game group revealed a significant correlation (Pearson's $cor = 0.501$, $t(22) = 2.71$, $p = 0.013$) between the result in the exam and the amount of levels solved during the training period.

The analysis of the home group revealed no significant correlation between the result in the knowledge assessment test and the predictor variables. No correlation was found between the result and the amount of solved levels (Pearson's $cor = -0.202$, $t(13) = -0.745$, $p = 0.469$).

B. Motivational effects

The questionnaire was completed by 55 participants, 34 of which were GEtiT players and 21 belonged to the paper group. The two individual GEtiT groups got merged for the joy of

TABLE II
MEAN JOY OF USE RATINGS OF BOTH GROUPS (GAME GROUP: $n = 34$, PAPER GROUP: $n = 21$).

Q	game (SD)	paper (SD)	t(53)	p	Cohen's D
Q1	3.76(1.02)	3.24(1.22)	1.728	0.089	0.479
Q2	4.06(0.92)	4.24(1.09)	−0.654	0.516	0.182
Q3	4.12(0.98)	4.19(0.98)	−0.268	0.789	0.074
Q4	3.00(1.15)	3.05(1.07)	−0.153	0.879	0.042
Q5	3.76(0.78)	2.57(0.98)	4.995	< 0.001	1.386
Q6	3.71(1.12)	3.62(0.86)	0.304	0.762	0.085
Q7	3.85(0.96)	3.19(1.03)	2.421	0.019	0.672
Q8	4.00(0.89)	3.38(1.12)	2.275	0.027	0.634
Q9	4.00(0.92)	3.52(1.12)	1.712	0.093	0.475
Q10	4.24(1.10)	–	–	–	–
Q11	4.12(1.09)	–	–	–	–
Q12	3.91(1.00)	–	–	–	–
Q13	3.21(1.17)	–	–	–	–
Q14	3.56(1.16)	–	–	–	–

use evaluation as both groups played the same version of the game. Also, the questionnaire was designed to only evaluate GEtiT and not its implementation in a class-based or home-based training.

Although no significant difference between both groups could be found (see Table II), the GEtiT players slightly agreed that they have enjoyed playing the game, whereas the paper group neither agreed nor disagreed that they have enjoyed solving the paper tasks (Q1). The GEtiT players agreed that solving puzzles inside the game using AT operations (Q9) was enjoyable whereas the paper group neither agreed nor disagreed that they have enjoyed utilizing their knowledge to solve the assignments. Both groups agreed that their training method has helped them to develop a better understanding of the AT (Q2) and that they noticed a knowledge gain (Q3) over the course of the training sessions. Both groups neither agreed nor disagreed that the raise in the difficulty level matched their knowledge gain (Q4) and that the difficulty level of the tasks was well adjusted (Q6). The understandability of the game tasks was significantly ($p < 0.001$) rated higher than the understandability of the regular assignments (Q5). In total, the GEtiT players slightly agreed that the tasks inside the game were easy to understand whereas the paper group slightly disagreed with the understandability of their assignments. The GEtiT players gave a significantly higher rating ($p = 0.019$) on the motivational effects of a raise in the difficulty level over the course of the completed training tasks (Q7). Additionally, the GEtiT players gave a significantly higher rating ($p = 0.027$) on the overall enjoyment of the class (Q8).

All GEtiT players agreed that using the training game was more enjoyable than utilizing a regular training method to foster their knowledge (Q10). Furthermore, they would prefer to join a class that utilizes a training game (Q11) than joining a class that implements a traditional training method. The players also agreed that they experienced a higher motivation to train their knowledge using GEtiT than utilizing a traditional training method (Q12). The motivational effects of additional feedback mechanisms received an average rating (Q13) and was not really seen as an incentive to try again a certain level (Q14).

VI. DISCUSSION

A. Training Outcome

The results have shown that GEtiT yields a training effect that is similar to the training effect of a traditional paper-based training. In the exam, the results achieved by the game group and the home group were not significantly different to the results achieved by the paper group. As no correlation between the groups and the test results could be found, the results support the finding that both methods have a similar training effect. Also, the gamified training environment has a similar training effect independent from its application as a class-based or home-based training method. Both GEtiT groups yielded a similar result in the final exam. Hence, the results of the study *support hypothesis H1)* as GEtiT has achieved a training effect that is similar to the training outcome of a traditional training method.

The results also indicate a successful compilation of mental models and a successful training transfer on the side of the game groups. The exercises used in the final exam had a similar structure to the paper-based assignments and hence the paper group was able to directly apply their knowledge practiced during the training sessions. The GEtiT groups, however, were exposed to this type of exercise for the very first time. They not only had to solve the exercises, but also to develop an understanding of this particular representation and to transfer their knowledge while experiencing exam anxiety. This assumption is supported by the fact that the game groups had to deal with a different visual representation. In contrast to GEtiT's 3D environment, the visual representation used in the exam were reduced to 2D before-and-after pictures. Although both game groups had to deal with those additional challenges, they achieved a similar result to the paper group thus indicating a successful compilation of mental models for the AT learning content.

The signifiant positive correlation between the amount of solved levels and the test result validated the concept of the GKE. A more frequent application of the learning content and an increased amount of solved problems resulted in a gain of expertise in applying the AT. The visual demonstration of the effects supported the compilation and further improvement of mental models used to successfully transfer the training outcome from GEtiT to the paper-based exam. The results also indicate the importance of a periodical execution of the gamification metaphors to fully internalize the encoded meta-model for the knowledge.

In contrast to the performance of the game group, the home group showed no positive correlation between the gameplay and the test result. This phenomenon can be explained by the fact that the home group had not a clear playing schedule and might not have taken the knowledge training serious enough. Also, the gameplay of the home group took place in an uncontrolled environment. Hence, it is possible that some of the participants were not completely focussed on the gameplay as they might have played the game in a distractive environment.

B. Motivational Effects

The results of the joy of use evaluation support the finding that GEtiT has a similar training effect to a traditional training method. The GEtiT players and the participants of the paper group agreed that their training method has helped them to develop a better understanding of the AT. Also, they noticed a knowledge gain over the course of the training sessions which is a crucial outcome. The awareness of making progress gives learners the feeling that the implemented training method is useful thus increasing their acceptance and motivation. Moreover, this result indicates the effectivity of the GKE as the AT gamification metaphor not only achieved an effective knowledge training, but also seemed useful to the learners.

For the purpose of creating an engaging training environment and fulfilling the conditions for optimal learning, it is necessary to provide the learners with clear tasks that increase in difficulty over time to keep the motivation high. In contrast to the paper group, the GEtiT players gave a significant higher rating on the understandability of the training tasks in the evaluation. In total, the GEtiT players even slightly agreed that the tasks were easy to understand whereas the paper group slightly disagreed with the understandability of their assignments.

The evaluation has shown that finding the right difficulty level is a critical part of creating effective training environments. Both groups neither agreed nor disagreed with the overall adjustment of the difficulty for each individual assignments and the raise in the difficulty over time. Creating a constant stream of new challenges is one of the biggest strengths of computer games as this contributes to their flow-inducing characteristics. Players feel motivated when the game constantly provides them with new task thus keeping them challenged [41]. Once they have exhausted a challenge, their skill level has increased and they are prepared for the next challenge to put their skills to a test, again. The effectivity of motivational effects of an increasing difficulty level in the game was supported as the GEtiT players gave a significantly higher rating on the motivational effects of reaching higher difficulty levels.

This result also shows the importance of matching the learners' individual knowledge gain with the increase in the difficulty level to create an engaging learning environment. By adding more complex knowledge rules to the gamification metaphors over time, learners are not overwhelmed by the complexity and abstraction of the learning content. Instead, they can intuitively practice the knowledge and update their mental models as they progress through the training levels. Thus, the results *support hypothesis H3* as the knowledge moderation during the encoding process is crucial to intuitively introduce learners to a complex knowledge.

Finally, the GEtiT players agreed that they enjoyed playing the game and solving the game's puzzles using their AT knowledge to practice the targeted learning content. The paper group neither agreed nor disagreed to these three questions. As a result of this, GEtiT has not only achieved a similar training outcome to the traditional training method, but also proven to yield a higher motivation to tackle the learning content. Thus, the results of the study *support hypothesis H2* and show that GEtiT achieves a higher quality of learning.

VII. Conclusion

GEtiT was developed as a demonstrator for the GKE and uses GMs to require and to demonstrate the encoded learning content in an engaging way. During the gameplay, players are locked into sealed rooms from which they can only escape by solving spatial puzzles requiring the application of the AT learning content. Once a puzzle is solved, players can proceed to the next challenge by leaving the level through an exit. GEtiT moderates the learning content's level of abstraction by providing four different difficulty levels. Each difficulty level encodes a subset of the AT knowledge rules thus achieving a certain distance to the learning content which is decreased over time. In this way, GEtiT intuitively presents and requires the learning content. Learners practice the AT knowledge by periodically executing player-bound GMs encoding the AT knowledge and receiving immediate feedback from interacting game-bound GMs.

The present study compared the training effects and motivational aspects of GEtiT with a traditional training method of using paper-based assignments to practice the AT. Although GEtiT players had to invest the same amount of time to practice the learning content, they derived more enjoyment from the gameplay than learners who used a traditional paper-based training method. Additionally, GEtiT presents the tasks in a clear way and provides the users with constant and immediate feedback about their progress. A final knowledge assessment test revealed that GEtiT and the paper-based training method yield a similar training effect. Also, the study validated GEtiT's effectivity for transfer-oriented knowledge training as the participants were successful at transferring their training outcome from the training environment to a real world exam. Thus, GEtiT ultimately achieved a higher learning quality in comparison to a traditional training method.

Future research should be aimed at follow-up projects that utilize the GKE framework to encode specific knowledge in interacting GMs. This is critical as it would test for its general applicability. Concerning GEtiT, the next important steps are to improve and to subsequently evaluate the moderating effects of its audiovisual presentation. Also, it is critical to test the effects of a higher visual immersion on the training outcome by evaluating a virtual reality version of GEtiT.

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