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Learning Effects of Augmented Reality and Game-Based Learning for Science Teaching in Higher Education in the Context of Education for Sustainable Development

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Abstract: In the course of digitalization, new technologies and innovations are continuously introduced to the educational sector. For instance, augmented reality (AR) is increasingly applied in science teaching in both school and higher education. Combining real and virtual content potentially enhances interactivity and understanding of the learning process. This teaching and learning approach can positively impact various learning outcomes, such as learning gains and motivation. This paper aims to investigate the positive learning effects of AR using a game-based AR learning environment: "Beat the Beast". In line with the concept of an education for sustainable development (ESD) topic, microplastics, this learning environment follows an interdisciplinary approach, combining the subjects of biology, chemistry, and engineering. To determine and distinguish the effects of implementing the technology AR in science learning environments as well as the principles of game-based learning, we contrasted the learning environment into two factors: one with AR and one without AR and the other with a game and without a game. A quasi-experimental design with 203 pre-service teachers of the first semester of all subjects was chosen to evaluate the four different types of settings with questionnaires on motivation, technology acceptance, user engagement, cognitive load, computer self-efficacy, knowledge, and ESD outcomes in higher education. Our research demonstrates that although augmented reality (AR) imposes a relatively elevated cognitive load, it does not negatively affect learning effects. In spite of the increased cognitive load, learners in AR settings do not exhibit lesser knowledge acquisition compared to those in alternative environments. Moreover, our investigation highlights AR's potential to amplify motivation and user engagement. Contrary to expectations, in the context of the selected subject matter and target audience, game-based adaptations of the educational environment fail to enhance learning outcomes. These versions actually underperform compared to other formats in both motivational and engagement metrics.

Keywords: augmented reality; game-based learning; science teaching; engineering teaching; motivation; technology acceptance; user engagement; cognitive load; computer self-efficacy; DPACK; TPACK

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1. Introduction

As digitalization progresses, technologies, as well as devices, are merging their way into the educational sector. Augmented reality (AR) is a significant advancement increasingly applied in science and engineering education. This is demonstrated by the growing amount of AR applications developed and investigated to teach various scientific topics [1–7]. AR is a technology that integrates digital content into the real world, allowing users to experience an overlay of the real and digital worlds. Krug and colleagues [3,8,9] defined AR as a combination of real and virtual content, where reality is supplemented with digital content that is interactive, in real time, and has functional 3D registration. This definition combines the key aspects of both the definitions of Milgram and colleagues [10] and Azuma [11].

In science and engineering education, difficult-to-visualize and abstract concepts are frequently encountered, requiring a high degree of imagination and conceptualization. As AR integrates virtual content into the real environment, it enables visualization of these challenging concepts [12]. AR also allows for increased interactivity, facilitating students to actively engage with AR scenarios and enhance their understanding of facts and relationships. Additionally, AR potentially permits personalized learning by adapting to individual learning progress or providing stepped assistance that students can use as needed. This way, a wide range of needs and learning styles can be accommodated.

There are now numerous examples of AR applications (AR apps) in science and engineering education. In biology, AR apps are frequently used to represent and explore virtual models of biomolecular functions and relationships [13,14] or anatomical structures [15–17]. Additionally, AR can visualize representations of the biological levels of organization from macroscopic to submicroscopic phenomena [18].

In chemistry, AR opens new possibilities, such as digitally enhanced chemistry laboratories [19,20], manipulable molecules [21–24], and simulation of complex chemical reactions [25]. This not only simplifies understanding of concepts such as bonding and reactions but also allows for safe experimentation by displaying safety instructions or fully replacing hazardous experiments that are no longer permitted in schools [26].

In physics, AR can enhance the understanding of physical principles such as mechanics, electricity, and optics, which are difficult to illustrate in traditional classrooms. With AR, digitally enhanced experiments enable the construction and visualization of invisible phenomena like magnetism, electron motion, and more [27].

In engineering education, the benefits of AR range from enhancing students' spatial ability [28,29] in knowledge acquisition [30] to a better understanding of invisible concepts in the field of engineering physics [31] and increased motivation [32].

As described in several research projects, AR can have a positive impact on learning. Primary positive effects of AR are reported as benefits for motivation, engagement, cognitive load, and knowledge acquisition [2,4,5,33–37]. While some research generally describes the potential of AR to foster self-regulated learning [38], few report evidence of improved self-efficacy [36,39].

1.1. Augmented Reality Combined with Gamification and Game-Based Learning

Gamification is defined as the integration of game-like elements in a non-game context [40]. In education, this can be achieved by adding badges, points, and rewards or implementing story-telling. Game-based learning goes further and incorporates learning content into a game framework. Enriching the learning process in this manner has the potential to serve as an intriguing, fun, and interesting experience. It also may increase motivation, interest, engagement, and performance [41], foster friendly competition, and reward effort [42].

Gamification and game-based learning in science and engineering education can be applied by integrating digital media, for instance, the combination of gamification and AR [42,43]. The explorative nature of AR facilitates the integration of game into the learning environment, increasing diversity, and thereby enhancing interactivity. The combination of game and AR might result in several educational benefits, such as increased motivation, engagement, self-efficacy, and immersion, as well as knowledge acquisition and critical thinking skills [44]. In their systematic review, Lampropoulos and colleagues [42] highlight the effectiveness of gamification for science teaching and further report that the interplay of AR and gamification has great potential, though it is emphasized that a proper integration is necessary, considering educational strategies, learner's knowledge, and characteristics. Following Lampropoulos and colleagues [42], game-based AR fosters participation and engagement, increases curiosity, interest, and enjoyment, and improves performance and learning outcomes.

Moreover, the playful manner of game-based learning has the potential to reduce technostress. Technostress is a negative effect of introducing new technologies [45]. It may feel like tension or pressure occurs when one feels unable to operate or accept a certain technology. More generally, it can occur when trying to keep up with ever-emerging new technologies. Users may fail to see the benefit of adapting to a new technology or find its operation too overwhelming [46]. Fajri and colleagues [46] found that incorporating gamification into e-learning can enhance enjoyment and reduce technostress. However, they notice it will need further research. Combining innovative digital media, such as AR, with familiar game elements may lower the threshold for students to use new technology and create an intriguing experience.

The combination of AR and game-based learning is promising [20], yet findings are inconclusive. The study of Nguyen and Meixner [47] demonstrates this by comparing game-based AR training versus non-game-based AR training for engineering. They found improved engagement and performance for both AR designs, yet there was no statistically significant difference among them. Comparing a digital but non-AR, game-based approach to a game-based approach with AR on biodiversity, Meekaew and Ketpichainarong [48] found the students using AR to significantly show higher motivation and better understanding. In the comparison of interventions with/without AR and game elements, Chen [49] finds both aspects significantly enhance motivation, whereas game elements positively affect learning and flow state.

Although AR and game-based learning each offer various benefits for science and engineering teaching, further research on the effect of both is vital. Xu and colleagues [4] also mention the need for further research in the combination of game-based AR learning. When combining AR and game-based learning for science and engineering teaching, the interplay, as well as the impact of each aspect on the learning effects, is yet unclear.

1.2. The Effects of Augmented Reality on the Leraner's Motivation

Learning motivation can be defined as the intention to acquire specific content or skills in order to achieve certain goals [50]. This is also described in the Self-Determination Theory of Motivation proposed by Deci and Ryan [51], which is related to the study of human behavior in relation to motivation and the pursuit of goals. The Self-Determination Theory underscores the tight interconnection between intrinsic motivation and the fulfillment of psychological basic needs (autonomy, competence, and social relatedness). Individuals are most motivated and attain peak performance when they have the opportunity to govern their actions autonomously, perceive competence, and experience social recognition and acceptance [51]. Especially within the educational context, the Self-Determination Theory of Motivation bears significant implications for the design of learning environments. It emphasizes the importance of choices, self-directed learning, and appreciative feedback to foster intrinsic motivation and long-term learning engagement. Considering this theory, the potential of utilizing AR as an interactive and stimulating medium becomes evident, as it can support the development of autonomy, competence, and social relatedness. Numerous studies have found AR can enhance the motivation and interest of students [52–55]. The research by Ferrer-Torregrosa and colleagues [56] and Ibáñez and colleagues [57] accentuates that AR can heighten learner autonomy while concurrently facilitating knowledge acquisition.

1.3. Technology Acceptance When Using Augmented Reality

When introducing new technologies in educational settings, both teachers' and students' acceptance of such is a crucial aspect. Implementation of innovative technologies in the classroom is often hindered by a lack of teacher acceptance [58]. Contrarily, students mostly value innovative technologies for learning, such as AR.

Technology acceptance cannot be generally associated with a specific type of technology [58]. To measure technology acceptance, various aspects such as the setting, design, execution, and type of participant have to be considered. Therefore, technology acceptance has been repeatedly assessed in diverse studies on digitalization in education [59].

When developing AR applications or learning scenarios using AR, technology acceptance should also be taken into account since new technologies tend to unsettle users, especially when they lack prior experience. This assumption follows from a study performed by Tiede and colleagues [60], who were able to show that teachers' prior experience and self-efficacy in dealing with digital media are predictors of teachers' attitudes toward using AR as well as their technology acceptance. These findings are consistent with a study by Joo and colleagues [61], who demonstrated a positive correlation between self-efficacy, perceived usefulness of a technology, and its perceived ease of use.

1.4. Augmented Reality and User Engagement

User engagement is a strong factor in the user experience of digital media. It is defined as the investment a learner is ready to commit when interacting with a digital system based on the quality and intensity of the interaction [62]. High levels of engagement may attract the user, hold the attention and interest, improve performance, and thus contribute to the effectiveness of learning [47,63]. Several research works have investigated the aspect of engagement with AR learning environments and report that AR has the potential to increase engagement [35,47,57,63,64]. Higher levels of engagement are connected to AR, as it offers and promotes different forms of interaction with the system, media, or technology [65,66].

1.5. Augmented Reality's Impact on the Learner's Cognitive Load

Handling cognitive load through proper instructional design has been extensively examined in the past decades, resulting in guidelines like the Cognitive Theory of Multimedia Learning [67]. Digital media and especially innovative technologies have the potential risk of boosting the extraneous load, e.g., when learners are overwhelmed and occupied with the handling of the technology instead of engaging with the learning content itself [68].

In terms of AR, evidence of its effect on cognitive load is presently inconclusive [35,69]. A review targeting cognitive load in connection with AR [69] found that in most studies, a reduced cognitive load is reported, resulting in improved performance. However, they also detected studies reporting a higher cognitive load with the use of AR compared to traditional learning materials. Furthermore, some publications state AR reduces cognitive load [38,70,71], while others report AR impairs cognitive load [18,72,73]. Overall, they conclude that the use of AR as a teaching/learning tool can reduce cognitive load and explain this with both the split-attention effect and the "spatial and temporal contiguity principle" [67], which suggests presenting connected information spatially simultaneously and at the same time, so there is no need for shifting the focus while learning.

1.6. The Learner's Self-Efficacy When Using Augmented Reality

Self-efficacy reflects the individual perceptual pattern regarding a learner's own skills and competencies. The potency of this self-efficacy directly influences the efforts invested by a learner, thereby precipitating an immediate impact on the outcome of the learning process. Self-efficacy expectation represents an individual's personal conviction in their ability to tackle novel and challenging tasks based on their perceived competencies [74]. Following Bandurra [75], four sources can be identified from which individual expectations regarding one's own abilities can be derived. These encompass performance outcomes in the form of personal successes and failures, observation of behavioral patterns in others as vicarious experiences, verbal encouragement, as well as physiological and emotional states. These sources can be hierarchically ordered based on their differentiated degrees of influence [74]. AR technology holds the potential to augment the self-efficacy expectations of learners. This is facilitated through the creation of an interactive and visually oriented learning environment, which eases the comprehension of complex and abstract concepts.

Consequently, this technology has the potential to empower students to enhance their performance in these domains, thus enabling individual instances of achievement. Such instances of success, in turn, contribute to the alteration of the personal perception of individual agency in a positive manner, constituting a fundamental facet in the formation of one's self-efficacy belief [74]. The validity of this assertion is likewise affirmed by the work of Cai and colleagues [36], who discovered that the integration of AR into mathematics education exerts a positive effect on self-efficacy. These beneficial impacts are reflected in heightened focus and optimized learning approaches by the learner. Such constructive learning experiences empower learners to significantly influence the expectation of their individual self-efficacy, potentially leading to a progressive enhancement in self-confidence, perceived competency, and achievement. Furthermore, this development may extend to fostering elevated self-efficacy expectations even within non-AR-supported learning environments. Self-efficacy toward technology usage was found to influence a user's attitude toward technologies and affect a user's perceived ease of use and, therefore, the intention to use technologies [76,77]. Therefore, self-efficacy in the form of computer self-efficacy is a determinant when using technologies in the classroom.

1.7. Sustainable Development Goals and Education for Sustainable Development

Within the Agenda 2030, the UN defined 17 Sustainable Development Goals (SDGs) for the transformation toward a sustainable society [78]. These are based on three dimensions: economic, social, and environmental. Education for Sustainable Development (ESD) is the approach to include these aspects in education. ESD is a step in the process toward achieving the SDGs by teaching both knowledge and competencies. Germany started the process of implementing ESD in education in 2015 systematically [79]. ESD is understood as enabling the learner to make informed decision making and take action. Learners shall become aware and understand interconnected global challenges on an individual and collective extent, including influences and consequences on economic, social, and environmental levels. Appropriate knowledge, skills, and values for this are taught by implementing interdisciplinary topics, enabling learners to act as agents of change [80]. Thus, it involves three aspects: cognitive learning outcomes (knowledge and understanding), affective components (values and attitudes), and behavioral components (intentions and skills). The interplay of all three will help learners not only understand current situations but also question their own behavior and shape change [78]. Changing values, attitudes, and intentions to show more sustainable behavior is a long-term process that short-term interventions can only begin to achieve [81]. It turns out that playful approaches seem to be suitable, with which at least changes in sustainability-related attitudes can be initiated [82]. In their literature review, Janakiraman et al. [82] outline how digital game-based learning in ESD is a promising tool to foster attitudinal change. Additionally, other examples of combining game-based learning with digital technologies have shown the potential to foster awareness and knowledge of topics of ESD. Some of the approaches include various topics and learning effects: gamifying information on climate change can enhance pro-environmental behavior [83], an AR mobile game on nature conservation reports being able to strengthen positive attitudes [84], an AR mobile game on climate change improves knowledge and attitude [85] and a serious game with AR on microplastic also transfers knowledge and improves behavioral intentions [86]. Porro et al. [86] further describe their preliminary testing of the serious game to show high acceptance, providing a joyful and engaging learning experience and stimulating curiosity and imagination. However, as some have undergone preliminary testing with small sample sizes, the majority of serious games applied to topics of ESD remain concept-based approaches or commentaries [87]. Hallinger et al. [87] and Janakiraman et al. [82] emphasize the need for further investigation of the learning efficiency acquired by empirical research and experimental design. This shall provide a deeper understanding of the effect of game-based and digital learning experiences on knowledge, motivation, and behavior concerning sustainability issues.

To generally assess the effects of AR in terms of knowledge acquisition throughout various studies on AR used in education is challenging. While some studies identify the use of AR as a critical variable [18,36,71,88,89], this is not the case in other studies [15,39,57,72,73,90,91]. Combining and comparing the multitude of approaches measuring knowledge acquisition, understood as knowledge-related learning gains, has not yet led to a substantiated understanding. Knowledge acquisition must be based on the object of research and its design. This entails different research questions, measuring instruments, and intervention settings. We find some to use a control group design [38,89,90], while others merely evaluate an AR intervention without contrast [15,17]. There are also differing terms for what we define as knowledge acquisition: Weng and colleagues [89] state no significant learning outcomes, such as remembering, understanding, and analyzing. Celik and colleagues [17] report achieved developments on a cognitive level. Küçük and colleagues [38] use an academic achievement test and report higher academic achievements of the AR group. Korenova and Fuchsova [15] use self-assessment and observation methods to conclude improved knowledge and a deeper understanding of the AR group. Tarng and colleagues [90] apply pre-post tests and mention in terms of learning effectiveness; the AR group scores higher. They thus conclude AR can improve learning.

Various factors, such as the applied content and topic, the target audience, the setup and design of the AR environment, or even the research design and applied measuring instruments, potentially affect the outcome. Consequently, this work merely aims to add another perspective and component to the understanding of AR's impact on knowledge acquisition.

To ensure the promotion of education for sustainable development (ESD) through digital technology in the educational context, it is imperative for teachers to possess the requisite competencies. For this purpose, the established DiKoLAN (Digital Competencies for Teaching in Science Education) framework was employed [92].

The DiKoLAN framework is predicated on various initiatives aimed at advancing digitization in schools, such as the "European Framework for the Digital Competence of Educators" (DigCompEdu) [93], the TPACK framework [94], and the DPACK model [95].

This framework serves as a guide for higher education teacher trainers who are responsible for training prospective science teachers. It provides an organizational structure comprising seven core areas of digital competency specifically tailored for instruction in science education (physics, chemistry, and biology). These seven core areas can be further classified into four general categories (documentation, presentation, communication/collaboration, and 117 information search and evaluation) and three subject-specific categories (data collection, data processing, and simulation and modeling. Within these seven core competency areas, subordinated, operationalizable competency expectations are organized according to the TPACK and DPACK models and levels of competency (identification, description, and application).

1.8. Research Focus on Selected Competencies

The unit under discussion here focuses on competencies in the area of "Simulation and Modeling" within the DiKoLAN framework. Vogelsang and colleagues [96] have demonstrated that prior experience in academic settings significantly impacts the "Attitudes Towards Learning with Digital Technology" and the "Self-Efficacy Expectations" of pre-service teachers. These factors, in turn, directly influence motivational orientation. Such prior experiences are shaped, e.g., by the acceptance of technology, effects on cognitive load, current motivation, and so forth. Therefore, understanding these factors is essential for evaluating the effectiveness of digital technology in the context of ESD.

Therefore, this paper aims to add data on the effects of AR technology and game-based learning for science and engineering teaching regarding a specific topic of ESD. For this purpose, a learning environment with AR and game-based learning was designed. To determine and distinguish the impact of implementing the technology AR in a learning environment as well as the principles of game-based learning, we contrasted the learning environment into two factors: the first being with and without AR and the second with and without game. Following the state of research presented, we study.

RQ: How do the settings (with/without AR, with/without game) differ in terms of motivation (M), technology acceptance (TA), user engagement (UE), cognitive load (CL), self-efficacy (CSE), knowledge (K), and education for sustainable development in the dimensions action and motivation (ESDa, ESDm)?

2. Materials and Methods

Combining AR and games, we created a game-based AR learning environment, expected to spark motive elements, engage the users, help better understand scientific content, and positively affect student technology acceptance and self-efficacy toward the use of AR technology. Game-based learning is incorporated in terms of the framework's parameter "game elements" and will entail all eight elements, based on Krug and colleagues [3].

"Beat the Beast" (Figures 1–3) is a game-based learning AR app about "microplastic" designed for pre-service teachers at the university. It is conducted in the first semester, at the beginning of the course of study. All subjects of pre-service teachers undergo this intervention in order to present new technologies in combination with and expose them to interdisciplinary topics of sustainability. In line with the concept of ESD, this learning environment follows an interdisciplinary approach, combining the subjects of biology, chemistry, and engineering.

The game's concept is set up to provide an overview and understanding of the issue, teach about material characteristics and alternatives, and educate players about their scope of action, allowing them to make connections to their everyday lives and gain agency. The narrative and associated task entails everyday issues and tasks close to the student's reality: transportation, shopping, waste disposal, spending, and expenses. They are exposed to various dilemma situations concerning plastic waste, financial situations, or comfort versus eco-friendly alternatives. This shall impel the process of evaluation and decision making on different levels: individual, political, ecological, and societal. To lower the threshold for introducing AR, the learning environment is designed as a hybrid with both analog and digital components. Familiar game mechanics, such as traditional dice and player figures, game board, and point system, are interconnected with a digital game manager via tablet app, which keeps score, displays buttons for game tasks, plays audio, and shows quiz questions [97].

Figure 1. Group setting A: the game-based learning environment with augmented reality "Beat the Beast".

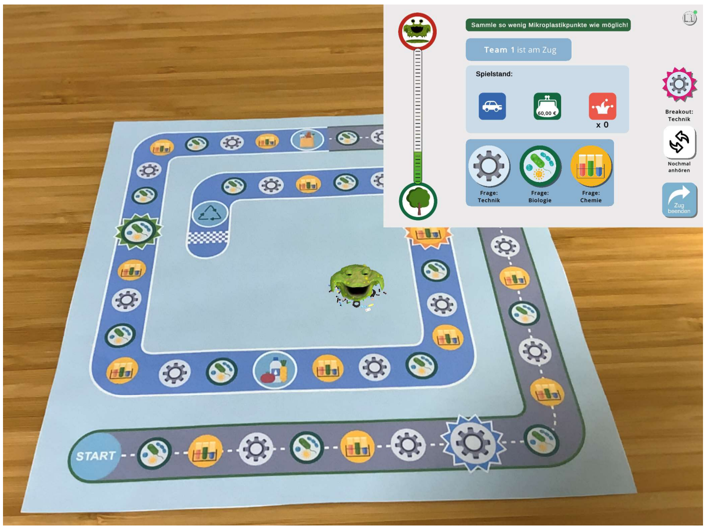

Figure 2. Group setting A: the game-based learning environment with augmented reality "Beat the Beast".

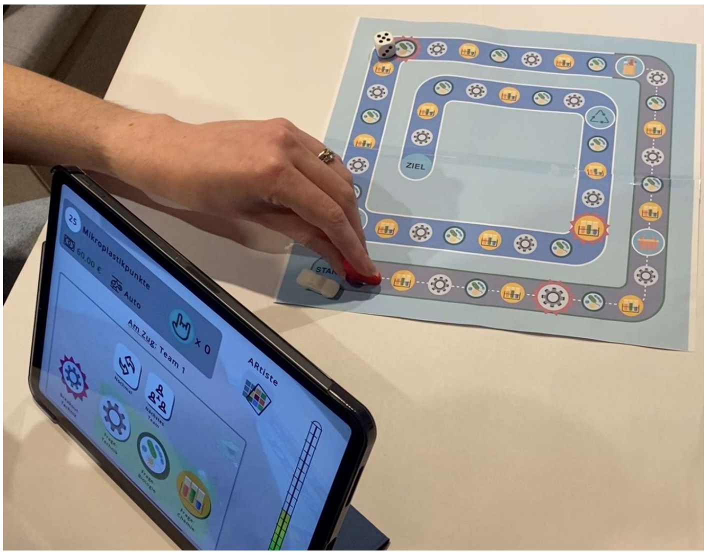

Figure 3. Group setting A: the game-based learning environment with augmented reality "Beat the Beast".

The study contrasted 4 different settings (A–D) of a learning environment (Table 1) regarding the role of micro- and nanoplastics on the three pillars of sustainability (economic, social, and environmental). All settings were identical regarding their brief introduction beforehand and reflection and discussion afterward. In sum, this intervention took place in one class of about 120 min. It was designed to investigate the learning environment's 2 factors as independent variables: AR and game.

Table 1. The 2 × 2 research design of the intervention study.

Setting A: with AR with game	Setting B: with AR/without game
Setting C: without AR/with game	Setting D: without AR/without game

The original intervention setting (group A) was developed in a design-based research (DBR) approach. The design of the learning environment is based on the design criteria to incorporate affordances of perspectives of design aspects, AR-technological features, and didactical principles [3].

The variations (groups B–D) were derived from this original setting. The content was consistent throughout. Technology and media were substituted, and/or the structural setup was varied in order to eliminate game.

The study is conducted as a 2 × 2 design [98] (Table 1), with the evaluated factors "AR" and "game" as independent variables. The participants were randomly and equally divided into four groups, alternately switching each factor on or off. Therefore, we have the following group settings: (A) with AR/with game, (B) with AR/without game, (C) without AR/with game, and (D) without AR/without game. All four groups have identical learning objectives and content. In each setting, four participants were grouped together and received a tablet to execute the intervention.

Generally, in the groups "with AR", the participants explore three "breakout rooms" for the three subjects: biology, chemistry, and engineering. In contrast, in "without AR" groups, the breakout rooms are supplemented with the same content but executed with analog experiments. The factor "game" is designed as the above-mentioned learning environments with quiz questions, an antagonist, a coherent narrative, a game board, point systems, and certain decision points affecting the course of the game [97]. For the groups "without game", these components are left out. They are designed as an interactive presentation (H5P) with essentially the same content and similar tasks. An overview of the group setting's features and similarities is provided in Table 2.

Table 2. Overview of group settings.

Setting	Features	Similarities
A: with AR with game	Game board with dice and digital game manager, storyline with 6 chapters and according tasks; 3 subject-specific breakout rooms with AR	Content of the 6 tasks and 3 breakout rooms, duration, groups of 4–5 participants, equipment: 1 tablet
B: with AR without game	Interactive presentation with 6 individual, unconnected, and non-chronological tasks; 3 subject-specific breakout rooms with AR	Content of the 6 tasks and 3 breakout rooms, duration, groups of 4–5 participants, equipment: 1 tablet
C: without AR with game	Game board with dice and digital game manager, storyline with 6 chapters and according tasks; 3 analog stations with subject-specific tasks	Content of the 6 tasks and 3 breakout rooms, duration, groups of 4–5 participants, equipment: 1 tablet
D: without AR without game	Interactive presentation with 6 individual, unconnected, and non-chronological tasks; 3 analog stations with subject-specific tasks	Content of the 6 tasks and 3 breakout rooms, duration, groups of 4–5 participants, equipment: 1 tablet

Group A: With AR/with game—This group uses the originally developed AR app "Beat the Beast". The four participants were divided into two playgroups and received headsets (to hear the audio but not disturb the other groups), a game board, one dice, and two game figures. The game runs via an AR app, which guides the game mechanism. Starting this app, an explanatory video, as well as a written game manual, will first advise the players on the general principles and tasks of the game. Players move the game characters across the board while pressing the equivalent buttons on the app and get confronted with decisions and tasks to fulfill. The game's antagonist, the "plastic monster", symbolizing the great Pacific garbage patch, accompanies the players through the game and instructs via audio. The course of the game is narrated as an everyday life story with six main chapters: (1) transportation, (2) grocery shopping, (3) unpacking, (4) consuming the goods, (5) disposing of packaging, and (6) donating to a (good) cause. This is intended to create a greater proximity to the subject matter. The main goal is to keep the plastic waste low and hinder feeding the plastic monster with plastic points. The five chapters are designed as dilemma situations in which the players have to choose and decide on their actions. Their decisions result in more or less plastic points. They can also control the score by answering the quiz questions correctly. This particular group constellation is designed with partners to create a feeling of togetherness while allowing exposure to two different playing strategies used to try to conquer the mutual enemy.

The first breakout room covers the subject of engineering and offers five different materials: three different plastics, wood, and metal. AR markers trigger an augmentation of the molecular structure of each material. Additional buttons on the screen offer "influencers": UV radiation, temperature increase, electricity, or water. Pressing each will show players what happens when material is exposed to this influencer. The second breakout room is on biology and starts with microscopic images of four different plastics. These also function as AR markers, which trigger the associated everyday object and a short description. In the next step, the players use two AR markers to augment and position a 3D model of the digestive tract to a teammate. Combining the microscopic image (marker) with the augmented intestine will trigger a simulation of the consequence of swallowing or inhaling said plastic particles. The last breakout room, in chemistry, lets the players perform an augmented experiment: they wash everyday clothing, filter the water, and examine the residue under the microscope.

Group B: With AR/without game—In this group setting, the game was eliminated, and the game was supplemented with an interactive H5P presentation. This application was not accompanied by a coherent narrative, and the users could self-pace through the different tasks. Participants could freely choose when to complete each chapter or enter breakout rooms. They received automated feedback on the performed tasks, but there was no way of winning and no points. The structure of the content was based on the six story chapters as tasks, as listed above in group A, but not chronologically tied together by any story.

The three breakout rooms were designed as buttons on this presentation. Clicking on it will lead to an AR marker initiating the application. Content and technology remained the same as described above in group A.

Group C: Without AR/with game—This group setting used the same game as group A for the intervention. But, instead of the AR breakout rooms, the learning environment entails analog stations. When clicking on the buttons for the breakout rooms, the players were guided to these analog stations. To match up with the digital AR breakout rooms, these analog stations were conducted with printouts or real objects instead of augmentations. The molecular structures of engineering were printouts. Biology's everyday objects were real everyday objects; the intestine and simulations were printouts. The experiment in chemistry was conducted traditionally, using pieces of fabric, a magnetic stirrer with agitator, filters, and a microscope.

Group D: Without AR/without game—This group used the interactive presentation as described in group B as well as the analog stations described in group C.

A quasi-experimental design was chosen to test the four different types of settings. Eight seminar groups were randomly assigned to these four settings. In a pre-post design, participants completed questionnaires on motivation (M) [99], technology acceptance (TA) [76], user engagement (UE) [62], cognitive load (CL) [100], computer self-efficacy (CSE) [76], knowledge (K) (developed for this project), and Education for Sustainable Development in two dimensions: motivation (ESDm) and action (ESDa) [101]. The group settings were used as independent variables, and the questionnaire's constructs were used as dependent variables.

The intervention was conducted in December 2022 in a freshman course for all first-semester students of the Weingarten University of Education (N = 203). The curriculum did not include the topic of microplastics, gamification/game-based learning, or technology AR, so all students were equally new to these aspects. This course was randomly divided into eight generally equal sessions with approximately 30 students each. These sessions were again randomly assigned to each group setting: A–D.

The motivation was measured with the short scale of intrinsic motivation (KIM) [99], which is a shortened version of the "intrinsic motivation inventory" [102]. It encompasses four factors: interest/enjoyment, perceived competence, perceived choice, and pressure/tension with 12 items.

When it comes to measuring TA, the most commonly used tool is the Technology Acceptance Model [103] and its various advancements, like TAM 2, TAM 3, or UTAUT. Concerning AR, the core constructs of TAM, "Perceived Ease of Use" and "Usefulness", have proven that TAM is a reliable tool for assessing technology acceptance since it could be confirmed that perceived ease of use and perceived usefulness influence the attitude toward using the technology, as well as the attitude influencing the behavioral intention to use it. Perceived usefulness reflects the personal benefit of using this medium. The items of this substructure highlight the participant's estimate of how valuable the learning environment is perceived. Perceived ease of use is the participant's judgment on how well he/she can manage the technology or how easy it is to use. Together, both constructs provide insight into the participant's attitude and readiness to use the evaluated technology in the specific setting/design [103]. However, Holden and Rada [76] outlined the need for a refined TAM in order to explain more of the variance in the original model. To achieve this, they extended perceived ease of use with "usability". Incorporating usability by adding four additional items on learnability, functionality, navigation, and memorability, Preece and colleagues [104] proved to be functional and explained more variance than the original model. When introducing innovative technology such as AR, with its combination of real and virtual content, the user requires new skills. For this reason, incorporating the aspect of usability in TAM2 is especially beneficial to evaluate AR technology [105].

UE, as a quality of the user experience, is outlined by the attention, interest, and commitment to a task. This abstract and multifaceted concept is impacted by the technology's affordances, the underlying motives and attitudes of users, content, and its association or even stigma. Therefore, it is "highly context dependent". O'Brien and colleagues [62] offer a widely used, well-established, and revised instrument for measuring this construct. They base their work on Jacques [106] and Webster and Ho [107]. Within the principles of educational multimedia theory, the former constitutes six attributes of UE: attention, motivation, perception of control, satisfaction of needs, perception of time, and positive or negative attitude. The latter, however, differentiate attributes on engagement (attention focus, curiosity, intrinsic interest) and influences on engagement (challenge, control, feedback, variety). From this, O'Brien [62] derives the attribute-based approach to UE. The original UE scale (UES) entails 6 dimensions and 31 items. In a revision, it was split up into four factors: Focused attention, perceived usability, aesthetic appeal, and reward factor. This short form of the questionnaire (UES-SF) consists of three items per factor, resulting in 12 items.

Based on the assumption that the capacity of the working memory is limited, learning can only take place when enough cognitive resources for the learning process are available. CL is considered the strain of learning content and learning process on the working memory. Cognitive load theory [108] differentiates three components affecting the capacity of our working memory when learning: "Intrinsic Load" was understood as the extent and complexity of the content, "Extrinsic Load" as the extent and presentation of the material not contributing to the learning material, and "Germaine Load" as the process of transferring and incorporating information by creating schemata. Accordingly, the extrinsic load should be minimized to obtain more capacity for Intrinsic and Germaine Load. Complementary to this well-established theory, CL can also be defined as a two-dimensional construct, including the factors "Mental Load" and "Mental Effort" [109]. Mental load refers to content complexity, and mental effort captures the participant's individual strain to complete the task [100,109]. Krell [100] offers a questionnaire outlining these two aspects of the learning material: (1) content and complexity and (2) ease of use. Capturing CL with this instrument bridges CL and TAM.

"Self-efficacy towards technology usage" reflects a user's belief of mastering a new technology, has an influence on aspects of TAM, and is found to be a moderating variable [76,77]. Holden and Rada [76] differentiate in CSE and technology self-efficacy (TSE).

The general construct, CSE, has been proven to influence TA by Vekantesh [77], yet not in their own study. However, TSE has impacted aspects of TA. The TSE and CSE constructs are made up of 10 items using a 10-point Guttman scale (1 = not at all confident to 10 = totally confident). Both constructs use the same 10 items but different introduction phrases. The questionnaire applied here measures a user's self-efficacy toward using digital media due to the different settings. We, therefore, measure self-efficacy in the broader sense, as in CSE. Even before using a new technology or system, a user's general belief toward computers moderates their perceived ease of use. So, a participant's attitude and conception of technologies may influence the course of a digital learning environment. the perceived ease of use, and general experience. By using and experiencing a technology, this perception may adjust [77]. Therefore, this construct, CSE, is assessed in a pre-post test. We measure the participant's belief and confidence in being able to master digital media technologies prior to usage (CSE pre) and match them with their perception after using the technology (CSE post).

To assess knowledge (K) in this specific intervention, a questionnaire was developed, following the content of the learning environment. Originally, it contained 27 items, made up of three items for each subtopic of the learning environment: the three subject-specific breakout rooms and six story chapters. In the pilot testing, this was condensed to 13 items to reach acceptable reliability yet ensure that each subtopic is covered with at least one item. Each question of this single-choice test offered three response options of which one was right. Crossing off the wrong option, no option, or more than one option equals a false answer. It will be applied as a pre-post test to ensure a homogeneous starting point of all group settings in terms of knowledge of microplastics.

ESD is measured using the "outcome indicator test" by Günther and colleagues [101] on the aspects of knowledge and understanding, values and attitudes, and intentions and skills. A total of approximately 900 items is set up as a pool of potential items, which are selected in the process of the questionnaire based on the participant's previous answers. Selecting the respective age group reduces the item pool to about 400 items. All items are divided into six action domains, which again are subdivided into sub-domains. Each item refers to one or multiple SDGs, sometimes overlapping content-wise. Rating these statements will provide an indicator of the individual's intentional propensity toward their own action competence regarding sustainability. Accordingly, the OIT measures ESD as the individual's scope of action and influence on sustainability. Results are theta values ranging from -4 to +4 for each of the three levels: action (ESDa), knowledge (ESDk), and motivation (ESDm). ESDk is omitted, as a knowledge test specifically designed for the learning environment topic and content is applied.

The constructs CSE and K are derived from pre-post values and demonstrate a progression in connection to the intervention: discrepancy of self-efficacy = CSE (CSE post minus CSE pre) and discrepancy of knowledge gains = K (K post minus K pre). Therefore, the potential values range from -10 to 10 for SE and from -13 to 13 for LG. Negative values indicate a decrease, as in a deterioration.

The OIT automatically provided three theta values for each dimension: ESDa, ESDk, and ESDm. We will be further working with ESDm and ESDa.

The results were calculated in SPSS using one-way ANOVA. The data were analyzed using IBM SPSS Statistics (Version 29).

The data collection was executed with questionnaires. The set of questionnaires measuring these variables was split up into three measuring points: pre, post1, and post2, as shown in Figure 4 below. This was performed for two reasons: (1) to help the participants by reducing the number of items to a manageable level and (2) to specify which learning environment aspect the questionnaires refer to. Post1 refers directly to constructs directly affected by each of the four interventions. Pre and Post2 refer to the participant's starting point and after finishing the learning environment as a whole.

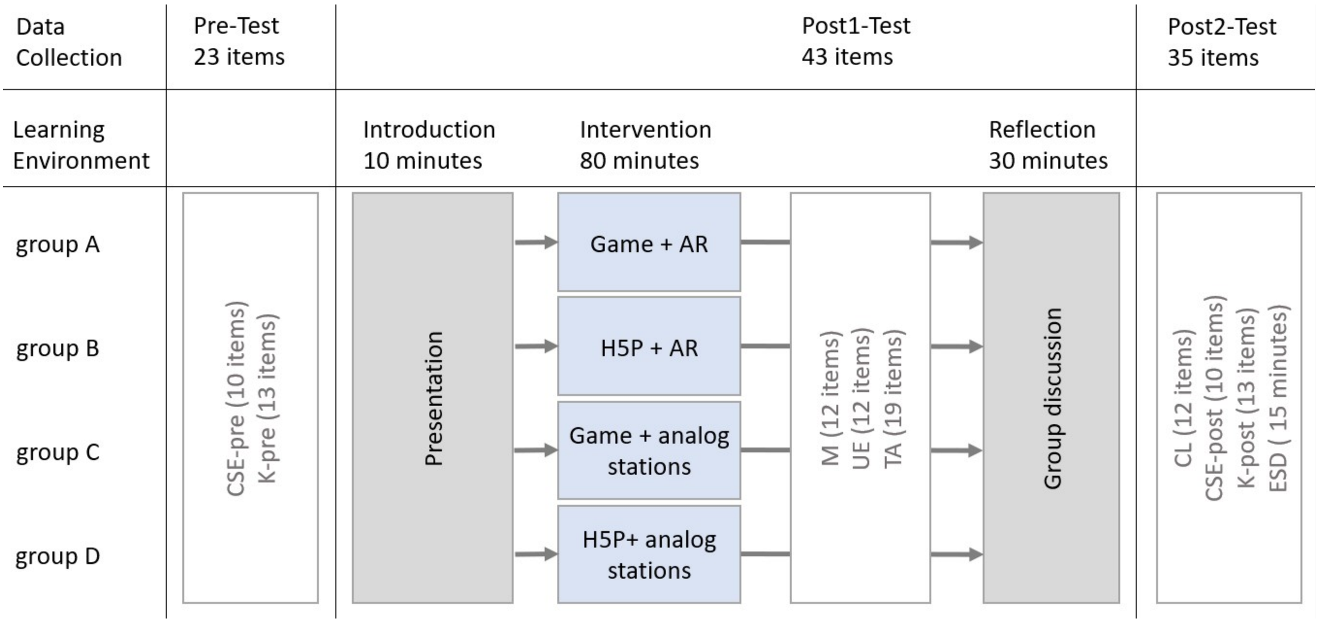

Figure 4. Evaluation design with three measuring points. Four different group settings are evaluated in terms of eight variables: motivation, technology acceptance, user engagement, cognitive load, computer self-efficacy, knowledge, and Education for Sustainable Development in the dimensions of action and motivation.

The learning environment comprises a total of 120 min and is embedded in the curriculum of the freshman course, so both the amount of time and the content promise high ecological validity.

Measuring point one was a pre-test to assess the participant's knowledge and self-efficacy expectations. This questionnaire entails 10 items on CSE with a 10-point Guttmann scale [76] and a 13-item single-choice test with three response options to identify K (developed for this project and based on the learning environments chapters).

Post1-test is the second measuring point after the divergent interventions. This questionnaire assesses M with 12 items and a 5-point Likert scale [99], TA with 19 items and a 7-point Likert scale [76], and UE with 12 items and a 5-point Likert scale [62].

The final measuring point is placed at the end of the entire learning environment after the discussion and reflection. Here, CL with 12 items and a 7-point Likert scale [100], and repeatedly, the 10 items of CSE and 13 items for K gains are applied. After this, the participants completed the OIT, assessing the ESD dimensions: action and motivation [101]. The OIT was conducted as a 15-min self-paced online survey. In this timespan, the participants rated ESD statements chosen from a pool of over 400 items. The automated item selection is based on the participants' previously provided answers, which means the responses lead to the instrument's individual trajectory.

The questionnaires were handed out as printouts to improve the response rate. The questionnaire on "education for sustainable development" (OIT) was conducted online as no other version was available. An overview of all measuring instruments is shown in Table 3.

Table 3. Overview of measured construct: all questionnaires with the number of items.

Construct and Questionnaire	Items and Scale	Reference
Motivation (KIM)	12 items, standard 5-point Likert scale	[99]
Technology Acceptance (TAM2)	19 items, standard 7-point Likert scale	[76]
User Engagement (UES-SF)	12 items, standard 5-point Likert scale	[62]
Cognitive Load	12 items, standard 7-point Likert scale	[100]
Computer Self-Efficacy	10 items, 10-point Guttman scale	[76]
Knowledge	13 items, single choice, 3 response options	Self-developed
Education of Sustainable Development (OIT)	15 min; items chosen from a pool of 400 items	[101]

3. Results

The sample resulted in 203 participants (age 18–36, M = 20.23, SD = 2,351) studying elementary school education (64.4%), secondary (WHRS) (27.4%), others (6.8%), and missing values (1.4%). As expected for this course of study (mainly teaching profession), the gender distribution was 76.3% female, 22.8% male, and 0.9% missing values. No participants had crossed off the third option, "divers". The four group settings were of similar size: A (= 55), B (= 50), C (= 56), and D (= 58). Due to missing values by survey, the sample sizes slightly vary and can be found in Table 4 below.

Table 4. Group's sample sizes and mean values, structures by measured construct. The sample size for ESDm and ESDa are considerably lower due to different inquiry formats (online survey).

Descriptive Statistics: Variable's Means									
Variable **Scale**		**M** **1–5**	**TA** **1–5**	**UE** **1–7**	**CL** **1–7**	**CSE** **−10 to +10**	**K** **−13 to +13**	**ESDm** **−4 to +4**	**ESDa** **−4 to +4**
Group A	Sample Mean	55 3.1742	46 4.3822	51 3.4542	50 4.6650	46 0.4152	55 0.5273	39 0.1715	39 0.1678
Group B	Sample Mean	46 3.3551	43 4.5998	46 3.8297	45 4.5833	45 0.3044	48 0.4167	27 0.2074	27 0.1397
Group C	Sample Mean	51 3.1340	49 4.1332	53 3.3915	38 4.0066	38 0.2158	48 −0.6250	38 0.3126	38 0.2202
Group D	Sample Mean	51 3.2206	56 4.5771	54 3.6698	48 3.9983	48 0.5250	50 0.8400	46 0.3534	46 0.31376
Total	Sample Mean	203 3.2167	194 4.4238	204 3.5797	181 4.3297	177 0.3740	201 0.3035	150 0.2695	150 0.2208

Cronbach's alpha [110,111], assessing reliability for the measured constructs, is shown in Table 5 below. Generally, all constructs resulted in acceptable internal consistency except for the pre-test results of knowledge. As this questionnaire is based on the learning environment domain-specific content, and all first-semester students of various different subjects participated, the focus is rather set on the post-test value. For the ESD measuring instrument, "OIT", no Cronbach's alpha could be assessed. The course of this test and the individually chosen items vary per participant. Therefore, there is no access to the individual items. The authors report adequate reliability [101].

Normal distribution was assessed using the Shapiro–Wilk test. Table 6 below shows an overview of the calculated p-values of each specific construct in the individual intervention groups as well as the total sample. In total, normal distribution was achieved for TA, UE, CL, and ESDm.

Table 5. Cronbach's alpha for the measuring instrument's reliability, indicating an acceptable internal consistency.

Reliability: Cronbach's Alpha								
Construct	**M**	**TA**	**UE**	**CL**	**CSE**	**K**	**ESDm**	**ESDa**
Number of Items	12	19	12	12	10	13	Varies (15 min.)	Varies (15 min.)
Cronbach's Alpha	0.753	0.747	0.822	0.816	Pre 0.911 Post 0.924	Pre 0.473 Post 0.791	x	x

Table 6. Wilk–Shapiro test for normal distribution. *p*-values above 0.05 indicate normal distribution of the data.

Normal Distribution: Shapiro–Wilk								
Variable	**M**	**TA**	**UE**	**CL**	**CSE**	**K**	**ESDm**	**ESDa**
***p*-Value**	**Sig.**	**Sig.**	**Sig.**	**Sig.**	**Sig.**	**Sig.**	**Sig.**	**Sig.**
Group A	0.086	0.077	0.343	0.916	<0.001	<0.001	0.709	0.687
Group B	0.003	0.003	0.680	0.161	0.193	0.003	0.393	0.127
Group C	0.074	0.374	0.484	0.116	0.644	<0.001	0.927	0.446
Group D	0.405	0.646	0.003	0.827	0.008	<0.001	0.465	0.092
Total	<0.001	0.054	0.151	0.214	<0.001	<0.001	0.625	0.38

Applying the Levene (Table 7) test revealed variance homogeneity for M, TA, CL, CSE, ESDa, and ESDm. Variance homogeneity was not provided for UE and K.

Table 7. Levene test revealing variance homogeneity of the group variable's means values. *p*-values above 0.05 indicate homogeneity of variance.

Variance Homogeneity: Levene Test								
Variable	**M**	**TA**	**UE**	**CL**	**CSE**	**K**	**ESDm**	**ESDa**
***p*-Value**	**Sig.**	**Sig.**	**Sig.**	**Sig.**	**Sig.**	**Sig.**	**Sig.**	**Sig.**
Total	0.442	0.405	0.043	0.289	0.877	<0.001	0.386	0.452

3.1. Kruskal–Wallis for Identification of Group Differences

As requirements for ANOVA were not provided, non-parametric tests were performed. Some groups' sizes were slightly under 50, and normal distribution and variance homogeneity were not provided for all (Table 4, Table 6, and Table 7). The Kruskal–Wallis test results, in Table 8 below, revealed that the intervention groups significantly differed in terms of M, TA, UE, and CL. No significant effect could be found for the remaining variables CSE, K, ESDm, and ESDa.

Table 8. Kruskal–Wallis tests result in significant effects for the variables M, TA, UE, and CL. *p*-values below 0.05 indicate a significant effect and, therefore, a difference between the groups.

Kruskal–Wallis								
Variable	**M**	**TA**	**UE**	**CL**	**CSE**	**K**	**ESDm**	**ESDa**
df	3	3	3	3	3	3	3	3
Test statistics	8.69	25.42	24.40	29.95	4.12	1.50	4.25	1.31
p-value	0.034	<0.001	<0.001	<0.001	0.682	0.249	0.235	0.726

3.2. Analysis of Contrast Groups

Post hoc tests were applied to further analyze contrast groups. Dunn–Bonferroni was used to investigate the significant differences between the calculations above. Table 9 illustrates the contrast groups:

- Significant effects of M results from differences between groups A and B and B and C;
- Significant effects of TA results from differences between groups A and B, A and D, B and C, and C and D;
- Significant effects of UE results from differences between groups A and B, A and D, B and C, and C and D;
- Significant effects of CL results from differences between groups A and C, A and D, B and C, and B and D;
- No groups significantly differ from one another in terms of CSE, K, ESDm, and ESDa.

Table 9. Paired group comparison using Dunn–Bonferroni post hoc test. *p*-values below 0.05 indicate a significant effect and, therefore, a difference between the groups.

		A vs. B	A vs. C	A vs. D	B vs. C	B vs. D	C vs. D
M	*p*-value	0.023	0.585	0.355	0.006	0.178	0.149
	z-value	−2.269	0.547	−0.925	2.752	1.346	−1.445
	Effect size r	0.23			0.28		
TA	*p*-value	0.016	0.067	0.022	<0.001	0.774	<0.001
	z-value	−2.416	1.831	−2.283	4.252	0.287	−4.244
	Effect size r	0.26		0.23	0.44		0.41
UE	*p*-value	0.002	0.211	0.025	<0.001	0.322	<0.001
	z-value	−3.133	1.252	−2.244	4.380	0.991	−3.536
	Effect size r	0.32		0.22	0.44		0.34
CL	*p*-value	0.792	<0.001	<0.001	<0.001	<0.001	0.931
	z-value	0.264	3.948	4.111	3.611	3.743	−0.087
	Effect size r		0.42	0.42	0.40	0.39	

4. Discussion

AR is an area of digitization that is increasingly being employed in the field of science and engineering education. The combination of AR with game-based learning is assumed to have great potential in terms of its learning efficiency [69–71].

In the interdisciplinary field of sustainability, AR provides benefits, as its explorative and interactive nature may spark interest and engagement and tie together aspects of different domains [86]. With the aim of investigating the benefits of AR used for education for sustainable development, the topic of the intervention was tied to a theme that is important for science and engineering education regarding education for sustainable development: the use and consequences of using plastics.

The game "Beat the Beast" uses a narrative of the player's everyday activities to allow them to connect the learnings to their own lives. The game's structure is divided into sub-topics: consumption and use, waste and pollutants, substitution, and possible solutions. Different challenges, dilemma situations, and points of decision let the players interact and reflect on the topic of using plastics from different perspectives. This is supposed to spark agency on an individual and societal level.

A similar concept has recently reported positive results of preliminary testing with a small sample [86]. Porros [86] describes their experimental design of an AR game on microplastics as well accepted, considered engaging, and motivating and reports the potential to improve learning. Additionally, previous studies have found that game-based learning [83,112] and AR [84–86], applied to other topics of sustainability, have the potential to promote knowledge, increase motivation, and strengthen positive attitudes toward sustainability topics. Yet, the state of research on AR and game-based learning for sustainability is still nascent and lacking extensive investigation of its learning efficiency. The majority of research in this field is made up of commentaries and non-empirical research designs [87]. Hallinger et al. [87] and Janakiraman et al. [82] highlight the need for more empirical research to strengthen this field. A few studies have been published to date that examine learning efficiency in a controlled manner. The objective was to investigate the effect of a learning environment that combines AR and game-based learning with respect to selected aspects of learning. In order to be able to make statements about the learning efficiency of the variables "AR" and "game", a 2×2 design was chosen for this purpose, in which the combination of AR and game was compared with learning environments that included either only AR, only the game, or neither of the two dependent variables.

Data were collected on motivation, technology acceptance, user engagement, cognitive load, and CSE. In addition, knowledge about plastics and the waste they produce (micro- and nanoplastics), as well as ESDa and ESDm, was recorded.

There are inconsistent findings on the question of how the use of AR affects the cognitive load [35,69]. Some studies report higher cognitive load with the AR intervention groups and some lower cognitive load [18,72,73]. Our data show that the intervention with AR is perceived as more cognitively demanding than without AR. The effect of a higher cognitive load is evident regardless of whether the AR is included in a game (setting A) or not (setting B) (Table 9). The group comparisons each show a mean effect, according to Cohen [113], between r = 0.39 and r = 0.42.

User engagement differs in particular according to whether the learning environment contains a game or not. The game-based learning environments (A and C) show lower user engagement compared to the non-game-based learning environments (B and D). Effect sizes demonstrate a small effect comparing A with D (r = 0.22) and medium effects comparing A and B (r = 0.32), B and C (r = 0.44), and C and D (r = 0.34). When the AR learning environment is offered without a game (setting B), user engagement is higher than for the combined learning approach (A) (r= 0.32) (Table 9). Our study thus supports the results of previous studies according to which AR can help to strengthen user engagement [35,47,57,63,64].

Comparing a game-based AR environment with a non-game-based AR environment for engineering, Nguyen and Meixner [47] find increases in engagement and performance, with no differences between the designs. Our data indicate that the approach with AR but without game (B) is significantly different from the approach without AR but with game both in terms of user engagement and motivation. Our data are consistent with the results of Meekaew and Ketpichainarong [48] in terms of the effect on the motivation of the AR-based non-game approach. Contrary to what was reported by Chen [49], the integration of games has a negative effect on student motivation. Xu and colleagues [4] point out the need for further research on the interplay of AR and game elements. We support this assessment. Based on our data, for future research, we would like to suggest controlling for other variables such as the type of game design, the age and education level of the players, and the domain in which the game is set.

Technology acceptance is considered an important predictor of the readiness to use a new technology; in our case, AR is also for one's own teaching activities [61]. It turns out that technology acceptance is high in all settings (Table 4). It is lowest in the setting without AR but with game (C). The result supports the interpretation that technology acceptance is less influenced by the technology used than by its inclusion in the game. In both settings (B and D) without a game, TA is significantly higher than in the settings with AR and game (A) or without AR but with game (C). The differences between A and D (r = 0.23), B and C (r = 0.44), and C and D (r = 0.41) are significant with a small and medium effect, respectively. When AR is combined with game (A), TA is lower than in the AR non-game-setting (B) (r = 0.26).

With small samples, it has been demonstrated that AR, embedded in a game-based learning environment, can improve knowledge [85,86]. Although we can support this observation with our findings, we cannot find significant effects among the different group settings. Therefore, we can deduce that integrating the factors of AR and game allow knowledge acquisition of sustainability-related content, yet both neither improve nor hinder knowledge acquisition. We assume effects could be achieved when embedding in a specific course for ESD or the addressed subjects (biology, chemistry, and engineering) and designing the intervention as a long-term intervention.

AR, embedded in a game-based learning environment, can foster engagement and motivation when learning sustainability topics [84,86]. Concerning the investigated factor AR, our findings align with this observation. The intervention settings with AR components were found to be more engaging and motivating. This, however, does not apply to the factor game. With regard to motivation, user engagement, technology acceptance, and cognitive load, it becomes evident that the incorporation of games into the learning environment does not yield a favorable impact on the examined factors. Consequently, our findings differ from the results of Lampropoulos and colleagues [42], who highlight the effectiveness of game-based learning for science teaching and further emphasize the potential that the interplay of AR and games has for learning. A possible explanation for the fact that Lampropoulos and colleagues come to different results than we do could be associated with the selected target demographic for the study, namely, freshmen students, who may not perceive any discernible benefits in utilizing the game for their learning experiences. It might be a question of age whether the integration of games into the learning environment brings advantages for learning. Since our game-based learning environment can be used in secondary school as well as in early semesters of pre-service teachers' course of study, it seems obvious to extend the study to pupils to test this hypothesis.

The primary aim of this article was to investigate the impact of four different learning environments on various learning parameters. As such, we do not present longitudinal data, such as knowledge acquisition outcomes. Augmented reality (AR) and game-based learning have garnered attention for their potential to enhance learning outcomes, both individually and when employed in tandem [42,47–49]. However, there exists a notable dearth of studies that systematically compare AR and game-based instructional designs with alternative learning settings. Our study contributes to this comparative analysis. Comparing the learning environments with AR and games with those without these features, the settings do not differ in terms of knowledge acquired, regardless of whether the learning environment contains only AR or games or both in combination. There are also no benefits when compared to the conventional learning environment (D) (Table 9).

For ESDm, ESDa, and CSE, no advantages can be identified for any of the settings either. However, these are constructs whose change requires a longer-term intervention [81] than that of our learning environments, each of which lasted only 120 min.

5. Limitations

This research design tested a learning environment on the use of plastics by contrasting the two factors "AR" and "game". The sampling procedure included all first-semester students at our university. Hence, this procedure did not allow a strictly random sampling. Including all ages and semesters would provide data of students with a deeper understanding of teaching and didactics as well as digital technologies like AR. The division into intervention groups was based on the random assignment of the particular course.

The knowledge questionnaire's reliability is a noteworthy limitation in this research design. The reliability scores of the questionnaire on knowledge (K pre and K post) strongly differ from one another. The knowledge questionnaire directly refers to the learning environment's content. This may explain the Cronbach's alpha of 0.473 before the intervention and 0.791 after the intervention.

The sample size for the measured learning effects ESDm and ESDa is considerably smaller than the other learning effects. This is owed to the different inquiry methods. The OIT is an online survey and requires the participant's devices as well as an Internet connection. Both could not be guaranteed throughout.

The OIT, measuring ESDa and ESDm, was only applied after the intervention. As mentioned above, a strong experimental design calls for a pre-post design. For a deeper understanding of the intervention's effect on the sustainability dimensions (action and motivation), it is critical to evaluate this aspect in a pre-post design. We aim to add further evaluations to consolidate our findings and refine our learning game approach. For this, an alternative measuring instrument will be necessary due to the time requirements of the OIT, which needs a completion time of at least 15 min.

The intervention was planned and carried out as a single event in the semester. This may be too short and nonrecurring to observe any effects or changes in ESDm, ESDa, and CSE. Long-term interventions are necessary here.

As this intervention was tested with first-semester students, the novelty effect of AR could weigh on several learning effects, such as M, UE, and CL. Furthermore, our results can only be generalized for AR learning environments that are similarly constructed as the one we presented. To enable a comparison with similar learning environments, we applied the evaluation grid by Krug et al. [8,9] to capture its parameters (see Figure 5). If other augmented reality-based learning environments are comparable to ours in these parameters, similar results should be expected, according to Krug et al. [3,8].

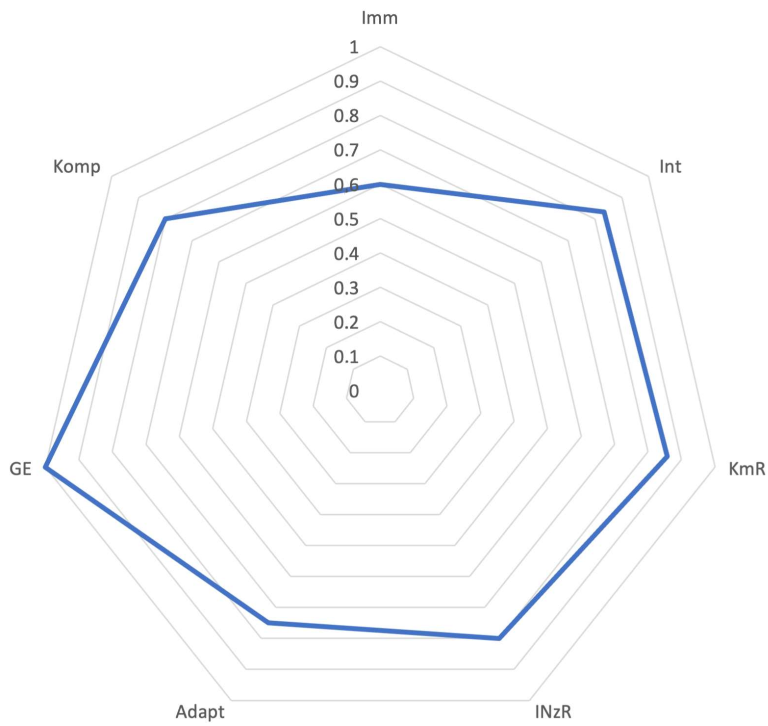

Figure 5. Design parameters of our AR learning environment with game-based learning approaches.

6. Conclusions

We developed an AR and game-based learning environment for education for sustainable development, specifically the topic of microplastics. This playful approach is chosen to lower the threshold new technologies, such as AR, and complex topics, such as education for sustainable development, can impose on students. The interdisciplinary issue of microplastics calls for a combination of different science domains (biology, chemistry, and engineering) embedded in the context of individual and societal topics (consumption, waste, substitution). Bridging the affordances of this interdisciplinary content and the novel technology applied, we have based the design on selected media-didactic and subject-didactic criteria. We compared this learning environment with learning environments that either contained no AR, no game or lacked both. Our study thus contributes to the state of research that not only investigates the effect of individual learning environments on different learning parameters but also examines them in comparison to each other and thus tests their respective learning effectiveness. Our findings reveal that AR, despite inducing a comparatively higher cognitive load, does not detrimentally influence learning outcomes. Despite the higher cognitive load, the subjects do not have a smaller increase in knowledge than the subjects in the other settings. Additionally, our study underscores the capacity of AR to enhance motivation and user engagement.

At least with regard to the chosen content and the chosen target group, the game-based variants of the learning environment do not have a positive effect on learning. On the contrary, these variants perform worse than the other variants in terms of both motivation and user engagement.

For future studies, further research is needed that investigates the potential of AR for learning domain-specific knowledge in control group designs. The extent to which the integration of games into AR-based learning environments can provide additional benefits also needs to be investigated in greater depth. For this purpose, a comparison of different age groups and knowledge from different scientific domains may be useful.

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