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Design and Evaluation of Task-Based Waste Sorting Mechanics in Virtual Reality Learning Application

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Abstract
Virtual Reality (VR) can support environmental learning through embodied interaction, task-based activity, and immediate feedback. This study presents the design and evaluation of task-based waste-sorting mechanics in a virtual beach application developed in Unity and deployed on a PICO 4 headset. Thirty high-school and university students completed a 10–15-minute session and responded to the Game Experience Questionnaire (GEQ). The revised analysis follows the official GEQ procedure by scoring each component separately on a 0–4 scale and by avoiding an overall score across constructs with different directions. The experience profile was mixed. In the In-Game Module, positive affect (M = 3.05) and sensory and imaginative immersion (M = 2.85) were relatively strong, but tension (M = 3.05) and negative affect (M = 2.83) were also elevated. Post-game positive experience (M = 2.77) co-occurred with negative experience (M = 2.83), tiredness (M = 2.00), and difficulty returning to reality (M = 1.97). These findings indicate that the mechanics supported engagement in some aspects of play but also introduced interaction strain or discomfort. Because the study did not include pre-test/post-test measures or objective task logs, it does not establish learning gains or technical task effectiveness.

Keywords—Virtual Reality, Gamification, Waste Sorting, Environmental Learning, Game Experience Questionnaire.

1 Introduction

Virtual Reality (VR) has increasingly become an important medium for educational innovation because it enables learners to experience simulated environments through embodied interaction, spatial exploration, and direct manipulation of virtual objects. In contrast to conventional multimedia learning, VR can provide a stronger sense of presence and agency by allowing users to interact with learning materials as if they were situated inside the learning context[1], [2]. Recent systematic reviews show that immersive VR has been widely adopted in higher education, training, science education, and serious games because it supports experiential learning, situated practice, and interactive visualization [3], [4], [5]. Meta-analytic evidence also suggests that immersive VR can improve learning outcomes when it is supported by appropriate instructional design, although its effects may vary across domains, intervention duration, and learning objectives[6], [7]. Therefore, VR should not be treated only as a visualization tool, but as an interactive learning environment that requires meaningful tasks, clear feedback, and structured user engagement.

Despite its potential, VR-based learning does not automatically guarantee effective learning. Prior studies have emphasized that immersion may increase interest and motivation, but it can also introduce cognitive load when learners are not properly guided [8], [9]. The Cognitive Affective Model of Immersive Learning explains that presence and agency are important psychological affordances of VR, yet these affordances need to relate to instructional factors such as task structure, self-efficacy, motivation, embodiment, and self-regulation [10]. This means that VR learning applications should be designed around purposeful activities rather than passive observation. Learners need opportunities to act, receive responses, and reflect on the consequences of their actions. In this context, task-based interaction becomes central because it transforms VR learning from a visual experience into an active learning process.

Gamification provides a relevant design strategy for structuring interaction in VR learning applications. It refers to the use of game design elements, such as goals, challenges, feedback, progression, and rewards, in non-game contexts to increase user engagement and motivation [11], [12]. In educational settings, gamification has been reported to produce positive effects on cognitive, motivational, and behavioral learning outcomes, although the effectiveness depends on how game elements are aligned with learning objectives [13], [14]. Recent reviews further highlight that gamified learning environments need to move beyond superficial points or rewards and should instead integrate meaningful actions, feedback loops, and contextual challenges [15], [16]. For VR learning, gamification can be particularly useful because users are already situated inside an interactive environment where learning tasks can be translated into physical or embodied actions, such as finding, grabbing, classifying, and placing objects.

Environmental education is one area where VR and gamification can provide meaningful learning opportunities. Environmental problems such as pollution, waste accumulation, and unsustainable consumption require not only conceptual understanding but also behavioral awareness and practical decision-making. Recent systematic reviews on digital tools in environmental education indicate that technologies such as VR, augmented reality, simulations, and serious games can increase learners' sustainability awareness and engagement when the learning experience is contextual and interactive [17], [18]. Serious games have also been increasingly used for environmental education because they can combine environmental information with problem-solving activities, decision-making scenarios, and behavioral reflection [19], [20]. However, many environmental learning applications still focus on presenting information rather than allowing learners to practice concrete environmental actions in a realistic context.

Waste sorting is a relevant environmental learning topic because it requires users to recognize waste types, make classification decisions, and perform correct disposal behavior. Studies on waste sorting education have shown that digital games and immersive technologies can help learners understand waste categories through interactive tasks rather than through text-based explanation alone [21], [22]. Recent work on augmented reality-assisted environmental learning also shows that structured waste sorting activities can support children's environmental knowledge and engagement when the task is designed progressively and supported by feedback [23]. Similarly, technology-based waste management models that integrate gamification indicate that digital feedback and task completion can support sustainable behavior-related learning [24]. These findings suggest that waste sorting education can benefit from interactive task mechanics that require users to act directly within a simulated environment.

In addition to task mechanics, user experience is an important consideration in VR learning application design. A learning application that is technically functional may still fail when users experience confusion, discomfort, low engagement, or weak perceived competence. Prior studies on immersive learning emphasize that evaluation should consider not only learning outcomes, but also user experience dimensions such as immersion, flow, affect, competence, social presence, and post-use comfort [25], [26]. Social interaction and virtual characters can also influence perceived realism and engagement in immersive environments, especially when they provide contextual support, guidance, or social cues [27], [28]. Nevertheless, in task-based VR learning applications, social and contextual elements should support the main learning activity rather than replace it. The core design challenge is to ensure that the learning task remains clear, interactive, and meaningful.

Based on these issues, this study presents the design and evaluation of task-based waste-sorting mechanics in a Virtual Reality learning application. The application places users in a virtual beach environment where they identify, collect, classify, and dispose of waste objects through controller-based interaction. The study focuses on implemented task mechanics and evaluates the resulting player-experience profile at the level of individual GEQ components. It does not treat positive and adverse GEQ constructs as a single continuum and does not claim learning improvement, comfort, or technical task effectiveness without corresponding evidence. Accordingly, the research question is: how can task-based waste-sorting mechanics be designed in a VR learning application, and what component-level experience profile emerges during and after their use?

This study contributes to applied research in information technology and computer science in three ways. First, it provides a practical design of task-based gamification mechanics for waste-sorting education in VR. Second, it documents how waste identification, object grabbing, classification, bin placement, and corrective feedback were implemented as an embodied task sequence. Third, it provides a diagnostic, component-level GEQ profile that identifies both favorable experiences, such as positive affect and immersion, and adverse experiences, such as tension, negative affect, and post-game negative experience. The contribution is therefore limited to system design and self-reported experience; learning gains and objective task performance remain to be tested.

2 Research methods

2.1 *Research Design*

This study employed a design, implementation, and evaluation approach to develop and assess task-based waste-sorting mechanics in a Virtual Reality learning application. The evaluation was designed to examine self-reported player experience after interaction with the prototype. The revised analysis follows the official component structure of the GEQ and avoids combining constructs that represent different or opposing experiences. Because no pre-test/post-test design, comparison condition, or complete objective task-event log was included, the evaluation does not test learning effectiveness or comparative instructional superiority.

The research process consisted of requirement analysis, task-based mechanics design, system architecture design, VR application implementation, participant testing, GEQ data collection, component-level scoring, and cautious interpretation of the findings and limitations. The overall methodological flow is shown in Figure 1.

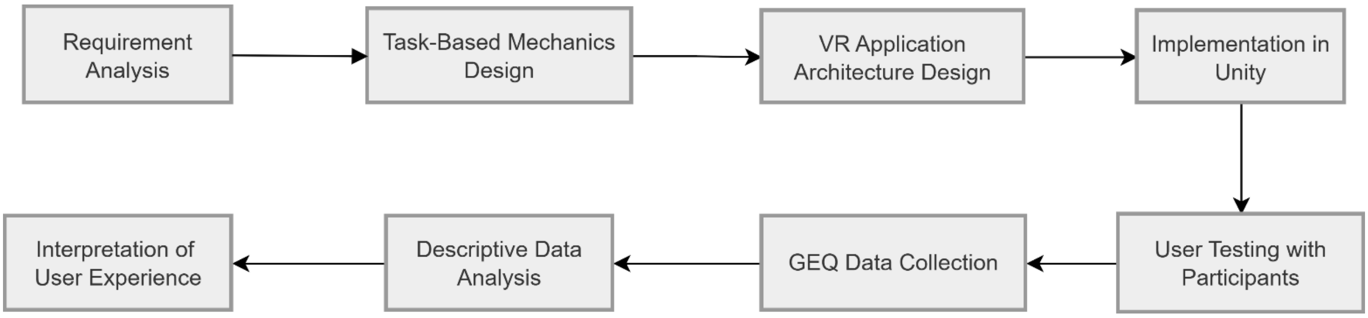

Figure 1. Research Method Flow

2.2 *Requirement Analysis*

The requirement analysis focused on identifying the learning, interaction, and technical requirements needed to support waste sorting education in a VR environment. The learning requirement was formulated based on the need to provide users with direct experience in identifying, collecting, sorting, and disposing of waste objects in a simulated beach tourism context. Environmental education research indicates that digital and immersive tools can support sustainability awareness when learners are actively involved in contextual and experiential learning activities [17], [18]. Therefore, this application was designed to encourage users to perform environmental actions directly rather than only observe information.

The interaction requirements included VR-based exploration, object grabbing, object placement, task completion, and feedback delivery. These requirements were aligned with previous findings that immersive VR learning environments need interaction mechanisms that support agency, presence, and task engagement [9], [26]. The technical requirements included real-time object interaction, controller-based input, a virtual beach environment, waste objects, disposal bins, tutorial support, and user experience data collection.

2.3 *Application Architecture*

The application architecture was designed to support interaction between the user, VR input devices, learning tasks, feedback mechanisms, and the virtual environment. The architecture consists of five main layers: the user input layer, interaction layer, learning task layer, feedback layer, and evaluation layer shown in figure 2. Similar layered design logic is commonly used in immersive learning development because it separates user control, interaction mechanics, learning functions, and evaluation components [7], [10].

The user input layer handles controller input from the VR device. The interaction layer manages object grabbing, object release, object placement, and collision detection with waste bins. The learning task layer controls the waste sorting mission, including task instructions, object identification, and task completion conditions. The feedback layer provides responses based on user actions, such as correct or incorrect placement. The evaluation layer collects user experience responses using the Game Experience Questionnaire after the gameplay session.

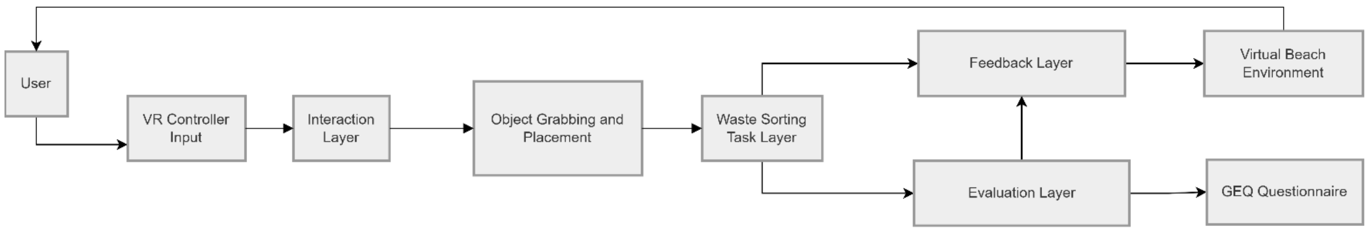

Figure 2. Architecture of the VR Waste Sorting Learning Application

2.4 *Task-Based Gamification Mechanics*

The core design of the application is task-based gamification. The task requires users to complete a waste sorting mission in a virtual beach environment. The design follows the principle that gamification should not only add superficial game elements, but should organize meaningful learning activities through goals, challenges, immediate feedback, and task progression [11], [12], [15]. In this study, the gamification mechanics were represented through mission-based learning, object interaction, waste classification, feedback, and task completion.

The task-based mechanics consist of five main components: mission-based task, waste identification, object grabbing, waste sorting, and feedback shown in table 1. These components guide users to clean the virtual beach by observing waste objects, picking them up with VR controllers, placing them into appropriate disposal categories, and receiving feedback on their actions. This design supports active learning because users must make decisions and perform concrete learning actions inside the virtual environment. The interaction flow of the application is shown in Figure 3.

Table 1. Mapping of Task-Based Mechanics and Learning Functions

No	Mechanics	User Action	Learning Function	System Response
1.	Mission-based task	Accept the waste sorting mission	Introducing learning goal	Task instruction appears
2.	Waste identification	Observe waste objects	Recognize waste type	Waste objects become interactable
3.	Object grabbing	Pick up waste object	Practice direct interaction	Object follows the controller
4.	Waste sorting	Place object into a bin	Classify waste category	System checks the placement
5.	Feedback	Receive response	Reinforce correct behavior	Feedback is displayed
6.	Task completion	Finish mission	Complete learning activity	Completion message appears

2.5 *Implementation*

The VR learning application was implemented using Unity as the game engine and deployed on a PICO 4 VR headset. The environment was designed as a virtual beach tourism area containing beach assets, waste objects, disposal bins, tutorial instructions, and contextual support elements. Unity was selected because it is widely used for VR learning and serious game development due to its support for real-time interaction, 3D environments, physics-based object manipulation, and cross-platform deployment [4], [7].

The implementation focused on three main aspects. The first aspect was the virtual environment, which provided the spatial context for environmental learning. The second aspect was the object interaction system, which enabled players to grab, move, and place waste objects using VR controllers. The third aspect was the feedback system, which responded to users' sorting actions. Non-playable characters were included as contextual support elements to enrich the learning environment, but the focus of this paper is the design and evaluation of the task-based waste sorting mechanics.

2.6 *Participant and Testing Procedure*

The user evaluation involved 30 participants consisting of high school and university students. The participants were selected because the application targets young learners and students as potential users of environmental learning media. Each participant completed one VR learning session using the PICO 4 headset. The session lasted approximately 10 to 15 minutes and consisted of tutorial interaction, beach exploration, waste object identification, waste object grabbing, waste sorting, and task completion.

Before the testing session, participants received a short explanation of the application, basic VR safety, and controller operation. Each participant then completed the 10–15-minute session. The Core, Social Presence, and Post-Game modules were administered immediately afterward. The concise In-Game items were also answered immediately after the session with instructions to refer specifically to the active gameplay period. Because the official In-Game version was designed for repeated administration during play, its retrospective administration in this study is acknowledged as a methodological limitation. No standardized cybersickness instrument or qualitative follow-up interview was administered.

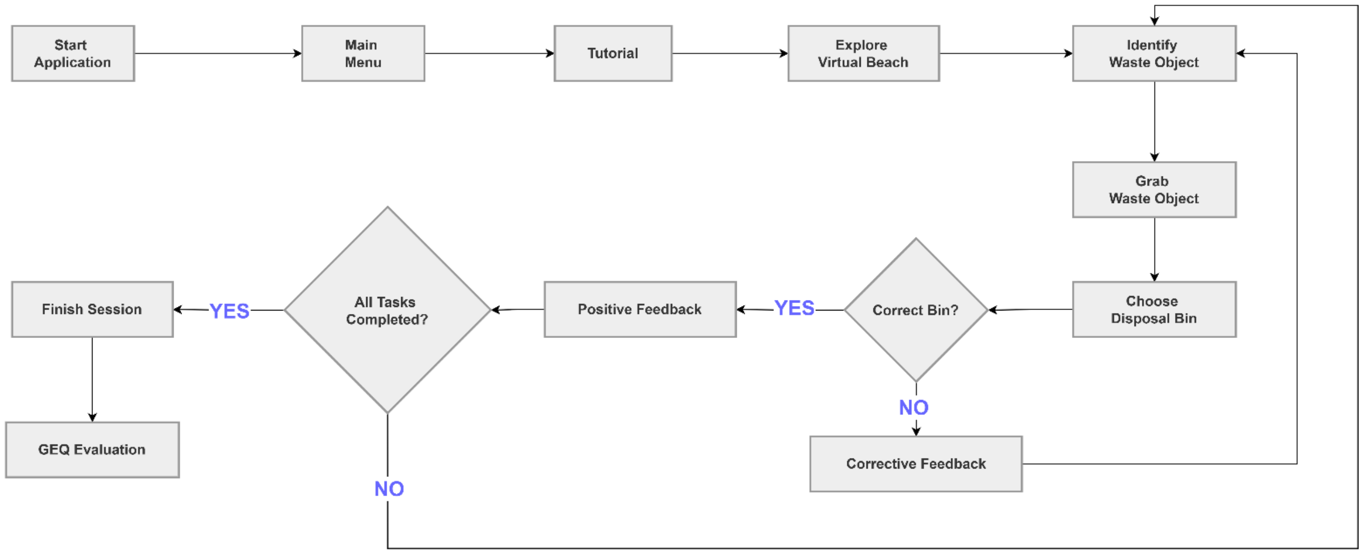

Figure 3. User Interaction Flow in the VR Waste Sorting Task

2.7 *Evaluation Instruments*

The evaluation used the Game Experience Questionnaire (GEQ) [29]. The official response anchors are not at all (0), slightly (1), moderately (2), fairly (3), and extremely (4). The submitted analysis had encoded the same five anchors numerically as 1–5, which produced component means above the official maximum of 4. In the revised analysis, one point was subtracted from each response before component scores were calculated, thereby restoring the official 0–4 metric. GEQ responses indicate the intensity of the named experience and are not agreement scores.

Four GEQ modules were used. Core Module components were scored as follows: competence (items 2, 10, 15, 17, 21), sensory and imaginative immersion (3, 12, 18, 19, 27, 30), flow (5, 13, 25, 28, 31), tension/annoyance (22, 24, 29), challenge (11, 23, 26, 32, 33), negative affect (7, 8, 9, 16), and positive affect (1, 4, 6, 14, 20). In-Game components used two items each: competence (2, 9), immersion (1, 4), flow (5, 10), tension (6, 8), challenge (12, 13), negative affect (3, 7), and positive affect (11, 14). Social Presence components were empathy (1, 4, 8, 9, 10, 13), negative feelings (7, 11, 12, 16, 17), and behavioral involvement (2, 3, 5, 6, 14, 15). Post-Game components were positive experience (1, 5, 7, 8, 12, 16), negative experience (2, 4, 6, 11, 14, 15), tiredness (10, 13), and returning to reality (3, 9, 17). Component scores were the arithmetic means of their items. No items were reverse-coded, and adverse constructs were retained in their original direction.

2.8 Data Analysis and Interpretation

Each GEQ component was analysed separately using participant-level item responses. The dataset contained 30 complete participant records. Three blank rows and five appended scale-key rows were excluded because they did not represent participant responses. No missing GEQ responses were found among the 30 valid cases. The questionnaire used a 1–5 agreement scale, ranging from *Strongly Disagree* to *Strongly Agree*. To align the numerical range with the official 0–4 GEQ scale, each recorded response was transformed by subtracting one. This transformation only changed the numerical origin of the scale and did not alter the direction of any item. No items or adverse components were reverse-coded. Therefore, a higher score indicates a greater presence of the named experience. For example, higher positive affect indicates a stronger positive experience, whereas higher negative affect, tension, tiredness, or negative experience indicates a stronger adverse experience. Because the GEQ components measure distinct constructs with different interpretive directions, no Core, In-Game, Social Presence, Post-Game, or overall GEQ mean was calculated.

For each participant, a component score was calculated by averaging the responses to the items assigned to that component according to the GEQ scoring procedure. The analysis reported the mean, sample standard deviation, two-sided 95% confidence interval, and reliability coefficient for each component. The 95% confidence interval was calculated using:

$$CI_{95\%} = M \pm t_{0.975,n-1} \times \frac{SD}{\sqrt{n}} \quad (1)$$

where M is the component mean, SD is the sample standard deviation, and $n = 30$. Cronbach's alpha was used for components containing three or more items. The Spearman–Brown coefficient was used for two-item components, including all In-Game components and the Post-Game Tiredness component. Reliability estimates below conventional acceptance levels were retained and reported, but the corresponding component results were interpreted cautiously. One participant selected the same response category for all 81 GEQ items. Because no exclusion criterion had been specified before the analysis, this response was retained. A sensitivity analysis excluding this participant changed the component means by no more than 0.07 points, indicating that the overall interpretation remained stable.

3 Results and Discussion

3.1 *Overview of the Developed VR Learning Application*

The result of this study is a Virtual Reality learning application that supports environmental education through task-based waste sorting activities. The application places users in a virtual beach environment where they can explore the area, identify waste objects, pick up objects using VR controllers, and place them into appropriate disposal bins. The learning experience is designed around active participation, where users do not only observe environmental information but also perform concrete learning actions through object-based interaction.

The implemented application includes tutorial guidance, waste object interaction, disposal bin selection, task completion, and contextual feedback. These components form the core task-based mechanics of the application. The virtual beach environment functions as the learning context, while interactive objects and feedback mechanisms support the learning process. Contextual characters and dialogue elements are used as supporting features to enrich the environment and provide additional guidance, but the focus of this paper remains the design and evaluation of waste sorting mechanics.

Figure 4. Example of Contextual Dialogue Support in the VR Learning Application

Figure 4 illustrates an example of contextual dialogue used in the application. Although the main learning activity is waste sorting, contextual dialogue supports the user by providing explanation, guidance, or feedback during interaction. This feature helps the application maintain a more meaningful learning environment because users receive support while performing task-based activities.

3.2 *Implementation of Task-Based Waste Sorting Mechanics*

The waste sorting mechanics were implemented as a sequence of learning actions in which users first enter the application and receive initial instructions through the main menu and tutorial, then explore the virtual beach environment to identify waste objects, grab them using VR controllers, classify the waste, place it into the appropriate disposal bin, and receive feedback based on their actions. This implementation shows that the learning activity is not presented as passive information delivery, but as an interactive process that requires decision-making and object manipulation. Through repeated interaction with waste objects and feedback, users are encouraged to understand waste sorting as a procedural learning activity. In this context, the mechanics of identifying, grabbing, sorting, and receiving feedback become the central learning process. The implemented mechanics can also be interpreted as an applied form of gamified environmental learning, where the mission provides a clear learning goal, object interaction supports active engagement, waste sorting encourages classification practice, and feedback helps users evaluate their actions. This structure is suitable for environmental learning because waste management behaviour requires procedural understanding, not only conceptual knowledge.

3.3 *User Experience Evaluation Using GEQ*

The component-level GEQ results are presented in Table 2. User experience was evaluated using the Game Experience Questionnaire. The evaluation involved four modules: Core Module, In-Game Module, Social Behaviors Involvement, and Post-Game Module.

Table 2. Recalculated GEQ Component Scores on the Transformed 0–4 Metric

Module	Component	M (0–4)	SD	95% CI	Reliability
Core	Positive affect	3.03	0.65	2.79-3.28	α=0.848
	Negative affect	1.28	0.71	1.01–1.54	α = 0.706
	Competence	2.69	0.73	2.42–2.97	α = 0.860
	Sensory and imaginative immersion	2.91	0.59	2.69–3.13	α = 0.784
	Flow	2.33	0.76	2.04–2.61	α = 0.735
	Tension/annoyance	1.00	0.99	0.63–1.37	α = 0.940
	Challenge	1.60	0.68	1.35–1.85	α = 0.721
In-Game	Positive affect	3.05	0.72	2.78–3.32	SB = 0.788
	Negative affect	1.17	0.72	0.90–1.44	SB = 0.192
	Competence	2.72	0.76	2.43–3.00	SB = 0.736
	Sensory and imaginative immersion	2.85	0.71	2.59–3.11	SB = 0.483
	Flow	2.20	1.05	1.81–2.59	SB = 0.743
	Tension	0.95	0.66	0.70–1.20	SB = 0.484
	Challenge	2.30	0.96	1.94–2.66	SB = 0.677
Social Presence	Psychological involvement – empathy	2.54	0.59	2.32–2.76	α = 0.747
	Psychological involvement – negative feelings	1.67	0.60	1.44–1.89	α = 0.593
	Behavioural involvement	2.26	0.65	2.01–2.50	α = 0.795
Post-Game	Positive experience	2.77	0.60	2.55–3.00	α = 0.775
	Negative experience	1.17	0.75	0.89–1.45	α = 0.839
	Tiredness	2.00	0.75	1.72–2.28	SB = 0.069
	Returning to reality	1.97	0.66	1.72–2.21	α = 0.318

$N = 30$. Values are reported on a transformed 0–4 numeric metric. Higher scores indicate a greater presence of the named component. Adverse components were not reverse-coded. Cronbach's alpha was used for components containing three or more items, whereas the Spearman–Brown coefficient was used for two-item components. No module-level or overall GEQ mean was calculated.

3.4 *Core Game Experience*

The Core Module showed a mixed experience profile. Positive affect (M = 2.95), sensory and imaginative immersion (M = 2.73), and competence (M = 2.65) indicate that participants experienced enjoyment, environmental involvement, and a sense of ability. However, tension/annoyance (M = 2.93) and negative affect (M = 2.67) were also substantial. Flow was moderate (M = 2.33), while challenge was lower (M = 1.65). These results do not support the earlier claim that the application was comfortable or free from excessive difficulty. Instead, they indicate that positive engagement coexisted with frustration, annoyance, boredom, or tiredness. Potential explanations include unfamiliar VR controls, object-grab precision, collision or bin-placement sensitivity, repeated corrective feedback, and individual susceptibility to VR discomfort. These explanations remain hypotheses because qualitative follow-up and cybersickness measures were not collected.

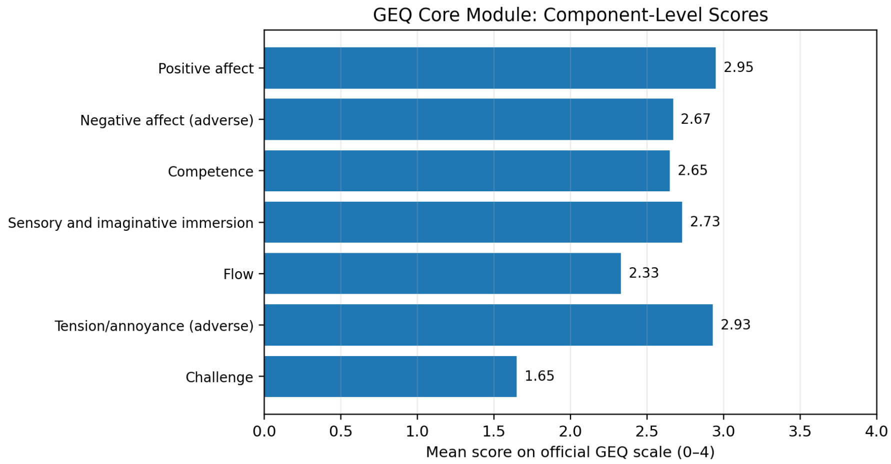

Figure 5. Component-Level GEQ Core Module Scores on the Official 0–4 Scale

3.5 *In-Game Experience*

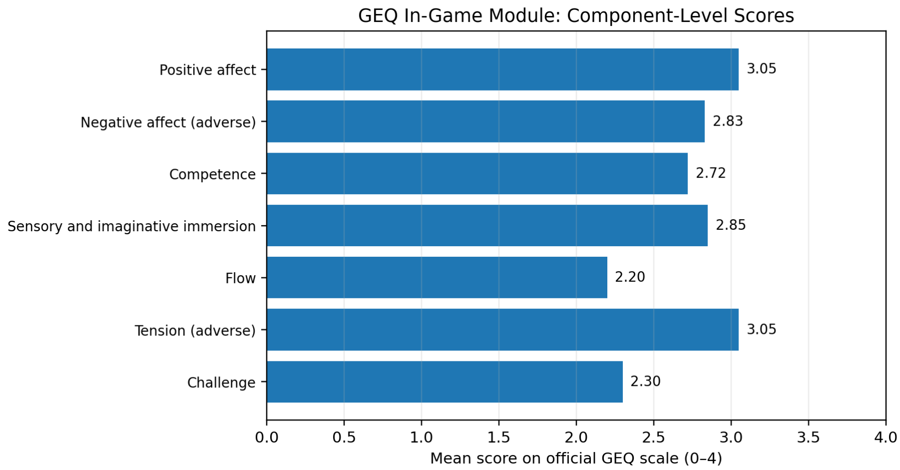

Figure 6. Component-Level GEQ In-Game Module Scores on the Official 0–4 Scale

The In-Game component scores also show simultaneous engagement and strain. Positive affect (M = 3.05), sensory and imaginative immersion (M = 2.85), and competence (M = 2.72) were relatively strong. At the same time, tension (M = 3.05) was as high as positive affect, and negative affect was elevated (M = 2.83). Flow (M = 2.20) and challenge (M = 2.30) were lower. The task therefore cannot be described as uniformly positive. Participants may have enjoyed the activity while also experiencing control friction, pressure, irritation, or fatigue. In addition, because the In-Game items were answered retrospectively after the session rather than repeatedly during play, these scores should be interpreted cautiously.

3.6 Social Presence Experience

The Social Presence Module produced an empathy score of M = 2.54, a negative-feelings score of M = 2.33, and a behavioural-involvement score of M = 2.26. These components should not be averaged because empathy, negative social feelings, and behavioural interdependence represent different experiences. The results suggest that participants noticed and engaged with contextual characters, but this engagement was accompanied by some jealousy, revenge, schadenfreude, or mood-related responses represented by the negative-feelings component. The social elements therefore provided contextual presence but were not uniformly favourable.

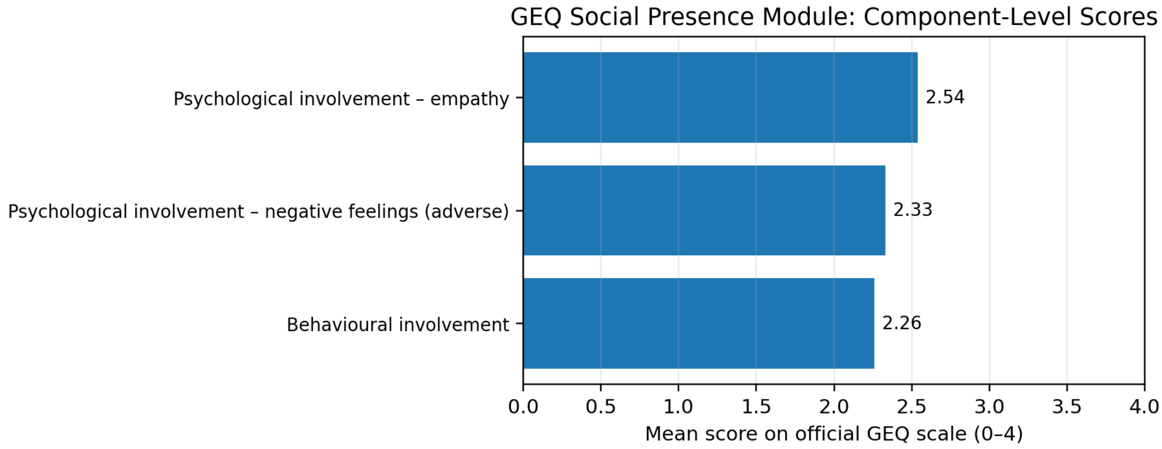

Figure 7. Component-Level GEQ Social Presence Scores on the Official 0–4 Scale

3.7 *Post-Game Experience*

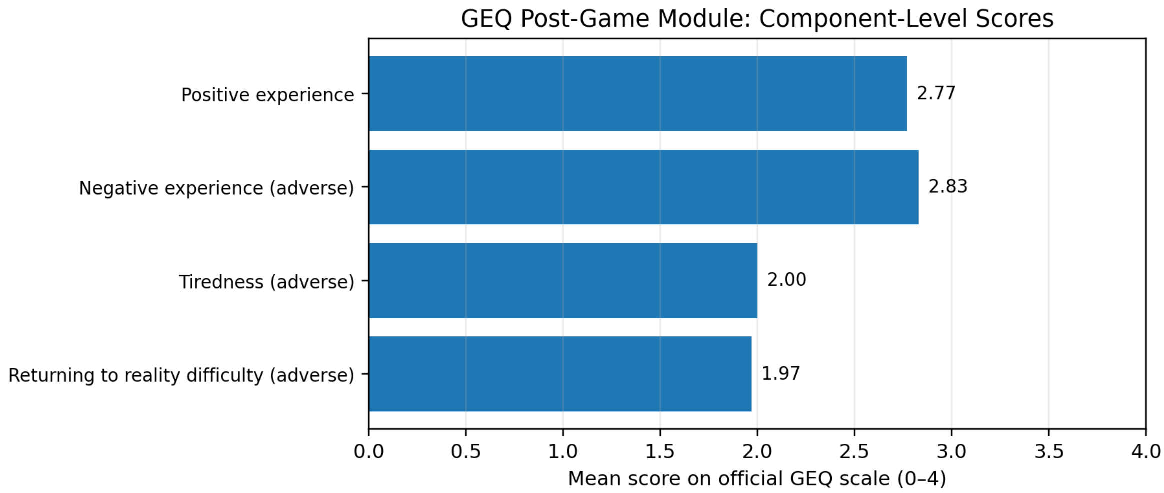

Figure 8. Component-Level GEQ Post-Game Scores on the Official 0–4 Scale

The Post-Game Module further demonstrates why opposite constructs must be reported separately. Positive experience was M = 2.77, while negative experience was slightly higher at M = 2.83. Tiredness reached M = 2.00, and difficulty returning to reality reached M = 1.97. The coexistence of positive and negative reactions means that the session cannot be characterized as simply favourable or comfortable. Some participants may have felt satisfied or energised while others, or the same participants, also experienced regret, fatigue, disorientation, or a sense that the session was unproductive. The study did not collect item-level qualitative explanations, simulator-sickness scores, or interview data, so the precise causes of these responses remain undetermined.

3.8 Objective Task Performance and Learning Evidence

The original evaluation focused on participants' self-reported experiences and did not capture a complete event log or structured observation dataset for objective task performance. Consequently, sorting accuracy, incorrect placements, task-completion time, corrective-feedback frequency, completion rate, and category-level performance could not be calculated retrospectively from the available GEQ responses. The GEQ measures subjective experience and does not provide evidence of whether participants selected the correct bins, completed every required task, or made fewer classification errors. Table 3 therefore reports on the availability of each objective measure rather than presenting estimated or reconstructed values.

Table 3. Required Objective Task-Performance Measures

Metric	Operational definition	Result
Sorting accuracy	Correct first placements ÷ total sortable objects × 100%	Not recorded in the original evaluation
Incorrect placements	Number and type of objects placed in an incorrect bin	Not recorded in the original evaluation
Task-completion time	Elapsed time from task start to successful completion	Not recorded in the original evaluation
Corrective-feedback events	Number of system responses triggered by incorrect placements	Not recorded in the original evaluation
Completion rate	Participants completing all required sorting tasks ÷ total participants × 100%	Not estimable from the available data
Category-level performance	Accuracy and error count for each waste category	Not recorded in the original evaluation

Although 30 participants submitted complete GEQ responses, questionnaire completion cannot be treated as evidence that every participant completed all waste-sorting tasks correctly. The available dataset therefore supports conclusions about participants' subjective experiences but not about their behavioural accuracy, efficiency, or technical task success. Claims that the mechanics improved sorting performance, reduced errors, or enabled successful task completion have consequently been removed from the revised interpretation.

The evaluation also did not include a pre-test, post-test, delayed retention test, or comparison condition. Therefore, the study cannot determine whether participants' waste-classification knowledge improved after the VR session or whether the application was more effective than another learning method. The terms *learning improvement*, *learning effectiveness*, and *knowledge gain* are not used as empirical conclusions in the revised manuscript. Instead, the application is described as providing an interactive opportunity to practise waste identification and classification.

Based on the available evidence, the empirical contribution of the study is limited to the design and implementation of the task-based VR waste-sorting mechanics and the component-level assessment of participants' self-reported experiences. Future evaluations should implement automatic event logging for object selection, placement attempts, selected bin categories, corrective-feedback events, task timestamps, and task completion. Objective performance records should then be combined with pre-test and post-test knowledge measures to evaluate both task execution and learning outcomes.

3.9 *Discussion*

The revised results present a mixed rather than uniformly positive experience. Positive affect, immersion, and competence indicate that the virtual beach and object-based task generated meaningful involvement for participants. However, tension/annoyance, negative affect, negative social feelings, and negative post-game experience were also substantial. The application therefore appears capable of engaging users while simultaneously imposing interaction friction or discomfort. This pattern is plausible in a short VR session that requires novice users to learn controller operation, locate objects, manipulate them accurately, and respond to corrective feedback. Nevertheless, the present data cannot determine which interface event caused each adverse response. Future evaluation should combine GEQ with event logs, think-aloud or interview data, and a standardized cybersickness measure. The task-based mechanics demonstrate a viable implementation of environmental actions in VR, but their understandability and technical effectiveness must be demonstrated through sorting accuracy, error profiles, completion time, corrective feedback counts, completion rate, and category-level performance. Similarly, environmental learning impact requires pre-test/post-test evidence or a comparative design. The conclusions are therefore restricted to implementation and the observed component-level experience profile.

4 Conclusion

Based on the design, implementation, and revised component-level evaluation, the conclusions are as follows:

1. The study developed a VR application with task-based waste-sorting mechanics comprising object identification, grabbing, bin selection, placement checking, corrective feedback, and task completion.
2. The GEQ results form a mixed profile rather than a single positive score. Positive affect and immersion were accompanied by elevated tension, negative affect, and post-game negative experiences.

3. The prototype demonstrates how waste-sorting procedures can be represented as embodied and interactive actions in a virtual beach setting.
4. The available evidence does not justify claims that the application was comfortable, technically effective, or educationally effective because adverse experience scores were substantial and objective task and learning measures were absent.
5. The principal limitations are the absence of participant-level dispersion and reliability statistics in the submitted draft, retrospective administration of the In-Game items, no standardized cybersickness or qualitative follow-up measure, no objective task-event metrics, and no pre-test/post-test or comparison condition.
6. Further development should reduce interaction friction and investigate the sources of negative social and post-game responses through richer logging, observation, and participant feedback.

5 Suggestion

Based on the limitations identified in this study, several suggestions for further research are proposed as follows:

1. Future evaluation should include validated pre-test and post-test measures of waste-sorting knowledge and, where feasible, a comparison with a non-VR or alternative instructional condition.
2. Future studies should involve more diverse participants and report relevant characteristics such as age, education level, prior VR experience, and susceptibility to motion sickness.
3. The application should record task-start and task-end timestamps, first-attempt accuracy, incorrect placements, corrective-feedback events, completion status, and performance for each waste category.
4. The application should include more waste categories and object variations only after the current interaction mechanics have been tested for accuracy, clarity, and accessibility.
5. Social and contextual interaction should be refined using participant feedback, while adverse social-presence items should be examined at the item level rather than hidden in an average score.
6. Future analyses should report component means, standard deviations, 95% confidence intervals, and reliability coefficients and should avoid overall GEQ scores across differently directed constructs.
7. User comfort and fatigue should be evaluated with a standardized cybersickness instrument, direct observation, and post-session interview, particularly when sessions become longer or more complex.

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