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A systematic review on Digital Game Based Learning for Emotional Intelligence training

Sara Torre^a, Olga Rosa Maria Armigero^b, Morena Bottalico^c, Luana Bruno^d, Alejandro Iborra Cuéllar^e, Maria Beatrice Ligorio^f

Abstract

Emotional intelligence (EI) can be enhanced through formal programs such as Digital Game-Based Learning (DGBL). However, effective design practices remain unclear. This review examines DGBL for EI, following the PRISMA guidelines for systematic reviews. Searches in Scopus, PubMed, and Google Scholar identified 13 peer-reviewed studies, analyzed by two independent reviewers. The impact of each DGBL was scanned through the lens of the DGBL Effectiveness Evaluation Framework, which helped us navigate through the multitude of evaluation design, methods and criteria. Results show that game mechanics lead to different learning and motivation outcomes. Conclusions are drawn about DGBL resource management and their indications for future development in the field of game-based emotional training.

Keywords: Emotional Intelligence; Digital Game Based Learning; Empathy; Learning Outcomes; Education; Gamification

a Università degli Studi di Bari "Aldo Moro", <https://orcid.org/0009-0001-7399-6692>

b Università degli Studi di Bari "Aldo Moro", Italy, <https://orcid.org/0009-0001-8101-5508>

c Order of Psychologists of the Puglia Region, Italy, <https://orcid.org/0009-0001-3448-2023>

d Universidad Complutense de Madrid, Spain, <https://orcid.org/0000-0001-7052-7228>

e Universidad de Alcalá, Spain, <https://orcid.org/0000-0001-8373-8622>

f Università degli Studi di Bari "Aldo Moro", Italy, <https://orcid.org/0000-0003-3028-5046>

Corresponding author: s.torre3@phd.uniba.it

Introduction

In the past 30 years Digital Game Based Learning (DGBL) has been established as an innovative and engaging tool to train any knowledge or skill. From science learning (Hussein et al., 2019), to health literacy (Ambarini et al., 2025), any topic can be gamified and taught. Likewise, lately emotional intelligence (EI) became a desirable skill to be scaffolded to avoid emotional illiteracy at any age (Bruzzone, 2023). The growing number of studies on DGBL aimed at developing emotional intelligence sparked numerous reviews that reported on common training practices and design trends. For instance, Ramos et al. (2025) reviewed the use of digital games to enhance children's emotional competencies. The authors assert that the most effective interventions are the ones that involve identifying and recognizing emotions, empathy, and emotional regulation. Interactive social scenarios

seem to be effective for such purposes. EI can be trained in adults (Hodzic et al., 2018), individuals with Autism Spectrum Disorder (ASD), and people undergoing therapy (Pek et al., 2025). Overall, evidence suggests that when DGBL is effective in training EI skills, learners' motivation is also enhanced. However, DGBL is studied by a diverse scientific community, which means that there is a lack of a shared methodology and guidelines in interventions and evaluation (Mayer et al., 2014; Ramos et al., 2025). About the theoretical background, DGBLs in digital education frequently draw on the model proposed by Mayer and Salovey (1997), which conceptualizes EI as the ability to perceive and understand emotions that are used to facilitate thinking. Ekman's (1992) and Levenson's (1994) are also considered when emotions are conceptualized as biologically hardwired, discrete, and universally triggered states, shaping EI training around the recognition, labeling, and regulation of a limited set of basic emotions. The theory of Constructed Emotion (Barrett, 2006) conceives emotions as not biologically fixed nor universal but constructed by the brain, through dynamic and context-sensitive processes of prediction and categorization. These theoretical perspectives are not interchangeable, as they imply different assumptions about what emotional intelligence training should target. Whereas essentialist models tend to support game tasks focused on recognizing and labeling discrete emotions, constructionist approaches are more compatible with context-sensitive, socially situated, and interpretive forms of emotional training. These theories may appear in the selected studies as part of the conceptual background of the DGBLs. However, theoretical frameworks were not coded as a formal analytical dimension in this review, because the information reported in the selected studies did not allow reliable comparisons between theoretical assumptions, game mechanics, and outcomes. Accordingly, we use theory only as an interpretive lens to contextualize design tendencies rather than as a basis for causal claims.

Review aims

The goal of the present review is to gather and analyze studies about DGBL meant to enhance EI regardless of the type of user and to trace an overview of how EI is taught in games. Although no publication year limits were imposed to retrieve empirical study about relevant DGBL, we noticed that most of the publications appeared between 2011 and 2024; therefore we restricted our analysis to such a period. After describing the process of EI training, we aim to draw conclusions about the most effective game design through comparison of results. In summary, the research question of the present review can be formulated as follows:

1. What are the most common game mechanics of DGBL to train EI?
2. What outcomes are reported regarding the effectiveness of such DGBL?

To answer these questions the game mechanics and evaluation practices of DGBL will be analyzed.

Methodology

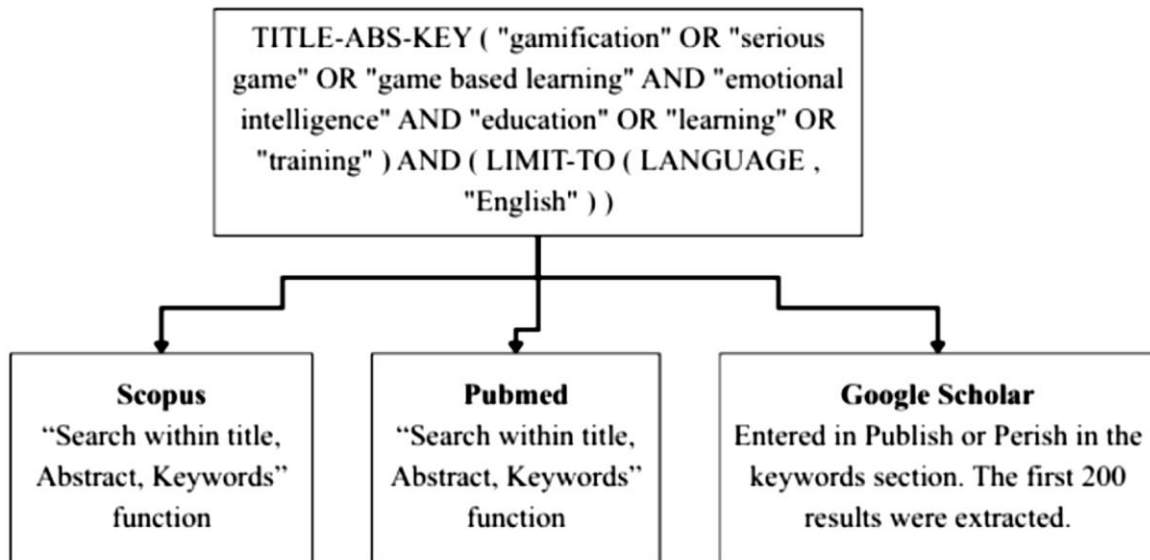
Search Strategy

The PRISMA checklist and guidelines for systematic reviews (Page et al., 2021) were followed as a review protocol. The identification of the papers was conducted on Scopus, PubMed, ERIC, Web of Science, EBSCO, while Google Scholar was adopted as an additional source. Scopus was chosen for its proven ability to include more articles when compared to other databases (Giganti et al., 2024). PubMed was included due to the relevance of DGBL tools for EI in the neurodevelopmental population. Furthermore, its recent functions and advanced filters improve precision and completeness of bibliographic research (Kang et al., 2021). From Google Scholar only the first 200 results were considered (Haddaway et al., 2015) and it was used as a supplementary source to improve coverage, particularly for grey literature in the social sciences and computer science fields (Halevi et al., 2017).

The search string was entered on March 31st, 2025, and the strategy is presented in Figure 1.

Figure 1.

The search string and search settings



The search string included “game-based learning” to detect games with educational purposes. In addition, “gamification” and “serious game” were added in combination with “education”, “learning” and “training” to sift through games with no educational purpose. Pairing every form of gamified educational tool helps tracking down studies about DGBL, even if authors did not identify them as such.

Screening results and inclusion criteria

The search on Scopus resulted in 52 results, the search on Pubmed returned nine results, and the first 200 results from Google Scholar were extracted.

Inclusion criteria were:

- A. Studies published in peer reviewed journals;
- B. Studies include an educational game or games, including any variety of game, that is game based learning, serious games, and gamification;
- C. Studies where the educational game is digital;
- D. Studies with an explicit educational purpose;

The following exclusion criteria were determined:

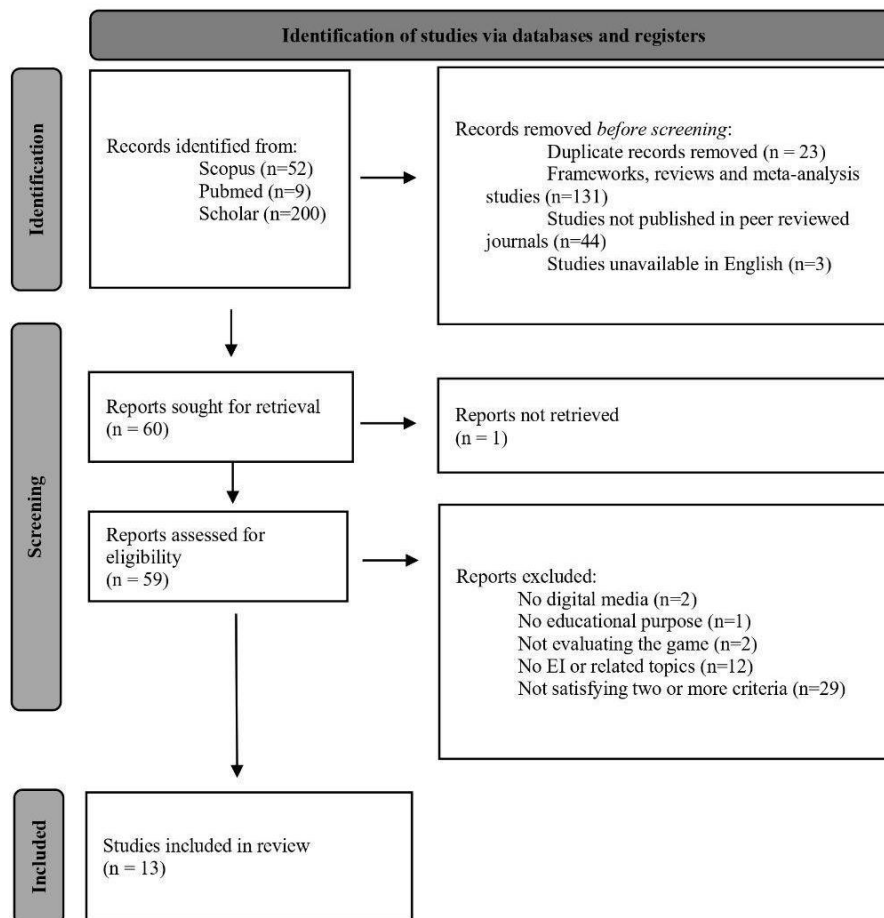
- E. Studies that did not describe the experimentation of a gamified tool.
- F. Reviews and meta-analysis studies;
- G. Studies where educational concern is not on EI;
- H. Studies including gamified tools, but no game mechanics were described.

Critical appraisal process

Following screening, the first two authors of this paper excluded a total of 32 entries from Scopus (14 reviews, one meta-analysis, six framework papers, and 11 conference papers), two from PubMed (one review and one framework); and finally 145 results from Google Scholar were excluded (80 reviews, two meta-analyses, 26 framework papers, 29 conference papers, four theses, three non-

English papers, and one unavailable study). The titles and metadata of the papers were combined into an MS Excel spreadsheet and duplicates were identified through the conditional formatting function. The first two authors manually checked the dataset for additional duplicates that were not automatically detected. 23 duplicates were eliminated, resulting in 59 studies to be examined. Two independent researchers iteratively screened the studies for inclusion, achieving substantial interrater agreement, with Cohen's $K=0.76$. All disagreements were resolved through discussion with a third researcher until full consensus was reached, resulting in the selection of 13 studies for further analysis. Figure 2 summarizes the selection process.

Figure 2.
The selection process



Searches in ERIC (n=10), EBSCO (n=463), and Web of Science (n=35) yielded no additional eligible studies after removing duplicates and excluding non-empirical works, conference papers, and studies not meeting the inclusion criteria.

The two reviewers agreed on a protocol to evaluate compliance with the selection criteria, which is summarized in Table 1 in Appendix.

Data extraction strategy

The games' names were extracted from the paper's title, abstract or full text, and the label "*Unnamed Game*" was attributed when the name could not be found.

A qualitative approach was employed for data extraction. The first two authors singled out the dimensions of interest, which are game mechanics and evaluation methods. Every instance of disagreement with data extraction was discussed with a third researcher until an agreement was reached. The theme identification followed a Qualitative Content Analysis approach (Vaismoradi & Snelgrove, 2019).

Game mechanics were identified through the classification proposed by Toda et al. (2019) including avatar customization, branching scenarios, contextual emotion recognition, drawing, facial emotion recognition, instructional content, journaling of emotions, and non-playable characters (NPCs). Evaluation methods were classified as: research methods, experimental design, evaluation tools and criteria.

Results

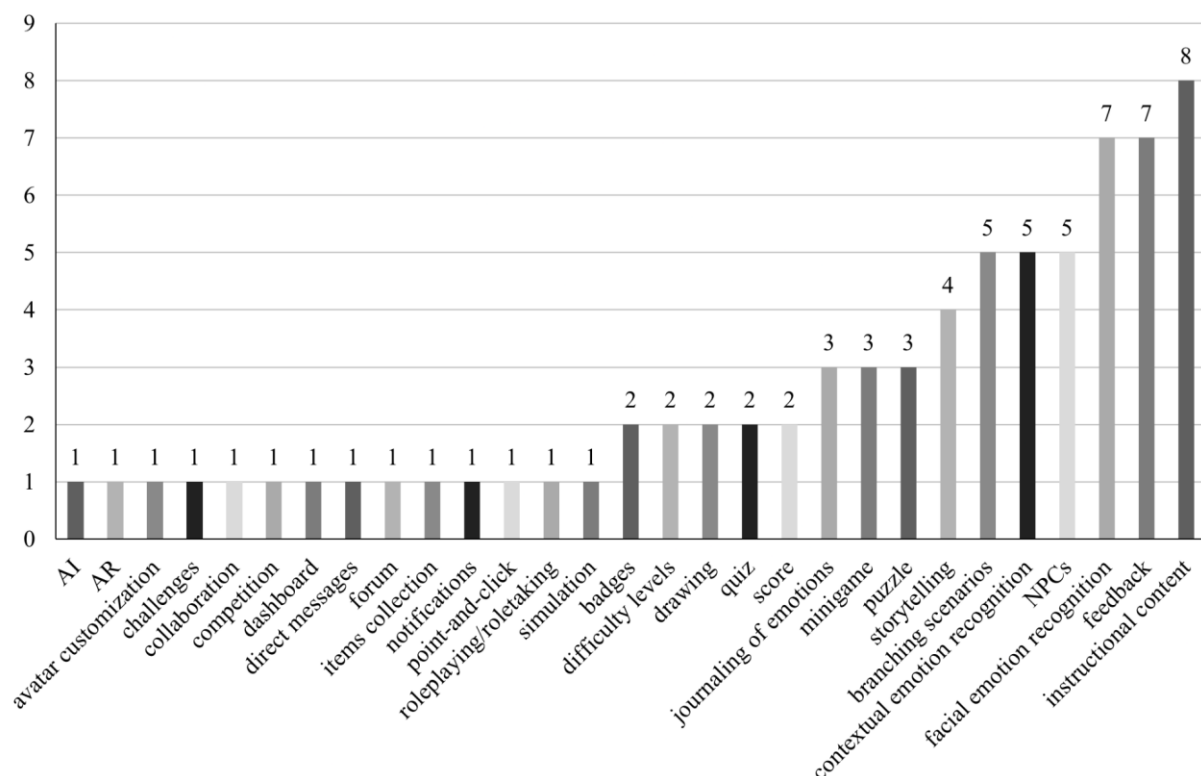
Descriptive results

Table 2 in Appendix summarizes the games tracked down from the selected papers.

Game mechanics occurrence is reported in Figure 3.

Figure 3.

Game mechanics occurrence



The most prevalent game mechanic is the inclusion of instructional content, that is an explanation of EI and related concepts. The next most frequent game mechanics are the recognition of emotion based on facial cues and feedback about game performance. Branching scenarios, emotions recognition based on context, the presence of NPCs and storytelling are common, and they serve as game mechanics to convey contextual and interpersonal cues about emotion recognition and emotionally intelligent behavior. The rest of the game mechanics span across common gamification features, such

as scores and badges, to more novel ones, such as drawing and journaling of emotions and many others.

Evaluation approaches were primarily quantitative ($n=7$) or mixed-methods ($n=6$), while no study relied exclusively on qualitative methods. Five studies included control groups, and one compared three conditions: Face-to-face training, DGBL, and a no-training control group. Data collection methods included closed-ended surveys and tests ($n=6$ each), discussions ($n=4$), open-ended surveys ($n=3$), observations ($n=2$), and interviews and quizzes ($n=1$ each). Evaluation criteria most frequently addressed increases in emotional intelligence ($n=7$), followed by User Experience ($n=5$) and personal well-being ($n=4$). Other outcomes included scores and general perceptions ($n=3$ each), knowledge (declarative), enjoyment, satisfaction, school grades, and engagement ($n=2$ each), as well as immersion, interest to learn, motivation, perceived effectiveness, and perceived performance ($n=1$ each). Three DGBLs were alpha tested, and one was beta tested, which are frequent practices for digital development. Alpha and beta testing consist of software assessments designed to audit functionality, detect bugs, and improve usability and reliability. The methodology of each selected study is reported in Appendix.

Framework for DGBL evaluation

Because of heterogeneous designs, methods and criteria, direct comparison was impractical. Therefore, results were framed using All et al.'s (2015) DGBL effectiveness framework, which defines effectiveness through learning (interest, performance, transfer), motivational (enjoyment, learning motivation), and efficiency (time and cost) outcomes. Two independent coders agreed upon a protocol to classify the outcomes. The protocol included the following steps :

1. Four types of outputs were possible: “positive”, “partial”, “not reached”, and “not addressed in the study”. Table 3 in Appendix describes more in detail the possible cases.
2. The results and discussion sections of each study were read multiple times by the independent judges. Each coder attributed an output for the outcomes of each selected study.
3. The two coders compared the outputs. Agreement reached 80.22%, and disagreements were repaired through discussion with a third coder. When 100% of the consensus was reached, Table 4 in Appendix was compiled to summarize the outputs.

Given the methodological heterogeneity of the studies, the assessment framework was used as a thematic guide to conduct a critical synthesis of the findings rather than a quantitative comparison of outcomes.

Situational interest was considered as an evaluation criterion only by two games: *Unnamed game 2* and *YoungRes*. However, the “partially reached” output was claimed by both games because no data were reported about the actual extent of learners’ interest on the topics of the games.

Learning performance was the most common outcome to be measured. Most commonly, authors intend learning performance either as an increase in emotional intelligence measured by standardized tests, or as an increase of declarative knowledge about the concept of emotional intelligence. However, some studies only partially achieved learning performance, either because results were mixed (*Aislados*; *EmoTIC*; *Crossing the Bridge*; *YoungRes*), or because the results were mentioned but not properly reported (*Unnamed game 2*).

Transfer of knowledge was conceptualized in two ways across the selected studies: as the impact of DGBL on real-life behaviors, such as school grades (*Developing Emotional Intelligence*, *Unnamed game 1*), or as improvements in general well-being and reduced anxiety levels (*Aislados*, *Ajivar*, *EmoFindAR*, *EmoTIC*). In both cases, the acquired knowledge about emotional intelligence impacted the participants’ quality of life, assessed with standardized tests, surveys, and focus group discussions.

Enjoyment of the gaming experience was either evaluated through questionnaires about the enjoyment and motivation experienced while playing (*EmoFindAR*, *Youngres*) or emerged in group discussions with players (*League of Emotions learners*, *Mindful Activity*). The second motivational outcome, motivation towards DGBL, was far more elusive as *Mindful Activity* and *Unnamed game 2* were only evaluated on the participants' interest in playing more.

All et al. (2015) framework also includes efficiency outcomes, that is time management and cost effectiveness. However, these criteria were not mentioned in the selected studies, with the only exception of the *Unnamed game 2* study, where it is stated that the US military is using videogames to limit educational costs. However, the paper does not mention if the game was actually effective in reducing the cost of training.

Analysis through the framework

In this paragraph, the characteristics of DGBL will be cross-examined in conjunction with each outcome.

Only two DGBL—*Unnamed game 2* and *Youngres*—measured and achieved situational interest in the content of DGBL. These DGBLs share two game mechanics: the presence of NPCs and the recognition of emotions based on contextual clues.

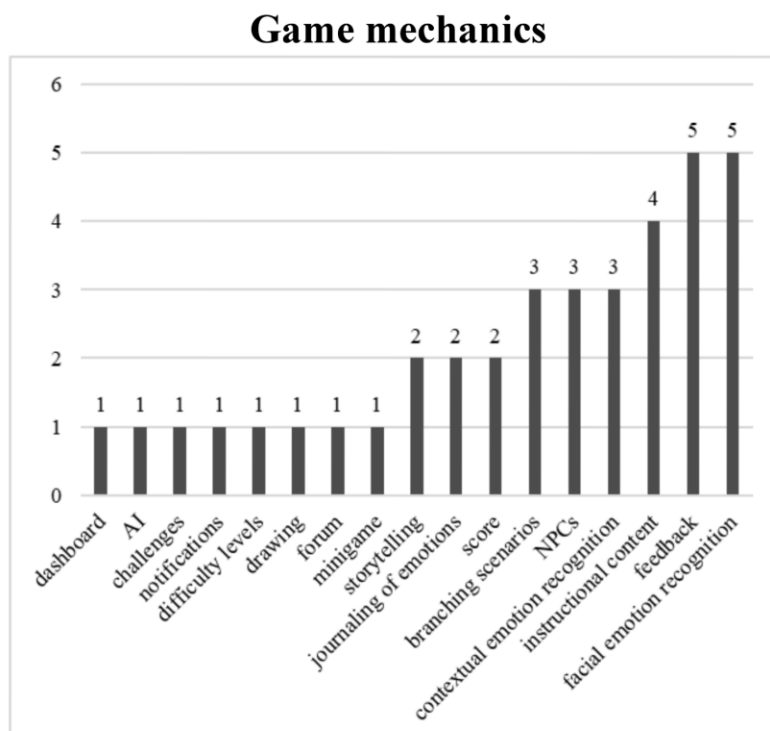
Learning performance, a further learning outcome, was far more prevalent than situational interest. The analysis of DGBL that successfully improved the performance of players is synthesized in Figure 4.

Figure 4.

Game mechanics of DGBLs that achieved performance

DGBL tools that achieved LO2 (Performance)

Ajivar, FLIGBY, Mindful Activity,
League of Emotions learners, The Park of Emotions,
Developing Emotional Intelligence



Among the studies assessing learning performance, six of them achieved it. The most prevalent game mechanics of these DGBLs were emotion recognition based on facial cues and the occurrence of feedback during gameplay, followed by the presence of instructional content. Storytelling, journaling of emotions, branching scenarios, and NPCs were less common game mechanics used in effective DGBL.

Figure 5 represents the characteristics of DGBL that evaluated and successfully promoted transfer of knowledge.

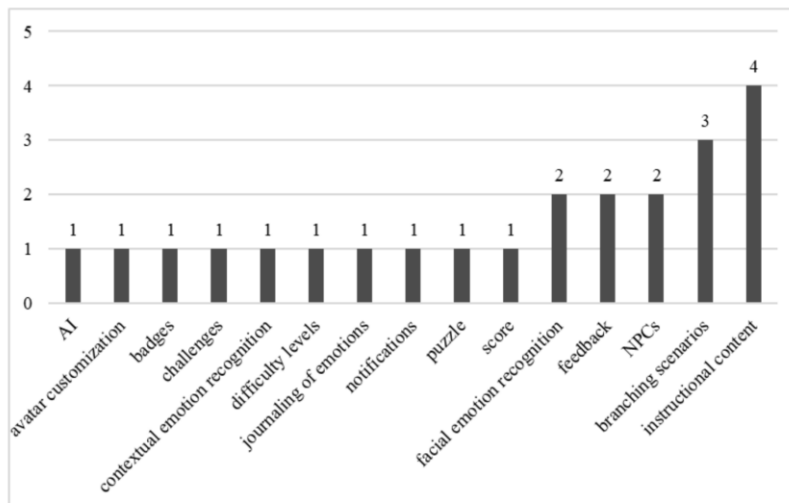
Figure 5.

Game mechanics of DGBLs that achieved knowledge transfer

DGBL tools that achieved LO3 (Transfer)

Ajivar, EmoFindAR, Fligby, Unnamed game 1,
League of Emotions Learners, Aislados

Game mechanics



Transfer of knowledge was slightly more common when DGBLs provided instructional content and branching scenarios.

Figure 6 represents DGBL assessing enjoyment and its attainment.

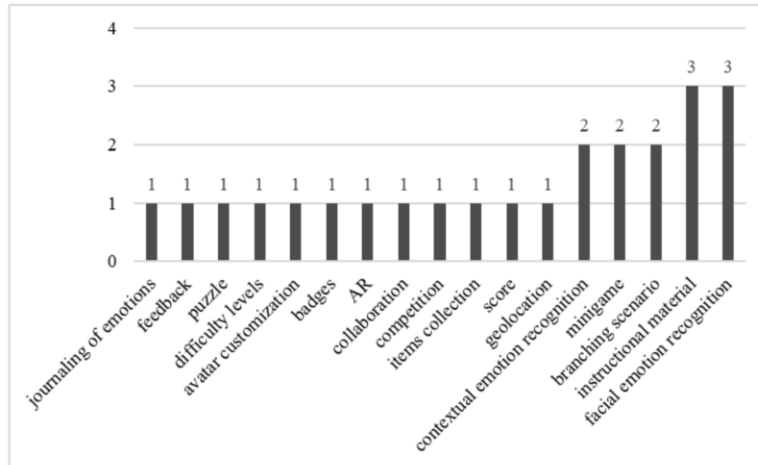
Figure 6.

Game mechanics of DGBLs that achieved enjoyment

DGBL tools that achieved MO1 (Enjoyment)

Mindful Activity, League of Emotions Learners,
EmoFindAR, YoungRes

Game mechanics



Overall, each of the four DGBL that considered enjoyment as an outcome reported successful results on this dimension. Game mechanics such as facial emotion recognition and instructional materials, were the most frequent game mechanics.

Finally, only two DGBLs, *Mindful activity* and *Unnamed Game 2*, were assessed on their ability to elicit motivation towards DGBL, and they partially reached this goal. These DGBLs featured journaling, feedback, NPCs, puzzles and instructional content as game mechanics.

Further analysis was not carried out for the Efficiency outcomes, as none of the selected studies accounted for time and resource management of DGBL.

Discussion

This review provides an analytical perspective on DGBL for EI, aiming to identify game design practices that foster learning and motivational outcomes. It examines trends in game mechanic, and evaluation procedures to answer the first research question on design strategies, followed by considerations of assessment methods to address the second question on DGBL outcomes.

What are the most common game mechanics of DGBL to train EI?

The most common game mechanic is the inclusion of instructional material in the DGBL, which presents the content of the DGBL with a lesson or presentation of core concepts. The aim of instructional material is to embed explanations of abstract concepts into ludic activities. For how common and intuitive this solution might be to deliver teaching, it does not seem to fully embrace the ludic potential of DGBL. As Coleman and Money (2019) noted, this strategy could break players' immersion and compromise deep learning. The game mechanic of emotion recognition based on facial cues, however, is an interactive and easy way to implement game features in the DGBL. Emotion recognition is a core skill for emotional intelligence and matching images with emotion labels is particularly useful to develop emotional literacy, especially in case of neurodivergence (Atherton & Cross, 2021; Papoutsis et al., 2018). However, the prevalence of emotion recognition based on facial expressions seems to represent a consistent trend when the DGBL is based on the relationship between emotions and their physical manifestations. On the contrary, the presence of NPCs, branching scenarios, and emotion recognition based on contextual cues allow players to

understand that emotions are flexible, depending on the context and on the relationship with a fictional character. Considering the value of these context-driven mechanics, it is surprising that they were not so common in the examined games. From the perspective of the Theory of Constructed Emotion (Barrett, 2006), game mechanics that embed emotions within social situations and relational contexts may offer a conceptually richer way to train emotion understanding than decontextualized labeling tasks alone.

Another common game mechanic is feedback, which is a quintessential feature of DGBL. Digital tools are particularly suitable to deliver immediate and specific feedback (Engelhardt, 2024), and in-game feedback supports educational actions (Patino & Romero, 2017).

These considerations highlight the need to further examine how specific game mechanics can be translated into learning opportunities for emotional intelligence and how to empower context-rich interactive designs to provide even more effective training.

What outcomes are reported regarding the effectiveness of such DGBL?

Evaluation practices in experimental DGBL research were examined, but heterogeneous designs and instruments preclude definitive conclusions, as studies rarely share methodology. This lack of convergence, also noted in prior work (Sylado, 2024), justifying the use of the DGBL Effectiveness Evaluation Framework (All et al., 2015) to structure analysis.

Interest in learning and motivation towards DGBL were examined in so few studies that further analysis was not feasible. Learning performance was assessed more consistently, which unveils the importance attributed to this feature. This is consistent with results of other reviews, highlighting how knowledge acquisition seems to be the most sought result of DGBL (All et al., 2014; Hussein et al., 2025). Furthermore, all studies measuring learning performance reported successful outcomes. This finding may be interpreted either as evidence of well-established and effective DGBL practices, or as a manifestation of reporting bias - whereby null or negative results may have been omitted calling for caution in the interpretation of the findings. Notwithstanding this limitation, our analysis indicates that effective DGBL often included feedback, instructional content, and facial-based emotion recognition. While these game mechanics were not the only one occurring in successful DGBLs, they emerged as the most consistently impactful so to be considered as priority design features to foster learning outcomes.

Learning transfer appears to be commonly measured and achieved by DGBLs with instructional content and branching scenarios. Instructional content seems to enhance assimilation of concepts and appears to facilitate the transfer to real-life situations. Branching scenarios might help teach emotionally intelligent behavior through modeling of desirable behaviors.

Only four DGBLs measured and positively evaluated enjoyment. These DGBLs often involved instructional material and emotion recognition through faces. This suggests that inclusion of educational content is enjoyable for players. Enjoyment of facial emotion recognition likely stems from humans' innate, evolutionarily rooted sensitivity to faces, which makes this mechanic intuitive, attention-grabbing, and emotionally engaging (Ruiz et al., 2017). Facial recognition systems leverage social cues deeply rooted in human experience, which intrinsically capture attention, making the mechanics intuitive and emotionally engaging. Including this game mechanic can increase the chances of creating an enjoyable DGBL based on emotional intelligence.

Conclusions about motivation toward DGBL are inconclusive, given that only one study addressed this outcome. In fact, motivation towards DGBL is seldom addressed in literature (All et al., 2015). However, motivation should not be assumed as automatically generated by the DGBL since it depends on specific design conditions, such as the balance between educational content and game

mechanics (Barz et al., 2023). However, the choice to adopt DGBL in educational contexts often depends on their ability to enhance motivation (All et al., 2015).

Measures of efficiency outcomes are entirely absent from the selected studies, highlighting a broader issue within the field; researchers have paid little attention to the evaluation of the economic and temporal costs associated with implementing DGBL in education. Either DGBL is regarded as a high-cost endeavor (Bakhsh et al., 2022) or there is a lack of systemic investigation of resource demands as confirmed by the work of All et al. (2021). It should not be overlooked that the amount of time and resources required to adopt an instructional method is a fundamental factor for teachers and educators, which might struggle with limited institutional resources (All et al., 2015).

Conclusions

This review analyzed game design practices and evaluation methodologies of DGBL about emotional intelligence.

From a game design standpoint, the most frequent mechanics include instructional material, emotion recognition through facial cues, and feedback. However, these mechanics appear to rely on essentialist approaches to emotions, to the detriment of contextual mechanics such as branching scenarios and NPCs, which are more consistent with the constructivist and situated nature of emotional intelligence.

Strictly from an evaluation standpoint, methodological heterogeneity precludes drawing definitive conclusions. Learning performance is the most assessed outcome, with generally positive results. Learning transfer appears to be facilitated by instructional content and branching scenarios, while enjoyment appears to be linked to facial recognition. Motivation and resource efficiency remain largely unexplored areas. Despite such heterogeneity, some recurring mechanics consistently support effective DGBL outcomes; prioritizing them may strengthen emotional intelligence, learning, and motivation. Instructional content appeared to be effective in increasing learning performance (along with feedback, facial emotion recognition), user enjoyment (combined with facial emotion recognition), and support knowledge transfer together with branching scenarios.

In summary, although the DGBLs analyzed show good potential for promoting IE, more methodologically convergent studies that consider the full range of outcomes, including motivation, costs, and transferability, are needed to effectively guide researchers and professionals in the education sector.

In conclusion, this review advances understanding of the structure and efficacy of DGBL about EI, identifies key research gaps, and highlights effective design practices that support learning, motivation, and a constructivist view of EI. By emphasizing mechanics such as feedback, instructional content, and facial and contextual emotion recognition, it aims to inform designers and educators in developing more impactful interventions to foster EI skills.

Limitations and Future directions

This review is limited by the small number of included studies, the exclusion of conference proceedings and imbalanced target populations. The limited numerosity restricts generalizability and may amplify inference bias. The addition of grey literature or focusing on specific populations could balance depth and coverage. The reliance on All et al.'s (2015) framework is risky, as while it is useful to identify good practices, it may constrain alternative effective outcomes. Nevertheless, based on our results we can suggest that future research should adopt more interdisciplinary perspectives, employ rigorous and comparable evaluation methods, and integrate constructionist approaches to support context-sensitive EI.

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During the preparation of this manuscript/study, the author(s) used ChatGPT for the purposes of correcting sentence structure and improving text clarity. The authors have reviewed and edited the output and take full responsibility for the content of this publication.

Conflicts of Interest: The authors declare no conflicts of interest.

Data is available on request to the corresponding author.

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