IJCDS 1571062331

International Journal of Computing and Digital Systems
ISSN (2210-142X)
Int. J. Com. Dig. Sys. #, No.# (Mon-20..)

A Review of the Trends, Methods, and Impacts of Dynamic Game Balancing

Mario Mario[1], Audrey Levina[1], and Yulyani Arifin[2]

[1]Computer Science Department, BINUS Graduate Program - Master of Computer Science, Bina Nusantara University, Jakarta, Indonesia, 11480
[2]Computer Science Department, BINUS Graduate Program - Doctor of Computer Science, Bina Nusantara University, Jakarta, Indonesia, 11480

E-mail address: mario007@binus.ac.id, audrey.levina@binus.ac.id, yulyaniarifin@binus.ac.id

Received ## Mon. 20##, Revised ## Mon. 20##, Accepted ## Mon. 20##, Published ## Mon. 20##

Abstract: A method of maintaining player enjoyment in video games is by automatically matching its challenge level with the player's skill, also known as Dynamic Game Balancing (DGB). This systematic review aims to present a comprehensive overview regarding the characteristics of the game prototypes using DGB, as well as the variety of DGB algorithms utilized and their evaluated impact on player satisfaction. Following the PRISMA framework, 7 scholarly databases were searched between December 2023 and January 2024 to be filtered for publications discussing DGB implementation within the past 5 years. After excluding duplicate titles, unretrievable papers, and those irrelevant to DGB implementation, 91 papers were selected for full-text analysis. Many different categorized characteristics were studied in every paper, which covers the game prototype architectures, gameplay design, DGB systems, and testing results. It should be noted that some bias and inconsistency within the classification processes may exist due to potentially overgeneralizing the convoluted intricacies within the game and its DGB systems. Results show that development in DGB has expanded to many game types, purposes, and technologies. They leverage a multitude of algorithms and techniques to effectively measure player proficiency and modify the game's difficulty in various methods which leads to an overall better player satisfaction compared to non-DGB games. This review helps readers and potential game developers to better understand the current trends and patterns in DGB innovations that contribute to better adaptive gameplay and user experience in video games.

Keywords: Dynamic Game Balancing, Dynamic Difficulty Adjustment. Difficulty Balancing Algorithms, PRISMA framework, Player Engagement, Video Game Design,

1. INTRODUCTION

In the rapidly evolving landscape of gaming, intensified competition among developers necessitates strategies to engage and retain players [1]. DGB emerges as a key tactic to enhance player involvement [2]. This practice stands in contrast to static game balancing, where all players are given identical challenges regardless of their skill levels. Unlike static balancing, which offers uniform challenges such as "Easy" or "Hard," DGB adjusts difficulty in response to player proficiency, ensuring personalized experiences [3]. While static balancing may lead to player disengagement due to a mismatch between their skill and the game's difficulty, DGB adapts challenges in real time to match evolving player skills. But how prevalent are these DGB techniques, what methods do developers commonly employ, and what patterns can be found from research implementing DGB?

Before delving deeper, it's essential to acknowledge the various technical terms that share a similar meaning with DGB. Examples include Dynamic Difficulty Adjustment (DDA) [4] and Automatic Content Balancing (ACB) [5]. Despite nuanced differences in definition and usage, these phrases generally denote the same concept. To streamline this study, the term Dynamic Game Balancing (DGB) will be exclusively utilized, given its relative popularity and clear association with computer games.

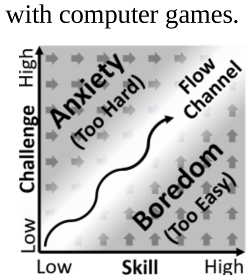

Figure 1. Csikszentmihalyi flow

mario007@binus.ac.id, audrey.levina@binus.ac.id, yulyaniarifin@binus.edu

DGB is deeply rooted in the concept of flow as proposed by Mihaly Csikszentmihalyi [6]. The optimal flow experience, depicted in Figure 1, emphasizes the balance between an individual's skill level and the challenge presented by an activity, forming the "flow channel" for maximum engagement. Video game designers strive to achieve this balance, catering to players of various skill levels from amateurs to professionals [7].

Several literature reviews on DGB in the past have been studied. [8] discusses the various components of adaptive gamification, including implementation methods and frameworks. However, its explanations are short and brief. [9] focuses on player experience by delving into the integration of machine learning with player modeling in DGB. It analyzed the types of data gathered from players and examined the purpose and genre of games with DGB systems. [10] explores adaptation and personalization techniques, investigating how evaluation models capture player emotions and the impact of these adaptations on player experience.

Compared to previous DGB reviews, this review covers a broader range of aspects, including the characteristics of game prototypes, DGB techniques or algorithms used, and their observed improvements. It delves deeper into developers' choices and reasoning behind their prototypes. A dedicated section highlights methods and procedures to balance gameplay difficulty based on estimated player skill. Additionally, it includes notes on research validation and a synthesis of results. All of these offer valuable insights for readers interested in DGB research, especially novice game developers. Overall, this review provides a more comprehensive overview of the current state of DGB research. To explore the landscape and emerging trends in DGB, three research questions (RQ) are posed:

- RQ-1: What factors or components characterize the games employing DGB?
- RQ-2: What techniques and algorithms are utilized for DGB implementation?
- RQ-3: What improvements have the DGB systems brought about and how are they measured?

This research will employ a specific guideline for systematic literature reviews known as the PRISMA framework [11] to methodologically gather, filter, and analyze relevant scientific publications. Furthermore, the information gathered from every selected paper will be summarized into 10 distinct factors which provide a comprehensive understanding of the various aspects and impacts of DGB systems. These valuable insights regarding DGB in a research context will help readers understand current trends in game design and help lay the foundations for future advancements and innovations in this field.

2. Methodology

A. PRISMA Framework

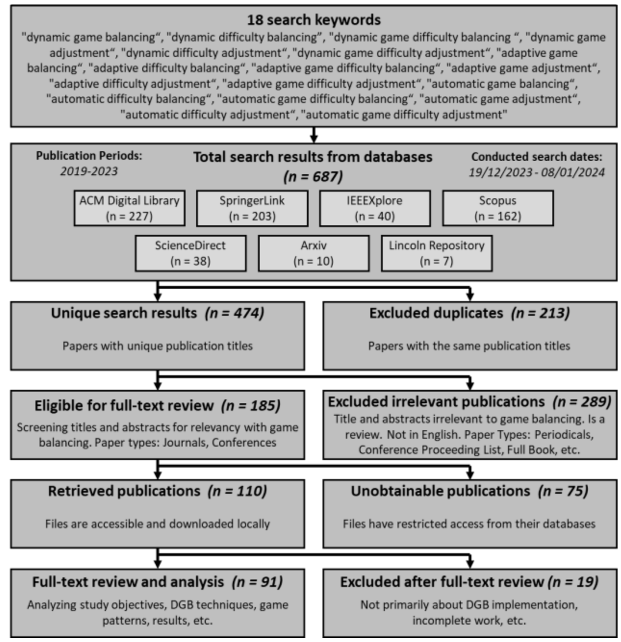

Figure 2. PRISMA chart for systematic literature review

Figure 2 shows the PRISMA flowchart which illustrates the processes of retrieving scientific articles up until deciding which studies to are to be included in this review. The first phase is the systematic database search, which involves selecting keywords that would be used to search for publications from various scholarly databases. As previously stated, there are multiple phrases that different publications use to describe dynamic game balancing. Hence, several commonly used synonyms for the words within the search keyword must be used to reduce the number of relevant publications that are unintentionally skipped.

TABLE I. SEARCH KEYWORD COMBINATIONS

First Word	*Second Word(s)*	*Third Word*
dynamic	game	balancing
adaptive	difficulty	adjustment
automatic	game difficulty	

Table 1 shows how a keyword phrase will be constructed from three parts. These keywords were decided based on the writers' empirical experience when browsing through databases. There is a total combination of 18 different phrases that can be formed by choosing 1 of 3 options as the first word, then 1 of 3 options as the second word, and 1 of 2 options as the third word. It was eventually decided that those 18 phrases were the search keywords that would be used to browse through 7 scholarly databases: ACM Digital Library, SpringerLink, Scopus, IEEEXplore, ScienceDirect, Arxiv, and Lincoln

mario007@binus.ac.id, audrey.levina@binus.ac.id, yulyaniarifin@binus.ac.id

Repository. Additionally, only publications in the last 5 years (2019 – 2023) will be searched to discover DGB's state-of-the-art research. The dates when the search was conducted lasted from 19th December 2023 to 8th January 2024.

As shown in Figure 2, 687 papers were obtained using the 18 search keywords on 7 scholarly databases. To prevent duplicate publications, screening was conducted on the selected publications. Of the 687 publications, only 474 were unique, while the other 213 were duplicates. Then, publications that were eligible for full-text review were selected. In this section, only titles and abstracts related to dynamic game balancing were selected. Additionally, the publication type and its language were also checked, where only journal and conference publications in English were included. After this selection process, a total of 185 publications were eligible for the next phase, whereas the remaining 289 publications were marked as irrelevant. However, out of these 185 publications that were sought for retrieval, 75 of them were unobtainable due to their databases' restricted access for the full text. Hence, there were 110 publications left whose contents will be fully studied. Publications that were deemed to have a primary focus other than DGB development or had an incomplete structure were excluded from the analysis. After reviewing and analyzing the publications, there were a total of 91 publications that will be discussed in this literature review.

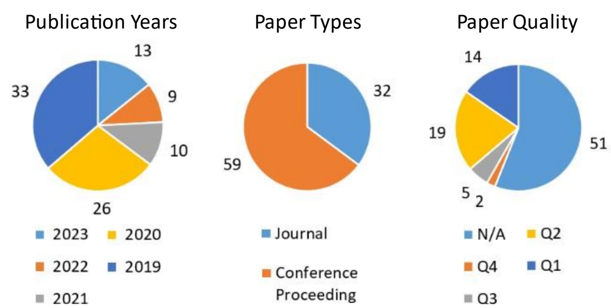

Figure 3. Bibliometric Distributions

Figure 3 shows a brief bibliometric overview of the 91 selected studies regarding their publication years, paper types, and paper quality (based on the quartiles from the Scimago Journal and Country Rank scoring method).

3. Discussion of Findings

A. *Factors and Components Characterizng Games Employing DGB (RQ1)*

To observe the factors or components characterizing games with DGB, this section explores the following characteristics of the game prototypes in each study: game engine, game purpose, input devices and genres. Each one of these aspects are examined to observe some of the common patterns, trends, and unique approaches used across different studies.

TABLE II. Distribution of Game Engines Used

Game Engine	*Total Papers*	*References*
Unity	28	[4], [5], [12], [13], [14], [15], [16], [17], [18], [19], [20], [21], [22], [23], [24], [25], [26], [27], [28], [29], [30], [31], [32], [33], [34], [35], [36], [37]
Half Life	2	[38], [39]
Godot	1	[40]
Android Studio	1	[41]
Swift	1	[42]
Havok	1	[43]
Mario AI Championship	1	[44]
Ubisoft Quebec	1	[45]
Python*	1	[46]
Java*	1	[47]

A game engine is a software framework with tools and features to aid video game development. This offers insight into developers' preferences in DGB-implemented games for research. As shown in Table 2, Unity is the most popular choice among the studies that mentioned their game engines. Reasons include integrated 3D features for VR games [21], availability of many free assets [12], helpful toolkits like Unity's Machine Learning Agents [5], etc. Other than that, Unity is known for its user-friendly development environment, extensive features, tutorials, and community support [48].

Other game engines mentioned include Half-Life and Unreal Engine, though their selection reasons weren't explicitly stated. While Python and Java aren't game engines, they can be used for game development with various libraries and frameworks. Some researchers develop game prototypes from scratch, while others modify existing games like Assassin's Creed [45], Angry Birds [32], Minecraft [49], Starcraft 2 [43], etc. Ultimately, despite Unity's popularity, the choice of a game engine depends on the game's design and the developer's familiarity with the software.

TABLE III. Distribution of Game Purpose

Game Purpose	*Total Papers*	*References*
Enter-tainment Focused	48	[4], [5], [13], [14], [16], [18], [23], [25], [27], [30], [32], [33], [34], [36], [38], [39], [40], [42], [43], [44], [45], [46], [47], [49], [50], [51], [52], [53], [54], [55], [56], [57], [58], [59], [60], [61], [62], [63], [64], [65], [66], [67], [68], [69], [70], [71], [72], [73]
Serious Game	43	[12], [15], [17], [19], [20], [21], [22], [24], [26], [28], [29], [31], [35], [37], [41], [74], [75], [76], [77], [78], [79], [80], [81], [82], [83], [84], [85], [86], [87], [88], [89], [90], [91], [92], [93], [94], [95], [96], [97], [98], [99], [100], [101]

The purpose of a game can be roughly divided into two categories: entertainment or improving a real-life skill (serious games) like physical exercise. This helps identify the game's primary intent and understand how DGB might be tailored differently for entertainment versus serious games. It's worth noting that any game can provide both entertainment and real-life skill improvement (e.g., hand-eye coordination). As shown in Table 3, there is an even distribution of serious and entertainment-focused games.

Some games, especially those for scientific research, aim to help people accomplish tasks better through gamification. DGB in these serious games tailors the learning process to each player's (or patient's) capability, and can be further split into four overlapping subcategories:

1) *Education:* These games make learning engaging and interactive, adjusting question complexity through DGB, allowing students to learn more effectively compared to traditional textbooks. Subjects include math [78], [81], chemistry [35], [90], coding [82], [99], etc.

2) *Rehabilitation:* Designed for individuals with physical or mental disabilities, these games aid in recovery while ensuring players do not overexert themselves through DGB. Physical rehab includes arm movements [76] and finger coordination with exoskeletons [93]. Mental rehab includes games for dyslexia [101] and speech disorders [85]. DGB plays a vital role in ensuring that rehabilitation players do not exert beyond their limits.

3) *Exercise*: Also known as Exergames, these games promote physical activity by adjusting the required movement intensity as needed. Examples include GPS-based running games [75] and motion capture games [12], [15]. For those with physical challenges, exercises are tailored to their abilities, such as balance games on a Nintendo Wii [15] and upper body sports [86].

4) *Cognitive*: These games enhance cognitive skills, where DGB systems adjust cognitive load based on the player's capabilities. This include games like "Simon Says" [94], simulated shopping activities [100], tile-matching games [41], [95], color separation [77], etc.

Conversely, Numerous DGB techniques have been tested and utilized by developers to maximize fun and boost sales in entertainment-focused games [2]. Unlike serious games, entertainment-focused games don't typically provide any external benefits to their players outside gameplay satisfaction. Hence, DGB systems here have a higher priority in maintaining player interest by ensuring their skills are consistently matching with the right level of challenge. These DGB systems can be later implemented into commercial games to extend the game's lifecycle [1]. These entertainment games can come in a myriad of forms of gameplay mechanics and DGB systems. Entertainment-focused games cover a majority of games within the "fast-paced action", "strategy", "horror" and "rhythm" genres.

TABLE IV. DISTRIBUTION OF INPUT DEVICE TYPE

Input Device Type	***Total Papers***	***References***
Mouse, Keyboard	40	[5], [13], [14], [22], [25], [29], [30], [32], [34], [35], [38], [39], [43], [44], [45], [46], [49], [50], [54], [56], [58], [61], [62], [65], [67], [70], [71], [73], [74], [77], [78], [82], [83], [84], [85], [87], [88], [91], [99], [101]
Physiological Measures	19	[19], [21], [22], [24], [26], [28], [31], [37], [45], [54], [59], [67], [80], [87], [88], [92], [93], [98], [100]
Touchscreen	12	[4], [16], [17], [22], [32], [40], [41], [42], [49], [67], [75], [89]
Motion Capture	11	[12], [15], [29], [37], [45], [53], [76], [79], [88], [93], [97]
Virtual Reality Controllers	8	[18], [20], [21], [23], [24], [31], [86], [100]
Facial Recognition	6	[13], [25], [30], [34], [44], [67]
Microphone	4	[15], [78], [79], [85]
Console Controllers	4	[28], [30], [31], [45]
Eye Camera	4	[45], [57], [70], [72]

Input devices are the hardware used to interact with games. Studying them helps explore how the choice of input devices affects the implementation and performance of DGB systems, providing insights into technological constraints and opportunities across platforms. A study may employ multiple types of input devices from Table 4.

Using a mouse and/or keyboard is common for computer games, showing that laptops and desktops are frequent mediums for developing and delivering game prototypes for DGB research. Some studies developed prototypes for mobile devices, which are cheaper and more accessible despite its lower hardware capabilities that limit the game's complexity [40]. Numerous studies also used hand-held console controllers for shooter games [30], open-world role-playing games (RPG) [45], or driving simulators with steering wheel controllers [28].

Several sports-themed games used motion-capture equipment to track player input via body movement. This could involve a camera with specific software or specialized motion-capture cameras like Microsoft Kinect [79] to visually grasp a player's movements. Other non-camera equipment to track movement included Wii Balance Boards [15] or specialized exoskeletons [93].

Finally, several studies used cameras and sensors to monitor a player's focus and stress levels. Researchers used cameras to observe eye movements [72], pupil dilation [57] or their facial emotions [44]. Some researchers attached physiological sensors like electroencephalogram headsets [88] to measure their anxiety levels including galvanic skin response [37], heart rate [28], temperature [93], etc

.

mario007@binus.ac.id, audrey.levina@binus.ac.id, yulyaniarifin@binus.ac.id

TABLE V. DISTRIBUTION OF GENRE GROUPS

Genre Groups	*Total Papers*	*References*
Mental Training	44	[17], [19], [20], [22], [23], [26], [27], [28], [29], [31], [32], [35], [41], [46], [52], [59], [61], [66], [67], [72], [73], [74], [77], [78], [80], [81], [82], [83], [84], [85], [87], [88], [89], [90], [91], [92], [94], [95], [96], [97], [98], [99], [100], [101]
Fast-Paced Action	41	[4], [5], [12], [13], [14], [16], [17], [18], [23], [25], [27], [30], [33], [34], [36], [38], [39], [43], [44], [45], [49], [50], [51], [53], [54], [57], [58], [60], [62], [63], [64], [65], [67], [68], [69], [70], [71], [81], [88], [93], [99]
Exercise	14	[12], [15], [21], [24], [37], [47], [55], [75], [76], [77], [79], [86], [97], [101]
Strategy	12	[32], [39], [42], [43], [46], [47], [49], [56], [67], [69], [72], [88]
Horror	5	[14], [17], [18], [23], [25]
Rhythm	1	[40]

Genres categorize games based on themes, interaction styles, and core gameplay mechanics. Studying this helps determine which genres benefit most from DGB and how DGB systems need to adapt to various interactive elements to maintain balance. Since genre classifications vary, this review groups them into genre groups in Table 5, where a game can belong to more than one group.

Games in the "mental training" genre engage players in cognitive challenges and problem-solving activities, such as puzzles, logic, education, memory, and cognitive genres. Researchers often create games in this category for gamification, figuring out how DGB systems can tailor the learning process to be more enjoyable [78]. For example, DGB systems in educational math games might adjust the difficulty by changing the complexity or number of tasks based on the player's correct answer rate [80]. By tailoring the challenge level to the player's skill, these games can make learning both fun and effective.

The "fast-paced action" genre, which includes adventure, combat, shooter, platforming, survival, and arcade games, is a popular choice for DGB research due to the numerous variables available to adjust gameplay difficulty [45]. DGB systems in these games often track player performance metrics such as health, damage dealt, enemies defeated, and shooting accuracy to assess skill levels [38]. Based on these inputs, the DGB system might adjust enemy or player attributes like quantity, hit points, speed, and the Artificial Intelligence (AI) of enemies, making the game easier or harder depending on the player’s proficiency [49]. Additionally, the system can modify in-game resources, like health packs or ammunition, to further fine-tune the challenge [18].

Games in the "exercising" genre, including sports and rehabilitation games, adjust gameplay based on the player’s physical performance. Depending on the player’s current physical capabilities, these games can tweak the required muscle movement intensity to ensure an appropriate level of physical training [24]. The “exercising” genre also covers sport-themed games that don’t involve physical movement from the players, such as a soccer simulation game [47], [55]. Here, DGB systems control the difficulty of the opposing team players that fight against the player’s team.

“Strategy” games, including genres like tower defense [67], [88] and turn-based [39] games, require players to manage resources and make thoughtful decisions. DGB systems in these games might adjust resource availability, opponent intelligence, or other in-game variables based on the player’s performance. For example, the system might change the provision of health packs, ammunition, or other resources to maintain a balanced challenge [18]. A common application for strategy games is the recreation of traditional board games such as Othello [46], where DGB systems determine opponent intelligence levels to control the game’s difficulty.

“Horror” games aim to create a sense of unease and fear in players, often through varying levels of jumpscares [25] and psychological stressors [18]. In this genre, DGB systems might not focus on making win conditions harder but rather on challenging the player's concentration and emotional resilience. For instance, modifying the game's environment by controlling the color scheme [67], illumination [23], visibility [83], as well as other stress-inducing scenes. These adjustments alter the perceived difficulty, increasing or decreasing the tension without necessarily changing the core gameplay mechanics.

“Rhythm” games require players to synchronize their actions with the beat of the music. DGB systems in this genre adjust the difficulty by modifying the speed of the song or the complexity of the notes based on how well players keep the rhythm [40]. This dynamic adjustment ensures that the challenge remains in sync with the player’s skill level, maintaining the flow and enjoyment of the musical experience.

B. *Techniques and Algorithms Utilized for DGB Implementation (RQ2)*

This section will delve into the various DGB strategies used in past studies, taking note of their prevalence and innovativeness. It is important to note that some studies may use certain types of known algorithms for their DGB systems, but not explicitly mention its name.

Although similar, there is a difference between a “technique” and an “algorithm”. In this review, a “technique” is defined as a general, broader approach that is used to solve a problem. It could be a theoretical or practical approach. Whereas an “algorithm” is a set of well-defined procedures or rule to perform a specific task, hence making it more specific than a “technique”. For example, mathematical computation or processing.

TABLE VI. DISTRIBUTION OF TECHNIQUES USED FOR DGB

Technique	*Total Papers*	*References*
Recommender System	46	[4], [5], [12], [14], [15], [16], [17], [19], [20], [21], [24], [27], [28], [30], [31], [35], [38], [40], [41], [44], [49], [50], [54], [57], [60], [61], [65], [70], [72], [73], [74], [76], [77], [79], [80], [81], [82], [83], [85], [88], [91], [92], [96], [97], [99], [101]
Procedural Content Generation	10	[5], [12], [16], [17], [23], [33], [71], [96], [97], [99]
Emotion Recognition	9	[13], [18], [25], [30], [34], [67], [78], [79], [85]
Glicko-2 Rating System	4	[27], [61], [73], [84]
Trial and Error	2	[52], [75]
Player Agent	2	[32], [64]
Item Response Theory	1	[74]
Fuzzy Coordinator, Total Current Unit AI/Player Ratio	1	[43]
Dojo Matchmaking	1	[84]
Markov Decision Process	1	[56]
Tabu Search Exploration	1	[39]
Rule-Based Adaptation Mechanism	1	[29]
Adaptive Game Artificial Intelligence	1	[47]
Disjoint Skill Model	1	[60]
Visual Scaffolding	1	[90]
Logit Mixed-Effects Model	1	[91]
N-Back Task	1	[94]

As seen in Table 6, more than half of the papers used a recommender system for DGB implementation. In this review, a recommender system refers to an adaptive determination of difficulty based on a range the author has manually determined. In [57], the author tracks the player's pupil diameter and game performance to assess the game's difficulty. To summarize, while the variable range for recommender systems is typically determined manually by the author, the specific calculation formulas or algorithms employed can vary significantly across different implementations.

Some papers have used procedural content generation (PCG) as a method to create diverse and dynamic environments, enhance replayability, and provide unique experiences for each playthrough. [33] proposed an experience-driven PCG (EDPCG) tool called Diversity Regulated Adaptive Generator Online (DRAGON) to automatically generate monster archetypes in multiplayer games based on player preferences. PCG is commonly used to address the challenge of providing a large amount of content, and this technique is used to generate objects whose variables are modified through the DGB system.

Emotion recognition is also a commonly used technique for determining DGB changes. [25] uses facial emotion recognition to determine the player's stress level, which will affect the game's difficulty. The emotion classified by this technique is used as a variable for the game's DGB system. The emotions could be calculated based on the player's facial expression [13], [25], [30], [34], speech tone [78], [85], physiological signals [18], [67], and self-assessments such as talking with a virtual doctor [79].

To assess the player's skill, some research uses a rating system like Glicko-2 to determine the player's ranking. [96] observes that using a rating system like Glicko-2 and using a matchmaking algorithm could improve player engagement by calculating the probability of the player losing the level. This technique calculates the player's skill, which will be a variable for the DGB system.

TABLE VII. DISTRIBUTION OF ALGORITHMS USED FOR DGB

Algorithm	*Total Papers*	*References*
Machine Learning	30	[5], [18], [22], [26], [29], [31], [32], [33], [36], [39], [42], [44], [45], [51], [55], [56], [59], [63], [66], [68], [69], [74], [75], [78], [86], [87], [94], [95], [98], [100]
Deep Learning	7	[31], [37], [46], [58], [59], [82], [94]
Monte-Carlo Tree Search	4	[37], [46], [53], [62]
Fuzzy Logic	3	[78], [82], [89]
Increment/Decrement One Level	2	[21], [93]
Intelligent Trial-and-Error, A* Path Finding, One Step Look-Ahead, Greedy Tree Search, Random Search, Rolling Horizon Evolution	1	[52]
Multi-agent Reinforcement Training	1	[5]
State-Action-Reward-State-Action	1	[39]
+/−δ Algorithm	1	[63]
Partially Ordered Set Master	1	[93]
Adaptive Neuro Fuzzy Inference System	1	[94]
Evolutionary Algorithm	1	[69]

As seen in Table 7, one of the algorithms used in some papers was the Monte-Carlo Tree Search (MCTS). This algorithm can be used to handle large and complex search spaces. [46] applied MCTS to adjust the AI's skill against the opponent based on the estimated value gained from the deep neural network. As an algorithm for the DGB system, MCTS is commonly applied for movement decision [46] and plans appropriate difficulty levels based on the predicted player skill [46], [52], [53].

Among the researched papers, the machine learning algorithm is the most dominant. [98] used the Support Vector Machine (SVM) algorithm to classify and predict

mario007@binus.ac.id, audrey.levina@binus.ac.id, yulyaniarifin@binus.ac.id

the game's difficulty based on the player's physiological response. The use case of machine learning for DGB system includes estimating gameplay difficulty for player [32], [42], [44], [63], [66], [69], [74], [98], enhance AI Agent performance [5], [39], [52], [55], [56], [87], emotion recognition [18], [22], [26], [31], [59], [67], [78], [100], predict player skill [36], [51], [85], [94], [95], and object generation [33].

Deep learning, a subset of machine learning, is also often applied to DGB systems. [37] used an Adaptive Neural Network (ANN) to predict the risk on the player's squat exercise performance. The risk assessed will determine the level of exercise through the DGB system. The application includes estimating [37], [46], [58] and classifying [37], [54] a player's ability, as well as emotion recognition [31].

C. *Impacts of DGB Systems towards Player Satisfaction (RQ3)*

To study the improvements in DGB systems and how they are measured, this section will explore the following aspects of each study: testing method type, DGB conclusions, and improvement suggestions. This analysis will identify common testing methodologies, summarize the general sentiment of players towards a DGB system, and offer recommendations for further enhancing the impact of DGB systems on the gaming experience.

TABLE VIII. DISTRIBUTION OF TESTING METHOD TYPES

Testing Method Type	***Total Papers***	***References***
External human players	75	[4], [12], [13], [14], [16], [17], [18], [19], [20], [21], [22], [23], [24], [25], [26], [27], [29], [31], [34], [35], [36], [37], [38], [39], [40], [41], [43], [44], [45], [49], [50], [51], [53], [54], [57], [58], [59], [60], [61], [62], [63], [64], [65], [66], [67], [70], [71], [72], [73], [74], [75], [76], [77], [78], [79], [80], [81], [82], [84], [85], [86], [88], [89], [90], [91], [92], [93], [94], [95], [96], [97], [98], [99], [100], [101]
Simulated AI "human" agents	12	[5], [32], [39], [42], [46], [47], [52], [55], [56], [68], [83], [87]
Self (Alpha) Testing, or Unkown	5	[15], [28], [30], [33], [69]

In DGB research, there are multiple methods to test and validate a DGB system as shown in Table 8: either through external human beta-testers, simulated AI players, or self-testing. Studying these methods and their evaluation metrics can provide insights into the reliability and validity of the findings reported in DGB studies.

Obtaining human volunteers is by far the most common way to test out any computer game, where players would play the presented game prototype in a controlled environment, answering questionnaires (for example, the Game Experience Questionnaire (GEQ) [16]) and interviews to provide gameplay data. Sometimes researchers don't reveal to the players which version has DGB and which one does not, thereby reducing bias and making their feedback more reflective of their genuine experience [4]. However, obtaining a sufficiently large number of volunteers proved to be a challenge for some, which can be as low as 4 players [39] due to obstructions like the Covid-19 pandemic [23] to as high as 621 players [66] with the help of online distributors.

Rather than seeking human volunteers, some research opted for AI players instead. They would run several simulations of a dynamic-difficulty AI player against many static-difficulty AI players to see if the dynamic AI can adapt itself to different player skills without the need for human players [55].

Researchers used many standardized metrics to check if their proposed DGB system had significant improvements compared to the non-DGB versions of the game. Based on the gameplay data or questionnaire results, researchers were observed using various tests such as Mann-Whitney U [34], Analysis of Variance (ANOVA) [70], Shapiro-Wilk [73], Jendall's Tau-b correlation [21], Cohen's Kappa [59], etc. Several studies also chose to use basic descriptive statistics to prove that their DGB systems yielded significant improvements. Examples of this include mean difference [76], f1-score [22], accuracy [74], etc.

Finally, a few studies did not clearly state any testing procedure to validate the effectiveness of their DGB system. This implies that their conclusions are mainly based on the researcher's personal experiences [69], otherwise known as alpha-testing. It is advisable that such papers include valid evaluation metrics to ensure the credibility and reliability of their findings.

TABLE IX. DISTRIBUTION OF DGB CONCLUSIONS

DGB Conclusions	***Total Papers***	***References***
Player satisfaction or experience	60	[4], [12], [13], [14], [15], [16], [17], [18], [19], [21], [23], [24], [25], [26], [29], [30], [31], [34], [35], [36], [38], [39], [40], [41], [45], [49], [50], [53], [54], [57], [58], [59], [60], [62], [64], [65], [67], [71], [72], [73], [75], [76], [78], [81], [82], [84], [85], [88], [89], [90], [91], [92], [93], [94], [95], [96], [97], [98], [99], [100]
DGB performance comparison	40	[5], [26], [27], [31], [32], [34], [36], [37], [39], [42], [44], [46], [47], [51], [52], [55], [56], [57], [59], [61], [62], [63], [66], [68], [69], [74], [75], [77], [78], [79], [80], [86], [87], [91], [93], [95], [96], [98], [99], [100]
Player performance	28	[4], [16], [17], [19], [20], [24], [43], [50], [51], [54], [60], [62], [63], [65], [70], [72], [73], [81], [84], [85], [88], [89], [90], [92], [94], [95], [97], [101]
Novel system	4	[21], [22], [28], [33]

Analyzing conclusions from research papers highlights the objectives behind the development of DGB systems. The findings are categorized into four objectives as shown in Table 9: player satisfaction, player performance, DGB performance comparison, and novel systems.

Most papers discuss the impact of DGB systems on player satisfaction, influenced by factors such as immersion, challenge, flow, etc. [14] assessed player satisfaction towards their proposed method through the GEQ. Some authors aimed to improve player performance with their DGB systems. With DGB, players can progressively improve and tackle higher difficulties. [50] used DGB to increase competitiveness by adjusting game difficulty, concluding that the right competition level motivates skill improvement within players.

Other authors focused on comparing different DGB algorithms and techniques to find the most effective approach. [52] compared MCTS and random search algorithms for its AI player agents. It was concluded that AI agents with the MCTS algorithm have higher win rates when enemy entities are present, whereas random search is better for clearing levels without enemy entities. Finally, a few papers introduced novel DGB systems. [83] created a DGB system based on the game environment's fog level. This was a novel method of affecting difficulty through modifying the line of sight.

TABLE X. DISTRIBUTION OF IMPROVEMENT SUGGESTIONS

Improvement Suggestions	*Total Papers*	*References*
Improve the current DGB system, or combine it with other DGB systems	52	[4], [5], [13], [20], [21], [23], [24], [25], [26], [27], [28], [29], [31], [32], [33], [34], [35], [36], [37], [39], [40], [42], [43], [44], [46], [47], [51], [52], [54], [55], [56], [59], [60], [61], [62], [65], [66], [73], [74], [75], [83], [84], [86], [89], [91], [92], [95], [96], [97], [98], [100], [101]
More playtesting, input dataset, or variety of players	32	[12], [14], [15], [18], [20], [22], [23], [24], [28], [29], [34], [36], [37], [42], [44], [47], [52], [54], [58], [59], [68], [71], [75], [77], [80], [87], [89], [90], [93], [98], [99], [100]
Expand DGB implementation to other games/genres	23	[13], [14], [16], [17], [21], [25], [28], [32], [36], [46], [51], [56], [61], [69], [70], [73], [74], [80], [82], [86], [88], [92], [95]
Modifying ways to measure skill and change game difficulty	21	[13], [25], [26], [28], [30], [31], [49], [52], [57], [63], [65], [70], [71], [72], [78], [84], [86], [87], [89], [91], [94]
Better data analysis on the results	17	[12], [21], [41], [55], [58], [62], [63], [64], [65], [66], [72], [76], [79], [80], [82], [88], [100]
Better tutorials / UI / user guides	11	[12], [15], [19], [40], [41], [68], [76], [81], [96], [97], [99]

Future work in DGB focuses on further investigation based on study findings and limitations, pointing out emerging trends, research gaps, and potential exploration areas. Table 10 highlights various suggestions for DGB research. The most common ones involve improving current DGB systems or combining them with other methods. Some noted shortcomings in handling over-skilled players [91], identifying repetitive gameplay [47], or making difficulty adjustments smoother [68]. Others proposed integrating their systems with existing algorithms [55], optimizing processes [54], and incorporating real-time feedback mechanisms [84].

Some studies, especially those with limited playtesting data, suggested testing their DGB systems on more participants, expanding demographics [20], and increasing dataset sizes [37]. This would validate effectiveness, uncover issues, and enhance generalizability across different populations. There were also suggestions to apply DGB models to other game genres [46] and mechanics [51], which could reveal unique challenges and broaden the understanding of DGB's potential.

Regarding player performance metrics and difficulty adjustment mechanisms, researchers see potential in exploring more ways to measure a player's skill or state and adjusting difficulty. This could include adding input devices like heart rate monitors [87] or increasing game features, thereby introducing more variables for the DGB system to manage [13].

Numerous studies emphasized the need for better or continued data analysis. For example, some studies suggested monitoring physical performance further [76], or expanding evaluation metrics [100], highlighting the importance of robust measurement techniques. Lastly, several experiments noted that beta testers would have appreciated more comprehensive tutorials, guides, or an intuitive user interface to reduce confusion during experimentation [96].

4. CONLUSION AND FUTURE WORK

This literature review provides a concise guide for game developers interested in integrating DGB systems, highlighting key strategies for designing adaptive games. From 91 research articles, it's evident that recent DGB innovations span various genres, objectives, and technologies. Several key takeaways can be drawn from this review.

Unity is the dominant game engine for DGB development. Entertainment-focused and serious games are evenly represented, offering benefits in both enjoyment and gamification. Fast-paced genres excel due to the abundance of variables to measure and adjust difficulty, while mental training games, especially in education, also show promise. It's advantageous to use input devices that measure player skill or state, such as physiological and movement data.

mario007@binus.ac.id, audrey.levina@binus.ac.id, yulyaniarifin@binus.ac.id

Various techniques and algorithms have been tested for DGB systems. Recommender systems, PCG for dynamic content generation, and emotion recognition for difficulty adjustment are common. Skill assessment systems like Glicko-2 enhance player engagement, while MCTS aids in complex decision-making. Machine learning techniques, including SVM, GA, Neural Networks, and MLP, are useful for estimating gameplay difficulty, improving AI, emotion recognition, skill prediction, and content generation. Each technique has its specific application in DGB systems.

For scientific research, it's crucial to determine how gameplay data is obtained to measure the DGB system's impact. While human volunteers are standard, AI player simulations can be used when volunteer numbers are low. Researchers should use varied evaluation metrics to assess player satisfaction, DGB performance, or player improvement. Developers can build on existing DGB systems, explore different genres, or incorporate additional skill measurements while ensuring clear communication with game testers. A limitation of this review is the subjective classification of game or DGB properties. Future work should aim for a more objective classification approach for analyzing DGB systems in games.

REFERENCES

[1] D. Arsenault, "Video Game Genre, Evolution and Innovation," Eludamos. Journal for Computer Game Culture, vol. 3, no. 2, pp. 149–176, Oct. 2009,

[2] A. Becker and D. Görlich, "What is Game Balancing? - An Examination of Concepts," ParadigmPlus, vol. 1, no. 1, pp. 22–41, Apr. 2020,

[3] R. Koster, A Theory of Fun for Game Design. "O'Reilly Media, Inc.," 2004.

[4] Z. Yang and B. Sun, "Hyper-Casual Endless Game Based Dynamic Difficulty Adjustment System For Players Replay Ability," in IEEE Intl Conf on Parallel & Distributed Processing with Applications, Big Data & Cloud Computing, Sustainable Computing & Communications, Social Computing & Networking (ISPA/BDCloud/SocialCom/SustainCom), IEEE, Dec. 2020, pp. 860–866.

[5] H. C. Jeon et al., "RaidEnv: Exploring New Challenges in Automated Content Balancing for Boss Raid Games," IEEE Trans Games, pp. 1–14, 2023,

[6] M. Csikszentmihalyi, "Flow: The Psychology of Optimal Experience Flow-The Psychology of optimal experience," Jan. 1990,

[7] S. Reis, L. P. Reis, and N. Lau, "Player Engagement Enhancement with Video Games," in Advances in Intelligent Systems and Computing, Springer Verlag, 2019, pp. 263–272.

[8] R. Fahrur, R. Yusep, and D. Budiman, "A Systematic Literature Review on Adaptive Gamification: Components, Methods, and Frameworks," in International Conference on Electrical Engineering and Informatics (ICEEI), IEEE, 2019, pp. 9–10.

[9] P. D. Paraschos and D. E. Koulouriotis, "Game Difficulty Adaptation and Experience Personalization: A Literature Review," Int J Hum Comput Interact, vol. 39, no. 1, pp. 1–22, 2023,

[10] F. Mortazavi, H. Moradi, and A. H. Vahabie, "Dynamic difficulty adjustment approaches in video games: a systematic literature review," Multimed Tools Appl, 2024,

[11] M. J. Page et al., "The PRISMA 2020 statement: An updated guideline for reporting systematic reviews," International Journal of Surgery, vol. 88, Apr. 2021,

[12] C. El-Habr, X. Garcia, P. Paliyawan, and R. Thawonmas, "Runner: A 2D platform game for physical health promotion," SoftwareX, vol. 10, Jul. 2019,

[13] M. Taufik Akbar, M. Nasrul Ilmi, I. V. Rumayar, J. Moniaga, T. K. Chen, and A. Chowanda, "Enhancing game experience with facial expression recognition as dynamic balancing," in Procedia Computer Science, Elsevier B.V., 2019, pp. 388–395.

[14] A. Denisova and P. Cairns, "Player experience and deceptive expectations of difficulty adaptation in digital games," Entertain Comput, vol. 29, pp. 56–68, Mar. 2019,

[15] M. Pezzera, A. Tironi, J. Essenziale, N. R. Mainetti, and A. Borghese, "Approaches for increasing patient's engagement and motivation in exer-games-based autonomous telerehabilitation," in IEEE 7th International Conference on Serious Games and Applications for Health (SeGAH), 2019.

[16] J. Catarino and C. Martinho, "Procedural Progression Model for Smash Time," in IEEE Conference on Games (CoG), 2019.

[17] M. Hendrix, T. Bellamy-Wood, S. McKay, V. Bloom, and I. Dunwell, "Implementing adaptive game difficulty balancing in serious games," IEEE Trans Games, vol. 11, no. 4, pp. 320–327, Dec. 2019,

[18] S. Brambilla, G. Boccignone, A. N. Borghese, D. Croci, and L. A. Ripamonti, "Tuning Stressful Experience in Virtual Reality Games," in ACM International Conference Proceeding Series, Association for Computing Machinery, Sep. 2023.

[19] T. Bjørner, "Using EEG data as Dynamic Difficulty Adjustment in a serious game about the plastic pollution in the oceans," in ACM International Conference Proceeding Series, Association for Computing Machinery, Sep. 2023, pp. 6–15.

[20] A. J. A. Seyderhelm and K. L. Blackmore, "How Hard Is It Really? Assessing Game-Task Difficulty Through Real-Time Measures of Performance and Cognitive Load," Simul Gaming, vol. 54, no. 3, pp. 294–321, Jun. 2023,

[21] O. I. Caldas, M. Mauledoux, O. F. Aviles, and C. Rodriguez-Guerrero, "Behavioral and Psychophysiological Measures of Engagement During Dynamic Difficulty Adjustment in Immersive Virtual Reality," Journal of Universal Computer Science, vol. 29, no. 1, pp. 16–33, 2023,

[22] S. Arnab, P. Petridis, L. Karavidas, H. Apostolidis, and T. Tsiatsos, "Usability Evaluation of an Adaptive Serious Game Prototype Based on Affective Feedback," Information (Switzerland), vol. 13, no. 9, 2022,

[23] S. Palma, L. A. Ripamonti, N. A. Borghese, D. Maggiorini, and D. Gadia, "Player behaviour metrics for adjusting content in VR games: The case of fear," in ACM International Conference

Proceeding Series, Association for Computing Machinery, Jul. 2021.

[24] P. Ramasamy, S. Das, and Y. Kurita, “Ski for squat: A squat exergame with pneumatic gel muscle-based dynamic difficulty adjustment,” in Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), Springer Science and Business Media Deutschland GmbH, 2021, pp. 449–467.

[25] Andrew, A. N. Tjokrosetio, and A. Chowanda, “Dynamic difficulty adjustment with facial expression recognition for improving player satisfaction in a survival horror game,” ICIC Express Letters, vol. 14, no. 11, pp. 1097–1104, Nov. 2020,

[26] S. Nebel, M. Beege, S. Schneider, and G. D. Rey, “Competitive Agents and Adaptive Difficulty Within Educational Video Games,” Front Educ (Lausanne), vol. 5, Jul. 2020,

[27] A. Sarkar and S. Cooper, “Evaluating and Comparing Skill Chains and Rating Systems for Dynamic Difficulty Adjustment,” in Proceedings of the 16th AAAI Conference on Artificial Intelligence and Interactive Digital Entertainment, AIIDE 2020, AIIDE-20, 2020, pp. 273–279.

[28] S. A. Kamkuimo K, B. Girard, and B. A. J. Menelas, “Dynamic Difficulty Adjustment Through Real-Time Physiological Feedback for a More Adapted Virtual Reality Exposure Therapy,” in Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), Springer Science and Business Media Deutschland GmbH, 2020, pp. 102–111.

[29] L. Cardia da Cruz, C. A. Sierra-Franco, G. F. M. Silva-Calpa, and A. Barbosa Raposo, “A self-adaptive serious game for eye-hand coordination training,” in Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), Springer, 2020, pp. 385–397.

[30] D. Halbhuber et al., “The mood game - How to use the player’s affective state in a shoot’em up avoiding frustration and boredom,” in ACM International Conference Proceeding Series, Association for Computing Machinery, Sep. 2019, pp. 867–870.

[31] D. Bian, J. Wade, A. Swanson, A. Weitlauf, Z. Warren, and N. Sarkar, “Design of a physiology-based adaptive virtual reality driving platform for individuals with ASD,” ACM Trans Access Comput, vol. 12, no. 1, Feb. 2019,

[32] M. Stephenson and J. Renz, “Agent-Based Adaptive Level Generation for Dynamic Difficulty Adjustment in Angry Birds,” ArXiv, Feb. 2019,

[33] L. A. Ripamonti, F. Distefano, M. Trubian, D. Maggiorini, and D. Gadia, “DRAGON: diversity regulated adaptive generator online,” Multimed Tools Appl, vol. 80, no. 26–27, pp. 34933–34969, Nov. 2021,

[34] Y. A. Sekhavat, M. J. Sisi, and S. Roohi, “Affective interaction: Using emotions as a user interface in games,” Multimed Tools Appl, vol. 80, no. 4, pp. 5225–5253, Feb. 2021,

[35] P. Migkotzidis et al., “Enhanced Virtual Learning Spaces Using Applied Gaming,” in Advances in Intelligent Systems and Computing, Springer Verlag, 2020, pp. 710–721.

[36] Z. Amiri and Y. A. Sekhavat, “Intelligent Adjustment of Game Properties at Run Time Using Multi-armed Bandits,” The Computer Games Journal, vol. 8, no. 3–4, pp. 143–156, Dec. 2019,

[37] R. Tadayon, A. Vega Ramirez, S. Das, Y. Kishishita, M. Yamamoto, and Y. Kurita, “Automatic Exercise Assistance for the Elderly Using Real-Time Adaptation to Performance and Affect,” in Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), Springer Verlag, 2019, pp. 556–574.

[38] J. Knorr and C. Vaz De Carvalho, “Using Dynamic Difficulty Adjustment to Improve the Experience and Train FPS Gamers,” in ACM International Conference Proceeding Series, Association for Computing Machinery, Oct. 2021, pp. 195–200.

[39] E. Pagalyte, M. Mancini, and L. Climent, “Go with the Flow: Reinforcement Learning in Turn-based Battle Video Games,” in Proceedings of the 20th ACM International Conference on Intelligent Virtual Agents, IVA 2020, Association for Computing Machinery, Inc, Oct. 2020.

[40] R. Godfrey, M. Rimmer, C. Headleand, and C. Fox, “RhythmTrain: making rhythmic sight reading training fun,” in Proceedings of the ICMC, July 3rd - 9th, 2022, University of Limerick, Ireland, 2022, pp. 102–105.

[41] C. S. Zhunio, P. C. Orellana, and A. V. Patino, “A Memory Game for Elderly People: Development and Evaluation,” in 7th International Conference on eDemocracy and eGovernment, ICEDEG 2020, Institute of Electrical and Electronics Engineers Inc., Apr. 2020, pp. 248–252.

[42] M. Weber and P. Notargiacomo, “Dynamic difficulty adjustment in digital games using genetic algorithms,” in Brazilian Symposium on Games and Digital Entertainment, SBGAMES, IEEE Computer Society, Nov. 2020, pp. 62–70.

[43] M. D. B. S. Supriyadi, S. M. S. Nugroho, and Hariadi Mochamad, “Fuzzy Coordinator based AI for Dynamic Difficulty Adjustment in Starcraft 2,” in International Conference of Artificial Intelligence and Information Technology (ICAIIT), 2019.

[44] P. M. Blom, S. Bakkes, and P. Spronck, “Modeling and adjusting in-game difficulty based on facial expression analysis,” Entertain Comput, vol. 31, Aug. 2019,

[45] A. Fortin-Côté et al., “FUNii: The Physio-Behavioural Adaptive Video Game,” in Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), Springer Verlag, 2019, pp. 14–28.

[46] K. Fujita, “AlphaDDA: strategies for adjusting the playing strength of a fully trained AlphaZero system to a suitable human training partner,” PeerJ Comput Sci, vol. 8, 2022,

[47] S. P. Sithungu and E. M. Ehlers, “Adaptive Game AI-Based Dynamic Difficulty Scaling via the Symbiotic Game Agent,” in IFIP Advances in Information and Communication Technology, Springer, 2020, pp. 107–117.

[48] A. Barczak and H. Woźniak, “Comparative Study on Game Engines,” Studia Informatica, no. 23, pp. 5–24, Dec. 2020,

[49] Z. Zeng and P. Sweetser, “Dynamic Difficulty Adjustment in a Multiplayer Minecraft Server,” in ACM International Conference Proceeding Series, Association for Computing Machinery, Nov. 2022, pp. 319–324.

mario007@binus.ac.id, audrey.levina@binus.ac.id, yulyaniarifin@binus.ac.id

[50] J. L. Plass, B. D. Homer, S. Pawar, C. Brenner, and A. P. MacNamara, "The effect of adaptive difficulty adjustment on the effectiveness of a game to develop executive function skills for learners of different ages," Cogn Dev, vol. 49, pp. 56–67, Jan. 2019,

[51] M. Zamith, J. R. da Silva, M. Joselli, and E. W. G. Clua, "Applying hidden Markov model for dynamic game balancing," in Brazilian Symposium on Games and Digital Entertainment, SBGAMES, IEEE Computer Society, Nov. 2020, pp. 38–46.

[52] M. Gonzalez-Duque, R. B. Palm, D. Ha, and S. Risi, "Finding Game Levels with the Right Difficulty in a Few Trials through Intelligent Trial-and-Error," in IEEE Conference on Computatonal Intelligence and Games, CIG, IEEE Computer Society, Aug. 2020, pp. 503–510.

[53] T. Kusano, Y. Liu, P. Paliyawan, R. Thawonmas, and T. Harada, "Motion Gaming AI using Time Series Forecasting and Dynamic Difficulty Adjustment," in IEEE Conference on Games (CoG), 2019.

[54] E. A. Romero-Mendez, P. C. Santana-Mancilla, M. Garcia-Ruiz, O. A. Montesinos-López, and L. E. Anido-Rifón, "The Use of Deep Learning to Improve Player Engagement in a Video Game through a Dynamic Difficulty Adjustment Based on Skills Classification," Applied Sciences (Switzerland), vol. 13, no. 14, Jul. 2023,

[55] S. P. Sithungu and E. M. Ehlers, "A Gene Expression Programming Inspired Evolution Symbiont Agent for Real-Time Strategy Generation," in ACM International Conference Proceeding Series, Association for Computing Machinery, Nov. 2022, pp. 47–53.

[56] S. Reis, L. P. Reis, and N. Lau, "Game Adaptation by Using Reinforcement Learning Over Meta Games," Group Decis Negot, vol. 30, no. 2, pp. 321–340, Apr. 2021,

[57] C. Strauch, M. Barthelmaes, E. Altgassen, and A. Huckauf, "Pupil Dilation Fulfills the Requirements for Dynamic Difficulty Adjustment in Gaming on the Example of Pong," in Eye Tracking Research and Applications Symposium (ETRA), Association for Computing Machinery, Jun. 2020.

[58] J. Pfau, J. D. Smeddinck, and R. Malaka, "Enemy Within: Long-term Motivation Effects of Deep Player Behavior Models for Dynamic Difficulty Adjustment," in Conference on Human Factors in Computing Systems - Proceedings, Association for Computing Machinery, Apr. 2020.

[59] G. Chanel and P. Lopes, "User Evaluation of Affective Dynamic Difficulty Adjustment Based on Physiological Deep Learning," in Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), Springer, 2020, pp. 3–23.

[60] A. Sarkar and S. Cooper, "Using a disjoint skill model for game and task difficulty in human computation games," in CHI PLAY 2019 - Extended Abstracts of the Annual Symposium on Computer-Human Interaction in Play, Association for Computing Machinery, Inc, Oct. 2019, pp. 661–669.

[61] A. Sarkar and S. Cooper, "Using rating arrays to estimate score distributions for player-versus-level matchmaking," in ACM International Conference Proceeding Series, Association for Computing Machinery, Aug. 2019.

[62] S. Demediuk, M. Tamassia, X. Li, and W. L. Raffe, "Challenging AI: Evaluating the Effect of MCTS-Driven Dynamic Difficulty Adjustment on Player Enjoyment," in ACM International Conference Proceeding Series, Association for Computing Machinery, Jan. 2019.

[63] W. Rao Fernandes and G. Levieux, "δ-logit: Dynamic Difficulty Adjustment Using Few Data Points," in Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), Springer, 2019, pp. 158–171.

[64] J. Suaza, E. Gamboa, and M. Trujillo, "A Health Point-Based Dynamic Difficulty Adjustment Strategy for Video Games," in Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), Springer, 2019, pp. 436–440.

[65] D. S. Lora Ariza, A. A. Sánchez-Ruiz, and P. A. González-Calero, "Towards Finding Flow in Tetris," in Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), Springer Verlag, 2019, pp. 266–280.

[66] Y. Zhang and W. B. Goh, "Personalized task difficulty adaptation based on reinforcement learning," User Model User-adapt Interact, vol. 31, no. 4, pp. 753–784, Sep. 2021,

[67] M. Szwoch and W. Szwoch, "Using Different Information Channels for Affect-Aware Video Games - A Case Study," in Image Processing and Communications Challenges 10, 2019, pp. 104–113.

[68] N. N. Blackburn, M. Gardone, and D. S. Brown, "Player-Centric Procedural Content Generation: Enhancing Runtime Customization by Integrating Real-Time Player Feedback," in CHI PLAY 2023 - Companion Proceedings of the Annual Symposium on Computer-Human Interaction in Play, Association for Computing Machinery, Inc, Oct. 2023, pp. 10–16.

[69] G. Cui et al., "Reinforced Evolutionary Algorithms for Game Difficulty Control," in ACM International Conference Proceeding Series, Association for Computing Machinery, Dec. 2020, pp. 1–7.

[70] M. Lankes and A. Stöeckl, "Gazing at pac-man: Lessons learned from a eye-tracking study focusing on game difficulty," in Eye Tracking Research and Applications Symposium (ETRA), Association for Computing Machinery, Feb. 2020, pp. 1–5.

[71] J. Frommel, D. Puschmann, K. Rogers, and M. Weber, "Take back control: Effects of player influence on procedural level generation," in CHI PLAY 2019 - Extended Abstracts of the Annual Symposium on Computer-Human Interaction in Play, Association for Computing Machinery, Inc, Oct. 2019, pp. 371–378.

[72] K. Spiel, S. Bertel, and F. Kayali, "Adapting gameplay to eye movements – An exploration with Tetris," in CHI PLAY 2019 - Extended Abstracts of the Annual Symposium on Computer-Human Interaction in Play, Association for Computing Machinery, Inc, Oct. 2019, pp. 687–695.

[73] A. Sarkar and S. Cooper, "Transforming Game Difficulty Curves using Function Composition," in Conference on Human Factors in Computing Systems - Proceedings, Association for Computing Machinery, May 2019, pp. 1–7.

[74] M. Arevalillo-Herráez, S. Katsigiannis, F. Alqahtani, and P. Arnau-González, "Fusing ECG signals and IRT models for task difficulty prediction in computerised educational systems," Knowl Based Syst, vol. 14, pp. 3–23, Nov. 2023,

[75] L. F. Maia, W. Viana, and F. Trinta, "Transposition of Location-based Games: Using Procedural Content Generation to deploy balanced game maps to multiple locations," Pervasive Mob Comput, vol. 70, Jan. 2021,

[76] T. Alves, H. Carvalho, and D. Simões Lopes, "Winning compensations: Adaptable gaming approach for upper limb rehabilitation sessions based on compensatory movements," J Biomed Inform, vol. 108, Aug. 2020,

[77] S. S. Morimoto et al., "Targeting Cognitive Control Deficits With Neuroplasticity-Based Computerized Cognitive Remediation in Patients With Geriatric Major Depression: A Randomized, Double-Blind, Controlled Trial," American Journal of Geriatric Psychiatry, vol. 28, no. 9, pp. 971–980, Sep. 2020,

[78] C. Lara-Alvarez, H. Mitre-Hernandez, J. J. Flores, and H. Perez-Espinosa, "Induction of Emotional States in Educational Video Games through a Fuzzy Control System," IEEE Trans Affect Comput, vol. 12, no. 1, pp. 66–77, Jan. 2021,

[79] Pezzeram Manuel, A. Tironi, J. Essenziale, R. Mainetti, and Alberto. N. Borghese, "Dynamic difficulty adjustment in exer-games for rehabilitation: a mixed approach," in 2020 IEEE 8th International Conference on Serious Games and Applications for Health (SeGAH), 2020.

[80] W. C. Ung, F. Meriaudeau, M. Kiguchi, and T. B. Tang, "Functional near-infrared spectroscopy adaptive cognitive training system (FACTS) for cognitive underload and overload prevention: A feasibility study," IEEE Access, vol. 8, pp. 172939–172950, 2020,

[81] B. S. Avi Shena, B. Sitohang, and S. A. Rukmono, "Application of Dynamic Difficulty Adjustment on Evidence-centered Design Framework for Game Based Learning," in Proceedings of 2019 International Conference on Data and Software Engineering, ICoDSE 2019, Institute of Electrical and Electronics Engineers Inc., Nov. 2019.

[82] K. Chrysafiadi, M. Kamitsios, and M. Virvou, "Fuzzy-based dynamic difficulty adjustment of an educational 3D-game," Multimed Tools Appl, vol. 82, no. 18, pp. 27525–27549, Jul. 2023,

[83] F. Nugroho, P. Miladin, N. Safitri, A. Basid, F. Sahrul Bahtiar, and I. G. P. Asto Buditjahjanto, "Dynamic Difficulty Adjustment of Serious-Game Based on Synthetic Fog using Activity Theory Model," IJACSA) International Journal of Advanced Computer Science and Applications, vol. 14, no. 6, pp. 564–573, 2023,

[84] A. D. Stoneman, J. A. Miller, and S. Cooper, "Effects of Player-Level Matchmaking Methods in a Live Citizen Science Game," in Proceedings - AAAI Artificial Intelligence and Interactive Digital Entertainment Conference, AIIDE, 2022, pp. 199–206.

[85] S. Martins and S. Cavaco, "Customizable Serious Speech Therapy Games with Dynamic Difficulty Adjustment for Children with Sigmatism," in Studies in Health Technology and Informatics, IOS Press BV, Jun. 2022, pp. 924–928.

[86] K. Kamikokuryo, T. Haga, G. Venture, and V. Hernandez, "Adversarial Autoencoder and Multi-Armed Bandit for Dynamic Difficulty Adjustment in Immersive Virtual Reality for Rehabilitation: Application to Hand Movement," Sensors, vol. 22, no. 12, Jun. 2022,

[87] S. Philezwini Sithungu and E. Marie Ehlers, "A Reinforcement Learning-Based Classification Symbiont Agent for Dynamic Difficulty Balancing," in ACM International Conference Proceeding Series, Association for Computing Machinery, Nov. 2020, pp. 15–23.

[88] D. Thornton and F. Turley, "Analysis of player behavior and EEG readings in a cybersecurity game," in ACMSE 2020 - Proceedings of the 2020 ACM Southeast Conference, Association for Computing Machinery, Inc, Apr. 2020, pp. 149–153.

[89] V. Araujo, D. Mendez, and A. Gonzalez, "A Novel approach to working memory training based on robotics and AI," Information (Switzerland), vol. 10, no. 11, Nov. 2019,

[90] A. A. Supianto, M. Hafis, and H. Tolle, "Significance of dynamic difficulty adjustment in delivering instructional scaffolding on educational game for high school chemistry subject," in ACM International Conference Proceeding Series, Association for Computing Machinery, Jul. 2019, pp. 384–388.

[91] T. Constant and G. Levieux, "Dynamic difficulty adjustment impact on players' confidence," in Conference on Human Factors in Computing Systems - Proceedings, Association for Computing Machinery, May 2019.

[92] M. Ninaus, K. Tsarava, and K. Moeller, "A pilot study on the feasibility of dynamic difficulty adjustment in game-based learning using heart-rate," in Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), Springer, 2019, pp. 117–128.

[93] F. Ozkul, Y. Palaska, E. Masazade, and D. Erol-Barkana, "Exploring dynamic difficulty adjustment mechanism for rehabilitation tasks using physiological measures and subjective ratings," IET Signal Processing, vol. 13, no. 3, pp. 378–386, 2019,

[94] V. Araujo, A. Gonzalez, and D. Mendez, "Dynamic difficulty adjustment for a memory game," in Communications in Computer and Information Science, Springer Verlag, 2019, pp. 605–616.

[95] M. Rahimi, H. Moradi, A. Vahabie, and H. Kebriaei, "Continuous Reinforcement Learning-based Dynamic Difficulty Adjustment in a Visual Working Memory Game," ArXiv, Aug. 2023,

[96] P. J. Reber, E. Grandoit, K. D. Schmidt, T. C. Dixon, and C. P. McRobert, "Learning the Cognitive Skill of Topographic Map Reading Through Adaptive, High-Repetition Training," in Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), Springer Science and Business Media Deutschland GmbH, 2021, pp. 88–104.

[97] S. Lyu and R. Bidarra, "Procedural generation of challenges for personalized gait rehabilitation," in ACM International Conference Proceeding Series, Association for Computing Machinery, Apr. 2023, pp. 1–11.

[98] P. Lopes, F. Luz, A. Liapis, and H. Engström, "Physiological-Based Difficulty Assessment for Virtual Reality Rehabilitation Games," in ACM International Conference Proceeding Series, Association for Computing Machinery, Apr. 2023, pp. 1–4.

[99] C. Jemmali, M. S. El-Nasr, and S. Cooper, "The Effects of Adaptive Procedural Levels on Engagement and Performance in an Educational Programming Game," in ACM International

mario007@binus.ac.id, audrey.levina@binus.ac.id, yulyaniarifin@binus.ac.id

Conference Proceeding Series, Association for Computing Machinery, Sep. 2022, pp. 1–12.

[100] L. Reidy, D. Chan, C. Nduka, and H. Gunes, “Facial Electromyography-based Adaptive Virtual Reality Gaming for Cognitive Training,” in ICMI 2020 - Proceedings of the 2020 International Conference on Multimodal Interaction, Association for Computing Machinery, Inc, Oct. 2020, pp. 174–183.

[101] N. Tangsiripaiboon, L. Ramingwong, and S. Ramingwong, “The Analysis of Mouse Tracking Data in a Game for Detection of Dyslexia Risk: A Pilot Study,” in ACM International Conference Proceeding Series, Association for Computing Machinery, Aug. 2021, pp. 91–97.

Mario Mario is a Computer Science master’s student at Bina Nusantara University. His interest is in the field of human-computer interaction and game design.

Audrey Levina is a Computer Science master’s student at Bina Nusantara University. She has experience in game development and is pursuing a career in that field.

Yulyani Arifin completed her Bachelor's degree in Information Management at Bina Nusantara University in 1998, followed by a Master's in Managerial Management - Information Systems in 2006, and a Doctorate in Computer Science in 2021, all from the same institution. She began teaching at Bina Nusantara University's School of Computer Science (SOCS) in 1998. The subjects she teaches include Algorithm and Programming, Software Engineering, Multimedia Systems, Human-Computer Interaction, User Experience, Data Structures, and Program Design Methods. Her research focuses on Multimedia Applications, Gamification, Game Applications, Virtual Reality, Augmented Reality, Human-Computer Interaction, and Natural Language Processing.