Balancing Challenge and Enjoyment: An Experimental Study of Dynamic Difficulty Adjustment in Tower Defense Games

A Special Project Presented to the
Faculty of the Department of Computer Science,
College of Science,
University of the Philippines Cebu

In Partial Fulfillment
Of the Requirements for the Degree
Bachelor of Science in Computer Science

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CHAPTER 1: INTRODUCTION

1.1 Background of the Study

Digital games have evolved into highly interactive systems that combine entertainment, challenge, and psychological engagement. Among various game genres, tower defense games stand out due to their strategic nature, requiring players to make continuous decisions related to resource management, spatial planning, and threat prioritization. These games are heavily dependent on difficulty design, as player enjoyment is closely tied to how well game challenges align with the player's skill level. If the game is too easy, players may experience boredom; if it is too difficult, players may experience frustration and disengagement.

One of the central challenges in game design is creating a balanced difficulty curve that maintains player engagement over time. Traditionally, many games rely on static difficulty settings, such as easy, medium, or hard modes, which assume a uniform player skill level. However, research has shown that player skills differ widely and evolve during gameplay, making static difficulty settings insufficient for sustaining enjoyment (Bostan & Öğüt, 2009; Aponte et al., 2011). Static difficulty fails to respond to changes in player performance, learning speed, and strategic mastery, often resulting in a mismatch between challenge and skill.

To address this issue, researchers and designers have increasingly turned to Dynamic Difficulty Adjustment (DDA). DDA refers to systems that automatically adapt game difficulty in real time based on player performance, behavior, or inferred skill level. Studies suggest that well-designed DDA systems can maintain players within an optimal challenge–skill balance, often described through Flow Theory, thereby enhancing enjoyment, engagement, and persistence (Sepulveda et al., 2019; Hunicke, 2005; Sharek & Wiebe, 2011).

Flow Theory posits that optimal enjoyment occurs when challenge and skill are balanced, avoiding states of boredom and frustration (Sharek & Wiebe, 2011). In the context of tower defense games, DDA can be implemented by adjusting variables such as enemy spawn rate, health, resource availability, or wave complexity in response to player performance. When applied correctly, DDA allows players to feel competent and challenged without feeling overwhelmed or under-stimulated.

Despite growing research on DDA, there remains a need to empirically examine its impact on player enjoyment, particularly in strategy-based genres like tower defense games. Furthermore, enjoyment must be measured using validated instruments rather than anecdotal or purely behavioral indicators. Questionnaires such as the Player Experience of Need Satisfaction (PENS) and the Game Experience Questionnaire (GEQ) have been widely used and empirically validated to assess enjoyment-related constructs such as competence, autonomy, flow, challenge, and frustration (Ryan et al., 2006; Johnson et al., 2018).

This study therefore focuses on examining the impact of Dynamic Difficulty Adjustment on player enjoyment in tower defense games, grounded in established theories of flow and motivation, and measured using validated player experience instruments.

1.2 Research Objectives

The primary objective of this study is to investigate how Dynamic Difficulty Adjustment affects player enjoyment in tower defense games.

Specifically, this study aims to:

1. Examine the relationship between dynamic difficulty adjustment and player enjoyment in tower defense gameplay.
2. Analyze how DDA influences key enjoyment-related constructs such as flow, competence, challenge, frustration, and immersion.
3. Compare player experiences between static difficulty settings and dynamically adjusted difficulty systems.
4. Apply Flow Theory as a theoretical framework to explain the effects of difficulty adaptation on enjoyment.
5. Utilize validated player experience questionnaires (PENS and GEQ) to measure enjoyment and related psychological outcomes.

1.3 Significance of the Study

This study is significant to multiple stakeholders within the field of game studies and game development.

For game designers and developers, the findings provide empirical evidence on how DDA can be used to improve player enjoyment in tower defense games. Understanding how difficulty adaptation affects flow, competence, and frustration can guide more effective game balancing strategies.

For researchers in game studies, this study contributes to the growing body of literature on DDA by focusing on a strategy-based genre, which has been less explored compared to action or shooter games (Hunicke, 2005; Pfau et al., 2019). It also strengthens the methodological foundation of DDA research by combining theoretical models with validated measurement tools.

For players, improved understanding of DDA can lead to better-designed games that are more engaging, enjoyable, and accessible to players with different skill levels.

For educational and applied game research, the study demonstrates how adaptive systems can be evaluated using established psychological theories and metrics, potentially informing the design of serious games and training simulations.

1.4 Scope and Limitations

This study focuses specifically on tower defense games and may not fully generalize to other genres such as first-person shooters, role-playing games, or casual games. The investigation centers on single-player gameplay, excluding multiplayer or cooperative dynamics, which may introduce additional factors such as social presence and competition (Gajadhar et al., 2010).

The measurement of enjoyment relies primarily on self-report questionnaires, namely the PENS and GEQ. While these instruments are validated, self-reported data may still be subject to individual interpretation and response bias (Johnson et al., 2018).

Additionally, the implementation of DDA examined in this study is limited to specific difficulty parameters. Other forms of adaptation, such as narrative-based or AI-driven opponent behavior, are beyond the scope of this research.

CHAPTER 2: REVIEW OF RELATED LITERATURE

2.1 Flow Theory

Flow Theory, introduced by Csikszentmihalyi, describes a psychological state of optimal experience characterized by deep focus, enjoyment, and intrinsic motivation. Flow occurs when an individual's skill level is well matched with the challenge of a task, resulting in high engagement and satisfaction. When challenges exceed skills, frustration occurs; when skills exceed challenges, boredom emerges (Sharek & Wiebe, 2011).

In video games, flow has been widely recognized as a core determinant of enjoyment. Games naturally lend themselves to flow experiences because they provide clear goals, immediate feedback, and adjustable difficulty. Research shows that maintaining players within the flow channel significantly enhances engagement and prolongs playtime (Sepulveda et al., 2019; Sharek & Wiebe, 2011).

Flow Theory has been operationalized in game research by manipulating difficulty progression. Studies demonstrate that gradual increases in difficulty, aligned with player learning, are more effective at sustaining flow than constant low or constant high difficulty settings (Sharek & Wiebe, 2011). This theoretical framework provides a strong justification for the use of DDA systems, as they aim to dynamically preserve the balance between skill and challenge.

In tower defense games, flow is particularly relevant because players must continuously adapt strategies as enemy waves evolve. Poorly balanced difficulty disrupts flow, either by removing meaningful challenge or by overwhelming the player's decision-making capacity.

2.2 Problems of Static Difficulty

Static difficulty systems assume that players have similar skill levels and learning rates, an assumption that research consistently contradicts. Players differ widely in experience, cognitive abilities, strategic thinking, and reaction times. Static difficulty settings often fail to accommodate these differences, leading to reduced enjoyment and early player disengagement (Bostan & Öğüt, 2009; Aponte et al., 2011).

One major limitation of static difficulty is its inability to respond to skill progression. As players learn and improve, fixed difficulty settings become increasingly misaligned with player capability. This results in boredom for skilled players and frustration for less experienced players.

Furthermore, static difficulty relies heavily on playtesting and designer intuition, which can be time-consuming and subjective. Designers may struggle to accurately estimate how changes in low-level parameters affect overall difficulty, particularly in complex systems like strategy games (Aponte et al., 2011).

These limitations highlight the need for adaptive systems that can dynamically assess player performance and respond accordingly.

2.3 Dynamic Difficulty Adjustment

Dynamic Difficulty Adjustment (DDA) refers to game systems that modify difficulty in real time based on player performance, behavior, or inferred skill level. Unlike static difficulty, DDA acknowledges that player skill is dynamic rather than fixed, and that enjoyment depends on continuously maintaining an appropriate challenge level (Sepulveda et al., 2019).

Research shows that DDA can be implemented using various approaches, including heuristic rules, probabilistic models, machine learning techniques, and reinforcement learning (Sulyma, 2025; Pfau et al., 2019). These systems monitor variables such as success rates, reaction times, resource efficiency, and error frequency to infer player skill and adjust difficulty accordingly.

One major advantage of DDA is its ability to maintain players within the flow channel. By preventing prolonged frustration or boredom, DDA enhances perceived competence and sustains engagement (Sepulveda et al., 2019; Sharek & Wiebe, 2011). Empirical studies demonstrate that players exposed to adaptive difficulty experience fewer deaths, longer play sessions, and higher enjoyment compared to those playing under static difficulty conditions (Hunicke, 2005; Sulyma, 2025).

Another important consideration is player perception. Earlier concerns suggested that players might feel “cheated” by adaptive systems. However, research indicates that when DDA is implemented subtly, players often remain unaware of the adjustments, preserving their sense of autonomy and agency (Hunicke, 2005). This concept of “change blindness” is critical in ensuring that DDA enhances enjoyment without undermining player trust.

In strategy and tower defense games, DDA can be applied by adjusting enemy attributes, wave pacing, resource generation, or AI behavior. Such adjustments allow the game to remain challenging while respecting player learning curves. Advanced models, such as deep player behavior models, further demonstrate how adaptive opponents can increase interest and perceived competence without inducing frustration (Pfau et al., 2019).

Overall, the literature strongly supports DDA as an effective mechanism for improving enjoyment, engagement, and retention when grounded in flow theory and implemented with careful consideration of player experience.

2.4 PENS and GEQ Questionnaires

Accurate measurement of player enjoyment is essential for evaluating the effectiveness of DDA systems. Two of the most widely used instruments are the Player Experience of Need Satisfaction (PENS) and the Game Experience Questionnaire (GEQ).

The PENS is grounded in Self-Determination Theory, measuring core psychological needs such as competence, autonomy, and relatedness, as well as presence and intuitive controls (Ryan et al., 2006; Johnson et al., 2018). Research consistently shows that satisfaction of these needs predicts enjoyment, motivation, and continued engagement.

The GEQ provides a broader assessment of player experience, measuring constructs such as flow, immersion, challenge, positive affect, and frustration. Validation studies indicate that while some GEQ factors overlap, the instrument remains useful when applied carefully and interpreted appropriately (Johnson et al., 2018).

Both instruments have been widely validated and used across multiple game genres and contexts, making them suitable for evaluating enjoyment outcomes in DDA research. Their combined use allows for a comprehensive assessment of both motivational and experiential aspects of gameplay.

CHAPTER 3. METHODOLOGY

3.1 Research Design

This study employs a quantitative experimental research design to investigate the impact of Dynamic Difficulty Adjustment (DDA) on player enjoyment in tower defense games. An experimental approach is appropriate because the study aims to compare player experiences under two controlled difficulty conditions, static difficulty and dynamic difficulty, while measuring enjoyment using validated instruments.

The experiment follows a within-subjects comparative design, where participants play two versions of the same tower defense game:

1. A static difficulty version, where difficulty parameters remain fixed throughout gameplay.

2. A dynamic difficulty version, where game difficulty adapts in real time based on player performance.

Using the same core game for both conditions ensures that differences in enjoyment can be attributed primarily to the difficulty system, rather than to game mechanics, aesthetics, or genre-specific features. This design is consistent with prior empirical studies examining difficulty manipulation and player experience (Sepulveda et al., 2019; Hunicke, 2005; Pfau et al., 2019).

3.2 Game Platform and Selection

3.2.1 Tower Defense Genre Selection

Tower defense games were selected as the experimental platform due to their strong reliance on difficulty progression, strategic decision-making, and repeated player adaptation. The genre is particularly well-suited for studying difficulty systems because:

- Gameplay is structured around waves of enemies with escalating challenge.
- Players continuously refine strategies through trial, failure, and optimization.
- Difficulty can be adjusted through multiple parameters without altering core mechanics.

Previous research highlights that difficulty balancing is especially critical in strategy-based and defense-oriented games, where poorly tuned difficulty can lead to frustration or disengagement (Bostan & Öğüt, 2009; Aponte et al., 2011).

3.2.2 Game Source Code Selection

An open-source tower defense game inspired by titles such as *Plants vs. Zombies* is used as the base platform. The selected source code meets the following criteria:

- Availability of full source code for modification
- Clear wave-based progression system
- Adjustable parameters for enemy behavior and resource allocation
- Compatibility with data logging and experimental instrumentation

The base game is duplicated into two versions, static and dynamic, to ensure consistency in visuals, controls, mechanics, and game flow.

3.3 Difficulty System Design

3.3.1 Static Difficulty Implementation

In the static difficulty version, all gameplay parameters are predefined and remain constant throughout the session. These parameters include:

- Enemy health values

- Enemy spawn rate
- Enemy movement speed
- Resource rewards per wave
- Tower cost and damage values

This approach reflects traditional difficulty design commonly found in tower defense games, where difficulty is tuned during development and does not adapt to individual player performance (Bostan & Öğüt, 2009; Aponte et al., 2011).

While static difficulty offers predictability and consistency, prior literature identifies several limitations:

- It assumes a uniform player skill level
- It may lead to boredom for skilled players
- It may result in frustration for less experienced players (Sepulveda et al., 2019; Bostan & Öğüt, 2009)

3.3.2 Dynamic Difficulty Adjustment (DDA) Implementation

The dynamic difficulty version integrates a performance-driven adaptive difficulty system, informed by established DDA frameworks and player modeling approaches (Sepulveda et al., 2019; Hunicke, 2005; Pfau et al., 2019).

3.3.2.1 Performance Metrics for Adaptation

Difficulty adjustments are based on real-time monitoring of player performance variables, including:

- Number of enemies successfully reaching the base
- Player health remaining at the end of each wave
- Resource efficiency (resources spent vs. damage dealt)
- Frequency of tower placement changes
- Time taken to clear waves

These metrics are consistent with performance indicators used in prior DDA research (Sepulveda et al., 2019; Aponte et al., 2011).

3.3.2.2 Adaptation Logic

At the end of each wave, the system computes a performance score that estimates whether the player is:

- Overperforming (challenge too low)

- Underperforming (challenge too high)
- Performing within an optimal range

Based on this assessment, difficulty is adjusted incrementally by:

- Increasing or decreasing enemy health
- Modifying spawn intervals
- Adjusting enemy speed
- Slightly altering resource rewards

To preserve player agency, difficulty changes are:

- Gradual rather than abrupt
- Applied between waves, not mid-wave
- Hidden from explicit player awareness

This design aligns with research emphasizing unobtrusive DDA, which maintains fairness and avoids the perception that the game is "cheating" (Hunicke, 2005; Pfau et al., 2019).

3.3.2.3 Theoretical Basis

The DDA system is grounded in:

- Flow Theory, which emphasizes challenge–skill balance (Sharek & Wiebe, 2011)
- Probabilistic definitions of difficulty, linking challenge to likelihood of failure (Aponte et al., 2011)
- Self-Determination Theory, which highlights competence preservation (Ryan et al., 2006)

3.4 Participants

Participants are recruited from a population of college students and casual gamers with basic familiarity with digital games. Inclusion criteria include:

- Age 16 years or older
- Basic experience with computer or mobile games

A minimum sample size sufficient for questionnaire-based statistical analysis is targeted, consistent with prior player experience studies (Pfau et al., 2019; Johnson et al., 2018).

3.5 Experimental Procedure

1. Participants are briefed about the study and provide informed consent.

2. Each participant plays both versions of the game in a counterbalanced order to reduce order effects.
3. Gameplay sessions are time-controlled to ensure comparable exposure.
4. Gameplay telemetry data is automatically recorded.
5. After each condition, participants complete:
    - The PENS questionnaire
    - The GEQ questionnaire

3.6 Data Collection Instruments

3.6.1 Player Experience of Need Satisfaction (PENS)

The PENS questionnaire is used to measure:

- Perceived competence
- Autonomy
- Presence/immersion

PENS is grounded in Self-Determination Theory and has been empirically validated for measuring enjoyment-related psychological needs in games (Ryan et al., 2006; Johnson et al., 2018).

3.6.2 Game Experience Questionnaire (GEQ)

The GEQ is used to assess:

- Positive affect
- Negative affect
- Flow-related engagement
- Immersion
- Challenge perception

Validated factor structures from recent empirical analyses are followed to ensure measurement reliability (Johnson et al., 2018).

3.6.3 Behavioral Metrics

In-game telemetry includes:

- Total playtime
- Number of retries

- Wave progression
- Completion success rates

Behavioral measures complement self-report data and provide objective indicators of engagement (Sulyma, 2025; Aponte et al., 2011).

CHAPTER 4. CRITERIA AND METRICS FOR EVALUATING PLAYER ENJOYMENT

4.1 Rationale for Criteria Selection

Player enjoyment is consistently described in the literature as a multi-dimensional construct rather than a single outcome variable (Mekler et al., 2014; Schaffer & Fang, 2019). Across different theoretical perspectives, enjoyment is shown to arise from the interaction between challenge, player skill, emotional responses, cognitive engagement, and perceived control, rather than from game performance alone. This understanding is particularly important when studying difficulty systems, since difficulty directly influences several of these dimensions simultaneously.

Tower defense games provide a suitable context for studying enjoyment because their core mechanics revolve around escalating challenge, strategic decision-making, and repeated failure and refinement. These characteristics make the genre especially sensitive to changes in difficulty tuning. Dynamic Difficulty Adjustment (DDA) systems are designed to continuously regulate challenge based on player performance, with the goal of maintaining engagement and preventing frustration or boredom.

Based on the five reviewed articles, this study adopts an evaluation framework that integrates:

- Conceptual models of enjoyment and flow (Sweetser & Wyeth, 2005),
- Large-scale empirical evidence on enjoyment measurement (Mekler et al., 2014 and Schaffer & Fang, 2019),
- Validated enjoyment and player experience instruments (Johnson et al., 2018),
- Affective, cognitive, and behavioral components of enjoyment (Fang et al., 2010).

This integrated approach ensures that the criteria used in this study are theoretically grounded, empirically supported, and directly relevant to difficulty manipulation.

4.2 Evaluation Criteria

4.2.1 Challenge–Skill Balance

Challenge–skill balance is one of the most consistently identified determinants of enjoyment in games. According to flow theory and the GameFlow model, enjoyment is maximized when the difficulty of a task matches the player’s skill level, avoiding both boredom (when difficulty is too low) and anxiety (when difficulty is too high) (Sweetser & Wyeth, 2005). Dynamic difficulty systems are explicitly designed to maintain this balance by adjusting enemy strength, spawn rates, or resource availability based on player performance.

In tower defense games, where players continuously refine strategies across waves, DDA may help sustain an appropriate level of challenge throughout gameplay. This criterion is therefore essential for evaluating whether dynamic difficulty leads to a more enjoyable experience than static difficulty settings.

4.2.2 Perceived Competence

Perceived competence refers to the player's feeling of effectiveness and mastery while playing the game. Research grounded in Self-Determination Theory identifies competence as a core psychological need whose satisfaction strongly contributes to enjoyment and intrinsic motivation (Johnson et al., 2018). When players feel that they are improving, learning, and succeeding through their own actions, enjoyment is more likely to increase.

In tower defense games, competence is expressed through effective tower placement, successful defense strategies, and progression through increasingly difficult waves. Dynamic difficulty may support competence by preventing repeated failure while still allowing players to experience challenge, making this criterion critical for evaluating the impact of DDA on enjoyment.

4.2.3 Control and Autonomy

Control refers to the extent to which players feel that their actions meaningfully influence game outcomes, while autonomy reflects the freedom to choose strategies and play styles. Both concepts are emphasized in the GameFlow model and the Player Experience of Need Satisfaction framework as important contributors to enjoyment (Sweetser & Wyeth, 2005; Johnson et al., 2018).

Dynamic difficulty systems may influence perceived control in two opposing ways. On one hand, adaptive systems can enhance control by keeping the game fair and responsive to player performance. On the other hand, if adjustments are too noticeable or opaque, players may feel that the game is "playing for them." Evaluating control and autonomy helps determine whether DDA enhances or undermines the player's sense of agency in tower defense gameplay.

4.2.4 Immersion and Engagement

Immersion describes a state of deep involvement in the game, where players become less aware of their surroundings and more focused on the gameplay experience. Engagement refers to sustained attention and willingness to continue playing. Prior studies link immersion to consistent challenge, clear goals, and meaningful feedback (Sweetser & Wyeth, 2005; Schaffer & Fang, 2019).

Dynamic difficulty may support immersion by smoothing abrupt difficulty spikes that could otherwise break player focus. In tower defense games, immersion is reflected in continuous decision-making, monitoring enemy waves, and adapting strategies in real time. This criterion captures how difficulty design influences sustained engagement and focus during play.

4.2.5 Affective Responses

Enjoyment encompasses both affective and cognitive reactions, including positive emotions such as fun and satisfaction, as well as negative emotions such as frustration and tension (Mekler et al., 2014; Fang et al., 2010). Importantly, prior research indicates that frustration does not necessarily negate enjoyment; instead, enjoyment can emerge from overcoming challenges after moments of difficulty.

Evaluating affective responses allows this study to capture the emotional consequences of dynamic versus static difficulty. In tower defense games, repeated failure due to overly rigid difficulty may reduce enjoyment, while adaptive difficulty may help regulate negative affect without eliminating challenge.

4.2.6 Behavioral Engagement

Behavioral engagement refers to observable player behaviors that indicate enjoyment, such as time spent playing, number of retries, and willingness to continue after failure. Behavioral measures complement self-report data by providing objective indicators of player experience (Fang et al., 2010).

In this study, behavioral engagement is particularly relevant because dynamic difficulty may encourage players to persist longer and retry levels more often compared to static difficulty systems. These behaviors serve as indirect but meaningful indicators of enjoyment.

4.3 Metrics and Measurement Instruments

To operationalize the evaluation criteria, this study adopts validated instruments and behavioral measures supported by prior research. Perceived competence, autonomy, and presence are measured using selected subscales from the Player Experience of Need Satisfaction (PENS) questionnaire (Johnson et al., 2018). Immersion, flow-related engagement, and affective responses are measured using relevant subscales from the Game Experience Questionnaire (GEQ), following validated factor structures (Johnson et al., 2018).

In addition to self-report measures, in-game behavioral metrics are collected, including total playtime, number of retries, wave progression, and completion rates. These metrics provide objective evidence of player engagement and complement subjective enjoyment ratings (Mekler et al., 2014; Fang et al., 2010).

4.3.1 Summary of Criteria–Metric Alignment

CRITERION	**Measurement Method**
Challenge-Skill Balance	GEQ (Flow, Challenge-related items)
Perceived Competence	PENS (Competence)
Control/Autonomy	PENS (Autonomy)
Immersion	GEQ(Immersion), PENS (Presence)
Affective Responses	GEQ (Positive & Negative Affect)
Behavioral Engagement	Gameplay Telemetry, Behavior-related survey items

4.4 Overall Justification

The criteria and metrics used in this study are grounded in established theories of enjoyment and supported by empirical research. The GameFlow model provides a conceptual foundation for understanding enjoyment as a balance between challenge, skill, control, and immersion (Sweetser & Wyeth, 2005). Large-scale reviews highlight the multidimensional nature of enjoyment and the importance of affective, cognitive, and behavioral components (Mekler et al., 2014; Schaffer & Fang, 2019). Finally, validated measurement instruments such as PENS and GEQ ensure methodological rigor and comparability with prior studies (Johnson et al., 2018; Fang et al., 2010).

By applying these criteria within the context of tower defense games, this framework enables a systematic comparison between static and dynamic difficulty systems, allowing the study to evaluate whether dynamic difficulty enhances player enjoyment in a measurable and theoretically meaningful way.

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