

**Republic of Iraq
Ministry of Higher Education
and Scientific Research
University of Babylon
College of Information Technology
Software Department**



Adapting Gamification for Learners' Performance Improvement Based on Their Preferences

A Dissertation

Submitted to the Council of the College of Information Technology for
Postgraduate Studies of the University of Babylon in Partial Fulfillment of
the Requirements for the Degree of Doctor of Philosophy in Information
Technology-Software

By

Dhiaa Abdulhussein Darraj Therib

Supervised by

Prof. Dr. Eng. Sattar Bader Sadkhan

2023 A.D.

1445 A.H.

بِسْمِ اللَّهِ الرَّحْمَنِ الرَّحِيمِ

إِنَّ اللَّهَ وَمَلَائِكَتَهُ يُصَلُّونَ عَلَى النَّبِيِّ

يَا أَيُّهَا الَّذِينَ آمَنُوا صَلُّوا عَلَيْهِ وَسَلِّمُوا تَسْلِيمًا

صَدَقَ اللَّهُ الْعَظِيمَ

سُورَةُ الْأَحْزَابِ آيَةُ ٥٦

Supervisor Certification

I certify that the dissertation entitled (**Adapting Gamification for Learners' Performance Improvement Based on Their Preferences**) was prepared under my supervision at the Department of Software/ College of the Information Technology/ University of Babylon as partial fulfillment of the requirements of the degree of Doctor of Philosophy in Information Technology-Software.

Signature:

Supervisor Name: **Prof. Dr. Eng. Sattar B. Sadkhan**

Date: / /2023

The Head of the Department Certification

In view of the available recommendations, I forward the thesis entitled "**Adapting Gamification for Learners' Performance Improvement Based on Their Preferences**" for debate by the examination committee.

Signature:

Asst. Prof. Dr. Sura Zaki Alrashid

Head of Software Department

Date: / /2023

Certification of the Examination Committee

We, the undersigned, certify that (**Dhiaa Abdulhussein Darraj Therib**), a candidate for the degree of Doctor of Philosophy in Information Technology/Software, has presented his dissertation of the following title (**Adapting Gamification for Learners' Performance Improvement Based on Their Preferences**), as it appears on the title page and front cover of the dissertation, that the said dissertation is acceptable in form and content and displays a satisfactory knowledge of the field of study as demonstrated by the candidate through an oral examination held on **13/ 11/ 2023**.

Signature:
Name: **Dr. Faez Ali AL-Maamori**
Title: **Professor**
Date: / / 2023
(**Chairman**)

Signature:
Name: **Dr. Haider K. Hoomod**
Title: **Professor**
Date: / / 2023
(**Member**)

Signature:
Name: **Dr. Ali Hadi Hasan**
Title: **Asst. Professor**
Date: / / 2023
(**Member**)

Signature:
Name: **Dr. Noor D. Kadhem**
Title: **Asst. Professor**
Date: / / 2023
(**Member**)

Signature:
Name: **Dr. Lamis Hamood Muheisen**
Title: **Asst. Professor**
Date: / / 2023
(**Member**)

Signature:
Name: **Dr. Sattar B. Sadkhan**
Title: **Professor**
Date: / / 2023
(**Member and Supervisor**)

Approved by the Dean of the College of Information Technology, University of Babylon.

Signature:
Name: **Dr. Wesam S. Bhaya**
Title: **Professor**
Date: / / 2023
(**Dean of Collage of Information Technology**)

Declaration

I hereby declare that this dissertation entitled (**Adapting Gamification for Learners' Performance Improvement Based on Their Preferences**) submitted to the University of Babylon in partial fulfillment of requirements for the degree of Doctorate of Philosophy in Information Technology/Software, has not been submitted as an exercise for a similar degree at any other university. I also certify that the work described here is entirely my own, except for experts and summaries whose sources are appropriately cited in the references.

Signature:

Name: Dhiaa Abdulhussein Darraj Alalgawi

Date: / / 2023

Dedication

This dissertation is dedicated to my dear parents, especially my gentle and brave father (**Martyr Colonel Abdulhusein Darraj Alalgawi**); may Allah (SWT) grant him mercy. I want to offer my heartfelt gratitude and prayers to him for his efforts to assist me throughout my entire study trip while he was still alive. I pray to Allah to show him kindness.

Dhiaa Abdulhusein Darraj Alalgawi

Acknowledgment

Above all, praise and thanks go to **Allah**, who is all-powerful and the most forgiving and caring. Thank God for sending the **prophet Mohammad** (peace be upon him and his household), who was the light of science and the master of creation. He was sent to teach people a lot and be kind to everything.

I'm also thankful to my study adviser, **Prof. Dr. Eng. Sattar B. Sadkhan** from the University of Babylon gave me ideas and helped me through the dissertation process by closely examining things. Without his help, I'm sure I would not have been able to finish this dissertation.

Thank you to my **brothers** and **sisters** for always being there for me and being patient with me. My **family** has always believed in me, and I want to thank them.

It's too long to name everyone I want to thank, but I want to thank them all from the bottom of my heart for all the help and support they've given me. During my Ph.D. trip, I'm also thankful to my brother, **Prof. Dr. Alaa Alalgawi**, for always being there for me and encouraging me.

Dhiaa Abdulhussein Darraj Alalgawi

Abstract

The process of integrating elements of games, including leaderboards and badges, into non-gaming contexts, like e-learning platforms, is known as gamification. The "one-size-fits-all" nature of traditional gamification ignores the preferences and personality traits of the learners. Results are prone to failure in the absence of adaptability. Adaptive gamification, which customizes experiences based on user profiles, solves this issue. A thorough, adaptable gamification framework that considers user profiles and preferences is needed to close this gap.

In this dissertation, a strategy was proposed to determine the type of user group and their preferences. The proposed strategy is based on the matrix factorization method to determine the type of user group and their preferences toward gamification features. This strategy aims to improve learners' motivation and commitment in a gamified e-learning environment.

The user profile was created using the Hexad questionnaire. The SPSS program was used to identify the predominant user types within the participation group as well as the prime user type for each participant. Python programming was utilized to identify which gamification elements participants preferred depending on their dominant user type.

The proposed strategy showed that "achievers" and "players" were the most common user-type learners. The gamification component with the highest rating was "challenges," which indicates that it is suitable to motivate these individuals.

A gamified e-learning platform (EdApp) was used to test the proposed strategy in real-world situations by integrating the gamification features that abstracted from the strategy's outcomes to satisfy students' preferences.

According to the findings of this research, adaptive gamification based on user preferences improves student engagement and commitment. This is the first dissertation in Iraq that adapts gamification to student preferences.

Declaration Associated with this Dissertation

Some of the works presented in this dissertation have been published or accepted, as listed below.

1. D. Alalgawi and S. B. Sadkhan, "Gamification Trends in E-learning – A Survey," *2022 5th International Conference on Engineering Technology and its Applications (IICETA)*, Al-Najaf, Iraq, 2022, pp. 193-198, doi: 10.1109/IICETA54559.2022.9888570.
2. D. Alalgawi and S. B. Sadkhan, "Adapt Gamification to Learners' Preferences," *2022 Fifth College of Science International Conference of Recent Trends in Information Technology (CSCTIT)*, Baghdad, Iraq, 2022, pp. 260-264, doi: 10.1109/CSCTIT56299.2022.10145630.

Table of Contents

Dedication	i
Acknowledgment.....	ii
Abstract.....	iii
Declaration Associated with this Dissertation.....	iv
Table of Contents	v
List of Tables	viii
List of Figures.....	ix
List of Appendices.....	x
List of Symbols	xi
Chapter 1 : General Introduction	1
1.1 Introduction	1
1.2 Related Works	2
1.3 Comparison Among Related Works.....	7
1.4 Problem Statement and Challenges	7
1.5 Research Objectives	8
1.6 Contribution and Efforts to Solve the Research Problem	8
1.7 Dissertation Organization	9
Chapter 2 : Theoretical Background	11
2.1. Introduction	11
2.2. The Concept of Gamification	12
2.3. Gamification Approaches:.....	12
2.4. Self-Determination Theory (SDT)	13
2.5. Gamification Applications in E-learning	14
2.6. Gamification Adaptation	14
2.7. Adaptive Gamification Approaches	15
2.8. Considerations for Adaptive Gamification.....	15
2.6.1. Player Type Models	16
2.6.1.1. Hexad Model.....	16
2.6.1.2. BrainHex Model.....	18
2.6.1.3. BigFive Model	18
2.6.2. Motivation Strategies	18
2.6.3. User Profile:.....	20
2.6.4. The Context.....	20

2.9. Gamification Elements and their Relevant Hexad User Types	21
2.10. The Connection Between Hexad Model and SDT Theory	22
2.11. Gamification Analytics.....	23
2.12. Gamification Challenges:	24
2.13. Overcoming Gamification Challenges	25
Chapter 3 : The Proposed Strategy	26
3.1 Introduction	26
3.2 The Proposed Strategy.....	27
3.3 The Proposed Strategy Development Steps	28
3.3.1 Matrix B Initialization	28
3.3.1.1 Identify the Predominant User Type.....	28
3.3.1.2 Sample of Participants	29
3.3.2 Initialize Matrix-A	30
3.3.3 Generate Matrix R	31
3.3.3.1 Matrix-R Calculation (25 Participants).....	31
3.3.3.2 Algorithm of Matrix-R (<code>RMatrix.csv</code>) Generation Using Python Code.	33
3.4 The Proposed Strategy Test.....	34
3.4.1. EdApp Platform	34
3.4.2. Target Sample:.....	35
3.4.3. Data Analysis.....	35
Chapter 4 : Experimental Results	36
4.1. Introduction:	36
4.2. Implementing the Proposed Strategy	36
4.2.1 Pilot Study (25 Participants).....	36
4.2.1.1 Questionnaire Reliability (25 Participants).....	36
4.2.1.2 Matrix-B Initializing (25 Participants-First Method):.....	37
4.2.1.3 Predominant User Type Identification (25 Participants-First Method).....	38
4.2.1.4 Matrix-B Initializing (25 Participants-Second Method)	40
4.2.1.5 Predominant User Type Identification (25 Participants-Second Method):	41
4.2.1.6 Prime User Types Identification (25 Participants).....	42
4.2.1.7 Matrix-A Estimating	43
4.2.1.8 Matrix-R Calculation (25 Participants).....	44
4.2.1.9 Determining the Preferred Gamification Features:	45
4.2.2 Actual Study (100 participants)	46
4.2.2.1 Questionnaire Reliability (100 Participants).....	46

4.2.2.2 Matrix-B Initializing (100 Participants-First Method):.....	47
4.2.2.3 Predominant User Type Identification (100 Participants-First Method).....	51
4.2.2.4 Matrix-B Initializing (100 Participants -Second Method):	52
4.2.2.5 Predominant User Types Identification (100 Participants- Second Method):	55
4.2.2.6 Prime User Types Identification (100 Participants):.....	57
4.2.2.7 Matrix-A Initializing (100 Participants):	58
4.2.2.8 Matrix-R Calculation (100 Participants).....	59
4.2.2.9 Determine the Preferred Gamification Features (100 Participants):.....	62
4.3. Adaptive Gamified Platform:	64
4.3.1 EdApp Platform:	64
4.3.2 Sample and Experiment Design.....	65
4.3.3 Data Analysis	66
4.3.4 Discussion	67
4.4. The Limitations:	69
Chapter 5 : Conclusion and Future Works	70
5.1 Introduction:	70
5.2 Conclusion:.....	71
5.3 Future Works:.....	71
Appendix A: Hexad Questionnaire	78
Appendix B: Python script for multiplying matrices (25 students)	85
Appendix C: Python Script for Multiplying Matrices (100 students)	86
Appendix D: Published Paper (1).....	87
Appendix E: Published Paper (2).....	93

List of Tables

Table 1.1: The Efforts in Adaptive Gamification	5
Table 1.2: Comparison Among Related Works	7
Table 2.1: Marczewski's Hexad User-Type.....	16
Table 2.2: Gamification Elements and their Relevant Hexad User Types	21
Table 3.1: Matrix-B (Profile Matrix)	29
Table 3.2: Matrix-A (Experts' Matrix).....	30
Table 3.3: Matrix R (Result Matrix)	31
Table 4.1: Reliability Statistics by SPSS	37
Table 4.2 : Matrix-B Initializing (First Method).....	37
Table 4.3: Predominant User Types (First Method) S=25	39
Table 4.4: Matrix-B Initializing (Second Method)	40
Table 4.5: Predominant User Types (Second Method), S=25	42
Table 4.6: Matrix-A (Experts' Rating Scores), Pilot Study.....	43
Table 4.7: Matrix-R Calculation (25 Participants).....	44
Table 4.8: Preferred Features of Gamification, Pilot Study.....	45
Table 4.9: Reliability Statistics by SPSS, Actual study	47
Table 4.10: Matrix-B initializing first method for actual sample (100 students).....	48
Table 4.11: Predominant User Types (First Method) S=100.....	51
Table 4.12: Matrix-B initializing second method for actual sample (100 students).....	52
Table 4.13: Predominant User Types (Second Method), S=100	56
Table 4.14: Matrix-A (Experts Rating Scores), Actual Study	58
Table 4.15: Matrix-R Calculation for the actual sample (100 students).....	59
Table 4.16: Preferred Features of Gamification, Actual Study.....	62

List of Figures

Figure 1.1: Adaptive Gamification Generic Model [12].....	2
Figure 1.2: Recommender System for Personalized Gamification. [13]	3
Figure 1.3: General Adaptive Gamification Approach [8], [16].....	5
Figure 2.1: MDA Framework, adapted from [52]	19
Figure 2.2: DMC Framework [53]	20
Figure 2.3: The Relationship Between SDT Theory and Hexad Model	23
Figure 3.1: The Proposed Framework to Adapt Gamification.....	26
Figure 3.2: The Block Diagram of the Proposed Strategy	27
Figure 3.3: A Block Diagram of Matrix-R (RMatrix.csv) Generation Using Python Code	32
Figure 4.1: The Participants' Hexad User Type Distribution (25 Participants)	39
Figure 4.2: Participants' Prime User Type Frequency (25 Participants).....	42
Figure 4.3: Preferred Gamification Features by Participants (25 Participants).	46
Figure 4.4: The Participants' Hexad User Type Distribution (100 Participants).	56
Figure 4.5: Prime User Type Frequency among Participants (100 Participants).....	57
Figure 4.6: Preferred Gamification Features by Participants (100 Participants)	63
Figure 4.7: Preferred Gamification Features Distribution (100 Participants).....	63
Figure 4.8: The Three Courses used in the EdApp Platform	65
Figure 4.9: Gamification Analytics Tool	66
Figure 4.10: Highest Performing Course	68
Figure 4.11: Comparison of the Courses	68

List of Appendices

Appendix A: Hexad Questionnaire	78
Appendix B: Python script for multiplying matrices (25 students)	85
Appendix C: Python Script for Multiplying Matrices (100 students).....	86
Appendix D: Published Paper (1)	87
Appendix E: Published Paper (2).....	93

List of Symbols

Abbreviation	Description
CSV	Comma Separated Value
DMC	Dynamics, Mechanics, and Components
EdApp	Educational Application
GE	Gamification Element
GUI	Graphical User Interface
ICC	Intra Class Correlation
KNN	K-Nearest Neighbours
MDA	Mechanics, Dynamics, and Aesthetics
NMF	Non-negative Matrix Factorization
RMSE	Root Mean Square Error
SDT	Self Determination Theory
SPSS	Statistical Package for the Social Sciences
SQRT	Square Root
SVD	Singular Value Decomposition

Chapter 1 : General Introduction

1.1 Introduction

Gamification is a concept in which game design elements are involved in non-game activities, such as e-learning contexts, to keep motivation, increase engagement, and get successful results [1]. Education is one of the most commonly used domains for gamification [2]. One of the applications that gamify electronic learning is EdApp [3], a mobile learning management system. The idea behind gamification is that it can improve engagement and increase motivation [4]. Educational institutions and academics try to adopt gamification to enhance learning by increasing students' motivation [5]. Gamification effectively motivates and engages individuals to achieve their activity objectives [1].

Self-determination theory (SDT) is the theory that is most often used to explain motivation [6]. According to SDT, there are three categories for learners' motivation: "intrinsic," "extrinsic," and "amotivation." When a task or activity meets the needs and objectives of the learner, motivation is "intrinsic." The term "extrinsic" refers to the external elements that contribute to a learner's motivation, such as rewards. A lack of motivation is referred to as "amotivation."

The main challenge of gamification in e-learning is that each learner has his or her own personality and preferences, and they have different motivations when interacting with gamified systems [7]. In other words, specific gamification elements that motivate one learner might negatively affect another [8].

Adaptive gamification that personalizing gamified experiences according to user profiles, is an effective way to overcome this challenge and an alternative approach to the traditional approach that involves the same

gamification elements for all users [9]. The Hexad user type [10] is better suited to creating a user profile for an adaptive gamified system than other user types due to restrictions in scope and applicability [11]. Hexad user type is based on SDT theory [6], which is concerned with the psychological motivational needs of different individuals. SDT is the most common theory used to clarify motivation.

This dissertation targets Iraqi students in secondary schools to propose an adaptive gamification strategy that tailors game design elements according to learners' profiles by identifying learners' types and their preferred gamification elements. The finding would give stakeholders a better understanding of game design elements and gamified approaches that meet educational targets.

1.2 Related Works

Relevant literature on gamification in e-learning is examined in this section. Adaptation efforts that integrate user typologies with gamification elements are also being investigated in order to keep learners engaged and committed.

1. In 2017, a study was done by Monterrat et al. [12] to propose a gamification strategy using two models, namely the player model and the learner model, as shown in **Figure 1.1**.

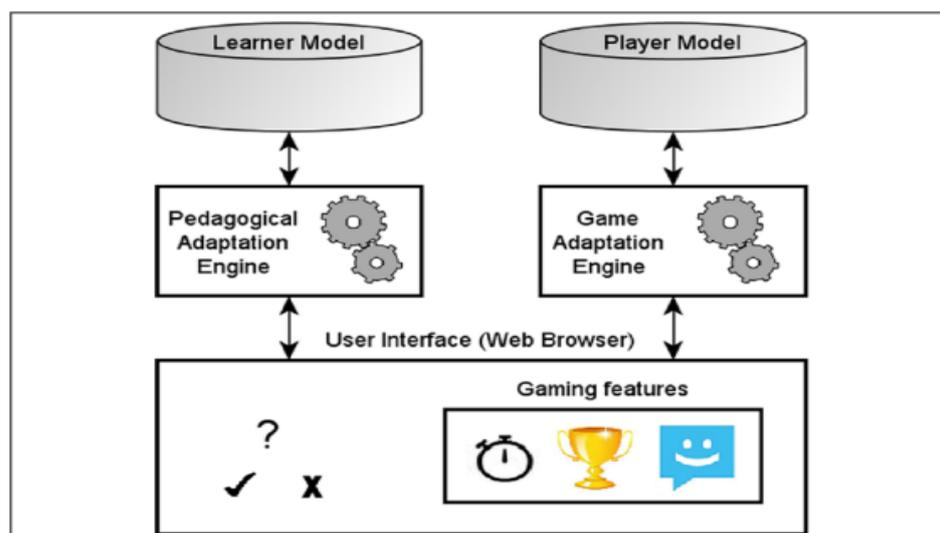


Figure 1.1: Adaptive Gamification Generic Model [12]

The player model is based on learner preferences using BrainHex typology; a specific questionnaire was used to gather the data for the profile. The learner model is based on the learner's skills. Adaptation in an e-learning environment depends on user actions and learning activities. This method was used with middle school students in an e-learning environment. According to the findings, increasing the number of gamification elements increased complexity and had an undesirable effect; consequently, learners should be offered a restricted number of features. The results demonstrated that gauging user motivation was based on self-reported activities; additional research is needed to assess user motivation and commitment based on real-world actions, such as the **time spent** executing a task or activity. The results demonstrated that the association between player typology and learner behavior can aid in developing learner profiles. Overall, the results show that the adaptation process did not result in the expected increase in learner engagement.

- In 2017, Tondello et al. [13] proposed a framework for adapting gameful apps in any context using a recommendation system that links gamification features to user preferences. This approach is indicated in **Figure 1.2**.

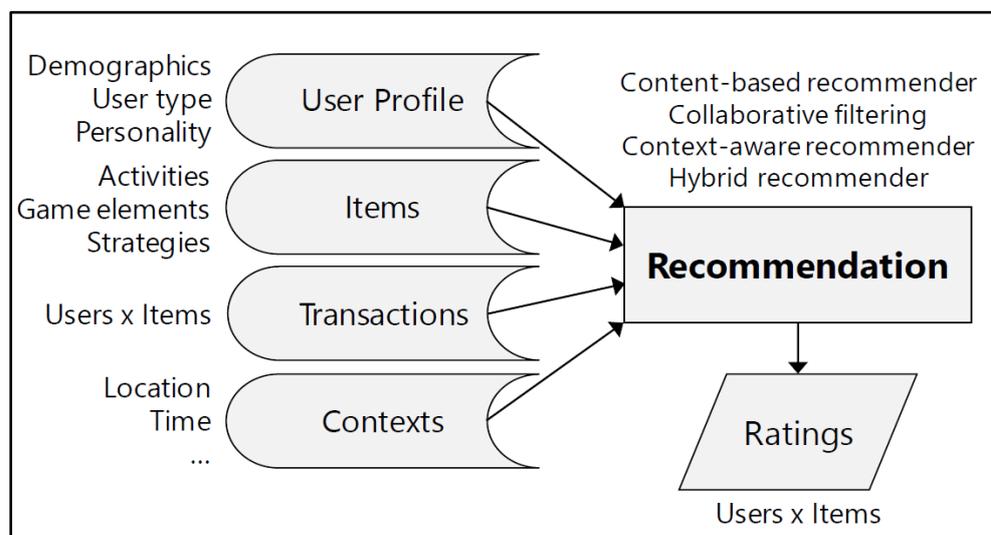


Figure 1.2: Recommender System for Personalized Gamification. [13]

The inputs, outputs, and processes that make up the essential parts of the suggested system are described in the framework. Input components include user profiles, the objects to be rated, the transactions between the users and the items to be assessed, and the context, such as location or environment. The recommender system's estimated ratings are included in the output.

3. In 2019, a study conducted by Lavoué et al. [14] built on a previous trial that updated gamification features based on user types by employing a linear strategy between BrainHex player type and gamification elements. Gamification specialists completed matrix-A by analyzing gamification elements concerning the seven user types in the BrainHex model. Voltaire is the name of an online course that teaches French grammar and spelling. The strategy was used in an online learning environment. According to the study's findings, there is no statistically significant difference in the amount of time students who used adaptive gaming elements spent on the e-learning platform and those who did not.

4. In 2020, a study was carried out by Oliveira et al. [15], to investigate the effects of adaptive gamified e-learning systems on students' flow experiences using the BrainHex player type model. Brazilian primary school pupils participated in the experiment, which followed the suggested approach's five steps [8]. The study found no significant difference in student flow experience between tailored and non-tailored e-learning system versions, contradicting recent findings in this field. The study suggests adopting a different user-type model instead of the BrainHex model since the BrainHex model's unexpected and inconsistent results may make it ineffective. The inconsistency of the study's findings indicates that further experimental research is required to enhance the evidence in this open field of research.

5. In 2022, a study was conducted by Oliveira et al. [16]. The five steps of the adaptation process were adapted from [8], as shown in **Figure 1.3**. The study looked at the flow experience of users who used two types of gamified systems: adaptive and non-personalized gamified systems. The user-type model was BrainHex, and the intended audience was primary school children. Personalization had no significant associations with students' feelings of flow or motivation, contradicting recent literature findings. According to the study's recommendations, further research should be done to develop gamified e-learning platforms.

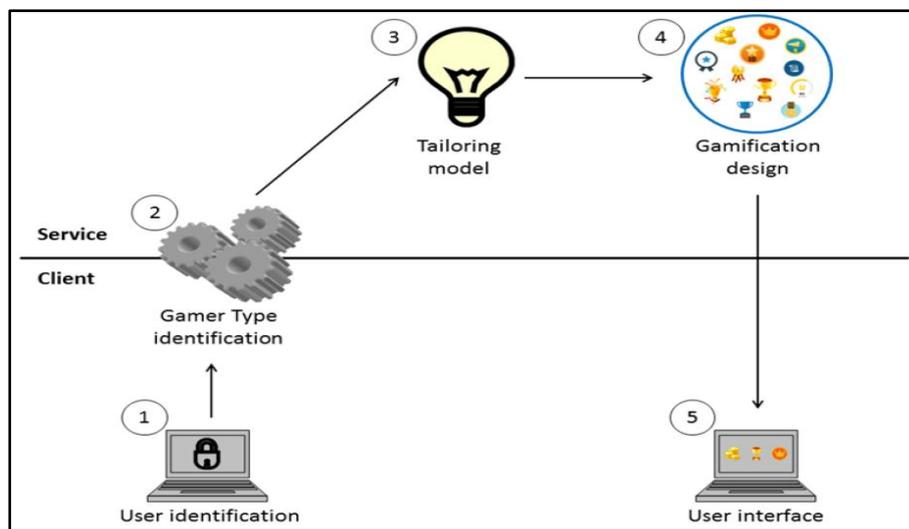


Figure 1.3: General Adaptive Gamification Approach [8], [16]

Table 1.1 illustrates the existing efforts and significant challenges based on the previously stated literature:

Table 1.1: The Efforts in Adaptive Gamification

Seq.	Ref.	year	Strategy	Player type	Findings
1.	[12]	2017	Adaptive gamification approach	BrainHex	<ul style="list-style-type: none"> Overall, the results show that the adaptation process did not result in the expected increase in learner engagement. The results showed that measuring user motivation was based on self-reported behaviours; further study is required to gauge user commitment based on actual actions, such as the amount of time spent carrying out a task or activity.

					<ul style="list-style-type: none"> The study indicated that students have their own personalities and preferences toward gamification features.
2.	[13]	2017	Framework for adapting gameful apps	BrainHex	<ul style="list-style-type: none"> This framework is generic and can be implemented in any environment or context. The study suggests that this framework be tested in a specific domain or context.
3.	[8]	2018	A tailored gamification approach	BrainHex	<ul style="list-style-type: none"> The adaptive gamification features led to increased time spent by learners in the online learning environment. The level of motivation was higher in learners with non-adapted gamification features. The findings of the study are conflicting. The conflicting findings of the study contradict recent theoretical studies, indicating the need for additional research in this field.
4.	[14]	2019	Linear strategy	BrainHex	<ul style="list-style-type: none"> According to the research findings, there are no significant differences in time spent on the e-learning platform between students who utilized adaptive gaming features and students who did not use adaptive gaming features.
5.	[15]	2020	A tailored gamification approach	BrainHex	<ul style="list-style-type: none"> The study found no significant difference in students' flow experience when comparing adaptive and non-adaptive versions of the e-learning system. This result is inconsistent with the results of recent studies in this field. The study suggests adopting a different user-type model instead of the BrainHex model since the BrainHex model's unexpected and inconsistent results may make it ineffective. The inconsistency of the study's findings indicates that further experimental research is required to enhance the evidence in this open field of research.
6.	[16]	2022	A tailored gamification system	BrainHex	<ul style="list-style-type: none"> Personalization had no significant associations with students' feelings of flow or motivation. It contradicted recent literature findings. It recommends that further research should be done to develop gamified e-learning platforms.

1.3 Comparison Among Related Works

The types of players are an important factor to take into account when developing an adaptive gamification approach since every player group has a unique personality and drive [9]. Choosing a trustworthy user-type model helps in choosing the appropriate elements of gamification that inspire and motivate users [17].

To overcome the shortcomings and difficulties of the earlier works and adopt reliable user type models that result in the prediction of relevant gamification features, it is crucial to compare equivalent works in the form of user type models. Comparisons between the related works are shown in **Table 1.2**.

Table 1.2: Comparison Among Related Works

Seq.	References	year	Player Type Models		
			Hexad Model	BrainHex Model	BigFive Model
1.	[12]	2017	×	✓	×
2.	[13]	2017	×	✓	×
3.	[8]	2018	×	✓	×
4.	[14]	2019	×	✓	×
5.	[15]	2020	×	✓	×
6.	[16]	2022	×	✓	×
The proposed strategy			✓	×	×

1.4 Problem Statement and Challenges

Gamification is increasingly used in e-learning platforms to increase learner motivation and engagement. Traditional gamification strategies, on the other hand, frequently use a "one-size-fits-all" approach, which ignores learners' diverse preferences and personality types [8]. This lack of personalization may result in ineffective or harmful results [18]. Although adaptive gamification aims to address this by adapting experiences

to individual user profiles, there is no standardized technique for its implementation [9]. Furthermore, present research on adaptive gamification in e-learning is limited and inconsistent [16], particularly when aligning gamification elements with specific player types. As a result, there is an urgent need for a comprehensive, adaptive approach to gamification that considers user preferences based on their profiles.

The development of an adaptive gamification framework for e-learning platforms is the primary issue that this dissertation intends to solve. The framework will maximize motivation and engagement by adapting gamification features to user preferences.

1.5 Research Objectives

In this dissertation, the following primary objectives will be covered:

1. **An adaptive Gamification Framework:** To propose an adaptable gamification framework that describes the main elements for building an adaptive gamification strategy, such as gamification strategies, user profiles, user typologies, and context.
2. **An adaptive Gamification Strategy:** To propose an adaptive gamification strategy that predicts gamification elements based on the preferences of the target learner group to improve learners' motivation and commitment on e-learning platforms.

1.6 Contribution and Efforts to Solve the Research Problem

The key contributions and efforts of this dissertation are summarized as follows:

1. It proposes an adaptive gamification **framework** outlining the essential components to consider when designing the adaptive strategy.
2. It proposes an adaptive **strategy** that predicts gamification components based on the preferences of the target learner group to improve learners' motivation and commitment to e-learning platforms.

The other contributions of this dissertation are summarized below:

1. It determines the appropriate user typology (Hexad) model for the proposed adaptive strategy.
2. It determines the predominant user type for the participant's group based on the Hexad model questionnaire.
3. It determines the prime user type for each participant in the group based on the Hexad model questionnaire.

1.7 Dissertation Organization

This dissertation is divided into five chapters, the first of which is chapter one, and structured as follows:

1. Chapter 1 contains a general introduction. This chapter offers and compares relevant works that tend to tailor gamification to identify issues and gaps and highlight solutions to these challenges. After identifying the problem statement, this chapter discusses the study's aims and contributions.
2. Chapter 2 provides a theoretical background for the adaptive gamification approach. This chapter discusses fundamental gamification concepts, gamification components, motivation theories, user profiles, player types, and other factors to consider while developing gamified platforms.

3. Chapter 3 presents the proposed gamification framework and adaptive gamification strategy. The proposed strategy determines user group type and preferences.
4. Chapter 4 presents experimental and implementational results. Implemented strategies and other contributions are discussed, as are their results in reaching dissertation objectives.
5. Chapter 5 provides the conclusion and most significant results, as well as recommendations.

Chapter 2 : Theoretical Background

2.1. Introduction

Gamification refers to the act of involving game elements within a non-game context, such as e-learning, for the sake of motivating individuals to perform target tasks [1]. Gamification tends to transform tasks or activities into game-like experiences[19]. The main benefits of gamification are to increase individuals' motivation [20] and keep their engagement to achieve the goals of the target activity [1]. To gain this benefit, educational institutions and academics put effort into adopting gamification in e-learning to improve the learning process through motivating students [5].

Education is one of the most commonly used domains for gamification [21]. EdApp [3] is a learning management system that employs gamification in e-learning. Gamification is widely used in e-learning to improve learners' performance [9], increase engagement, and keep their motivation [14]. However, learners have their reactions to gamification components [22]. In other words, gamification elements that may motivate one user tend to fail to inspire another due to the diversity of player types and their personalities[23].

Traditional gamified experiences use the same game design elements for all user groups, leading to a "one-size-fits-all" approach that fails to motivate all people [23]. As a result, this traditional gamification method fails to satisfy user preferences and inspire all kinds of people.

Creating a gamified e-learning environment personalized to a group of learners as an alternative to traditional methodologies that use a one-size-fits-all approach is one of the most challenging difficulties with gamification [8].

The success of gamification lies in the suggestion of game design elements that carefully meet user preferences [17]. With the goal of improving user experience in gamified platforms, the current trend in gamification is adaptive, implying that game features are adaptive to user preferences [9].

The main challenge facing gamification approaches is adapting or tailoring gamified e-learning systems [15], i.e., suggesting game design elements according to learners' preferences and individuals' different personalities and motivations [9]. However, the relationship between gamification elements and learner profiles was not considered [14]. One main challenge of gamification is providing a gamified e-learning environment tailored according to learners' types as an alternative to traditional methods that adopt a one-size-fits-all approach [8]. Recently, efforts have tended to propose techniques to correlate gamification elements to different user profiles [9].

2.2. The Concept of Gamification

Gamification, as a term, was first used in 2008 and was widespread at the end of 2010 in several academic conferences [1]. In 2011, the first definition was proposed by Deterding et al. [1] as using game design elements in a non-game context to increase user motivation and participation in a specific activity or task. In 2012, Huotari and Hamari [24] defined gamification as improving service with gamified experiences to support the user and achieve the target. Accordingly, gamification involves game elements within a non-game context, such as e-learning, to motivate individuals to perform target tasks [1].

2.3. Gamification Approaches:

Gamification may be done in two ways: "traditional" and "adaptive." [25] Traditional gamified system design adopts a one-size-fits-all strategy, applying the same gamification components to every participant in

the gamified experience. This strategy often fails because it ignores variety and unique reasons[26]. The adaptive approach is an alternative to the standard method. It takes into account that each person has a unique personality and set of playing motives, and it applies gamification components based on user preferences [27].

2.4. Self-Determination Theory (SDT)

The gamification approach is mainly based on the concept of motivation theory, more specifically on Self-Determination Theory (SDT), which was developed by Ryan [6]. The SDT theory is the most common theory used to clarify motivation. The idea behind SDT is that individuals are intrinsically motivated to be involved in activities that meet humans' three basic psychological needs. These needs are, namely, competence, autonomy, and relatedness. Individuals do their best to achieve these three needs to reach well-being. In other words, individuals need autonomy in their decisions, competence in their activities, and relatedness in their social environments.

Learners' motivation is classified according to SDT into three types, namely intrinsic, extrinsic, and amotivation. Motivation is intrinsic when the tasks or activities meet the learner's goals and needs. Motivation can be extrinsic when it includes external factors such as rewards that enhance a learner's motivation. Amotivation refers to a lack of motivation [6].

Motivational strategies are one of the main factors that must be considered while designing gamification interventions [28]. Most studies focused on the level of game **mechanics**, often called **motivational** or **persuasive strategies** [29].

2.5. Gamification Applications in E-learning

Digital technologies and game design are combined in an approach called gamification [5]. In e-learning contexts, it often improves students' performance, engagement, and motivation [9]. Gamified application software is used to increase motivation in a range of tasks and to encourage individuals in different ways [30]. Gamification strategies have been more successfully used to maintain student interest and learning engagement due to the advances in technology, platforms, smart devices, and advanced learning concepts [31].

Gamification elements such as levels, prizes, challenges, feedback, badges, and points have been shown to be employed in e-learning [32]. These results demonstrate that gamification is gaining popularity as a useful learning strategy for creating more interesting learning environments. Furthermore, elements in gamified e-learning environments promote and facilitate student involvement [33]. In recent years, gamification strategies in e-learning have gained popularity due to positive results [34].

2.6. Gamification Adaptation

Gamification is an effective strategy for increasing learners' motivation and participation in educational online courses [35]. However, different learners react differently to gamification features. Because of this diversity, it is essential that gamification features be adaptable for users. Adapting gamification components to user preferences is known as adaptive gamification. Adaptive gamification's main principle is the recommendation of game design components that match user preferences [36].

Adaptation is an alternative to a 'one-size-fits-all' strategy [37]. Adaptation refers to the practice of adapting gamification components to user preferences [38]. The primary goal of adaptation is to enhance the experience of users when they engage with the e-learning platform [39]. Several factors need to be taken into account when gamification is adapted [40]. Gathering

user data to be used as a foundation for adaptation is the first step. The preferences of the user may be reflected in this data. The use of the user model in the development of the adaptive strategy is the next step in the adaptation process. The approach ought to predict gamification features based on user preferences [41].

It may be concluded that using an adaptive gamification strategy in e-learning has the ability to overcome the gamification challenges that might arise when employing more traditional gamification strategies. Improve the learners' motivation; this was accomplished by attempting to adapt gamification features to their preferences. Identifying the different types of learners and recommending relevant gamification features for every kind of learner to achieve adaptation is essential.

2.7. Adaptive Gamification Approaches

Two methods of adaptive gamification exist: "static" and "dynamic." [26] Static adaptation works by first generating a learner profile prior to the learner engaging in a gamified experience, and then recommending that game features align with that profile [42]. One drawback of a static method is that it ignores behavioral changes that users experience over time while using a gamified application [43]. To get around this problem, utilize a dynamic adaption strategy that records user behavior in real time and leverages game features according to user preferences [44]. However, the dynamic method modifies gamification in real time according to the user profile; that is, it makes adjustments depending on the user's actions throughout the gamification process. [45]

2.8. Considerations for Adaptive Gamification

According to existing literature and adaptive gamification strategies, there are exciting considerations when designing personalized

gamification [28] In the following, more details on these considerations are provided:

2.6.1. Player Type Models

One of the critical considerations to consider while developing adaptive gamified systems is the model of player types [9]. Discovering player typologies and game components that link to certain player types is vital to identifying user preferences in adaptive gamified systems. The phrase "player type" was first used by Bartle [46] in 1996 when he classified gamers into four categories: "achievers," "socializers," "killers," and "explorers." This classification was created based on each player type's preferred game activities. The Hexad model, developed by Marczewski [10], the BrainHex model, developed by Nacke [47], and the BigFive model, developed by Goldberg [48], are the most popular models of user typologies.

2.6.1.1. Hexad Model

Because of their popularity and ease of implementation, subsets of game design components such as leaderboards, points, and badges are commonly chosen by designers using the traditional gamification method [49]. This approach disregards people's varied personalities and preferences.

Marczewski [10] suggested the Hexad user-type model to address this issue, which was the first original model designed for the gamification sector and is based on SDT theory [6]. As illustrated in Table 2.1, this model offers the appropriate motivational drives for each user type.

Table 2.1: Marczewski's Hexad User-Type

Seq.	User type	Motivation Drive	Motivation Features
1	Players	Reward	Rewards are used as extrinsic motivators to motivate "players." The "players" user type enjoys the leaderboards feature.
2	Achievers	Mastery	"Achievers" tend to overcome challenges and are intrinsically motivated by their skills. They prefer specific gamification features, namely challenges and levels.

3	Free Spirits	Autonomy	"Free Sprits" are intrinsically motivated by autonomy. "Free spirit" users prefer game elements, namely customization and unlockable gamification elements.
4	Socializers	relationships	"Socializers "are intrinsically motivated by relationships such as social connections. The "socializer" user type prefers competitive game elements.
5	Philanthropists	Purpose	"Philanthropists "are intrinsically motivated by purpose and do not seek financial reward.
6	disruptors	Change	Change is what motivates "disruptors".

"Philanthropists" are intrinsically motivated by purpose and do not seek financial reward. "Socializers" are intrinsically motivated by relationships such as social connections. "Free Spirits" are intrinsically motivated by autonomy. "Achievers" tend to overcome challenges and are intrinsically motivated by their skills. Extrinsic motivators such as rewards are used to encourage "players." Change is what motivates "disruptors" [6].

The Hexad model was proposed by Marczewski [10] as the first exclusive user-type model designed for the gamification domain and is based on motivation theory, namely SDT [6] A questionnaire was suggested by Tondello et al. [11] to measure user preferences based on the six Hexad user-type models proposed by Marczewski [10]. This Hexad user-type scale was validated empirically by Tondello et al. [50] to evaluate the reliability of this questionnaire.

A study was conducted by [28] to compare the Hexad model with other models, such as the BrainHex model and the BigFive model, in addition to investigating the relationships between user models and game elements. The results recommend that the Hexad model be adopted when designing tailored gamification. This result supports the evidence of previous studies [11] that the Hexad model is the most relevant to adoption in gamification when compared to the BrainHex model, which is relevant to games, and the BigFive model, which is relevant to personality traits.

A study was conducted by [9] to investigate the Hexad user types and relevant game elements. The results revealed that "achievers" user types prefer specific game elements, namely challenges, and levels, whereas the "free spirit" user type prefers game elements, namely customization and unlockable gamification elements. On the other hand, the "players" user type likes the leaderboards element. While the "socializers" user type prefers competitive game elements [9].

2.6.1.2. BrainHex Model

The BrainHex model [47] was initially developed for gaming specifically as a gamer typology and was inspired by neurobiological studies [51]. However, it applies to both games and gamification. The BrainHex model proposes seven types of players, namely: **Seeker**, who enjoys discovery; **Survivor**, who wants to escape; **Daredevil**, who enjoys playing on edge; **Mastermind**, who enjoys solving puzzles; **Conqueror**, who enjoys defeating opposer; **Socializer**, who enjoys interacting, and **Achiever** who wants task completion [47].

2.6.1.3. BigFive Model

The BigFive model [48] was applied in a few tailored gamifications to identify user preferences for game elements according to personality traits. This model focuses on personality traits, more specifically on five factors, namely "openness to experience," "conscientiousness," "extraversion," "agreeableness," and "emotional stability" [48].

2.6.2. Motivation Strategies

Motivational strategies are one of the main factors that must be considered while designing gamification interventions [28]. Most studies focused on the level of **game mechanics**, often called **motivational** or **persuasive strategies** [29]. Several frameworks classify and organize gamification elements to clarify the motivational process. Gamification

elements are a central existing and future research theme[17]. One of the challenges of gamification is that there is no uniform taxonomy for gamification elements and their categories.

For example, Hunicke, LeBlance, and Zubek in 2004 [52] developed the MDA model illustrated in **Figure 2.1**, which stands for "Mechanics, Dynamics, and Aesthetics." Mechanics represent the game design elements that are embedded in the user interface.

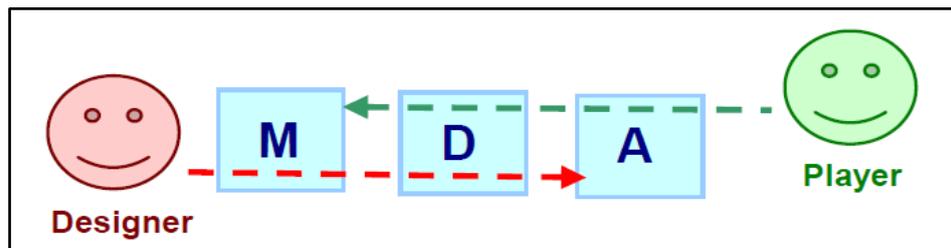


Figure 2.1: MDA Framework, adapted from [52]

Dynamics represent the highest level of abstraction. In other words, it means the interactive relationship between the player and interface elements. Aesthetics represent the emotional reaction of the player toward the dynamics. This model aims to understand game elements, player behavior, and their emotional responses.

On the other hand, in 2012, Werabach and Hunter [53] proposed the DMC (Dynamics, Mechanics, and Components) framework, as illustrated in **Figure 2.2**. The game element hierarchy progresses from the most generic to the most tangible game components.

Dynamics are the most fundamental and abstract aspect that cannot be directly entered into a gamification system, such as emotions. Mechanics are the process and way of achieving dynamics in the gamified system to motivate player engagement, such as challenges and competition. Components are the tangible forms of mechanics and dynamics, such as points, badges, and leaderboards, which are seen as building blocks for game mechanics and dynamics. In other words, components represent the specific

features of mechanics and dynamics.

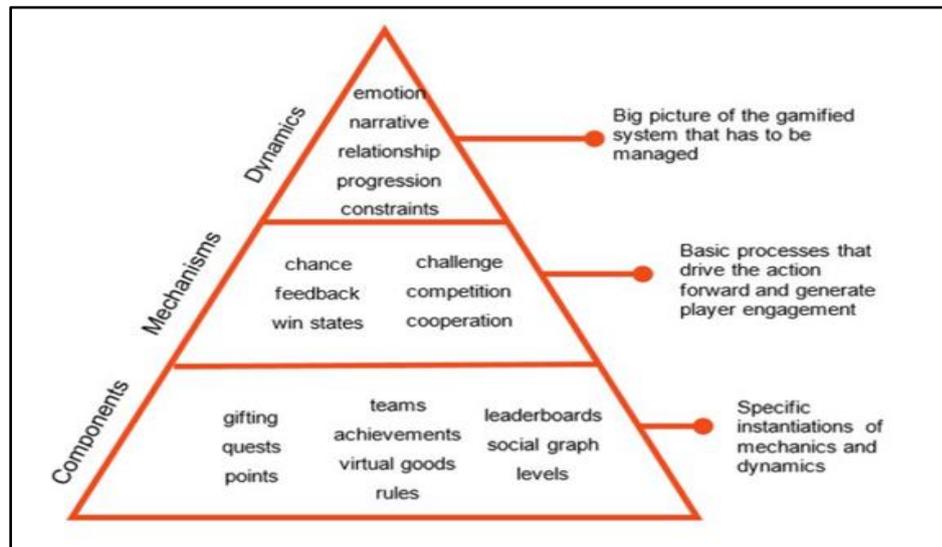


Figure 2.2: DMC Framework [53]

2.6.3. User Profile:

Another factor to consider is the user profile in adaptive gamification systems. An adaptive gamification approach suggests gamification components depending on the user's preferences. Current studies tend to predict gamification characteristics based on user profiles in gamified e-learning systems [9]. The acquisition of user information can be accomplished through two distinct methods: explicit means, which include the user providing information directly, and implicit means, which involve the observation and recording of user behavior and activities. Regardless of the approach, this data creates a user profile.

2.6.4. The Context

Another factor to consider is the context of gamification systems. A study conducted by [28] to investigate the factors to be considered for adaptive gamification indicated that the context of a gamified system should be considered. Another study [13] verified that the context should be regarded as in a gamified system. Furthermore, a study by [54] demonstrated that the context influences the motivational impact of gamification features.

2.9. Gamification Elements and their Relevant Hexad User Types

In 2020, Hamari et al. [9] reviewed the literatures on tailored gamification and investigated Hexad typology. According to the study, "players" prefer leaderboards, "socializers" prefer competition, "achievers" prefer challenges and levels, "free spirits" enjoy personalization, while "disrupters" and "philanthropists" are less thoroughly studied.

Based on existing literature on personalizing gamification, this dissertation identifies the most dominant gamification elements and associated user types according to the Hexad user type model; **Table 2.2** shows player types and related preferences for gamification elements of each kind of Hexad model.

Table 2.2: Gamification Elements and their Relevant Hexad User Types

Seq.	Motivation mode	Hexad Player Type	Mechanics (motive)	Relevant main elements
1.	Extrinsically	Players	Rewards [10]	Leaderboard [9] [55] Points (scores) [9] [56] Badges [9] [55] Challenges [55] [57] Competition [55] [58] Prize [55] [58] level [55] [11]
2.	Intrinsically	Achievers	Mastery Competence [10]	Challenges [9] [11] Levels [55] [57] Badges [9] [59] Progress bar [56] [57] Competition [55] [57] Timer [59] Customization [55] leaderboard [55] points (scores) [55]
3.	Intrinsically	Socializers	Relatedness [10] relationships	Competition [9] [55] Ranking [59] Badge [59] Customization [55] [58] leaderboard [55] level [55]

				Prize [55] [58] Feedback [58]
4.	Intrinsically	Free spirits	Autonomy [10] Self-expression	Customization [9] [58] Avatar [59] Challenges [55] [11] Badge [59] level [55] feedback [60]
5.	Intrinsically	Philanthropists	Purpose [10] Meaning	Challenges [55] Badge [11] [59] Customization [55] [59] level [55]
6.	Intrinsically	Disruptors	Changes [10]	Customization [9] [58] Competition [55] [58] Badge [59] Challenges [11] Level [11]

2.10. The Connection Between Hexad Model and SDT Theory

Enhancing learners' internal and extrinsic motivation to engage in certain activities is the goal of gamification [61]. In the process of creating gamification strategies, it is essential to understand the internal and external motivations that sustain learners' interest. The Hexad model is based on SDT theory, as was previously mentioned. According to the SDT theory, relatedness, competence, and autonomy are the three fundamental psychological needs that motivate intrinsic drives [6].

Figure 2.3 illustrates the relationships between the SDT theory [6] and the Hexad model [10] in order to completely comprehend the linkages between the two motivation drives of Hexad user types and the intrinsic motivation drives of the SDT theory, which motivates individuals intrinsically.

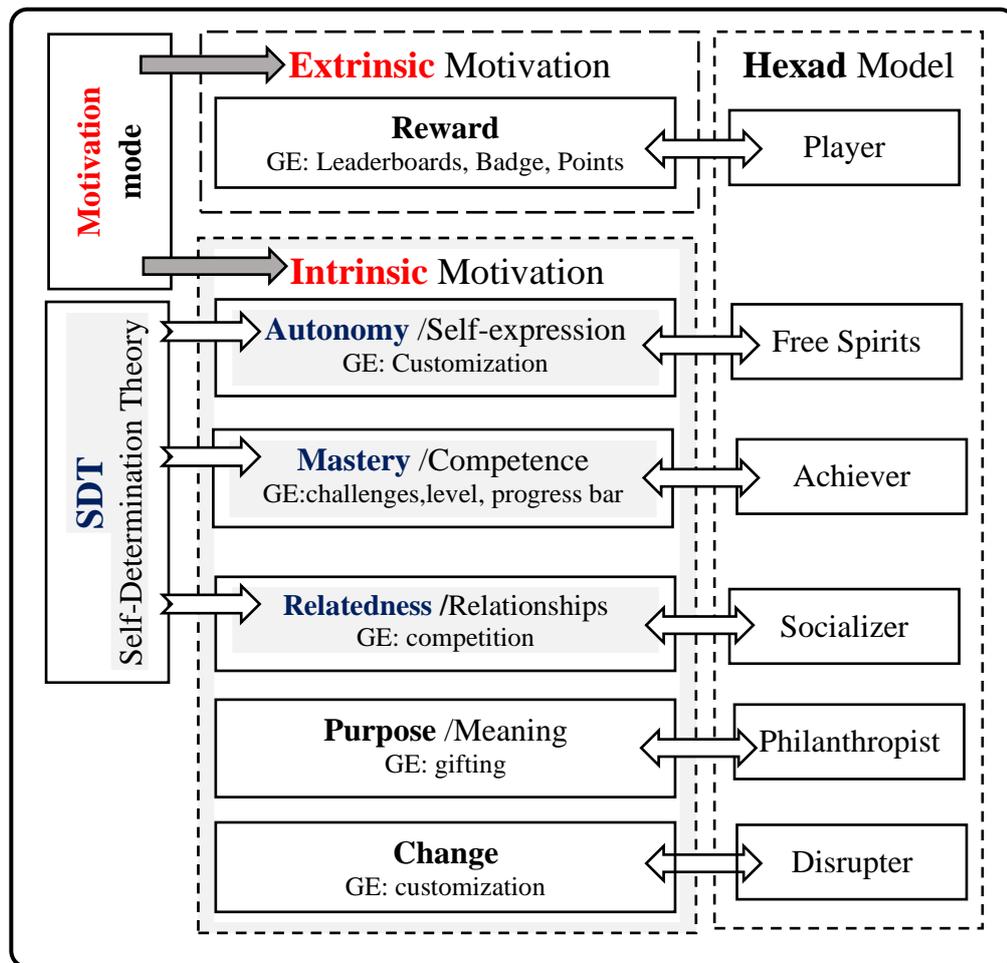


Figure 2.3: The Relationship Between SDT Theory and Hexad Model

2.11. Gamification Analytics

Gamification analytics is one of the most important instruments for analyzing user behavior in order to understand user preferences and measure the performance of gamification strategies [1].

By analyzing the effects of gamification elements like points, leaderboards, and challenges on user motivation and engagement, these tools seek to evaluate the efficacy of gamification strategies and subsequently enhance them [2].

In order to monitor important user behavior data, current gamification solutions often include gamification analytics. By examining user performance and behaviors, this data is utilized to gauge how well gamification strategies are succeeding. EdApp is a learning platform with an analytics tool built in that gives detailed data on student achievement by

tracking user activities. The analytics gamification tool includes data such as time spent on different platform activities, test scores, and task completion rates [3].

2.12. Gamification Challenges:

1. One of the main challenges identified in light of the findings related to gamification trends in e-learning is that the classic approach uses uniform application of gamification elements to all learners, i.e., "one size fits all," which tends to fail because each group of users reacts differently to different game elements due to the diversity of their personalities and preferences [9]. In other words, because player types and personalities differ significantly, gamification components that inspire one set of users may not motivate another [8]. By proposing a strategy for adaptive gamification in e-learning environments based on user preferences, this dissertation will assist in solving gamification challenges.
2. Another significant issue is the lack of a standardized taxonomy for gamification features and categories. For instance, Hunicke, LeBlance, and Zubek established the MDA model in 2004 [52] to identify and classify gamification elements into mechanics, dynamics, and aesthetics. In contrast, Werabach and Hunter in 2012 [53] divided gamification aspects into three groups: dynamics, mechanics, and components. By identifying the most prevalent gamification components relevant to their user type, which are most frequently used in the literature and included in gamified e-learning systems, this dissertation will help resolve gamification challenges.
3. The lack of a consistent player-type model is one of the critical problems with gamification. The existing literature results confirmed the importance of considering the player profile when designing gamification systems [9]. Finding player typologies and the game components corresponding to various player types is essential for categorizing user

preferences in adaptive gamified systems. Most literature still trends on how to tailor gamification and how user modeling, more specifically, which model of user type is adopted [15]. As a contribution to overcoming gamification issues, this dissertation will find the most relevant user-type model based on a set of criteria.

2.13. Overcoming Gamification Challenges

An alternate approach that addresses the challenges of gamification and narrows this gap is to use game elements according to the learner's preferences [14]. Most current research argues that game components should be adapted to learners' preferences to ensure the effectiveness of gamification and improve student experience[9]. This dissertation consequently focuses on the contributions and efforts made to adapt game components to user preference and, in response, provides a strategy for adaptive gamification to learners' preferences to increase user motivation in e-learning platforms.

Chapter 3 : The Proposed Strategy

3.1 Introduction

This dissertation proposes a framework that adapts gamification elements according to learners' preferences, taking into account the previously mentioned considerations.

Figure 3.1 depicts the main components of the proposed framework for adapting gamification while developing a gamified e-learning platform.

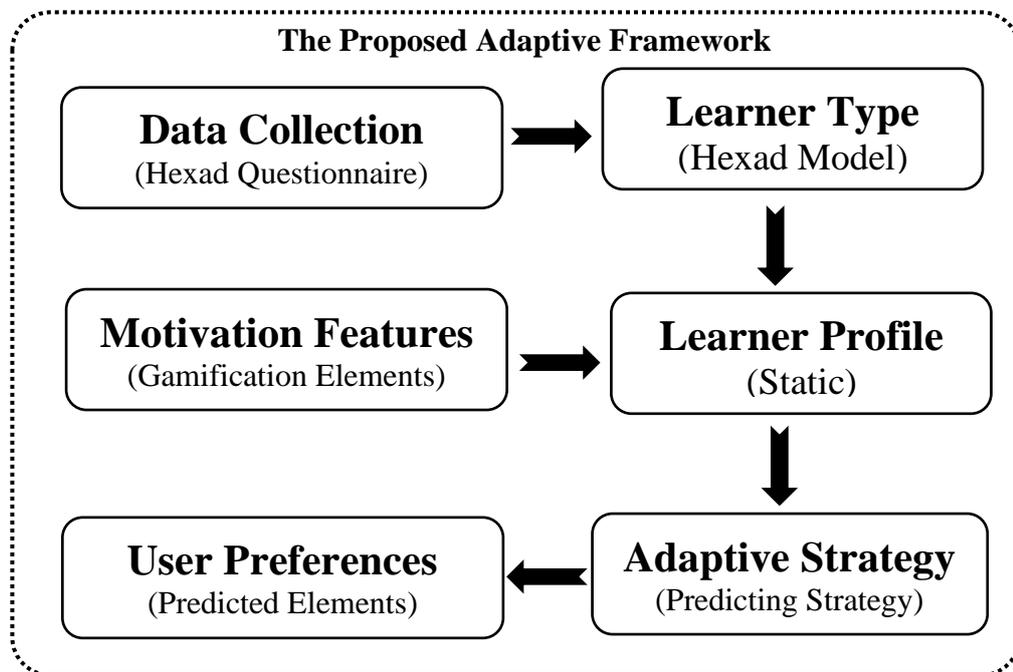


Figure 3.1: The Proposed Framework to Adapt Gamification

This dissertation proposes an adaptive strategy for adapting gamification features to meet player preferences to address the problems and difficulties with the traditional gamification approach previously discussed in Chapter 2. Based on the proposed framework, this strategy is proposed. The basic idea behind the proposed strategy is to predict gamification components for particular user types based on user profiles to meet user preferences and, as a result, increase user motivation.

More details about the proposed strategy will be covered in the sections of this chapter that follow.

3.2 The Proposed Strategy

The core idea behind the proposed strategy is to predict gamification components for specific user groups based on user profiles to satisfy user preferences and, as a result, keep users' engagement and motivation when using gamified e-learning platforms.

The main components of the proposed strategy are inputs, outputs, and processes. Each participant has affinity vectors toward the user type in matrix B, and each user type has affinity vectors toward gamification elements in matrix A. The matrix factorization methodology is used to multiply the two matrices to generate matrix R, which contains the affinity vectors for each participant toward the gamification feature. The output matrix will indicate each participant's preferred gamification element based on the high score of the given component, among other features. **Figure 3.2** depicts the essential aspects of the proposed strategy.

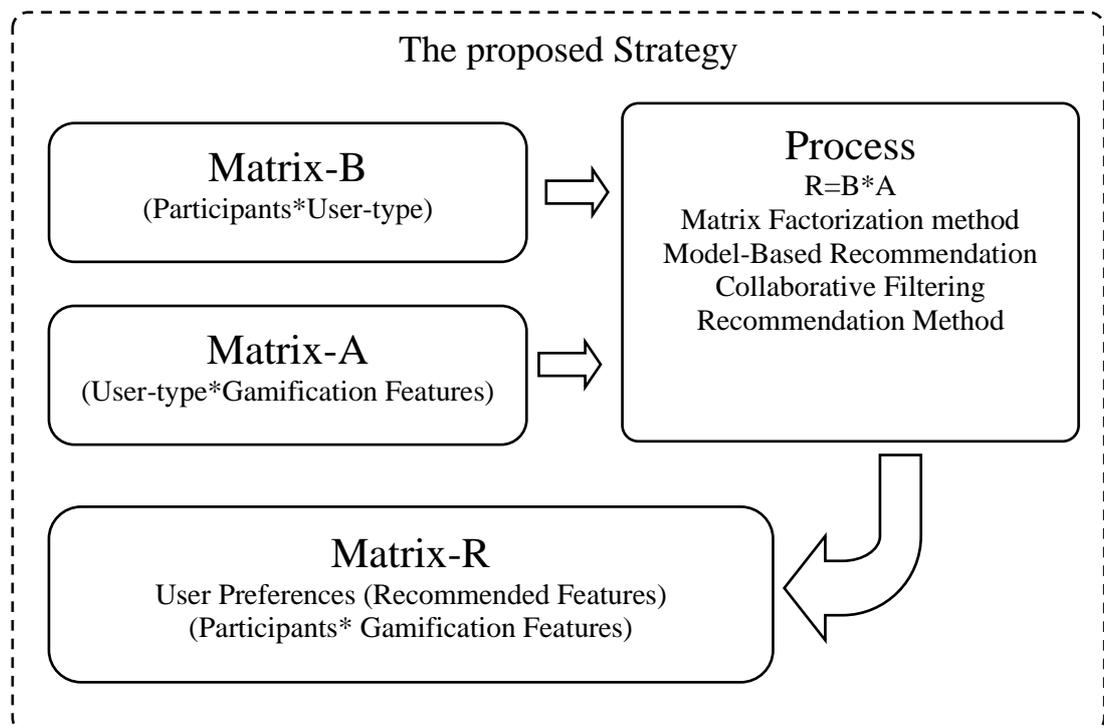


Figure 3.2: The Block Diagram of the Proposed Strategy

The proposed strategy uses a matrix factorization method based on the formula $R=B*A$, which means that any gamification element adaptive for the player is represented in matrix R and is formed by multiplying matrices B and A. Whereas matrix A represents the adaptive matrix, i.e., the weight of the degree of belonging between features and specific player categories, matrix B represents the user profile, with each user assigning a value based on their characteristics.

3.3 The Proposed Strategy Development Steps

There are various processes involved in creating the proposed strategy. The initial stage is to generate matrix B with the help of a specialized questionnaire. The second stage is to construct matrix A with the help of specialists. The third step is multiplying the two matrices (matrix B and matrix A) using the matrix factorization method based on the formula $R=B*A$. The resulting matrix (matrix R) represents the user preferences of participants regarding gamification elements. These steps are covered in the subsections that follow.

3.3.1 Matrix B Initialization

The participants' profile matrix for the gamified platform is shown in Matrix B. In order to create matrix B, the participant group's user-type model was defined using the Hexad questionnaire. For this proposed strategy, the Hexad model was chosen as the user-type model for a number of reasons, including its empirical validation and relationship to motivation theory.

3.3.1.1 Identify the Predominant User Type

Because each group has its own personality and motivation, the types of players are crucial when building adaptive gamification platforms.

Before using the gamified e-learning platform, participants must complete a Hexad questionnaire to determine the predominant user type.

Users (participants) are asked to rate how well each item represents them on a 7-point Likert scale in response to the Hexad user-type scale questionnaire. **Appendix A** contains the sample questionnaire. The questionnaire is divided into six subscales based on Hexad's six user types; each includes four questions.

Each user receives a vector of six values representing the six player types in the hexad model. These scores indicate how well the user matches each of the six-player types, ranging from 0 to 1. For example, if a user scores 60% player, 30% achiever, 40% socializer, 30% free spirit, 20% philanthropist, and 0% disruptor, encode the vector as follows: [0.6, 0.3, 0.4, 0.3, 0.2, 0.0]. Matrix-B structure is shown in **Table 3.1**.

Table 3.1: Matrix-B (Profile Matrix)

<i>Users</i>	P1 Player	P2 Achiever	P3 Socializer	P4 Free Spirit	P5 Philanthropist	P6 Disruptor
User 1						
User 2						
...						
User n						

3.3.1.2 Sample of Participants

Participants are fifth-stage secondary school students from Babylon's general directorate for education's Al-Waely secondary school for distinguished males. Students who wanted to participate in the experiment were sent a link to the questionnaire via social media and asked to complete the hexad-scale questionnaire.

100 of the 140 students who were in the fifth stage are included in this sample. Each of the six main player types had four pertinent questions in the Arabic translation of the Hexad questionnaire, which had 24 total items. The responses to the questionnaire were used to create matrix B,

which shows the participant's affinity vectors for each of the six user types in the Hexad model. The results of each participant's evaluations reveal the most relevant user type.

3.3.2 Initialize Matrix-A

To construct matrix-A, gamification experts and academics were requested to evaluate each component with the appropriate player type for each of the six hexad model types. The values show how each player type relates to the game feature. The affinity vector in the adaptive matrix (matrix-A) for each gamification feature is a set of scores that indicate how well matched each of the six learner types in the Hexad model is to that feature. The construction of the adaptive matrix is shown in **Table 3.2**. The values in matrix A show the degree to which game features are appropriate for specific player types.

Table 3.2: Matrix-A (Experts' Matrix)

Player model	leaderboard	Badge	Points	Competition	Customization	Challenge
Player						
Achiever						
Socializer						
Free Spirit						
Philanthropist						
Disruptor						

The components in matrix A are distributed from 0 to 1, and matrix R's elements have a similar magnitude to matrix B's. In this instance, 0 means no match, 0.25 means moderate matching, 0.5 indicates medium matching, and 0.75 indicates good matching. Finally, 1 shows robust matching. The median will be used for each of the six-player types to ensure the accuracy of the experts' assessments.

3.3.3 Generate Matrix R

Matrix-R is created by multiplying Matrix-B by Matrix-A using a **Python script**. The resulting matrix (matrix R) determines learners' preferences for each gamification feature based on the equation $R=B*A$. In other words, the preference matrix (matrix R) is created by combining the profile matrix (matrix B) and the expert matrix (matrix A). **Table 3.3** displays the matrix of results (matrix R).

Table 3.3: Matrix R (Result Matrix)

Users	leaderboard	Badge	Points	Competition	Customization	Challenge
User 1						
User 2						
.						
User n						

3.3.3.1 Matrix-R Calculation (25 Participants)

The Python script (**Appendix-B**) was used to obtain matrix-R (`RMatrix.csv`) by multiplying matrices matrix-B (`BMatrix.csv`) and matrix-A (`AMatrix.csv`). The Python script uses the Pandas and Numpy libraries to execute operations on data stored in CSV files. The block diagram shown in **Figure 3.3** provides a more detailed illustration of how to generate Matrix-R (`RMatrix.csv`) using Python code.

The Python approach begins by installing the required libraries, namely `Pandas` and `NumPy`, and setting up particular display configurations. Then, information from the `BMatrix.csv` and `AMatrix.csv` files is loaded into the main memory. While the `AMatrix` describes how each user type relates to various gamification features, the `BMatrix` offers user-specific scores that show each user's affinities toward different user types.

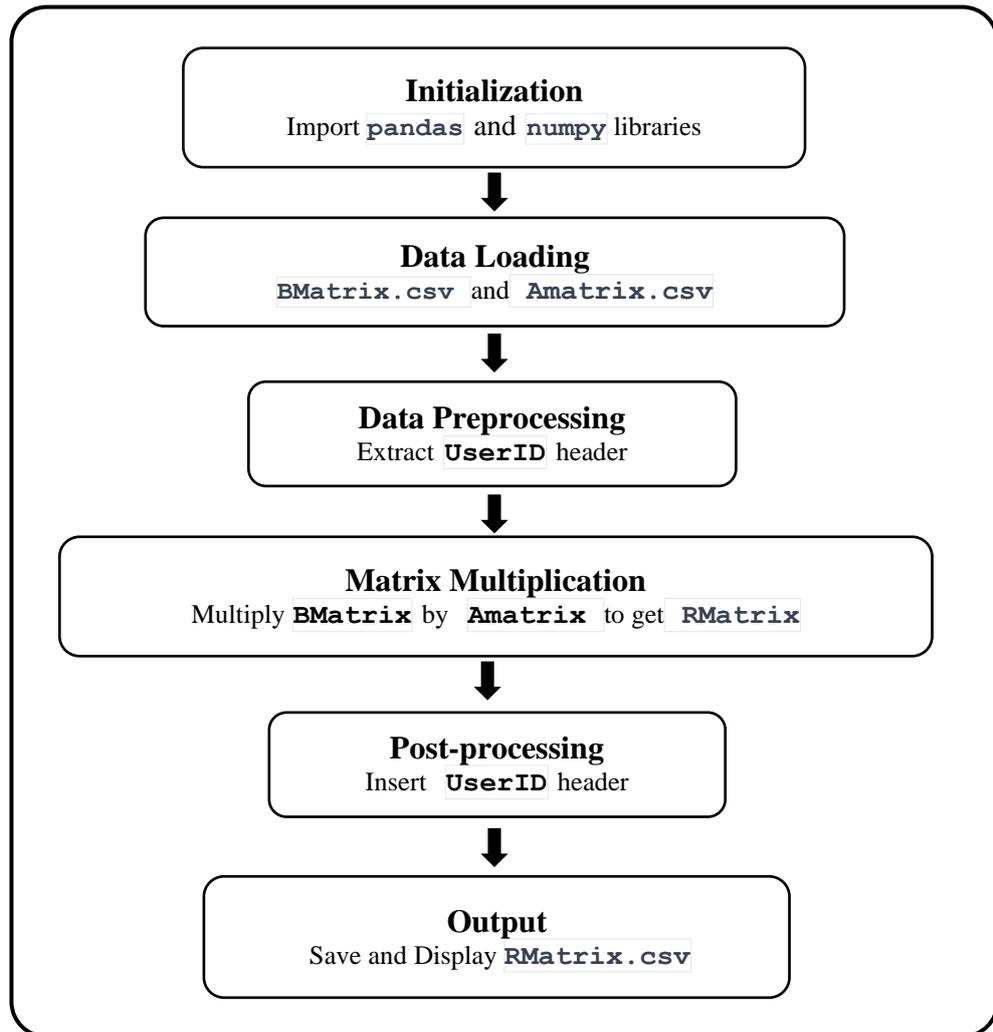


Figure 3.3: A Block Diagram of Matrix-R (`RMatrix.csv`) Generation Using Python Code

After that, the approach passes through a preparation stage where unnecessary columns like "`UserID`" and "`UserType`" are momentarily omitted to aid matrix multiplication. The `NumPy` library transforms the matrices into a format that can be multiplied after production. To create the resultant matrix, `RMatrix`, the processed `BMatrix` (which reflects users and their scores across user types) is multiplied by the `Amatrix` (indicating user type affinities toward gamification features). This matrix effectively sheds light on which gamification elements suit each user. Post-processing stages return the "`UserID`" column for context after the multiplication. Finally, the output matrix is shown for instant viewing and saved to a new file called `RMatrix.csv`.

3.3.3.2 Algorithm of Matrix-R (`RMatrix.csv`) Generation Using Python Code.

1. Initialization:

- Import required libraries: `pandas` and `numpy`.
- Configure pandas display settings to:
- Display all columns and rows.
- Disable wrapping for enhanced readability.

2. Data Loading:

- Load data from `BMatrix.csv` into the dataframe `BMatrix`.
- Load data from `AMatrix.csv` into the dataframe `AMatrix`.

3. Data Preprocessing:

- Extract the column headers for both matrices and store them in `BHeaders` and `AHeaders`.
- Store the `UserID` column from `BMatrix` in a separate variable for later use.
- Remove the `UserID` column from `BMatrix`.
- Ensure that only the columns present in `AHeaders` are used from `AMatrix` (i.e., remove the 'UserType' column).
- Convert both `BMatrix` and `AMatrix` dataframes to `numpy` arrays.

4. Matrix Multiplication:

- Multiply the `numpy` arrays of `BMatrix` and `AMatrix` using the dot product to obtain the resultant matrix, `RMatrix`.

5. Post-processing:

- Convert the `numpy` array `RMatrix` to `pandas dataframe` with columns from `AHeaders`.
- Insert the previously stored `UserID` column back at the beginning of the `RMatrix dataframe`.

6. Output:

- Save the `RMatrix dataframe` to a CSV file named `RMatrix.csv`.
- Display the `RMatrix dataframe` for visualization.

3.4 The Proposed Strategy Test.

The proposed strategy and the effect of the tailored gamification process on learner motivation and enjoyment should be tested through an experiment including participants. A gamified e-learning platform was implemented to adapt gamification features according to user preferences and assess the proposed strategy. The gamification features utilized were derived from the outputs of the proposed strategy and were selected based on their relevance to the predominant user type within the participant group. Using the EdApp platform as a gamified learning management system, gamification features obtained from the proposed strategy's outputs are adaptive to suit the preferences of the participants' most common user types. The following subsection will cover more details on the EdApp platform.

3.4.1. EdApp Platform

This dissertation contributes to adopting a platform for evaluating the proposed strategy. EdApp is used in this dissertation as a gamified e-learning management system. The experiment involves students assessing the proposed strategy by analyzing the influence of the personalized gamification process on learner motivation and enjoyment.

The gamification features that have been selected align with the strategy's outputs, which meet learners' primary needs and users' preferences as determined by SDT theory. These features are derived from effective designs identified through a comprehensive literature assessment in e-learning environments.

The gamified e-learning platform (EdApp) has been used to build three courses, namely a **traditional e-learning course**, a **traditional gamification course**, and an **adaptive gamification course**, to examine how each influences the learners' motivation and commitment.

3.4.2. Target Sample:

The target sample comprises fifth graders at Al-Waely Secondary School for Distinctive Boys, one of the public schools managed by Babylon's General Directorate of Education. The participants are emailed the password and link to the EdApp application.

After experimenting with a real-world setting for several weeks to determine user motivation, the data is analyzed using a **gamification analysis** tool to analyze how much time students spent in each course and, as a result, to gauge their commitment and engagement.

3.4.3. Data Analysis

The "**Gamification Analytics**" tool is an alternative to the conventional method, which employs a statistical approach to assess participants' motivation. The EdApp program has a **built-in gamification analytics tool** that monitors player actions and behavior during the experiment. The "Gamification Analytics" tool calculates how much time each user spends on each activity or task and how many times they repeat it.

Chapter 4 : Experimental Results

4.1. Introduction:

This chapter covers how the proposed strategy is executed and how its outcomes are assessed in a real-world experimental context. The contributions that resulted in the dissertation's aims being met will be explored.

4.2. Implementing the Proposed Strategy

The proposed strategy must be used in a pilot study with a small sample and in the actual study with a large sample to increase research quality and minimize methodology faults. The outcomes of the two samples were then compared to establish the reliability of our research. Various analysis methods were used to increase the quality of our research. The following sections of this chapter discuss the pilot and actual studies.

4.2.1 Pilot Study (25 Participants)

A pilot study was conducted with a limited sample of participants (25 students) to determine our study's feasibility and reliability and avoid methodological flaws.

4.2.1.1 Questionnaire Reliability (25 Participants)

When a scale is reliable, it produces the same findings when used on the same sample again. Validity is the quality of the scale measuring what it is intended to measure.

The Arabic version of the Hexad electronic User Type Scale questionnaire (**Appendix-A**) was distributed to 25 participants to evaluate the experiment instrument's reliability. The data collected from the electronic

survey was transformed into a format compatible with the Statistical Package for the Social Sciences (SPSS) software.

A pilot sample of 25 students was chosen using Cronbach's alpha reliability analysis. It was advised that this value should be at least 0.7 to validate the study's reliability and apply it to the entire population. With a Cronbach's alpha of 0.828, the questionnaire's reliability was acceptable. The SPSS analysis's findings are displayed in **Table 4.1**. There were just male participants. All of the participants ranged in age from 16 to 20.

Table 4.1: Reliability Statistics by SPSS

Cronbach's Alpha	No. of Items
0.828	24

4.2.1.2 Matrix-B Initializing (25 Participants-First Method):

Matrix-B was initialized by dividing each user type's "mean" value by 7 for each participant because a seven-scale is used. This process assigns each user a normalized affinity value between 0 and 1. The matrix-B in **Table 4.2** shows each participant's affinity vector toward the corresponding user types.

Table 4.2 : Matrix-B Initializing (First Method)

Users	Achiever	Player	Socializer	Philanthropist	Free Spirit	Disruptor
User 1	0.89	1.00	1.00	0.89	0.68	0.32
User 2	1.00	0.79	1.00	0.93	0.79	0.36
User 3	0.86	0.96	0.93	0.86	0.68	0.36
User 4	0.82	0.93	0.89	0.89	0.79	0.29
User 5	0.86	0.93	0.93	0.86	0.79	0.32
User 6	0.93	0.96	0.79	0.93	0.89	0.29
User 7	0.93	0.96	0.93	0.79	0.82	0.32
User 8	1.00	0.89	0.57	0.68	0.79	0.36

User 9	0.82	1.00	0.68	0.71	0.86	0.36
User 10	1.00	0.82	0.75	0.75	0.75	0.39
User 11	1.00	0.79	0.68	0.82	0.82	0.36
User 12	0.96	0.96	0.82	0.82	0.86	0.36
User 13	1.00	0.96	0.93	0.79	0.75	0.29
User 14	0.82	0.93	0.75	0.79	0.79	0.36
User 15	0.93	0.89	0.82	0.82	0.82	0.36
User 16	0.96	0.86	0.82	0.93	0.86	0.32
User 17	1.00	0.96	0.86	0.86	0.89	0.32
User 18	0.89	0.93	0.86	0.82	0.86	0.36
User 19	1.00	0.93	0.82	0.75	0.79	0.36
User 20	0.96	0.93	1.00	0.89	0.71	0.32
User 21	0.86	1.00	0.68	0.79	0.93	0.36
User 22	0.96	1.00	0.93	0.79	0.82	0.36
User 23	1.00	0.82	0.93	0.89	0.79	0.29
User 24	1.00	0.89	0.96	0.86	0.96	0.36
User 25	1.00	0.96	0.93	0.79	0.89	0.32
Mean Scores	0.94	0.92	0.85	0.83	0.82	0.34
Percent%	20%	20%	18%	18%	17%	7%

4.2.1.3 Predominant User Type Identification (25 Participants-First Method)

Each type's "mean scores" reflect the most predominant user type. To determine the most predominant user type among participants, the "mean scores" should be collected for each user type among all participants. The "mean scores" are obtained by adding the affinity scores for each user type and dividing by the total number of participants.

Each user type's percentage distribution tells which type is the most predominant. Two processes must be undertaken to calculate the percentage distribution of each user type according to the Hexad model among the participants.

The initial step involves computing the mean scores for each user type across the entire sample. Subsequently, the mean scores are determined by aggregating the affinity scores for each user type and dividing them by the total number of participants.

In order to determine the predominant user type, Table 4.3 shows the mean scores for each user type. The last step involves dividing each final "mean score" from the previous stage by the total of the mean scores for each of the six user groups, and then multiplying the result by 100.

Table 4.3: Predominant User Types (First Method) $S=25$

User type	N	Mean Value	percent
Achiever	25	0.94	20%
Player	25	0.92	20%
Socializer	25	0.85	18%
Philanthropist	25	0.83	18%
Free Spirit	25	0.82	17%
Disruptor	25	0.34	7%

Figure 4.1 illustrates the percent distribution for each user type in the Hexad model to more clearly highlight which user type is the most predominant.

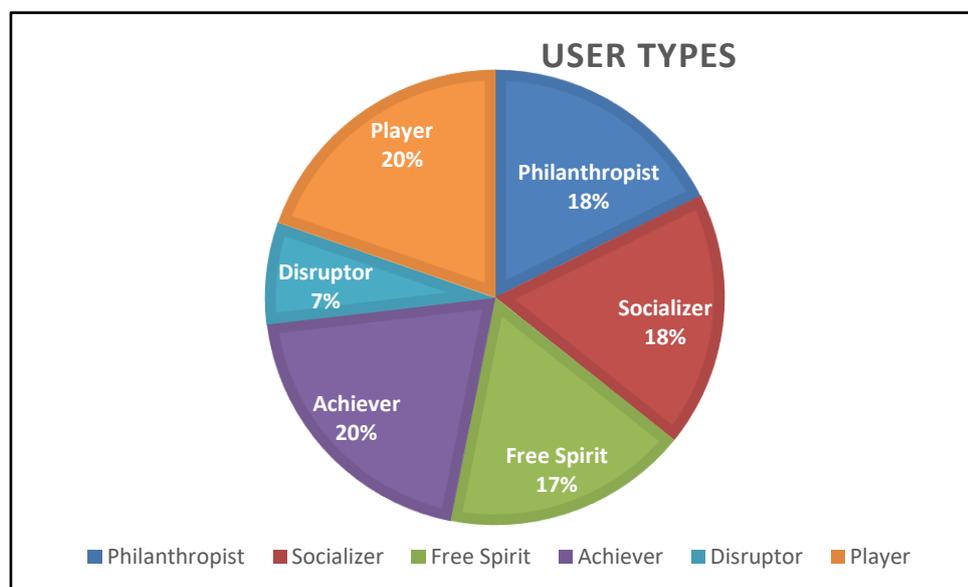


Figure 4.1: The Participants' Hexad User Type Distribution (25 Participants)

The highest percentage was for "player," with 20% of the total sample, and "achiever," with 20% of the whole sample, followed by "socializer," with 18% of the entire sample, "philanthropist," with 18% of the total sample, and "free spirit," with 17% of the whole sample. "Disrupter" had a lower percentage and was less representative (7%).

4.2.1.4 Matrix-B Initializing (25 Participants-Second Method)

A different analytic approach was adopted to initialize matrix B to improve our research's quality. The sum of the four responses for each user type should be computed because each type is represented by four statements on a 7-point Likert scale in the Hexad questionnaire. The result will have a minimum value of 4 and a maximum value of 28 when matrix-B is initialized.

As indicated in **Table 4.4**, the scores of each participant's affinity vector toward each user type indicate how much that participant fits within that Hexad user type.

Table 4.4: Matrix-B Initializing (Second Method)

Users	Achiever	Player	Socializer	Philanthropist	Free Spirit	Disruptor
User 1	25	28	28	25	19	9
User 2	28	22	28	26	22	10
User 3	24	27	26	24	19	10
User 4	23	26	25	25	22	8
User 5	24	26	26	24	22	9
User 6	26	27	22	26	25	8
User 7	26	27	26	22	23	9
User 8	28	25	16	19	22	10
User 9	23	28	19	20	24	10
User 10	28	23	21	21	21	11
User 11	28	22	19	23	23	10
User 12	27	27	23	23	24	10

User 13	28	27	26	22	21	8
User 14	23	26	21	22	22	10
User 15	26	25	23	23	23	10
User 16	27	24	23	26	24	9
User 17	28	27	24	24	25	9
User 18	25	26	24	23	24	10
User 19	28	26	23	21	22	10
User 20	27	26	28	25	20	9
User 21	24	28	19	22	26	10
User 22	27	28	26	22	23	10
User 23	28	23	26	25	22	8
User 24	28	25	27	24	27	10
User 25	28	27	26	22	25	9
Mean score	26.28	25.84	23.80	23.16	22.80	9.44
Percent%	20%	20%	18%	18%	17%	7%

4.2.1.5 Predominant User Type Identification (25 Participants-Second

Method):

Another analytical procedure that was used was determining the most common user types and the percentage distribution of each type among participants in the Hexad model. A variety of analysis methodologies were used to improve the quality of our research, including analysis tools such as SPSS and Microsoft Excel.

The mean of all participants' affinity scores for each Hexad user type must be computed to determine the predominant user type. To get the percent distribution for each Hexad user type, divide each mean score by the sum of all six mean scores, then multiply by 100.

The pilot sample participants received mean scores ranging from 4 to 28 using four statements on a 7-point Likert scale from 1 to 7 to assess user types. The mean score for each user type indicates how well each participant fits that user type.

The user types "Achiever" and "player" had the highest mean

scores, as demonstrated in **Table 4.5**. As a result, "Achiever" and "Player" user types are the most common, followed by "socializer," "philanthropist," and "free spirit," with "disrupter" user types coming in last.

Table 4.5: Predominant User Types (Second Method), S=25

User type	N	Mean Value	percent
Achiever	25	26.28	20%
Player	25	25.84	20%
Socializer	25	23.80	18%
Philanthropist	25	23.16	18%
Free Spirit	25	22.80	17%
Disruptor	25	9.44	7%

4.2.1.6 Prime User Types Identification (25 Participants)

The user type with the highest score for a participant is considered the prime user type. If two or more different user types received similar ratings, some individuals may have had more than one prime user type. The participant's prime user type is determined by the type for which they received the most significant score.

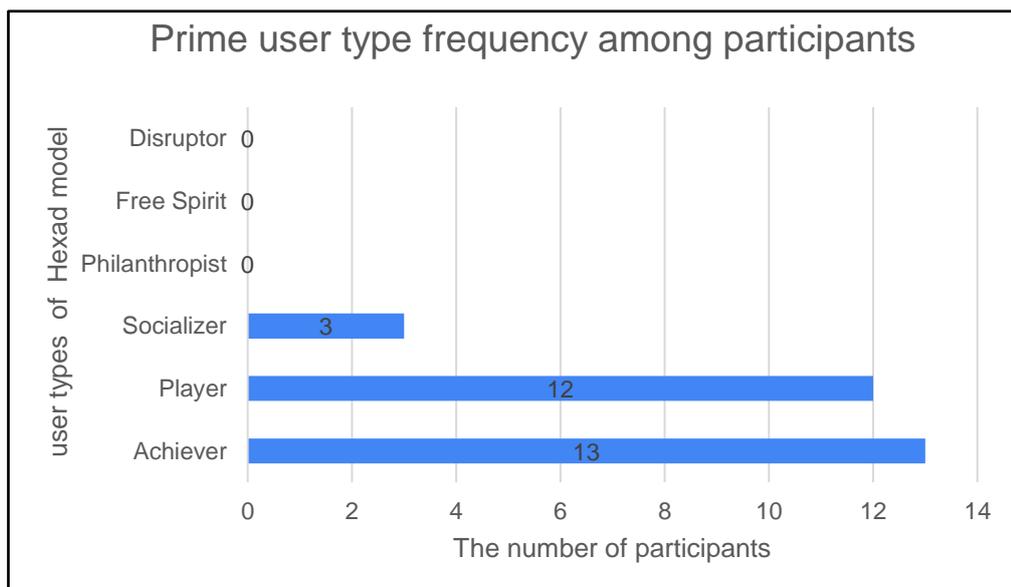


Figure 4.2: Participants' Prime User Type Frequency (25 Participants).

As shown in **Figure 4.2**, the analysis of all participant data revealed that the "Achiever" user type is the prime user type (the count of participants counted is 13), followed by the "Player" user type (the count of participants counted is 12), and the "Socializer" user type (the count of participants counted is 3), respectively. In contrast, "disruptor," "free spirit," and "philanthropist" were not present as the prime user type.

4.2.1.7 Matrix-A Estimating

The experts identified the game features most suitable for each type of player by asking them to rate each gamification element with the right player type for each of the six Hexad model player types. To gauge the level of inter-rater agreement, the intraclass correlation (ICC) function was utilized in the SPSS program. The calculated result of 0.73 is considered strong enough to support the raters' agreement.

For every score in matrix-A that the experts assessed, the median of these suggested ratings was determined. In order to prevent the consequences of high or low values, as some experts may have suggested, the median was used rather than the mean. The values in matrix A illustrate how well various player types are matched by the game's components. Matrix-A findings are shown in **Table 4.6**.

Table 4.6: Matrix-A (Experts' Rating Scores), Pilot Study

User types	leaderboard	Badge	Points	Competition	Customization	Challenge
Achiever	0.5	1	1	0.75	0.5	1
Player	0.75	1	1	1	0.25	1
Socializer	0.3	0.25	0.25	0.3	0.5	0.25
Philanthropist	0.25	0.25	0.25	0	0.5	0.25
Free Spirit	0	0.25	0	0.25	1	0.25
Disruptor	0.25	0	0	0.3	0.75	0.5

4.2.1.8 Matrix-R Calculation (25 Participants)

The matrix-R is created by multiplying matrix-B by matrix-A according to the formula $R=B*A$. The Matrix-R, or results matrix, displays user preferences for gamification components. The proposed strategy is based on a matrix factorization model with the relationship $R=B*A$, where matrix-B denotes the predominant user types for each participant and matrix-A depicts how gamification elements connect to different user types. According to the highest score obtained, the matrix-R results show user preferences for various gamification elements, as illustrated in **Table 4.7**.

Table 4.7: Matrix-R Calculation (25 Participants)

Users	leaderboard	Badge	Points	Competition	Customization	Challenge
User 1	1.798	2.533	2.363	2.234	2.560	2.693
User 2	1.715	2.470	2.273	2.146	2.723	2.650
User3	1.734	2.437	2.267	2.162	2.515	2.617
User 5	1.669	2.393	2.195	2.097	2.540	2.538
User 6	1.702	2.435	2.238	2.148	2.588	2.595
User 7	1.727	2.543	2.320	2.204	2.673	2.688
User 8	1.742	2.525	2.320	2.238	2.625	2.685
User 9	1.599	2.400	2.203	2.117	2.408	2.580
User 10	1.632	2.382	2.167	2.142	2.485	2.562
User 11	1.625	2.383	2.195	2.100	2.498	2.577
User 12	1.592	2.370	2.165	2.057	2.538	2.550
User 13	1.741	2.545	2.330	2.249	2.670	2.725
User 14	1.769	2.577	2.390	2.264	2.568	2.722
User 15	1.620	2.332	2.135	2.076	2.473	2.512
User 16	1.674	2.435	2.230	2.147	2.597	2.615
User 17	1.684	2.472	2.258	2.137	2.670	2.633
User 18	1.773	2.613	2.390	2.287	2.730	2.773
User 19	1.696	2.455	2.240	2.179	2.648	2.635

User 20	1.721	2.520	2.323	2.232	2.578	2.700
User 21	1.780	2.540	2.363	2.224	2.608	2.700
User 22	1.672	2.460	2.228	2.190	2.615	2.640
User 23	1.797	2.595	2.390	2.312	2.680	2.775
User 24	1.689	2.473	2.275	2.134	2.623	2.618
User 25	1.761	2.585	2.345	2.276	2.863	2.765
Mean	1.70	2.48	2.28	2.19	2.61	2.65

4.2.1.9 Determining the Preferred Gamification Features:

The preferred gamification elements are identified by computing "mean" scores by aggregating each component's affinity ratings and dividing by the total number of participants, with the highest rating being the most relevant. To calculate the percentage distribution of gamification features, divide each "mean" score by the total of six "mean" scores, which is then multiplied by 100.

Table 4.8 reveals that the "challenges" gamification feature (mean score = 2.65) and the "customization" gamification feature (mean score = 2.61) are the most popular gamification features among each user category. These features were followed by the "badge" gamification feature (mean score = 2.48), the "points" gamification feature (mean score = 2.28), and the "competition" gamification feature (mean score = 2.19), with the "leaderboard" gamification feature being the least gamified (mean score = 1.70).

Table 4.8: Preferred Features of Gamification, Pilot Study

User types	mean	percent
Challenge	2.65	19.1%
Customization	2.61	18.8%
Badge	2.48	17.8%
Points	2.28	16.4%
Competition	2.19	15.7%
leaderboard	1.70	12.2%

Figure 4.3 provides a detailed explanation of these findings, demonstrating that gamification's "Challenges" and "customization" components are the most used. Following these components are, in order, "badge," "points," "competition," and "leaderboard."

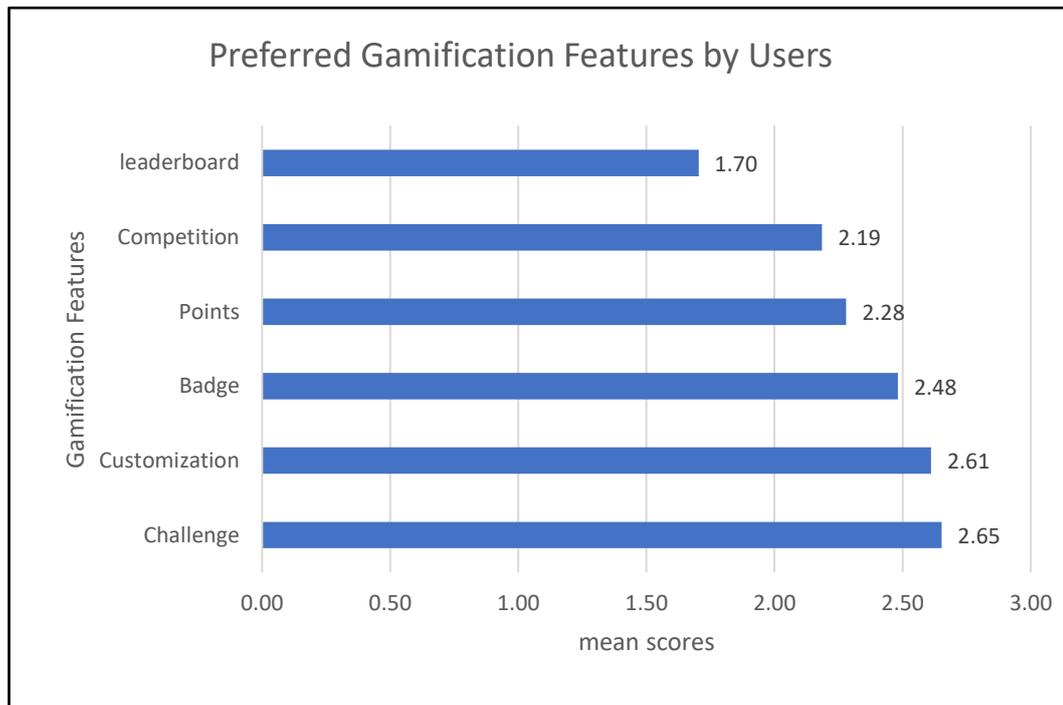


Figure 4.3: Preferred Gamification Features by Participants (25 Participants).

4.2.2 Actual Study (100 participants)

The actual study is carried out on the participants (100 students) to implement the proposed strategy and identify the predominant user types and the features of gamification that they prefer. The method for implementation will be covered in the following parts.

4.2.2.1 Questionnaire Reliability (100 Participants)

When a scale shows reliability, it consistently yields identical outcomes with each successive usage. The validity of a scale refers to its ability to accurately measure the concept or phenomenon it is intended to examine. Cronbach's alpha reliability study on the sample was used to demonstrate the instrument's reliability. The Arabic version of the Hexad

electronic User Type Scale questionnaire was distributed to 100 participants (**Appendix A**). The data collected via the electronic questionnaire was encoded to be compatible with SPSS software. The questionnaire's reliability was adequate, with a Cronbach's alpha of 0.812. **Table 4.9** lists the outcomes of the SPSS analysis. There were only male students among the participants. The participants ranged in age from 16 to 20.

Table 4.9: Reliability Statistics by SPSS, Actual study

Cronbach's Alpha	Number of Items
0.812	24

4.2.2.2 Matrix-B Initializing (100 Participants-First Method):

The Hexad electronic user type scale questionnaire (**Appendix-A**), suggested by Tondello et al., was implemented to initialize matrix-B.

The analysis of the Hexad questionnaire data helps to determine the most predominant user types, the prime user types for each participant, and which gamification features participants prefer based on their predominant user type.

The Hexad questionnaire has 24 statements designed to identify the predominant user type of participants. The Hexad model assigns four statements to each kind of user. Participants respond to each item on a Likert scale of 1 to 7, where 1 represents the most minor possible answer and 7 is the most significant possible response. The "mean" value for each user type for each participant is divided by seven because a 7-Likert scale is used. This process gives Each user a normalized affinity value between 0 and 1. As shown in **Table 4.10**, matrix B illustrates the affinity vector of each participant towards the relevant user type.

Table 4.10: Matrix-B initializing first method for actual sample (100 students)

Users	Achiever	Player	Socializer	Philanthropist	Free Spirit	Disruptor
User1	0.89	1.00	0.89	0.86	0.64	0.32
user2	1.00	0.79	0.86	0.79	0.71	0.36
User3	0.86	0.96	0.89	0.79	0.68	0.36
User4	0.86	0.93	0.86	0.82	0.75	0.29
User5	0.86	0.93	0.86	0.82	0.71	0.32
User6	0.93	0.96	0.79	0.79	0.79	0.46
User7	0.93	0.96	0.86	0.79	0.79	0.32
User8	1.00	0.89	0.64	0.68	0.64	0.36
User9	0.82	1.00	0.68	0.71	0.82	0.36
User10	1.00	0.86	0.79	0.71	0.68	0.39
User11	1.00	0.86	0.75	0.82	0.79	0.36
User12	0.96	0.96	0.86	0.75	0.75	0.36
User13	1.00	0.96	0.89	0.79	0.75	0.29
User14	0.82	0.93	0.82	0.75	0.68	0.36
User15	0.93	0.89	0.75	0.82	0.75	0.36
User16	0.96	0.86	0.82	0.79	0.82	0.32
User17	1.00	0.96	0.86	0.79	0.75	0.32
User18	0.89	0.93	0.82	0.79	0.79	0.36
User19	1.00	0.93	0.82	0.75	0.64	0.36
User20	0.96	0.93	0.89	0.86	0.64	0.32
User21	0.93	1.00	0.71	0.79	0.79	0.36
User22	0.96	1.00	0.86	0.75	0.79	0.36
User23	1.00	0.82	0.93	0.86	0.75	0.29
User24	1.00	0.89	0.89	0.79	0.75	0.36
User25	1.00	0.96	0.89	0.79	0.79	0.32
User26	0.96	1.00	0.89	0.86	0.75	0.50
User27	0.89	0.79	0.82	0.68	0.64	0.39
User28	0.79	0.79	0.71	0.75	0.75	0.54
User29	0.71	0.89	0.71	0.82	0.79	0.50
User30	0.96	1.00	0.79	0.86	0.75	0.36
User31	0.96	0.82	0.86	0.86	0.71	0.46

User32	0.93	0.93	0.79	0.82	0.71	0.39
User33	0.93	0.75	0.75	0.79	0.79	0.57
User34	0.93	0.89	0.89	0.79	0.79	0.46
User35	0.93	0.79	0.89	0.82	0.68	0.54
User36	0.89	0.79	0.89	0.79	0.71	0.46
User37	0.79	0.89	0.86	0.71	0.68	0.57
User38	0.96	0.96	0.89	0.86	0.79	0.43
User39	0.93	1.00	0.82	0.82	0.71	0.54
User40	0.96	1.00	0.82	0.82	0.68	0.54
User41	0.82	0.86	0.71	0.75	0.71	0.50
User42	0.96	0.79	0.68	0.79	0.79	0.29
User43	0.93	0.96	0.89	0.79	0.68	0.50
User44	0.82	0.86	0.71	0.82	0.75	0.57
User45	0.82	0.93	0.82	0.79	0.71	0.46
User46	0.96	0.93	0.82	0.79	0.68	0.46
User47	0.93	0.79	0.79	0.82	0.79	0.32
User48	0.82	0.96	0.82	0.75	0.79	0.46
User49	0.86	0.86	0.82	0.79	0.68	0.18
User50	0.93	0.71	0.79	0.82	0.79	0.36
User51	0.93	1.00	0.89	0.79	0.68	0.32
User52	1.00	0.82	0.93	0.86	0.71	0.36
User53	0.86	0.96	0.86	0.75	0.68	0.36
User54	0.86	0.93	0.86	0.82	0.75	0.46
User55	0.86	0.93	0.86	0.86	0.75	0.32
User56	0.93	0.96	0.79	0.89	0.82	0.29
User57	0.93	0.96	0.89	0.79	0.79	0.32
User58	1.00	0.89	0.64	0.68	0.75	0.36
User59	0.82	1.00	0.68	0.71	0.82	0.36
User60	1.00	0.82	0.79	0.71	0.68	0.39
User61	0.96	1.00	0.79	0.82	0.79	0.36
User62	0.96	0.82	0.86	0.79	0.68	0.25
User63	0.93	0.93	0.79	0.79	0.71	0.39
User64	0.93	0.71	0.75	0.82	0.79	0.57
User65	0.93	0.89	0.86	0.79	0.75	0.46
User66	0.93	0.79	0.89	0.79	0.71	0.54
User67	0.89	0.82	0.86	0.79	0.75	0.46
User68	0.79	0.89	0.82	0.71	0.71	0.57

User69	0.96	0.96	0.79	0.86	0.79	0.43
User70	0.93	1.00	0.79	0.79	0.86	0.54
User71	0.96	1.00	0.82	0.82	0.71	0.54
User72	0.93	0.96	0.89	0.79	0.75	0.32
User73	1.00	0.89	0.64	0.68	0.75	0.36
User74	0.82	1.00	0.68	0.71	0.82	0.36
User75	1.00	0.86	0.79	0.71	0.64	0.39
User76	1.00	0.82	0.75	0.79	0.75	0.36
User77	0.96	0.96	0.82	0.75	0.79	0.36
User78	1.00	0.96	0.86	0.71	0.71	0.46
User79	0.82	0.93	0.82	0.75	0.71	0.36
User80	0.93	0.89	0.79	0.79	0.79	0.36
User81	0.96	0.86	0.75	0.82	0.75	0.32
User82	1.00	0.96	0.86	0.79	0.82	0.32
User83	0.86	0.93	0.82	0.75	0.75	0.36
User84	0.93	0.89	0.79	0.75	0.79	0.36
User85	0.96	0.89	0.82	0.79	0.79	0.32
User86	1.00	0.96	0.82	0.79	0.79	0.32
User87	0.89	0.93	0.82	0.75	0.75	0.36
User88	1.00	0.93	0.79	0.71	0.71	0.36
User89	0.96	0.93	0.86	0.86	0.64	0.32
User90	0.93	1.00	0.71	0.71	0.86	0.36
User91	0.82	0.93	0.79	0.75	0.79	0.46
User92	0.86	0.89	0.82	0.79	0.68	0.46
User93	0.93	0.79	0.79	0.82	0.79	0.36
User94	0.89	1.00	0.82	0.86	0.68	0.32
User95	1.00	0.82	0.89	0.86	0.71	0.36
User96	0.86	0.96	0.86	0.79	0.68	0.36
User97	0.82	0.93	0.86	0.82	0.79	0.46
User98	0.86	0.93	0.86	0.82	0.75	0.32
User99	0.93	0.96	0.75	0.75	0.75	0.29
User100	0.93	0.96	0.79	0.79	0.79	0.32
Mean	0.92	0.91	0.81	0.79	0.74	0.39
Percent%	20%	20%	18%	17%	16%	9%

4.2.2.3 *Predominant User Type Identification (100 Participants-First Method)*

The "mean" ratings for each user type indicate which user type is the most predominant. The "mean" scores are calculated by summing the affinity ratings for each type of user and dividing them by the entire number of participants. The percentage distribution of each user type indicates the most predominant user type. The "mean" values for each type reveal the dominant user type.

Two steps are required to determine the **percentage distribution** of each Hexad model user type among participants. In the first step, the affinity scores are added and then divided by the total number of participants to determine each user type's "mean" scores across the whole sample. The second step involves multiplying the final "mean" score from the first step for each user type by 100 after dividing it by the sum of the "mean" scores for each of the six user types.

Table 4.11: Predominant User Types (First Method) S=100

User type	N	Mean Value	percent
Achiever	100	0.92	20%
Player	100	0.91	20%
Socializer	100	0.81	18%
Philanthropist	100	0.79	17%
Free Spirit	100	0.74	16%
Disruptor	100	0.39	9%

Table 4.11 illustrates the percent distribution for each user type in the Hexad model to more clearly highlight which user type is the most predominant. The highest percentage was for "**player**," with 20% of the total sample, and "**achiever**," with 20% of the entire sample, followed by "*socializer*," with 18% of the whole sample, "**philanthropist**," with 17% of the total sample, and "**free spirit**," with 16% of the whole sample. "**Disrupter**" had a lower percentage and was less representative (9%).

4.2.2.4 Matrix-B Initializing (100 Participants -Second Method):

A different analytic method was adopted to initialize matrix B to improve the quality of this research. Each user type in the Hexad questionnaire is represented by four statements on a 7-point Likert scale, so the sum of the four responses for each user type should be calculated. When matrix B is initialized, the outcome will range from a minimum value of 4 to a maximum weight of 28.

As indicated in **Table 4.12** , the scores of each participant's affinity vector indicate how much the participant fits into each user type of the Hexad model.

Table 4.12: Matrix-B initializing second method for actual sample (100 students)

Users	Achiever	Player	Socializer	Philanthropist	Free Spirit	Disruptor
User1	25	28	25	24	18	9
user2	28	22	24	22	20	10
User3	24	27	25	22	19	10
User4	24	26	24	23	21	8
User5	24	26	24	23	20	9
User6	26	27	22	22	22	8
User7	26	27	24	22	22	9
User8	28	25	18	19	18	10
User9	23	28	19	20	23	10
User10	28	24	22	20	19	11
User11	28	24	21	23	22	10
User12	27	27	24	21	21	10
User13	28	27	25	22	21	8
User14	23	26	23	21	19	10
User15	26	25	21	23	21	10
User16	27	24	23	22	23	9
User17	28	27	24	22	21	9
User18	25	26	23	22	22	10

User19	28	26	23	21	18	10
User20	27	26	25	24	18	9
User21	26	28	20	22	22	10
User22	27	28	24	21	22	10
User23	28	23	26	24	21	14
User24	28	25	25	22	21	10
User25	28	27	25	22	22	9
User26	27	28	25	24	21	14
User27	25	22	23	19	18	11
User28	22	22	20	21	21	15
User29	20	25	20	23	22	14
User30	27	28	22	24	21	10
User31	27	23	24	24	20	7
User32	26	26	22	23	20	11
User33	26	21	21	22	22	16
User34	26	25	25	22	22	13
User35	26	22	25	23	19	15
User36	25	22	25	22	20	13
User37	22	25	24	20	19	16
User38	27	27	25	24	22	12
User39	26	28	23	23	20	15
User40	27	28	23	23	19	15
User41	23	24	20	21	20	14
User42	27	22	19	22	22	8
User43	26	27	25	22	19	14
User44	23	24	20	23	21	16
User45	23	26	23	22	20	13
User46	27	26	23	22	19	5
User47	26	22	22	23	22	9
User48	23	27	23	21	22	13
User49	24	24	23	22	19	5
User50	26	20	22	23	22	10
User51	26	28	25	22	19	9
User52	28	23	26	24	20	10
User53	24	27	24	21	19	10
User54	24	26	24	23	21	8

User55	24	26	24	24	21	9
User56	26	27	22	25	23	8
User57	26	27	25	22	22	14
User58	28	25	18	19	21	10
User59	23	28	19	20	23	10
User60	28	23	22	20	19	11
User61	27	28	22	23	22	10
User62	27	23	24	22	19	7
User63	26	26	22	22	20	11
User64	26	20	21	23	22	16
User65	26	25	24	22	21	13
User66	26	22	25	22	20	15
User67	25	23	24	22	21	13
User68	22	25	23	20	20	16
User69	27	27	22	24	22	12
User70	26	28	22	22	24	15
User71	27	28	23	23	20	15
User72	26	27	25	22	21	9
User73	28	25	18	19	21	10
User74	23	28	19	20	23	10
User75	28	24	22	20	18	14
User76	28	23	21	22	21	10
User77	27	27	23	21	22	10
User78	28	27	24	20	20	8
User79	23	26	23	21	20	10
User80	26	25	22	22	22	10
User81	27	24	21	23	21	9
User82	28	27	24	22	23	9
User83	24	26	23	21	21	10
User84	26	25	22	21	22	10
User85	27	25	23	22	22	14
User86	28	27	23	22	22	9
User87	25	26	23	21	21	10
User88	28	26	22	20	20	10
User89	27	26	24	24	18	9
User90	26	28	20	20	24	10

User91	23	26	22	21	22	13
User92	24	25	23	22	19	14
User93	26	22	22	23	22	10
User94	25	28	23	24	19	9
User95	28	23	25	24	20	10
User96	24	27	24	22	19	10
User97	23	26	24	23	22	8
User98	24	26	24	23	21	14
User99	26	27	21	21	21	8
User100	26	27	22	22	22	9
Mean	25.81	25.47	22.79	22.00	20.76	10.89
Percent%	20%	20%	18%	17%	16%	9%

4.2.2.5 Predominant User Types Identification (100 Participants- Second Method):

The Hexad model was used to identify the predominant user types among participants. Various analysis methods, including SPSS and Microsoft Excel, were used to improve the research quality. The predominant user type was determined by calculating the average affinity scores for each Hexad user type. The percentage distribution of each kind was obtained by dividing the mean score for each type by the sum of all six mean scores and multiplying by 100.

From 4 to 28, the mean scores for study participants were determined. Each user type was assessed using four statements on a 7-point Likert scale of 1 to 7. Each participant's mean score for that user type shows their suitability.

Thus, "Achiever" and "Player" are the most predominant user types due to having the most significant mean scores, followed by "Socializer," "Philanthropist," and "Free Spirit," and "Disrupter" is the least predominant user type due to having a substantially lower mean score than the other user types. The mean score for each user type in the Hexad model

was determined based on the four sub-scale questions corresponding to each usage type, as shown in **Table 4.13**.

Table 4.13: Predominant User Types (Second Method), S=100

User type	N	Mean Value	percent
Achiever	100	25.81	20%
Player	100	25.47	20%
Socializer	100	22.79	18%
Philanthropist	100	22.00	17%
Free Spirit	100	20.76	16%
Disruptor	100	10.89	9%

The most predominant user type is determined by calculating the percentage distribution of each Hexad model user type among participants. This process involves two steps: computing the "mean" scores for each user type over the entire sample, adding affinity scores for each category, and dividing the result by the total number of participants. The final "mean" score is multiplied by 100 after being divided by the total scores for the six user types.

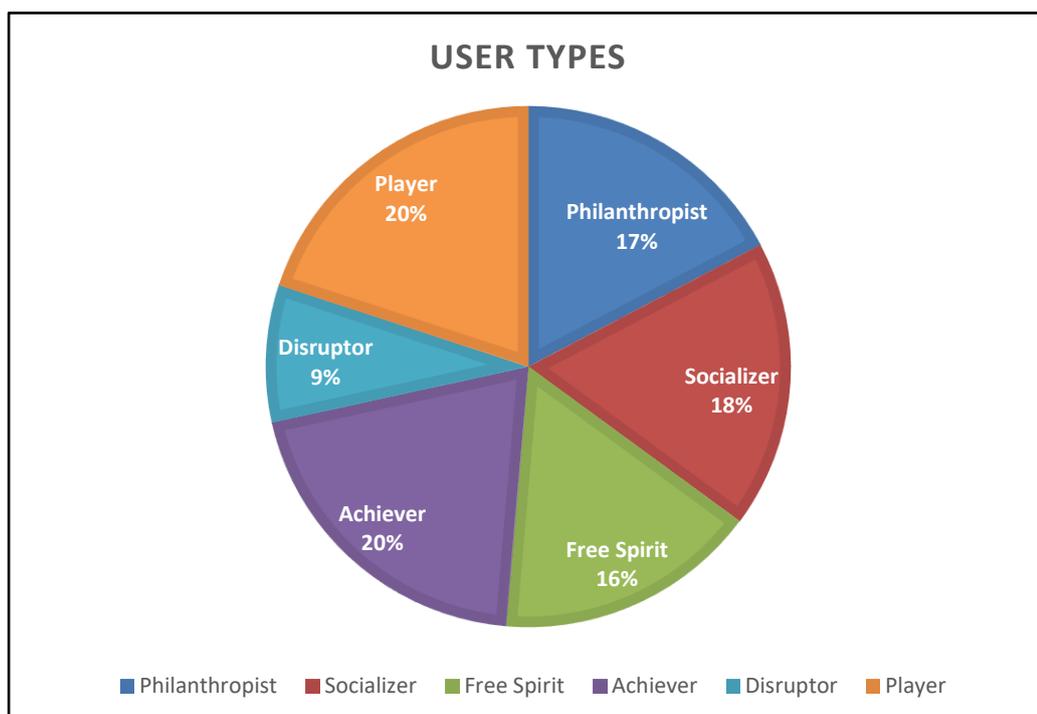


Figure 4.4: The Participants' Hexad User Type Distribution (100 Participants).

The Hexad model's percent distribution shows the most popular user types, with "Player" and "Achiever" having the highest percentages (20%) and "Socializer" (17%), followed by "Philanthropist" (17%) and "Free Spirit" (16%), respectively. "Disrupter" had a lower percentage (9%), indicating less representativeness. **Figure 4.4** displays the percentage distribution of each user type as a result of this operation.

4.2.2.6 Prime User Types Identification (100 Participants):

The user type in which a participant scored the highest is considered the prime user type for that participant, i.e., the participant's prime user type is the user type in which they scored the highest. Some participants may have had more than one prime user type if two or more different user types obtained similar ratings.

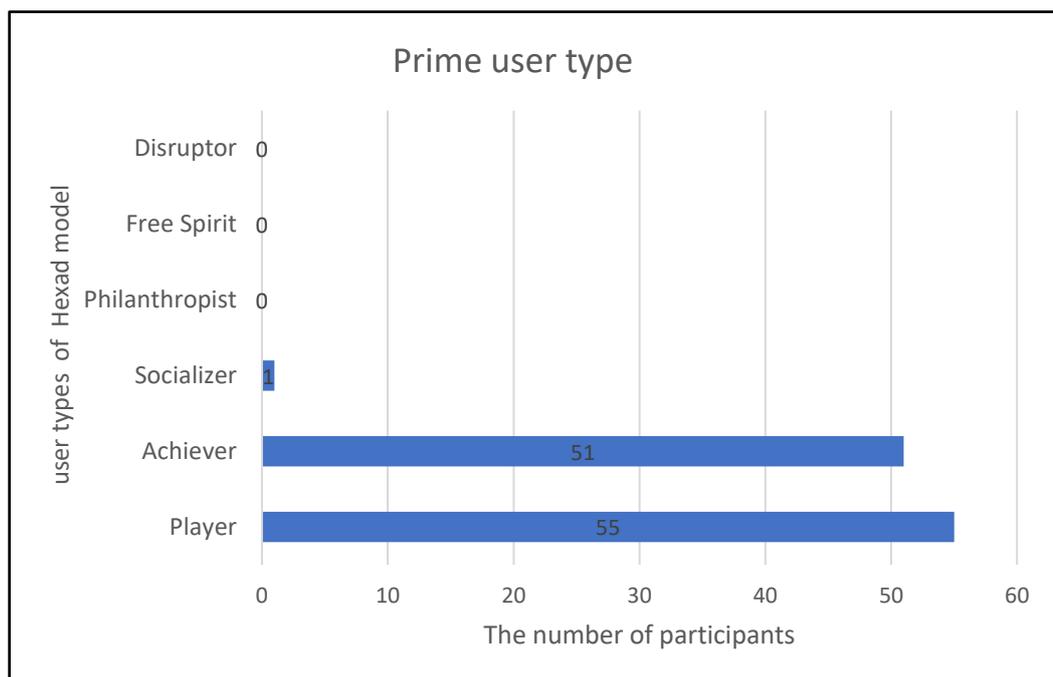


Figure 4.5: Prime User Type Frequency among Participants (100 Participants).

Figure 4.5 illustrates the results of the analysis of all participant data, which showed that the "player" user type was the prime user type (55 participants were counted), followed by "achievers" (51 participants were

counted), and "socializers" (one participant was calculated). There were no participants with the prime user types "disruptor," "free sprite," or "philanthropist."

4.2.2.7 Matrix-A Initializing (100 Participants):

Adopting expert opinion is one of the better methods for estimating matrix-A since it is more accurate. The experts were asked to identify the game features that were most relevant for each type of player by rating each gamification component according to its six associated player types in the Hexad model.

The level of inter-rater agreement was determined using the IntraClass Correlation (ICC) function of the SPSS program. The result was (0.773), considered reliable enough to confirm the raters' agreement.

For each expert-evaluated score in matrix A, the median of these suggested ratings was determined; the median was chosen over the mean to avoid the effects of extreme values that some experts may have suggested. The values in matrix-A demonstrate how well gamification elements match various player types; matrix-A findings are shown in **Table 4.14**.

Table 4.14: Matrix-A (Experts Rating Scores), Actual Study

User types	leaderboard	Badge	Points	Competition	Customization	Challenge
Achiever	0.5	1	1	0.75	0.5	1
Player	0.75	1	1	1	0.25	1
Socializer	0.3	0.25	0.25	0.3	0.5	0.25
Philanthropist	0.25	0.25	0.25	0	0.5	0.25
Free Spirit	0	0.25	0	0.25	1	0.25
Disruptor	0.25	0	0	0.3	0.75	0.5

4.2.2.8 Matrix-R Calculation (100 Participants).

User preferences for gamification components are displayed via matrix-R. **Table 4.15** shows the matrix-R findings, illustrating user preferences for various gamification components based on the highest score received. Matrix-R is created by multiplying matrix-B by matrix-A, as defined by the formula $R=B*A$, using a Python script (**Appendix-C**).

Table 4.15: Matrix-R Calculation for the actual sample (100 students)

Users	leaderboard	Badge	Points	Competition	Customization	Challenge
User 1	1.757	2.488	2.328	2.191	2.450	2.648
User 2	1.638	2.380	2.202	2.084	2.503	2.560
User 3	1.705	2.410	2.240	2.150	2.460	2.590
User 4	1.663	2.398	2.210	2.108	2.470	2.543
User 5	1.671	2.388	2.210	2.107	2.453	2.548
User 6	1.735	2.483	2.285	2.230	2.630	2.713
User 7	1.721	2.500	2.303	2.209	2.560	2.660
User 8	1.620	2.380	2.220	2.100	2.293	2.560
User 9	1.632	2.372	2.167	2.132	2.445	2.552
User 10	1.657	2.405	2.235	2.134	2.438	2.600
User 11	1.665	2.450	2.253	2.141	2.560	2.630
User 12	1.736	2.510	2.323	2.234	2.545	2.690
User 13	1.757	2.568	2.380	2.252	2.548	2.713
User 14	1.631	2.313	2.143	2.069	2.378	2.493
User 15	1.653	2.400	2.213	2.108	2.493	2.580
User 16	1.649	2.428	2.223	2.127	2.560	2.588
User 17	1.756	2.560	2.372	2.252	2.555	2.720
User 18	1.676	2.420	2.223	2.149	2.543	2.600
User 19	1.721	2.483	2.323	2.194	2.428	2.663
User 20	1.740	2.488	2.328	2.173	2.468	2.648
User 21	1.716	2.502	2.305	2.216	2.525	2.682
User 22	1.766	2.560	2.363	2.284	2.595	2.740

User 23	1.682	2.455	2.267	2.124	2.567	2.600
User 24	1.722	2.498	2.310	2.203	2.583	2.678
User 25	1.765	2.577	2.380	2.271	2.610	2.738
User 26	1.837	2.585	2.398	2.325	2.730	2.835
User 27	1.551	2.215	2.055	1.981	2.325	2.410
User 28	1.523	2.133	1.945	1.945	2.478	2.403
User 29	1.566	2.180	1.983	1.983	2.508	2.430
User 30	1.772	2.560	2.372	2.253	2.575	2.740
User 31	1.683	2.388	2.210	2.114	2.600	2.618
User 32	1.702	2.440	2.263	2.159	2.505	2.635
User 33	1.593	2.263	2.065	2.041	2.640	2.548
User 34	1.712	2.438	2.240	2.190	2.663	2.668
User 35	1.665	2.318	2.148	2.087	2.603	2.588
User 36	1.617	2.278	2.100	2.040	2.538	2.508
User 37	1.641	2.243	2.073	2.081	2.510	2.528
User 38	1.789	2.555	2.358	2.274	2.707	2.770
User 39	1.801	2.518	2.340	2.283	2.650	2.788
User 40	1.816	2.540	2.370	2.298	2.635	2.810
User 41	1.581	2.223	2.045	2.016	2.440	2.473
User 42	1.547	2.315	2.117	1.999	2.420	2.460
User 43	1.775	2.480	2.310	2.245	2.600	2.730
User 44	1.616	2.250	2.063	2.047	2.567	2.535
User 45	1.666	2.330	2.153	2.107	2.503	2.560
User 46	1.736	2.463	2.293	2.204	2.543	2.693
User 47	1.580	2.320	2.123	2.018	2.498	2.480
User 48	1.678	2.370	2.173	2.157	2.570	2.600
User 49	1.564	2.293	2.123	1.975	2.265	2.383
User 50	1.530	2.240	2.043	1.950	2.508	2.420
User 51	1.760	2.520	2.350	2.231	2.475	2.680
User 52	1.699	2.445	2.267	2.134	2.580	2.625
User 53	1.686	2.392	2.222	2.141	2.425	2.573
User 54	1.706	2.398	2.210	2.159	2.598	2.628
User 55	1.681	2.407	2.220	2.117	2.513	2.568
User 56	1.717	2.515	2.310	2.187	2.583	2.660
User 57	1.730	2.508	2.310	2.218	2.575	2.668
User 58	1.620	2.408	2.220	2.128	2.403	2.588

User 59	1.632	2.372	2.167	2.132	2.445	2.552
User 60	1.627	2.365	2.195	2.094	2.428	2.560
User 61	1.762	2.560	2.363	2.263	2.595	2.740
User 62	1.613	2.363	2.193	2.043	2.378	2.488
User 63	1.695	2.433	2.255	2.159	2.490	2.628
User 64	1.570	2.230	2.033	2.001	2.645	2.515
User 65	1.703	2.420	2.233	2.171	2.608	2.650
User 66	1.657	2.318	2.140	2.094	2.618	2.588
User 67	1.631	2.310	2.123	2.071	2.570	2.540
User 68	1.629	2.240	2.063	2.077	2.520	2.525
User 69	1.760	2.530	2.332	2.244	2.657	2.745
User 70	1.785	2.540	2.325	2.312	2.770	2.810
User 71	1.816	2.548	2.370	2.306	2.665	2.818
User 72	1.730	2.498	2.310	2.208	2.535	2.658
User 73	1.620	2.408	2.220	2.128	2.403	2.588
User 74	1.632	2.372	2.167	2.132	2.445	2.552
User 75	1.657	2.395	2.235	2.124	2.398	2.590
User 76	1.628	2.393	2.205	2.091	2.495	2.573
User 77	1.724	2.510	2.313	2.232	2.565	2.690
User 78	1.771	2.530	2.353	2.284	2.580	2.760
User 79	1.631	2.320	2.143	2.077	2.408	2.500
User 80	1.657	2.412	2.215	2.130	2.538	2.593
User 81	1.635	2.400	2.213	2.089	2.470	2.560
User 82	1.756	2.577	2.372	2.269	2.625	2.738
User 83	1.651	2.370	2.183	2.117	2.468	2.550
User 84	1.647	2.403	2.205	2.130	2.518	2.583
User 85	1.671	2.450	2.253	2.149	2.538	2.610
User 86	1.744	2.560	2.363	2.250	2.575	2.720
User 87	1.666	2.400	2.213	2.139	2.483	2.580
User 88	1.702	2.483	2.305	2.203	2.463	2.663
User 89	1.731	2.480	2.320	2.164	2.453	2.640
User 90	1.696	2.500	2.285	2.234	2.555	2.680
User 91	1.647	2.332	2.135	2.118	2.548	2.562
User 92	1.656	2.323	2.153	2.089	2.483	2.552
User 93	1.590	2.320	2.123	2.030	2.528	2.500
User 94	1.736	2.480	2.310	2.180	2.455	2.640

User 95	1.687	2.435	2.258	2.123	2.560	2.615
User 96	1.696	2.403	2.233	2.141	2.445	2.583
User 97	1.686	2.367	2.170	2.138	2.618	2.597
User 98	1.671	2.398	2.210	2.117	2.493	2.558
User 99	1.670	2.453	2.265	2.157	2.423	2.598
User 100	1.700	2.483	2.285	2.188	2.525	2.643
mean	1.53	2.09	1.95	2.14	2.51	2.60

4.2.2.9 Determine the Preferred Gamification Features (100 Participants):

The preferred gamification features are determined by calculating the "mean" scores by summing the affinity scores of each component and dividing them by the total number of participants, with the highest rating being the preferred feature.

The percentage distribution of each gamification feature was determined by dividing the "mean" score for each characteristic by the total sum of the six "mean" scores and multiplying by 100.

Table 4.16: Preferred Features of Gamification, Actual Study

User types	mean	percent
Challenge	2.60	20.3 %
Customization	2.51	19.6 %
Competition	2.14	16.7 %
Badge	2.09	16.3 %
Points	1.95	15.2 %
leaderboard	1.53	11.9 %

Table 4.16 reveals that the gamification features "challenges" (mean score = 2.60) and "customization" (mean score = 2.51) are the most popular among users, according to the obtained "mean" scores, followed by "competition" (mean score = 2.14), "badge" (mean score = 2.09), and "points" (mean score = 1.95). The "leaderboard" gamification element (mean score = 1.53) is the least popular among users. These results are explained in

detail in Figure 4.6.

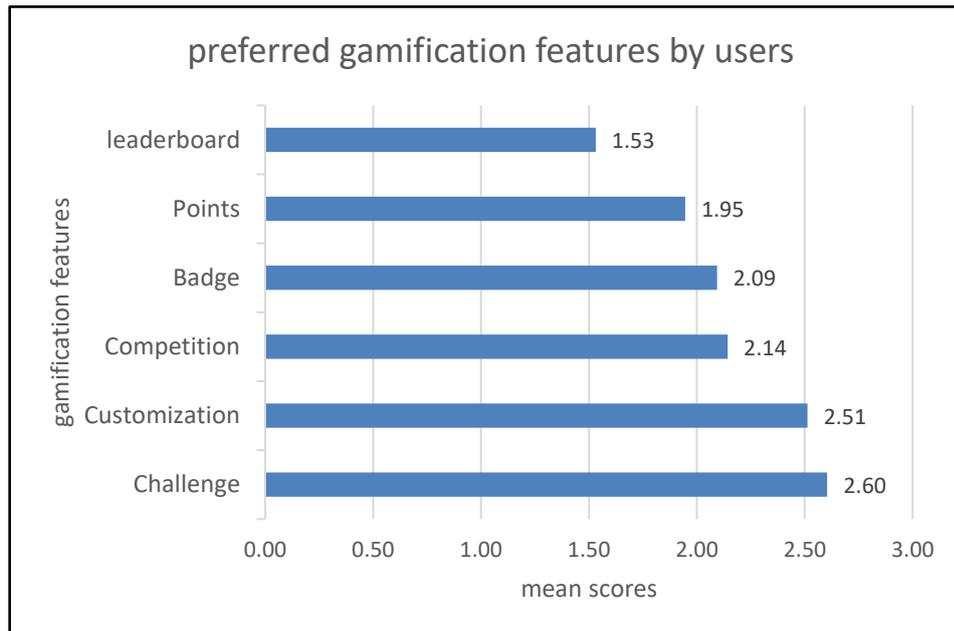


Figure 4.6: Preferred Gamification Features by Participants (100 Participants)

The percentage distribution of gamification traits is shown in **Figure 4.7**. Participants favored gamification elements like "challenges" (20.3%) and "customization" (19.6%). The gamification features "competition," "badge," and "points" ranked second, third, and fourth with 16.7%, 16.3%, and 15.2%. The gamification element "leaderboard" got the fewest votes (11.9%).

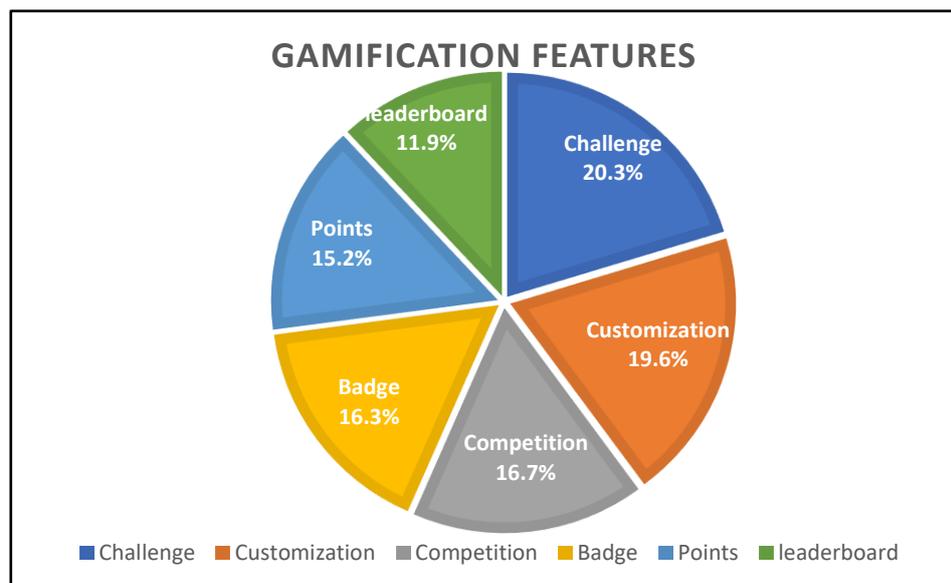


Figure 4.7: Preferred Gamification Features Distribution (100 Participants).

4.3. Adaptive Gamified Platform:

The EdApp [3] platform is adapted as a gamified e-learning management system for assessing the proposed strategy. The gamification components included in the EdApp platform are derived from the predicted components generated by the proposed strategy's outputs, with the aim of meeting users' preferences. This experiment assesses the proposed strategy by measuring the influence of the adaptive gamification process on learner motivation and enjoyment.

The EdApp platform was chosen for several reasons. The first justification is to support the features associated with "**achievements**" relevant to the "**achiever**" player type. The second justification is that design lesson templates support adaptive gamification components. The third justification is that it supports "**gamification analytics**" such as performance dashboards, App usage, activity feeds, user login data, course summaries, and user-completed course displays. These analytics also show each user's profile, activity, and how much time he spends in each course.

4.3.1 EdApp Platform:

This gamified platform aims to assess the effects of adaptive gamification components on students' motivation and engagement in gamified online learning systems. The EdApp platform has been developed with adaptive gamification elements based on student preferences collected from the proposed strategy. In other words, gamification components are tailored to student preferences to evaluate the proposed strategy by examining learner performance using "gamification analytics" built into the EdApp platform.

The gamified e-learning platform (EdApp) has been used to build three courses: a "**traditional e-learning**" course, a "**traditional gamification**" course, and a "**adaptive gamification**" course (**Figure 4.8**). The learning activities in the "**traditional course**" lacked gamification

features. In contrast, those in the "**traditional gamification**" course had generic gamification features without adaptation, and those in the third course, called "**adaptive gamification**," had adaptive gamification features according to the preferences of users, which were determined by the proposed strategy outcomes.

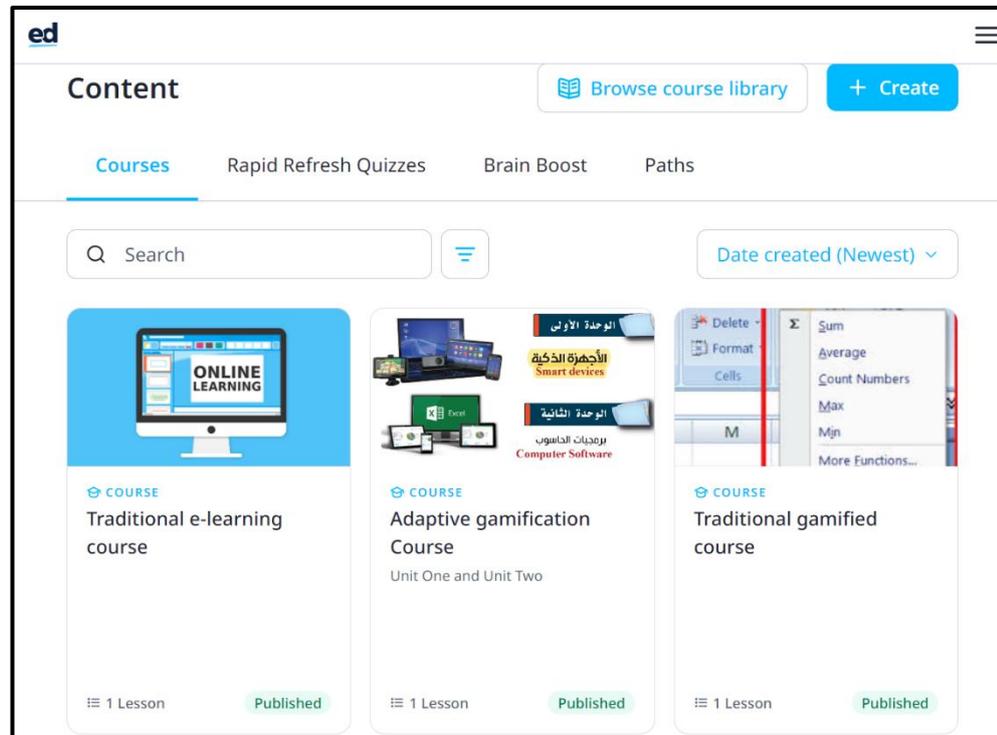


Figure 4.8: The Three Courses used in the EdApp Platform

The EdApp platform uses "gamification analytics" of learner profiles to evaluate the proposed approach and examine how adaptive gamification components affect students' commitment and motivation.

4.3.2 Sample and Experiment Design

This EdApp platform experiment involved 131 fifth-grade students from "Al-Waely Secondary School for Distinctive Boys," one of the public schools run by Babylon's general directorate of education. The experiment was carried out on the fifth stage of the computer subject during the first semester of the school year 2022–2023. The data were evaluated using "gamification analysis" and "descriptive statistical" techniques to

determine how much time students spent in each course and, as a result, assess their commitment and engagement.

4.3.3 Data Analysis

Instead of traditional statistics, the "**gamification analytics**" method included in the **EdApp** platform was adopted in this experiment to analyze students' motivation and commitment, as illustrated in **Figure 4.9**.

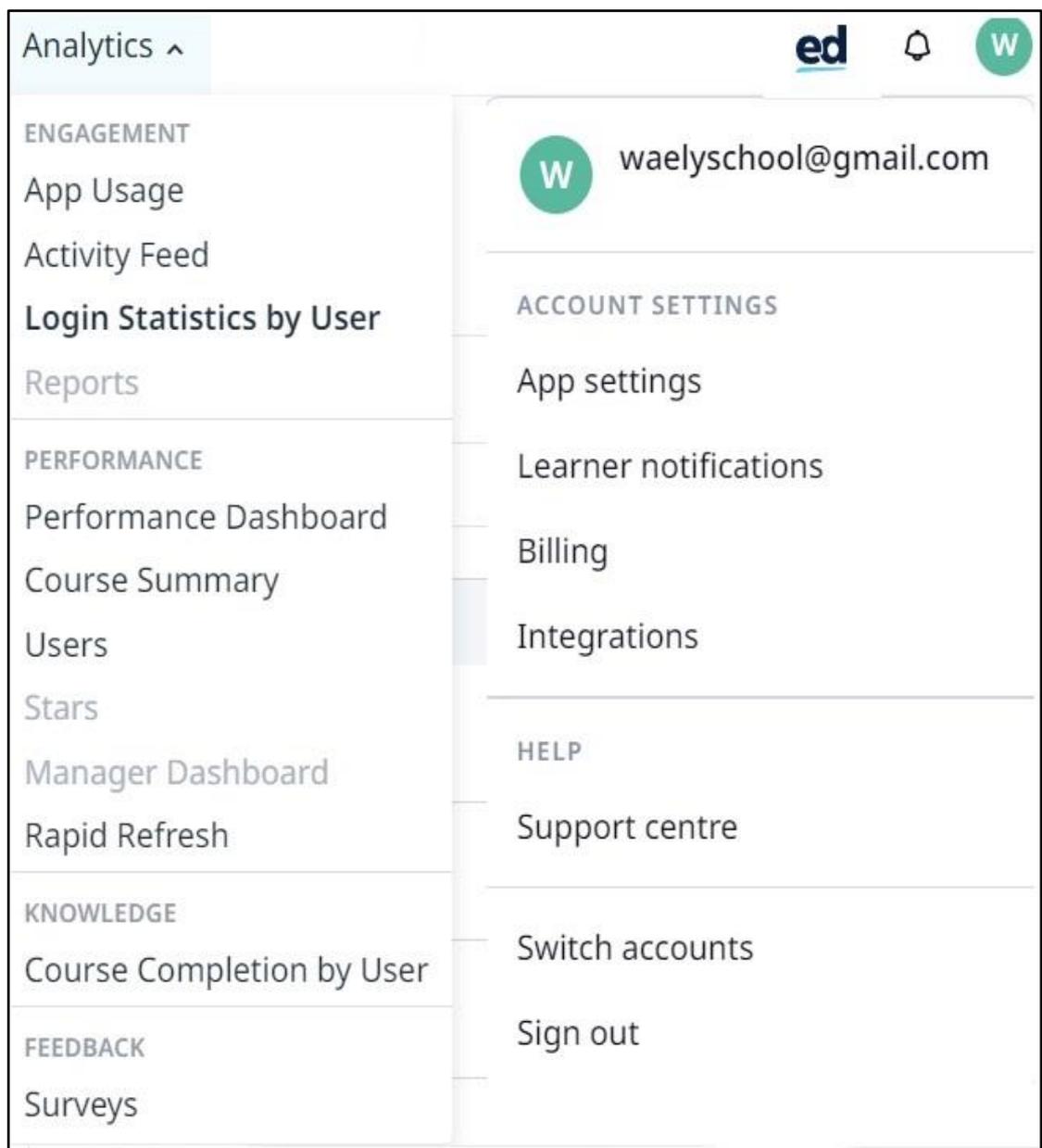


Figure 4.9: Gamification Analytics Tool

Monitoring user behavior concerning gamification features, analyzing performance to evaluate user motivation and commitment, and ultimately enhancing gamified e-learning systems are all part of "gamification analytics."

"gamification analytics" provide information on the frequency of task completion, average score, time spent, and number of logins. The data gathered from each user profile through the system is used to infer learner behaviors and activities using descriptive statistics. Students' interest and commitment are shown by how frequently they finish a course, log in, and how much time they spend on it.

The performance dashboard, log file, activity completion feed report, course completion by user, time spent in the course, and frequency of course completion were used to collect statistical information on students for the three courses from EdApp's "gamification analytics" to study how gamification features affect learner motivation and engagement.

4.3.4 Discussion

The most effective tool for determining user motivation and ensuring the success of gamified e-learning systems is "gamification analytics." EdApp is one of the systems that integrates "gamification analytics" into its design.

Students' motivation and commitment are shown by their high rate of course logins, number of completed tasks, and time spent on each activity.

According to the "gamification analytics" performance dashboard for the top-performing course, the "**adaptive gamification**" course had the highest completion rates (100 percent), followed by the "**traditional gamified**" course (86 percent), and the "**traditional e-learning**" course (83 percent), as shown in **Figure 4.10**.

Title	Completions	Completed
Customized gamification Course	131	100%
Traditional gamified course	113	86%
Traditional e-learning course	109	83%

Figure 4.10: Highest Performing Course

According to the findings of the courses' summary obtained from the "gamification analytics" report, as shown in Figure 4.11, learners spent 33 minutes in the "**adaptive gamification**" course, 3 minutes in the "**traditional gamification**" course, and just 1 minute in the "**traditional e-learning**" course. These findings revealed that students are **intrinsically** motivated in an "**adaptive gamification**" course.

Title	Avg Progress	Enrolled	<u>Avg Time Spent</u>
Customized gamification Course	100%	131	33m
Traditional gamified course	86%	131	3m
Traditional e-learning course	83%	131	1m

Figure 4.11: Comparison of the Courses

4.4. The Limitations:

1. The dissertation's focus is on Iraqi secondary school students; however, it may be strengthened by using more than one sample.
2. User profiles, or more precisely, user types, serve as the foundation for the adaptive gamification strategy, which may be strengthened by adding personality traits.
3. The proposed strategy creates a user profile using a Hexad questionnaire (direct method), but it may be enhanced by tracking user activity with a particular application (indirect method) to gather user preferences.
4. During the gamified experience, users' profiles stay static; this may be improved by creating a dynamic profile.

Chapter 5 : Conclusion and Future Works

This chapter presents an introduction, overview of the most important conclusions, explores the contributions made, and gives recommendations for future studies.

5.1 Introduction:

In this dissertation, a strategy was proposed to determine the type of user group and their preferences to adaptive gamification elements based on their preferences. The **proposed strategy** is based on the matrix factorization method to determine the type of user group and their preferences toward gamification features. This strategy improves learners' motivation and commitment in a gamified e-learning environment.

The proposed strategy is based on the formula $R = [B * A]$. Matrix-R is the product of two matrices (matrix-A and matrix-B), where matrix-A demonstrates how the gamification elements relate to each relevant player type, and matrix-B specifies the type of user for each participant. The **Hexad questionnaire** findings were used to create **matrix B**. The analysis of the Hexad questionnaire data leads to the determination of the most predominant user types among the participant's group and the prime user types for each participant. The gamification features participants prefer based on their relevant predominant user type. The **matrix-R** is formed by multiplying the two matrices together, and it will generate ratings for each participant's preferred gamification element based on the component with the highest score.

A gamified e-learning platform (EdApp) was used to test the proposed strategy in real-world situations by adaptive the gamification characteristics abstracted from the strategy's outcomes to satisfy students' preferences. This experiment can show how adaptive gamification improves student engagement and commitment. High course logins, task completion, and activity time demonstrate students' motivation and dedication

5.2 Conclusion:

The following is a brief overview of some of the accomplishments that have been reached and the efforts that have been put into this dissertation:

1. An adaptive gamification **framework** has been proposed to identify significant considerations, such as gamification strategies, user typologies, user profiles, and the system context to be implemented, that must be considered when designing an adaptive gamification strategy.
2. The proposed strategy was implemented to predict gamification elements that satisfy users' preferences based on user profiles.
3. The proposed strategy showed that "**achievers**" and "**players**" were the most common learners. The gamification component with the highest rating was "**challenges**," suggesting it may engage these individuals.
4. Students' motivation and commitment are shown by their high rate of course logins, number of completed tasks, and time spent on each activity when using EdApp experiment.
5. All "gamification analytics" statistics show that adaptive gamification increases student commitment and motivation.

5.3 Future Works:

1. The proposed strategy uses a Hexad questionnaire to create a user profile. In future work, adopting an indirect approach is recommended rather than a questionnaire to determine user preferences. Creating gamified programs, for example, that categorize users based on how they interact with particular gamification elements and suggest these elements to motivate them
2. The proposed framework is generic and can be used in any context. As a future work, applying it in additional contexts or domains using the same strategy is recommended.

3. The present adaptive gamification strategy is a static adaptation approach, which means that gamification features are only modified to the user once before they use the gamified tool based on a static user profile. In future works, dynamic adaptation that modifies gamification features depending on user behavior in real time may be used.

REFERENCES

- [1] S. Deterding, D. Dixon, R. Khaled, and L. Nacke, “From Game Design Elements to Gamefulness: Defining ‘Gamification,’” in *Proceedings of the 15th International Academic MindTrek Conference Envisioning Future Media Environments.*, ACM, 2011, pp. 341.
- [2] J. Koivisto and J. Hamari, “The rise of motivational information systems: A review of gamification research,” *International Journal of Information Management*, vol. 45. Elsevier Ltd, pp. 191–210, Apr. 01, 2019. doi: 10.1016/j.ijinfomgt.2018.10.013.
- [3] “The Mobile Learning Management System | EdApp: The Mobile LMS.” Accessed: Nov. 20, 2023. [Online]. Available: <https://www.edapp.com/>
- [4] D. Eseryel, V. Law, D. Ifenthaler, X. Ge, and R. Miller, “An Investigation of the Interrelationships between Motivation, Engagement, and Complex Problem Solving in Game-based Learning,” 2014.
- [5] J. Majuri, J. Koivisto, J. Hamari, and J. H. Fi, “Gamification of education and learning: A review of empirical literature,” in *GamiFIN Conference*, 2018.
- [6] R. M. Ryan and E. L. Deci, “Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being,” *American Psychologist*, vol. 55, no. 1, pp. 68–78, 2000, doi: 10.1037/0003-066X.55.1.68.
- [7] P. Bouvier, K. Sehaba, and É. Lavoué, “A trace-based approach to identifying users’ engagement and qualifying their engaged-behaviours in interactive systems: application to a social game,” *User Model User-adapt Interact*, vol. 24, no. 5, pp. 413–451, Oct. 2014, doi: 10.1007/s11257-014-9150-2.
- [8] W. Oliveira, J. Vassileva, W. Oliveira dos Santos, and I. Ibert Bittencourt, “Gamification Design to Tailor Gamified Educational Systems Based on Gamer Types,” in *SBGames 2018*, SBGames 2018, 2018. [Online]. Available: <https://goo.gl/NS6PCd>.
- [9] A. C. T. Klock, I. Gasparini, M. S. Pimenta, and J. Hamari, “Tailored gamification: A review of literature,” *International Journal of Human Computer Studies*, vol. 144, Dec. 2020, doi: 10.1016/j.ijhcs.2020.102495.
- [10] A. Marczewski, “EVEN NINJA MONKEYS LIKE TO PLAY UNICORN EDITION Gamification, Game Thinking and Motivational Design,” 2015. [Online]. Available: <https://www.gamified.uk/user-types/>
- [11] G. F. Tondello, R. R. Wehbe, L. Diamond, M. Busch, A. Marczewski, and L. E. Nacke, “The gamification user types Hexad scale,” in *CHI PLAY 2016 - Proceedings of the 2016 Annual Symposium on Computer-Human Interaction in Play*, Association for Computing Machinery, Inc, Oct. 2016, pp. 229–243. doi: 10.1145/2967934.2968082.
- [12] B. Monerrat, É. Lavoué, and S. George, “Adaptation of Gaming Features for Motivating Learners,” *Simul Gaming*, vol. 48, no. 5, pp. 625–656, Oct. 2017, doi: 10.1177/1046878117712632.
- [13] G. F. Tondello, R. Orji, and L. E. Nacke, “Recommender systems for personalized gamification,” in *UMAP 2017 - Adjunct Publication of the 25th Conference on User Modeling, Adaptation and Personalization*, Association for Computing Machinery, Inc, Jul. 2017, pp. 425–430. doi: 10.1145/3099023.3099114.

References

- [14] E. Lavoué, B. Monterrat, M. Desmarais, S. George, and É. Lavoué, “Adaptive Gamification for Learning Environments,” *IEEE Transactions on Learning Technologies, Institute of Electrical and Electronics Engineers*, vol. 12, no. 1, 2019, doi: 10.1109/TLT.2018.2823710i.
- [15] W. Oliveira *et al.*, “Does tailoring gamified educational systems matter? The impact on students’ flow experience,” in *Proceedings of the Annual Hawaii International Conference on System Sciences*, IEEE Computer Society, 2020, pp. 1226–1235. doi: 10.24251/hicss.2020.152.
- [16] W. Oliveira *et al.*, “The effects of personalized gamification on students’ flow experience, motivation, and enjoyment,” *Smart Learning Environments*, vol. 9, no. 1, Dec. 2022, doi: 10.1186/s40561-022-00194-x.
- [17] G. F. Tondello and L. E. Nacke, “Validation of User Preferences and Effects of Personalized Gamification on Task Performance,” *Front Comput Sci*, vol. 2, Aug. 2020, doi: 10.3389/fcomp.2020.00029.
- [18] S. Hallifax *et al.*, “Factors to Consider for Tailored Gamification,” in *Proceedings of the Annual Symposium on Computer-Human Interaction in Play*, 2019, pp. 559–572. [Online]. Available: <https://hal.archives-ouvertes.fr/hal-02185647>
- [19] J. Hamari, “Gamification,” in *The Blackwell Encyclopedia of Sociology*, Oxford, UK: John Wiley & Sons, Ltd, 2019, pp. 1–3. doi: 10.1002/9781405165518.wbeos1321.
- [20] S. Deterding, “The lens of intrinsic skill atoms: A method for gameful design,” *Human-Computer Interaction*, vol. 30, no. 3–4. Bellwether Publishing, Ltd., pp. 294–335, May 01, 2015. doi: 10.1080/07370024.2014.993471.
- [21] A. Mora, G. F. Tondello, L. E. Nacke, and J. Arnedo-Moreno, “Effect of personalized gameful design on student engagement,” in *2018 IEEE Global Engineering Education Conference (EDUCON)*, IEEE, Apr. 2018, pp. 1925–1933. doi: 10.1109/EDUCON.2018.8363471.
- [22] B. Monterrat, M. Desmarais, E. Lavoué, and S. George, “A Player Model for Adaptive Gamification in Learning Environments,” in *AIED2015, Jun2015, Madrid, Spain*, 2015, pp. 297–306. [Online]. Available: <https://hal.archives-ouvertes.fr/hal-01165497>
- [23] M. A. Hassan, U. Habiba, F. Majeed, and M. Shoaib, “Adaptive gamification in e-learning based on students’ learning styles,” *Interactive Learning Environments*, vol. 29, no. 4, pp. 545–565, 2019, doi: 10.1080/10494820.2019.1588745.
- [24] K. Huotari and J. Hamari, “Defining gamification,” in *Proceeding of the 16th International Academic MindTrek Conference*, New York, NY, USA: ACM, Oct. 2012, pp. 17–22. doi: 10.1145/2393132.2393137.
- [25] A. Khaldi, R. Bouzidi, and F. Nader, “Gamification of e-learning in higher education: a systematic literature review,” *Smart Learning Environments*, vol. 10, no. 1, p. 10, Jan. 2023, doi: 10.1186/s40561-023-00227-z.
- [26] S. Bennani, A. Maalel, and H. Ben Ghezala, “Adaptive gamification in E-learning: A literature review and future challenges,” *Computer Applications in Engineering Education*, vol. 30, no. 2. John Wiley and Sons Inc, pp. 628–642, Mar. 01, 2022. doi: 10.1002/cae.22477.
- [27] É. Lavoué, B. Monterrat, M. Desmarais, and S. George, “Adaptive Gamification for Learning Environments,” *IEEE Transactions on Learning Technologies*, vol. 12, no. 1, pp. 16–28, Jan. 2019, doi: 10.1109/TLT.2018.2823710.

References

- [28] S. Hallifax, A. Serna, J. C. Marty, G. Lavoué, and E. Lavoué, “Factors to consider for tailored gamification,” in *CHI PLAY 2019 - Proceedings of the Annual Symposium on Computer-Human Interaction in Play*, Association for Computing Machinery, Inc, Oct. 2019, pp. 559–572. doi: 10.1145/3311350.3347167.
- [29] R. Orji, J. Vassileva, and R. L. Mandryk, “Modeling the efficacy of persuasive strategies for different gamer types in serious games for health,” *User Model User-adapt Interact*, vol. 24, no. 5, pp. 453–498, Oct. 2014, doi: 10.1007/s11257-014-9149-8.
- [30] K. ERTAN and S. ARKÜN KOCADERE, “Gamification Design to Increase Motivation in Online Learning Environments: A Systematic Review,” *Journal of Learning and Teaching in Digital Age*, vol. 7, no. 2, pp. 151–159, Jul. 2022, doi: 10.53850/joltida.1020044.
- [31] C. Baah, I. Govender, and P. Rontala Subramaniam, “Exploring the role of gamification in motivating students to learn,” *Cogent Education*, vol. 10, no. 1, Dec. 2023, doi: 10.1080/2331186X.2023.2210045.
- [32] A. N. Saleem, N. M. Noori, and F. Ozdamli, “Gamification Applications in E-learning: A Literature Review,” *Technology, Knowledge and Learning*, vol. 27, no. 1, pp. 139–159, Mar. 2022, doi: 10.1007/s10758-020-09487-x.
- [33] A. N. Saleem, N. M. Noori, and F. Ozdamli, “Gamification Applications in E-learning: A Literature Review,” *Technology, Knowledge and Learning*, vol. 27, no. 1, pp. 139–159, Mar. 2022, doi: 10.1007/s10758-020-09487-x.
- [34] A. M. Toda, R. M. C. do Carmo, A. P. da Silva, I. I. Bittencourt, and S. Isotani, “An approach for planning and deploying gamification concepts with social networks within educational contexts,” *Int J Inf Manage*, vol. 46, pp. 294–303, Jun. 2019, doi: 10.1016/j.ijinfomgt.2018.10.001.
- [35] G. M. Chans and M. Portuguese Castro, “Gamification as a Strategy to Increase Motivation and Engagement in Higher Education Chemistry Students,” *Computers*, vol. 10, no. 10, p. 132, Oct. 2021, doi: 10.3390/computers10100132.
- [36] T. Jaguš, I. Botički, and H. J. So, “Examining competitive, collaborative and adaptive gamification in young learners’ math learning,” *Comput Educ*, vol. 125, pp. 444–457, Oct. 2018, doi: 10.1016/j.compedu.2018.06.022.
- [37] M. Maravanyika and N. Dlodlo, “An Adaptive Framework for Recommender-Based Learning Management Systems,” in *2018 Open Innovations Conference (OI)*, IEEE, Oct. 2018, pp. 203–212. doi: 10.1109/OI.2018.8535816.
- [38] R. Morales, N. Van Labeke, P. Brna, and M. E. Chan, “Open Learner Modelling as the Keystone of the Next Generation of Adaptive Learning Environments,” in *Intelligent User Interfaces*, IGI Global. doi: 10.4018/9781605660325.ch014.
- [39] K. M. Mbabu, R. O. Oboko, and S. Kamunya, “An Adaptive Gamification Tool for E-learning Platform,” *Open Journal for Information Technology*, vol. 2, no. 2, pp. 41–52, Dec. 2019, doi: 10.32591/coas.ojit.0202.03041m.
- [40] S. Hallifax, A. Serna, J.-C. Marty, G. Lavoué, and E. Lavoué, “Factors to Consider for Tailored Gamification,” in *Proceedings of the Annual Symposium on Computer-Human Interaction in Play*, New York, NY, USA: ACM, Oct. 2019, pp. 559–572. doi: 10.1145/3311350.3347167.
- [41] S. Hallifax, E. Lavoué, and A. Serna, “To tailor or not to tailor gamification? An analysis of the impact of tailored game elements on learners’ behaviours and motivation,” in

References

- Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, Springer, 2020, pp. 216–227. doi: 10.1007/978-3-030-52237-7_18.
- [42] G. Vasconcelos, W. Oliveira, A. Cláudia, G. Santos, and J. Hamari, “ReGammend: A method for personalized recommendation of gamification designs,” in *6th International GamiFIN Conference 2022 (GamiFIN 2022), April 26-29 2022, Finland, 2022*.
- [43] I. Rodríguez, A. Puig, and A. Rodríguez, “We Are Not the Same Either Playing: A Proposal for Adaptive Gamification,” in *Frontiers in Artificial Intelligence and Applications*, IOS Press BV, Oct. 2021, pp. 185–194. doi: 10.3233/FAIA210133.
- [44] I. Rodríguez, A. Puig, and À. Rodríguez, “Towards Adaptive Gamification: A Method Using Dynamic Player Profile and a Case Study,” *Applied Sciences (Switzerland)*, vol. 12, no. 1, Jan. 2022, doi: 10.3390/app12010486.
- [45] H. Stuart, A. Serna, J.-C. Marty, E. Lavoué, S. Hallifax, and J. Moulin Lyon, “Adaptive gamification in education: A literature review of current trends and developments,” in *European Conference on Technology Enhanced Learning (EC-TEL)*, 2019, pp. 294–307. [Online]. Available: <https://hal.archives-ouvertes.fr/hal-02185634>
- [46] R. Bartle, “HEARTS, CLUBS, DIAMONDS, SPADES: PLAYERS WHO SUIT MUDS,” *Journal of MUD research*, pp. 1–19, 1996.
- [47] L. E. Nacke, C. Bateman, and R. L. Mandryk, “BrainHex: Preliminary Results from a Neurobiological Gamer Typology Survey,” 2011. [Online]. Available: www.brainhex.com
- [48] Lewis R. Goldberg, “The Development of Markers for the BigFive factor Structure,” *The American Psychological Association, inc.*, 1992.
- [49] A. Mazarakis and P. Bräuer, “Gamification is Working, but Which One Exactly? Results from an Experiment with Four Game Design Elements,” *Int J Hum Comput Interact*, 2022, doi: 10.1080/10447318.2022.2041909.
- [50] G. F. Tondello, A. Mora, A. Marczewski, and L. E. Nacke, “Empirical validation of the Gamification User Types Hexad scale in English and Spanish,” *International Journal of Human Computer Studies*, vol. 127, pp. 95–111, Jul. 2019, doi: 10.1016/j.ijhcs.2018.10.002.
- [51] L. E. Nacke, C. Bateman, and R. L. Mandryk, “BrainHex: A neurobiological gamer typology survey,” *Entertain Comput*, vol. 5, no. 1, pp. 55–62, 2014, doi: 10.1016/j.entcom.2013.06.002.
- [52] R. Hunicke, M. Leblanc, and R. Zubek, “MDA: A Formal Approach to Game Design and Game Research,” 2004.
- [53] K. Werbach and D. Hunter, *For the win: How game thinking can revolutionize your business*. Wharton Digital Press., 2012.
- [54] A. Behl, N. Jayawardena, V. Pereira, N. Islam, M. del Giudice, and J. Choudrie, “Gamification and e-learning for young learners: A systematic literature review, bibliometric analysis, and future research agenda,” *Technol Forecast Soc Change*, vol. 176, Mar. 2022, doi: 10.1016/j.techfore.2021.121445.
- [55] G. F. Tondello, A. Mora, and L. E. Nacke, “Elements of gameful design emerging from user preferences,” in *CHI PLAY 2017 - Proceedings of the Annual Symposium on Computer-Human Interaction in Play*, Association for Computing Machinery, Inc, Oct. 2017, pp. 129–140. doi: 10.1145/3116595.3116627.

References

- [56] I. Rodríguez, A. Puig, and À. Rodríguez, “Towards Adaptive Gamification: A Method Using Dynamic Player Profile and a Case Study,” *Applied Sciences (Switzerland)*, vol. 12, no. 1, Jan. 2022, doi: 10.3390/app12010486.
- [57] A. Santos *et al.*, “The relationship between user types and gamification designs,” *User Model User-adapt Interact*, vol. 31, no. 5, pp. 907–940, Nov. 2021, doi: 10.1007/s11257-021-09300-z.
- [58] R. Orji, G. F. Tondello, and L. E. Nacke, “Personalizing persuasive strategies in gameful systems to gamification user types,” in *Conference on Human Factors in Computing Systems - Proceedings*, Association for Computing Machinery, Apr. 2018. doi: 10.1145/3173574.3174009.
- [59] S. Hallifax, A. Serna, J. C. Marty, and E. & Lavoué, “Dynamic gamification adaptation framework based on engagement detection through learning analytics,” in *Companion Proceedings of the 11th International Conference on Learning Analytics & Knowledge LAK21.*, 2021. [Online]. Available: <https://www.researchgate.net/publication/350837420>
- [60] D. Holmes, D. Charles, P. Morrow, S. McClean, and S. McDonough, “Rehabilitation Game Model for Personalised Exercise,” in *Proceedings - 2015 International Conference on Interactive Technologies and Games, ITAG 2015*, Institute of Electrical and Electronics Engineers Inc., Feb. 2015, pp. 41–48. doi: 10.1109/iTAG.2015.11.
- [61] P. Buckley and E. Doyle, “Gamification and student motivation,” *Interactive Learning Environments*, vol. 24, no. 6, pp. 1162–1175, Aug. 2014, doi: 10.1080/10494820.2014.964263.

Appendix A: Hexad Questionnaire

A questionnaire of user types scale in gamification system

Gamification is the application of game design components in non-game environments, such e-learning, to improve motivation and participation. These elements include points, badges, and virtual currency. For these apps to be effective, designers must understand the different types of players and take into account their preferences. This survey tries to determine which player types most accurately describe you in order to determine what motivates you and what elements of games you love. Please take a moment to respond to this brief survey. Noting that your response is totally confidential and can only be seen by the researcher for use in scientific research, it should be noted that the right response is the one that accurately represents your point of view.

* Required

1. Age *

Mark only one oval.

12-15

16-20

21-25

2. Gender *

Mark only one oval.

Male

Female

3. nickname when using game applications (in english language)

4. It makes me happy if I am able to help others. *

Mark only one oval.

- Strongly agree
 Agree
 Somewhat agree
 Neither agree nor did agree
 somewhat disagree
 Disagree
 Strongly disagree

5. I like helping others to orient themselves in new situations. *

Mark only one oval.

- Strongly agree
 Agree
 Somewhat agree
 Neither agree nor did agree
 somewhat disagree
 Disagree
 Strongly disagree

6. I like sharing my knowledge. *

Mark only one oval.

- Strongly agree
 Agree
 Somewhat agree
 Neither agree nor did agree
 somewhat disagree
 Disagree
 Strongly disagree

7. The wellbeing of others is important to me. *

Mark only one oval.

- Strongly agree
 Agree
 Somewhat agree
 Neither agree nor did agree
 somewhat disagree
 Disagree
 Strongly disagree

Appendices

8. I like being part of a team. *

Mark only one oval.

- Strongly agree
 Agree
 Somewhat agree
 Neither agree nor did agree
 somewhat disagree
 Disagree
 Strongly disagree

9. Interacting with others is important to me. *

Mark only one oval.

- Strongly agree
 Agree
 Somewhat agree
 Neither agree nor did agree
 somewhat disagree
 Disagree
 Strongly disagree

10. It is important to me to feel like I am part of a community. *

Mark only one oval.

- Strongly agree
 Agree
 Somewhat agree
 Neither agree nor did agree
 somewhat disagree
 Disagree
 Strongly disagree

11. I enjoy group activities. *

Mark only one oval.

- Strongly agree
 Agree
 Somewhat agree
 Neither agree nor did agree
 somewhat disagree
 Disagree
 Strongly disagree

12. It is important to me to follow my own path. *

Mark only one oval.

- Strongly agree
- Agree
- Somewhat agree
- Neither agree nor did agree
- somewhat disagree
- Disagree
- Strongly disagree

13. I often let my curiosity guide me. *

Mark only one oval.

- Strongly agree
- Agree
- Somewhat agree
- Neither agree nor did agree
- somewhat disagree
- Disagree
- Strongly disagree

14. Opportunities for self-expression are important to me. *

Mark only one oval.

- Strongly agree
- Agree
- Somewhat agree
- Neither agree nor did agree
- somewhat disagree
- Disagree
- Strongly disagree

15. Being independent is important to me. *

Mark only one oval.

- Strongly agree
- Agree
- Somewhat agree
- Neither agree nor did agree
- somewhat disagree
- Disagree
- Strongly disagree

16. I like defeating obstacles. *

Mark only one oval.

- Strongly agree
 Agree
 Somewhat agree
 Neither agree nor did agree
 somewhat disagree
 Disagree
 Strongly disagree

17. It is important to me to continuously improve my skills. *

Mark only one oval.

- Strongly agree
 Agree
 Somewhat agree
 Neither agree nor did agree
 somewhat disagree
 Disagree
 Strongly disagree

18. I enjoy emerging victorious out of difficult circumstances *

Mark only one oval.

- Strongly agree
 Agree
 Somewhat agree
 Neither agree nor did agree
 somewhat disagree
 Disagree
 Strongly disagree

19. I like mastering difficult tasks. *

Mark only one oval.

- Strongly agree
 Agree
 Somewhat agree
 Neither agree nor did agree
 somewhat disagree
 Disagree
 Strongly disagree

20. I like to provoke. *

Mark only one oval.

- Strongly agree
- Agree
- Somewhat agree
- Neither agree nor did agree
- somewhat disagree
- Disagree
- Strongly disagree

21. I like to question the status quo. *

Mark only one oval.

- Strongly agree
- Agree
- Somewhat agree
- Neither agree nor did agree
- somewhat disagree
- Disagree
- Strongly disagree

22. I dislike following rules *

Mark only one oval.

- Strongly agree
- Agree
- Somewhat agree
- Neither agree nor did agree
- somewhat disagree
- Disagree
- Strongly disagree

23. I see myself as a rebel. *

Mark only one oval.

- Strongly agree
- Agree
- Somewhat agree
- Neither agree nor did agree
- somewhat disagree
- Disagree
- Strongly disagree

Appendices

24. I like competitions where a prize can be won. *

Mark only one oval.

- Strongly agree
 Agree
 Somewhat agree
 Neither agree nor did agree
 somewhat disagree
 Disagree
 Strongly disagree

25. Rewards are a great way to motivate me. *

Mark only one oval.

- Strongly agree
 Agree
 Somewhat agree
 Neither agree nor did agree
 somewhat disagree
 Disagree
 Strongly disagree

26. Return of investment is important to me. *

Mark only one oval.

- Strongly agree
 Agree
 Somewhat agree
 Neither agree nor did agree
 somewhat disagree
 Disagree
 Strongly disagree

27. If the reward is sufficient, I will put in the effort. *

Mark only one oval.

- Strongly agree
 Agree
 Somewhat agree
 Neither agree nor did agree
 somewhat disagree
 Disagree
 Strongly disagree

Appendix B: Python script for multiplying matrices (25 students)

```

In [1]: # import necessary libraries
import pandas as pd
import numpy as np

In [2]: pd.set_option('display.max_columns', None) # Display all columns
pd.set_option('display.max_rows', None) # Display all rows
pd.set_option('display.expand_frame_repr', False) # Disable wrapping

In [3]: # Read BMatrix.csv with headers
BMatrix = pd.read_csv('BMatrix.csv')
#print(BMatrix)
# Read AMatrix.csv with headers
AMatrix = pd.read_csv('AMatrix.csv')
#print(AMatrix)

In [4]: # Extract the headers
BHeaders = BMatrix.columns[1:]
AHeaders = AMatrix.columns[1:]

In [5]: # Get the 'UserID' column from BMatrix.csv
UserID = BMatrix['UserID']

In [6]: # Remove the 'UserID' and 'UserType' columns from BMatrix for multiplication
BMatrix = BMatrix[BHeaders]
AMatrix = AMatrix[AHeaders]

In [7]: # Convert DataFrames to numpy arrays for matrix multiplication
BMatrix = BMatrix.to_numpy()
AMatrix = AMatrix.to_numpy()

In [8]: # Perform matrix multiplication
RMatrix = np.dot(BMatrix, AMatrix)

In [9]: # Create a DataFrame with headers and the result matrix, including 'UserID' column
RMatrix = pd.DataFrame(RMatrix, columns=AHeaders)

In [10]: # Insert the 'UserID' column into the DataFrame
RMatrix.insert(0, 'UserID', UserID)

In [11]: # Save the DataFrame to CSV file with headers and 'UserID' column
RMatrix.to_csv('RMatrix.csv', index=False)

In [12]: # Display the result with headers and 'UserID' column
print(RMatrix)

```

	UserID	leaderboard	Badge	Points	Competition	Customization	Challenge
0	1	1.7975	2.5325	2.3625	2.2335	2.5600	2.6925
1	2	1.7150	2.4700	2.2725	2.1455	2.7225	2.6500
2	3	1.7340	2.4375	2.2675	2.1620	2.5150	2.6175
3	4	1.6695	2.3925	2.1950	2.0965	2.5400	2.5375
4	5	1.7015	2.4350	2.2375	2.1475	2.5875	2.5950
5	6	1.7270	2.5425	2.3200	2.2040	2.6725	2.6875
6	7	1.7415	2.5250	2.3200	2.2375	2.6250	2.6850
7	8	1.5985	2.4000	2.2025	2.1165	2.4075	2.5800
8	9	1.6315	2.3825	2.1675	2.1420	2.4850	2.5625
9	10	1.6250	2.3825	2.1950	2.0995	2.4975	2.5775
10	11	1.5915	2.3700	2.1650	2.0570	2.5375	2.5500
11	12	1.7410	2.5450	2.3300	2.2490	2.6700	2.7250
12	13	1.7690	2.5775	2.3900	2.2635	2.5675	2.7225
13	14	1.6200	2.3325	2.1350	2.0755	2.4725	2.5125
14	15	1.6735	2.4350	2.2300	2.1465	2.5975	2.6150
15	16	1.6835	2.4725	2.2575	2.1370	2.6700	2.6325
16	17	1.7730	2.6125	2.3900	2.2865	2.7300	2.7725
17	18	1.6955	2.4550	2.2400	2.1785	2.6475	2.6350
18	19	1.7210	2.5200	2.3225	2.2315	2.5775	2.7000
19	20	1.7800	2.5400	2.3625	2.2235	2.6075	2.7000
20	21	1.6715	2.4600	2.2275	2.1895	2.6150	2.6400
21	22	1.7965	2.5950	2.3900	2.3120	2.6800	2.7750
22	23	1.6890	2.4725	2.2750	2.1335	2.6225	2.6175
23	24	1.7605	2.5850	2.3450	2.2760	2.8625	2.7650
24	25	1.7765	2.6125	2.3900	2.3075	2.7300	2.7725

Appendices

Appendix C: Python Script for Multiplying Matrices (100 students)

25	26	1.8370	2.5850	2.3975	2.3245	2.7300	2.8350
26	27	1.5510	2.2150	2.0550	1.9805	2.3250	2.4100
27	28	1.5230	2.1325	1.9450	1.9450	2.4775	2.4025
28	29	1.5655	2.1800	1.9825	1.9830	2.5075	2.4300
29	30	1.7720	2.5600	2.3725	2.2525	2.5750	2.7400
30	31	1.6830	2.3875	2.2100	2.1135	2.6000	2.6175
31	32	1.7020	2.4400	2.2625	2.1590	2.5050	2.6350
32	33	1.5925	2.2625	2.0650	2.0410	2.6400	2.5475
33	34	1.7120	2.4375	2.2400	2.1900	2.6625	2.6675
34	35	1.6645	2.3175	2.1475	2.0865	2.6025	2.5875
35	36	1.6170	2.2775	2.1000	2.0400	2.5375	2.5075
36	37	1.6405	2.2425	2.0725	2.0815	2.5100	2.5275
37	38	1.7895	2.5550	2.3575	2.2735	2.7075	2.7700
38	39	1.8010	2.5175	2.3400	2.2830	2.6500	2.7875
39	40	1.8160	2.5400	2.3700	2.2980	2.6350	2.8100
40	41	1.5805	2.2225	2.0450	2.0155	2.4400	2.4725
41	42	1.5465	2.3150	2.1175	1.9985	2.4200	2.4600
42	43	1.7745	2.4800	2.3100	2.2445	2.6000	2.7300
43	44	1.6155	2.2500	2.0625	2.0465	2.5675	2.5350
44	45	1.6660	2.3300	2.1525	2.1065	2.5025	2.5600
45	46	1.7360	2.4625	2.2925	2.2040	2.5425	2.6925
46	47	1.5795	2.3200	2.1225	2.0180	2.4975	2.4800
47	48	1.6785	2.3700	2.1725	2.1565	2.5700	2.6000
48	49	1.5635	2.2925	2.1225	1.9750	2.2650	2.3825
49	50	1.5295	2.2400	2.0425	1.9500	2.5075	2.4200
50	51	1.7595	2.5200	2.3500	2.2305	2.4750	2.6800
51	52	1.6990	2.4450	2.2675	2.1345	2.5800	2.6250
52	53	1.6855	2.3925	2.2225	2.1410	2.4250	2.5725
53	54	1.7055	2.3975	2.2100	2.1585	2.5975	2.6275
54	55	1.6805	2.4075	2.2200	2.1165	2.5125	2.5675
55	56	1.7170	2.5150	2.3100	2.1865	2.5825	2.6600
56	57	1.7295	2.5075	2.3100	2.2180	2.5750	2.6675
57	58	1.6195	2.4075	2.2200	2.1275	2.4025	2.5875
58	59	1.6315	2.3725	2.1675	2.1320	2.4450	2.5525
59	60	1.6270	2.3650	2.1950	2.0940	2.4275	2.5600
60	61	1.7620	2.5600	2.3625	2.2625	2.5950	2.7400
61	62	1.6130	2.3625	2.1925	2.0430	2.3775	2.4875
62	63	1.6945	2.4325	2.2550	2.1590	2.4900	2.6275
63	64	1.5700	2.2300	2.0325	2.0010	2.6450	2.5150
64	65	1.7030	2.4200	2.2325	2.1710	2.6075	2.6500
65	66	1.6570	2.3175	2.1400	2.0940	2.6175	2.5875
66	67	1.6305	2.3100	2.1225	2.0710	2.5700	2.5400
67	68	1.6285	2.2400	2.0625	2.0770	2.5200	2.5250
68	69	1.7595	2.5300	2.3325	2.2435	2.6575	2.7450
69	70	1.7845	2.5400	2.3250	2.3115	2.7700	2.8100
70	71	1.8160	2.5475	2.3700	2.3055	2.6650	2.8175
71	72	1.7295	2.4975	2.3100	2.2080	2.5350	2.6575
72	73	1.6195	2.4075	2.2200	2.1275	2.4025	2.5875
73	74	1.6315	2.3725	2.1675	2.1320	2.4450	2.5525
74	75	1.6570	2.3950	2.2350	2.1240	2.3975	2.5900
75	76	1.6275	2.3925	2.2050	2.0905	2.4950	2.5725
76	77	1.7235	2.5100	2.3125	2.2315	2.5650	2.6900
77	78	1.7705	2.5300	2.3525	2.2835	2.5800	2.7600
78	79	1.6310	2.3200	2.1425	2.0765	2.4075	2.5000
79	80	1.6570	2.4125	2.2150	2.1300	2.5375	2.5925
80	81	1.6350	2.4000	2.2125	2.0885	2.4700	2.5600
81	82	1.7555	2.5775	2.3725	2.2690	2.6250	2.7375
82	83	1.6510	2.3700	2.1825	2.1165	2.4675	2.5500
83	84	1.6470	2.4025	2.2050	2.1300	2.5175	2.5825
84	85	1.6710	2.4500	2.2525	2.1495	2.5375	2.6100
85	86	1.7435	2.5600	2.3625	2.2495	2.5750	2.7200
86	87	1.6660	2.4000	2.2125	2.1390	2.4825	2.5800
87	88	1.7020	2.4825	2.3050	2.2025	2.4625	2.6625
88	89	1.7305	2.4800	2.3200	2.1640	2.4525	2.6400
89	90	1.6955	2.5000	2.2850	2.2335	2.5550	2.6800
90	91	1.6470	2.3325	2.1350	2.1175	2.5475	2.5625
91	92	1.6560	2.3225	2.1525	2.0890	2.4825	2.5525
92	93	1.5895	2.3200	2.1225	2.0300	2.5275	2.5000
93	94	1.7360	2.4800	2.3100	2.1795	2.4550	2.6400
94	95	1.6870	2.4350	2.2575	2.1225	2.5600	2.6150
95	96	1.6955	2.4025	2.2325	2.1410	2.4450	2.5825
96	97	1.6855	2.3675	2.1700	2.1385	2.6175	2.5975
97	98	1.6705	2.3975	2.2100	2.1165	2.4925	2.5575
98	99	1.6700	2.4525	2.2650	2.1570	2.4225	2.5975
99	100	1.6995	2.4825	2.2850	2.1880	2.5250	2.6425
18	19	1.7210	2.4825	2.3225	2.1940	2.4275	2.6625
19	20	1.7395	2.4875	2.3275	2.1730	2.4675	2.6475
20	21	1.7155	2.5025	2.3050	2.2160	2.5250	2.6825
21	22	1.7655	2.5600	2.3625	2.2835	2.5950	2.7400
22	23	1.6815	2.4550	2.2675	2.1235	2.5675	2.6000
23	24	1.7220	2.4975	2.3100	2.2025	2.5825	2.6775
24	25	1.7645	2.5775	2.3800	2.2705	2.6100	2.7375

Appendix D: Published Paper (1)

5th International Conference on Engineering Technology and its Applications 2022- (5thIICETA2022)

Gamification Trends in E-learning – A Survey

1st Dhiaa Alalgawi
Information technology College
University of Babylon
Babylon, Iraq

dhiaa.alalgawi@student.uobabylon.edu.iq

2nd Sattar B. Sadkhan
Information technology College
University of Babylon
Babylon, Iraq

drengsattar@ieee.org

Abstract— Gamification is the use of game design elements for the sake of motivating individuals in non-game contexts. Most existing review papers on gamification revealed that e-learning is the most common context of gamification. E-learning faces a number of challenges, including lack of motivation. Hence, combining e-learning tools with gamification is the optimal solution to overcome this challenge. However, educational stakeholders need to understand more about the different gamification approaches and the trends that keep learners motivated and engaged in e-learning environments. This study aims to review the state-of-the-art of gamification trends in e-learning in order to provide clear insights for stakeholders. It investigates the literature that is relevant to gamification in e-learning based on scholarly papers that available on Google Scholar, Web of Science, and Scopus databases. The main interesting results revealed that the adaptive gamification approach which tailers gamification elements to the learners' preferences is an alternative to the traditional approach that uses a uniform application of gamification elements to all learners. The result of this study unfolds the state-of-the-art of gamification trends in e-learning. Further research and empirical experiments are required to increase the evidence of gamification approaches.

Keywords— Gamification, E-learning, Adaptive, Motivation.

I. INTRODUCTION

Gamification refers to the act of involving game elements within a non-game context for the sake of motivating individuals to perform target tasks [1]. To achieve this benefit, educational institutions and academics put their efforts into adopting gamification in education to improve the learning process through motivating the students [2]. The outcomes of recent literature indicated that the correct designing of gamification elements in education can improve learning process and meet targets. The idea behind the use of gamification in education is that it has the ability to improve engagement and increase motivation for learning. However, the main challenge of adopting gamification in e-learning is how to keep learners motivated on the long term, especially because learners tend to have different characters and preferences. However, the traditional approach uses the same game design elements for all users and does not take the learners personality into account, eventually causing the approach to fail [3] [4]. This study addresses the main research question, which involves identifying the recent trends and challenges of adopting gamification in e-learning. Hence, the aim of this study is to highlight the trends and the efforts towards alternative approaches that make use of game design elements tailored to the user preferences. The recent literature supports these aspects and indicates that the development of technology plays an essential role in transforming education toward an adaptation-oriented approach, which involves personalization based on the student's profile in order to keep them motivated on the long run [5]. This study highlights the

outcomes about the effect of gamification elements in e-learning and the most used elements in order to understand the trends and determine the gaps in gamification adoption with education context, based on the review of literature.

II. LITERATURE REVIEW

A. Gamification Concept

Gamification as a term was first used in 2008, and it was coined in the end of 2010 in several conferences and academia [1]. In 2011, the first definition was proposed by Deterding et al. [1], who define gamification as the use of game design elements in a non-game context in order to increase user motivation and participation within a specific activity or task. In 2012, Huotari and Hamari [6] defined the gamification as the process of improving the service with gamified experiences to support the user and achieve the goal of gamification.

B. Gamification Elements

The study conducted by [7] reviews the elements of gamification in e-learning environments. Their conclusions revealed that most elements are points, badges, and leaderboards based on the Problem Based Learning (PBL) framework. The study conducted by [8] is to identify game design elements in education environment. The results reported that the elements are points, badges, leaderboards, progress bars, feedback storyline and prizes. The authors in

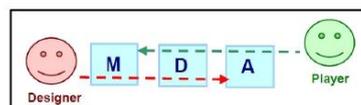


Fig.1 MDA framework adapted from [10]

[9] identify game design elements in e-learning environment. Their results reported that the elements are points, badges, leaderboards, levels, feedback and challenges.

C. Models of Gamification Elements

In 2004, Hunicke, LeBlance and Zubek [10] developed the MDA model illustrated in Fig. 1, which stands for Mechanics, Dynamics, and Aesthetics. Mechanics represent the game design elements that are embedded in the user interface. Dynamics represent the higher level of abstraction. In other words, it represents the interactive relation between the player and elements of interface. Aesthetics represent the emotional reaction of player toward the dynamics. This model aims to understand games elements, players behavior, and their emotional responses.

In 2012, Werabach and Hunter [11] classified gamification elements into three categories, namely Dynamics, Mechanics, and Components, as illustrated in Fig. 2. The hierarchy of

5th International Conference on Engineering Technology and its Applications 2022- (5thIICETA2022)

game elements is from the most abstract game elements to the most concrete game elements. Game dynamics such as progression, relationship and storyline narrative define how players will progress over time. It represents the high level in the hierarchy which can never be applied directly in the game system. Game mechanics such as challenge and competition represent the basic process which keep the user's engagement and makes a game exciting. In other words, it is the control mechanisms that is offered to the player inside the game. Game components such as points, badges, and leaderboard are seen as building blocks for game mechanics and dynamic. In other words, Components represent the specific features of mechanics and dynamics.

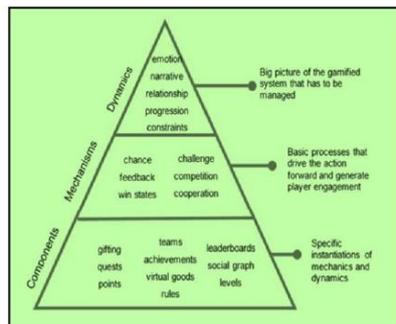


Fig 2 DMC framework adapted from [11]

D. Gamification features

Many educational institutions are starting to combine game elements with learning tools to improve the learning process. Research conducted by [12] investigates which game elements is most used in learning tools as well as the effect of applying gamified learning on students. The results indicated that points, badges and leaderboards are the most widely used elements in gamified learning. The results also indicated that using gamification in learning process increased the learning motivation of students and their engagement in classroom.

The review study conducted by [2] reported that the achievement and progression are the most gamification affordances used in motivation interventions in e-learning. On the other hand, immersion affordances such as the flow experience is significantly less frequent in the learning environment as compared to other gamification affordances.

The work in [13] discussed the gamification tools and their relationship with the engagement level in e-learning websites. Two methods were adopted, the first one is e-learning websites analysis and the second one is online survey with gamification experts' sample. The results indicated that most e-learning websites use the gamification elements. The findings would offer new learning strategies combined with gamification elements to learning designers and teachers in order to enhance student engagement. The findings recommended that future study of student's viewpoints is critical to develop a meaningful learning environment, as they are considered to be the center of improvements.

A review study on gamification in education was conducted by [3] in order to investigate the evidence on gamification effectiveness in student motivation and learning performance. They also analyzed the most used gamification elements. The results reported that the gamification is an effective strategy in education to improve the learning process by motivating students and keeping their commitment. The most used gamification elements in education are points, medals, rankings and narrative.

A review study was conducted by [14] to identify the trends of gamification strategies in the education process by applying the content analysis of recent literature. The outcomes highlighted that motivation, engagements, and performance are the main objectives of adopting gamification in e-learning. On the other hand, points, badges and leaderboard are most gamification elements used in learning strategies.

The review conducted by [15] investigates gamification in virtual learning environments. The outcomes of the content analysis reveal that badges, points, and leaderboards are the most gamification elements used in virtual learning environments. The results indicate a positive trend and recommend the application of gamification in virtual learning environments. At the same time, the main challenge remains how to select the suitable elements that keep the students' motivation and meet their learning objectives.

According to the study in [16], which investigates the trends of gamification features and e-learning concern young learners. The findings focused on four research aspects namely personalization, learner styles, gamification features, and learner engagement. The study reported that the commonly used gamification elements in e-learning are points, leaderboards, badges, and virtual levels.

The work in [17] investigates whether adopting gamification features in educational workshops can improve knowledge retention among students in secondary schools over a period of two years. The results revealed there is a positive effect on knowledge retention, independent of gender factor, and independent of age factor.

The study conducted by [18] analyzes the relation between adopting gamified smartphone applications and learning strategies through pilot tests, using the gamified application HGameApp. The study showed that the contentment of students be influenced by gamified application features.

In [19], an investigation is presented of the effects of gamification features on motivation levels of undergraduate students. The results revealed that their motivation increased significantly.

E. User preferences for gamification elements

The researchers in [20] investigated and evaluated user preferences related to the use of gamified tools. The results indicated that students prefer gamification in their learning environment instead of the traditional method. The results also showed that there is a relationship between motivation and engagement because motivation is one of the gamification elements. Based on the analyzed results, two issues should be taken under consideration: the ease of use, and keeping students motivated on the long term.

5th International Conference on Engineering Technology and its Applications 2022- (5thIICETA2022)

A gamified e-learning environment has been developed by [21] to improve the engagement of undergraduate students. According to the results, selecting gamification elements based on the individual's typology would improve the students' engagement. As for future works, the findings recommend the designing of gamified e-learning environments based on personality traits.

The research conducted by [22] is to identify the gamification elements that are currently adopted in science education. The findings reported that the competitive environment is critical to increase learning outcomes. Also, the findings reveal that the most effective gamification outcomes are motivation, engagement, achievement and social interaction.

An investigation is presented in [23] on the relation between the six user Hexad orientations, namely Player, Socializer, Disruptor, Achiever, Philanthropist, and Free Spirit with the five gamification designs according to five dimensions, being the Performance, Ecological, Social, Personal, and Fictional. These dimensions include twenty-one gamification elements. Storyboards were used to present the five dimensions for respondents in order to identify their preferences. The results identify that the gamification elements in the Performance dimension (points, level, progression) are be considered to be most suitable for all users, whereas the game elements in Fictional dimension such as storytelling were least preferred by respondents.

F. Gamification frameworks and guidelines

The gamification framework in [24] suggests to connect behavior situations and gamification elements in order to improve the learning process and keep the student's behavior over time. This framework has a multidisciplinary structure that could be used in any context.

The authors in [25] explored the guidelines and principles related to design gamified interventions, in order to obtain the desired outcomes based on review study of recent papers in various contexts. The identified principles were divided into three categories, the first one is user-oriented principles in order to keep desired behavior, the second one is system-oriented principles in order to obtain enjoyable user experience, and the third one is context principles in order to differentiate for each context factors and elements.

As for the work in [26], it reviews the literature related to the gamification role in teaching process enhancement. This study offers a conceptual model adapted from contributions of recent studies related games-based learning. The findings pointed that available studies have limitations in their evidences. Hence, the proposed model offers an opportunity for future studies to investigate empirical evidence of relationships.

G. Gamification Approaches

The classic approach that uses uniform application of gamification elements to all learners i.e. "One size fits all" is likely to fail because learners have different characters and they differ from each other in their typology. To bridge this gap, and adaptive approach should be used. The study conducted by [5] attempts to develop an adaptive gamification model based on user preferences. They used the Design Science Research Methodology (DSRM) through using an approach to propose the developed adaptive gamification

model within e-learning platforms, based on 15 adaptive gamification studies.

The crowdsourcing study conducted by [27] aims to identify the main factors that should be taken under consideration when design gamification elements tailoring to user profile. The findings revealed that there are two main factors which affect user motivation in tailored gamification, namely user typology and motivation strategy. An interesting finding of this study revealed that the motivational impact of certain gamification elements varies based on the gamified system domain or user activity. The study revealed that Hexad is the most suitable user typology to be adopted in tailored gamified system that is used to identify user preferences for gamification elements. Concerning motivation strategy, the results found that adopting the same motivation strategy in different implementations can have different effects on motivation.

The study in [28] proposes a linear model between gamification features and players typology to obtain adaptive gamification. This model is implemented in the learning environment and evaluated based on specialist experts. The findings indicate that learners spend more time in adapted gamification features. In other words, this model improves the learners' participation. Furthermore, the finding indicates that motivation and participation are two factors which are independently influenced by game design features. Related to the player types, the limitation of this model is that it does not take into consideration the users who not intended to play. Further research can overcome this challenge. Future versions of this model can bridge the gap concerning user types who are already intrinsically motivated, by providing no features to this user type for improving this model. Recommendations include using adaptive gamifications based on tracking user interactions from dynamic player profile such as assign high score to learner who interact frequently with a competitive feature.

A study conducted by [4] proposes a tailored gamified approach according to the learner types in order to overcome this challenge. This approach has been implemented on empirically with 121 students in an elementary school to evaluate the flow experience of students. The conflicted results indicated that further studies are needed in this field to improve the evidence with recent theoretical studies. Another empirical experience has been conducted to identify which gamification element is the most suitable to each user type, for the sake of providing guidelines for target stakeholders.

Michel C. Desmarais [29] proposed a simple model using non-negative matrix factorization to deriving Q-matrix in order to estimate students' skills to tailor class material and personalize interaction of learners. The idea relies on mapping tasks to skills after presenting question items and tasks to the students.

In [30], an adaptive gamification model is proposed to tailor features of gamification to the learner's profile adopting BrainHex player type. This model is generic and based on the association matrix which includes a linear relation between features of gamification and player types based on the formula $R=BA$, illustrated in Fig. 3 below. Matrix B represents the traits of users, and matrix A represents the weight of traits for each feature. Hence, matrix R represents the product of the two matrices, indicating the expected preferences of the users toward the game features.

5th International Conference on Engineering Technology and its Applications 2022- (5thIICETA2022)

	f1	f2	f3		C	S		#1	#2	#3	
u1	10	00	05	=	u1	10	00	C	1	0	1/2
u2	00	06	12	=	u2	00	12	x	S	0	1/2
u3	06	03	09	=	u3	06	06				
u4	-08	03	02	=	u4	-08	06				

Fig. 3: personalizing using linear model based on R = B.A [30]

H. Gamification and motivation

Gamification in e-learning is an approach that aims to motivate learners and increase their engagement through combining game design elements with the learning environment. However, the challenge is how to integrate the gamification elements within the educational context in an efficient manner to keep the learners motivated. There are currently no sufficient empirical evidences. Gamification in fact is a psychologically-driven approach that tends to increase individual's motivation to do an activity and achieve a specific target. To gamify the learning environment successfully, the target group should be taken into consideration, as well as their preferences of each group of learners relevant to game elements [31].

A review study is conducted by [32] to investigate the gamification effect on user's flow experience. In recent years, different studies suggest adopting gamification for the sake of improving of user's flow experience. In the same time, the results indicate that the interest and publications are increasing in this field, specifically in education. The result of recent studies indicates the importance of conducting new empirical studies that investigate gamification effectiveness on user's flow experience in education and other contexts. The main challenge in recent studies concerning gamification is understanding the effect of gamification on individuals' flow experience. Therefore, the findings of these studies recommend to conduct empirical studies for identifying gamification effects related to the Flow Theory.

III. RESEARCH METHODOLOGY

A. Research Objective

The main objective of the study is to understand the trends and determine the gaps in gamification adoption in e-learning, based on the recent reviews of literature. The specific objectives are to understand the effect of gamification elements on the learners, to identify the most used elements in gamified learning systems, and to clarify gamification approach challenges.

B. Research Questions

This study attempts to answer the research question related to the identification of recent trends and challenges in adopting gamification in e-learning?

More specifically, it aims to addresses the following questions: What is the effect of gamification on learners in e-learning? What are the most widely used elements in gamified learning? What are the gamification approaches in e-learning?

C. Searching procedure

To answer the research question, this study examines the gamification adoptions in educational environments in recent scholarly papers that available on Google Scholar, Web of Science and Scopus databases. The keywords "Gamification", "gamification in Education", "Gamification in E-learning", "gamification approaches" are used to retrieve these research

papers. The output was filtered based on inclusion and exclusion criteria.

D. Inclusion and exclusion criteria

The articles that are written in English and related to gamification in the educational context were selected as Inclusion criteria. On the other hand, articles that written in other than English, related to other contexts, white papers and duplicate articles were excluded.

IV. RESULTS AND DISCUSSION

Gamification is an effective approach in e-learning that aims to change the learners' behavior through improving their motivation and increasing their engagement. The recent literature indicates that the development of technology plays an essential role in transforming education towards adaptation-oriented approaches as well as personalization based on student profile, in order to keep them motivated in the long run [14]. The classic approach that uses uniform application of gamification elements to all learners i.e. "One size fits all" is likely to fail because learners have different characters and they differ from each other in their typology. To bridge this gap, the adaptive approach "one size does not fit all " should be adopted. In other words, an adaptive gamification model should be developed [5]. Player types should be taken into consideration during the design of gamifications to ensure that the gamification approach is suitable for all students [3]. One of the main challenges of gamification is providing a gamified e-learning environment that is tailored according to the learners' types as an alternative of the traditional method that adopts the "one size fit all" approach [4]. Furthermore, the relation between gamification and the user's flow experience still needs evidence. It is recommended to conduct empirical studies to identify gamification effective related to Flow Theory [32].

Based on the results of recent literature reviews, there are several challenges and trends for gamification in education. Table I shows these aspects and their references.

TABLE I. RESULTS OF RECENTS STUDIES

No.	Trends and Challenges	References
1.	Combining game features with e-learning improve learner motivation	[12],[2],[13], [3],[14], [15]
2.	Points, Badges and Leaderboards are the most widely used elements in gamified learning	[7][8][9][12]
3.	The classic approach that uses uniform application of gamification elements to all learners i.e. "One size fits all" is likely to fail. The alternative is using the adaptive approach that makes use of game features based on the learner's preferences.	[5],[28],[32], [26],[21], [20][4]

V. CONCLUSIONS AND FUTURE WORKS

Gamification represents one of the educational efforts that combine digital technology with game design elements in order to increase the learner's motivation and engagement in e-learning. In light of the findings related to gamification trends and challenges in e-learning, the main challenge identified is that the classic approach uses uniform application of gamification elements to all learners i.e. "One size fits all", which is likely to fail because learners have different characters and they differ from one another in their typology. To bridge this gap, the adaptive approach "one size does not fit all " is proposed as an alternative. In other words, an

5th International Conference on Engineering Technology and its Applications 2022- (5thIICETA2022)

adaptive gamification model should be developed. The Player types should be taken into consideration when designing the adaptive gamification model so as to ensure that the gamification approach is suitable for all students. The opinion is stated that the development of technology plays an essential role in transforming education towards the adaptation-oriented approach, as well as the personalization based on the learner's profile in order to keep them motivated on the long run.

This study contributes to the unfolding of current trends and overcoming the challenges related gamification in e-learning. It offers the adaptive gamification approach which suggests gamification elements according to the user preferences, as an alternative to the traditional approach that adopts the same elements to different users. Furthermore, this study contributes to the identification of the most used gamification elements and their efficiency in increasing learners' motivation. Further research and empirically experiments are required to increase the evidence of gamification approaches.

The outcomes of recent studies suggest to pay more attention on expanding the scope of adaptive gamification systems, and to focus more on user interaction in addition to user typology.

REFERENCES

- [1] S. Deterding, D. Dixon, R. Khaled, and L. Nacke, "From Game Design Elements to Gamefulness: Defining 'Gamification,'" in *Proceedings of the 15th International Academic MindTrek Conference Envisioning Future Media Environments.*, 2011, p. 341.
- [2] J. Majuri, J. Koivisto, J. Hamari, and J. H. Fi, "Gamification of education and learning: A review of empirical literature," 2018.
- [3] A. Manzano-León *et al.*, "Between level up and game over: A systematic literature review of gamification in education," *Sustainability (Switzerland)*, vol. 13, no. 4, pp. 1–14, Feb. 2021, doi: 10.3390/su13042247.
- [4] W. Oliveira, J. Vassileva, W. Oliveira dos Santos, and I. Ibert Bittencourt, "Gamification Design to Tailor Gamified Educational Systems Based on Gamer Types," 2018. [Online]. Available: <https://goo.gl/NS6PCd>.
- [5] P. (Paul M.) Cunningham, M. Cunningham, Institute of Electrical and Electronics Engineers, and IEEE Society on Social Implications of Technology, "An Adaptive Gamification Model for E-Learning," 2020.
- [6] K. , Huotari and J. & Hamari, "Defining gamification: a service marketing perspective," in *In Proceeding of the 16th international academic MindTrek conference (pp. 17-22)*, 2012, pp. 17–22.
- [7] F. Reinaldo and R. Pedro Lopes, "Elements of Gamification in Virtual Learning Environments: A Systematic Review," in *International Conference on Interactive Collaborative Learning*, 2017, pp. 86–96. [Online]. Available: <https://www.researchgate.net/publication/320244877>
- [8] F. Fui-Hoon Nah, Q. Zeng, V. Rajasekhar Telaprohu, A. Padmanabhan Ayyappa, and B. Eschenbrenner, "Gamification of Education: A Review of Literature," in *International conference on hci in business 2014*, 2014, vol. 8527, pp. 401–409. [Online]. Available: www.cuictr.co.uk
- [9] D. Strmečki, A. Bemik, and D. Radošević, "Gamification in e-learning: Introducing gamified design elements into e-learning systems," *Journal of Computer Science*, vol. 11, no. 12, pp. 1108–1117, 2015, doi: 10.3844/jcssp.2015.1108.1117.
- [10] R. Hunnicke, M. Leblanc, and R. Zubek, "MDA: A Formal Approach to Game Design and Game Research," 2004.
- [11] Kevin Werbach and Dan Hunter, *For the win: How game thinking can revolutionize your business*. Wharton Digital Press, 2012.
- [12] N. Limantara, A. Nizar Hidayanto, and H. Prabowo, "Achmad Nizar Hidayanto and Harjanto Prabowo, the Elements of Gamification Learning in Higher Education: a Systematic Literature Review," 2019. [Online]. Available: <http://iaeme.com/http://iaeme.com/Home/issue/IMET?Volume=10&Issue=2http://iaeme.com/Home/journal/IMET983>
- [13] S. Rebelo and P. Isaias, "Gamification As An Engagement Tool In E-Learning Websites," *Journal of Information Technology Education: Research*, vol. 19, pp. 834–854, 2019, doi: 10.28945/4653.
- [14] J. K. Acosta-Medina, ; Torres-Barreto, Martha L. ; Alvarez-Melgarejo, and Mileidy, "Literature mapping about gamification in the teaching and learning processes Mapeo de la literatura acerca de la gamificación en los procesos de enseñanza y aprendizaje," *Revista ESPACIOS*, vol. 41, no. 11, 2020.
- [15] F. Reinaldo and R. Pedro Lopes, "Elements of Gamification in Virtual Learning Environments: A Systematic Review," 2017. [Online]. Available: <https://www.researchgate.net/publication/320244877>
- [16] A. Behl, N. Jayawardena, V. Pereira, N. Islam, M. del Giudice, and J. Choudrie, "Gamification and e-learning for young learners: A systematic literature review, bibliometric analysis, and future research agenda," *Technological Forecasting and Social Change*, vol. 176, Mar. 2022, doi: 10.1016/j.techfore.2021.121445.
- [17] L. M. Putz, F. Hofbauer, and H. Treiblmaier, "Can gamification help to improve education? Findings from a longitudinal study," *Computers in Human Behavior*, vol. 110, Sep. 2020, doi: 10.1016/j.chb.2020.106392.
- [18] L. Aguiar-Castillo, A. Clavijo-Rodríguez, L. Hernández-López, P. de Saa-Pérez, and R. Pérez-Jiménez, "Gamification and deep learning approaches in higher education," *Journal of Hospitality, Leisure, Sport and Tourism Education*, vol. 29, Nov. 2021, doi: 10.1016/j.jhlste.2020.100290.
- [19] I. Yildiz, E. Topçu, and S. Kaymakci, "The effect of gamification on motivation in the education of pre-service social studies teachers," *Thinking Skills and Creativity*, vol. 42, Dec. 2021, doi: 10.1016/j.tsc.2021.100907.
- [20] J. Katherin Acosta-Medina, M. Liliana Torres-Barreto, and A. Felipe Cárdenas-Parga, "Students' preference for the use of gamification in virtual learning environments."
- [21] A. Pakinee and K. Puritat, "Designing a gamified e-learning environment for teaching undergraduate ERP course based on big five personality traits," *Education and Information Technologies*, vol. 26, no. 4, pp. 4049–4067, Jul. 2021, doi: 10.1007/s10639-021-10456-9.
- [22] M. Kalogiannakis, S. Papadakis, and A. I. Zourmpakis, "Gamification in science education: A systematic review of the literature," *Education Sciences*, vol. 11, no. 1, pp. 1–36, Jan. 2021, doi: 10.3390/educsci11010022.
- [23] A. C. G. Santos *et al.*, "The relationship between user types and gamification designs," *User Modeling and User-Adapted Interaction*, vol. 31, no. 5, pp. 907–940, Nov. 2021, doi: 10.1007/s11257-021-09300-z.
- [24] R. P. Oliveira, C. G. de Souza, A. da C. Reis, and W. M. de Souza, "Gamification in e-learning and sustainability: A theoretical framework," *Sustainability (Switzerland)*, vol. 13, no. 21, MDPI, Nov. 01, 2021, doi: 10.3390/su132111945.
- [25] J. Krath and H. F. O. von Korfflesch, "Designing gamification and persuasive systems: a systematic literature review," in *5th International GamFIN Conference*, 2021, pp. 100–109. [Online]. Available: <http://ceur-ws.org/Vol-2883/>
- [26] R. J. R. da Silva, R. G. Rodrigues, and C. T. P. Leal, "Gamification in management education: A systematic literature review," *BAR - Brazilian Administration Review*, vol. 16, no. 2, 2019, doi: 10.1590/1807-7692bar2019180103.
- [27] S. Halifax *et al.*, "Factors to Consider for Tailored Gamification," in *Proceedings of the Annual Symposium on Computer-Human Interaction in Play*, 2019, pp. 559–572. [Online]. Available: <https://hal.archives-ouvertes.fr/hal-02185647>
- [28] E. Lavoué, B. Monterrat, M. Desmarais, S. George, and É. Lavoué, "Adaptive Gamification for Learning Environments," *IEEE Transactions on Learning Technologies, Institute of Electrical and Electronics Engineers*, vol. 12, no. 1, 2019, doi: 10.1109/TLT.2018.2823710.
- [29] M. C. Desmarais, "Mapping Question Items to Skills with Non-negative Matrix Factorization," 2012. [Online]. Available: www.professeurs.polymtl.ca/
- [30] B. Monterrat, M. Desmarais, E. Lavoué, and S. George, "A Player Model for Adaptive Gamification in Learning Environments," in *In International conference on artificial intelligence in education*

5th International Conference on Engineering Technology and its Applications 2022- (5thIICETA2022)

(pp. 297-306). Springer, Cham, 2015, pp. 297–306. [Online]. Available: <https://hal.archives-ouvertes.fr/hal-01165497>

- [31] C. Dichev and D. Dicheva, "Gamifying education: what is known, what is believed and what remains uncertain: a critical review," *International Journal of Educational Technology in Higher Education*, vol. 14, no. 1. Springer Netherlands, Dec. 01, 2017. doi: 10.1186/s41239-017-0042-5.
- [32] W. Oliveira *et al.*, "Does gamification affect flow experience? A systematic literature review," Jun. 2021. [Online]. Available: <http://arxiv.org/abs/2106.09942>

Appendix E: Published Paper (2)

5th College of science International Conference on Recent Trends in Information Technology (CSCTIT 2022), AL-Mustansiriyah University, Baghdad-Iraq

Adapt Gamification to Learners' Preferences

Dhiaa Alalgawi
 Information Technology College
 University of Babylon
 Babylon, Iraq
 dhiaa.alalgawi@student.uobabylon.edu.iq

Sattar B. Sadkhan
 Information Technology College
 University of Babylon
 Babylon, Iraq
 drengsattar@ieee.org

Abstract— Adaptive gamification is the process of customizing game features to user preferences by offering game design elements that fit the users' profiles and preferences. Because people range in their personalities and preferences for gamification components, the traditional technique of applying gamification elements uniformly to all learners (i.e., "one size fits all") frequently fails because learners vary in their personalities and have distinct learning styles. Reviewing the efforts that have been done to adapt gamification in accordance with learners' preferences is the major objective of this study in order to address these issues. This aids in examining the most recent adaptive models and the crucial elements that must be considered while developing an adaptive gamification strategy. This study will highlight the many user profiles that have been employed as well as the user types model and adaptation models that have been adopted.

Keywords— Gamification, Motivation, Adaptive gamification, Tailoring, Personalization, E-learning.

I. INTRODUCTION AND BACKGROUND

The employment of game design features in non-gaming contexts such as e-learning is known as gamification [1]. Gamification is the process of transforming work or activities into game-like experiences [2]; the primary benefits of gamification include increased motivation [1] [3]. Gamification is frequently utilized in e-learning to improve learners' performance [4] [5], increase engagement, and maintain motivation [6]. Learners, on the other hand, have different reactions to gamification components [7] [4]. In other words, because of the diversity of player types and personalities, gamification components that may encourage one user may not motivate another [8][7].

Gamification's success is dependent on the proposal of game design components that closely match user preferences [9]. The practice of customizing gamification components to user preferences is known as adaptive gamification. The concept behind adaptive gamification is to offer game design elements based on user preferences [9]. Adaptive gamification components in e-learning have been shown to boost learner motivation and participation [4]. The adaptive techniques offer users a tailored gamification experience by giving game design components that correlate to their preferences and profiles. To improve user experience in gamified systems, the current trend in gamification is to customize elements to user preferences [10][11].

The key current problem for gamification approaches is determining how to personalize gamified e-learning systems [12] [4] [13], (i.e., how to recommend game design components based on learners' preferences in accordance with people's various personalities and motivations). According to recent research, the most tailored gamification efforts were in the educational environment [14]. Traditional gamified experiences employ the same game design features for all users, resulting in a "one-size-fits-all" strategy that fails to motivate all diverse individuals [7]. One of the most difficult problems of gamification is to provide a gamified e-learning environment tailored to the types of learners as an alternative to traditional techniques that use a one-size-fits-all approach [15].

The process of customizing gamification to user preferences is known as adaptive gamification. As a result, adaptive gamification based on learner choices is a viable alternative for overcoming this difficulty [4] [16]. Recent efforts have tended to suggest methods for correlating gamification aspects to various user profiles [4] [7]. The majority of studies have concentrated on the user model, specifically player categories, as well as their preferences for gamification components [5]. The Hexad model proposed by Marczewski [17], the BrainHex model proposed by Nacke [18], and the BigFive model proposed by Goldberg [19] are the most dominant player typologies. Marczewski [17] presented the Hexad model as the first exclusive user type model built for the gamification area, and it is based on motivation theory, specifically Self-Determination Theory (SDT) [20]. Individuals are naturally motivated to participate in activities that address the three basic psychological requirements of humans, according to the theory underpinning SDT. These requirements are skills, autonomy, and relatedness.

The Hexad model was used in several studies [11] [10] [21] [22]. Tondello et al. [23] validated this model. The Hexad model categorizes user preferences into six distinct user types based on two motivation modalities, intrinsic motivation and extrinsic motivation. These six categories are: (1) Philanthropists motivated by purpose; (2) Socializers motivated by relatedness; (3) Free Spirits motivated by autonomy; (4) Achievers motivated by competence; (5) Players motivated by prizes; and (5) Disruptors inspired by change [17].

5th College of science International Conference on Recent Trends in Information Technology (CSCTIT 2022),AL-Mustansiriyah University, Baghdad-Iraq

This study aims to investigate adaptive gamification strategies in e-learning that typically customize gamification features based on user preferences, as well as to present comparisons between adaptive gamification models based on types of user profiles and user typology models used in gamified experiences. It also aims to identify the key factors that must be taken into account when developing an adaptive gamification system.

II. LITERATURE REVIEW

Study done by [4] based on a previous study [24] done by the same authors to propose an adaptive gamification model in a learning environment. This model was based on existing player types and gamification elements. More specifically, using a linear model between player type (BrainHex) and five separate gamification features. This suggested adaptive model is general and is built on an association matrix that comprises a linear relationship between gamification elements and player categories based on the formula $R=BA$, as shown in figure 1.

	f_1	f_2	f_3		c	s		f_1	f_2	f_3	
u_1	10	00	05	=	u_1	10	00	c	1	0	$\frac{1}{2}$
u_2	00	06	12		u_2	00	12	s	0	$\frac{1}{2}$	1
u_3	06	03	09		u_3	06	06				
u_4	-08	03	02		u_4	-08	06				

Fig. 1: Linear model based in formula $R = BA$. [4], [24]

Where matrix-B shows the characteristics of users and matrix-A shows the importance of each characteristic for each feature. So, matrix-R is the product of the two matrices, which would be the users' expected preferences for the game features. In a gamification context, this model is put into action based on the opinions of experts. This model was tested in gamified e-learning, and the results showed that it was able to accurately predict how players would like to use gamification features. This study suggests that more research should be done in the future to look at how users interact in real time, such as turning on and off game mechanics in the user interface.

Figure 2 shows the results of a study done by [15] and expanded by [25] that proposes a general method for adapting a gamified educational system to different kinds of learners.

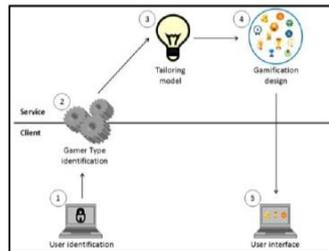


Fig.2: General adaptive gamification approach. Ref. [15] [25]

BrainHex is the user type model employed by this technique. This method has been scientifically used to 121 pupils in an elementary school in order to assess their flow experience. According to the findings of this research, the customized gamification system was more successful for certain user categories.

Another study was done by [26] to propose an adaptive model and process to improve learner motivation by offering gamification features that users prefer based on their player profiles. A certain questionnaire based on the BrainHex model of user type was used to get the information on the profile. Fig. 3 shows how the model was put into place in an e-learning setting based on the player model.

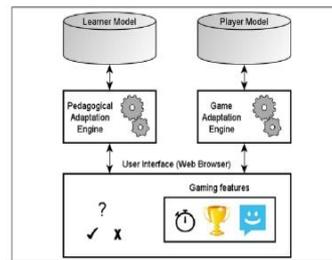


Fig. 3: Adaptive gamification generic model [26]

The results showed that the adaptive process didn't do what it was supposed to do, which was to make learners more interested, and that there wasn't a clear link between adaptive gamification and learners' motivation.

As shown in fig. 4, Tondello et al. [27] proposed a general architecture for creating a recommender system that personalizes gamified apps in any environment.

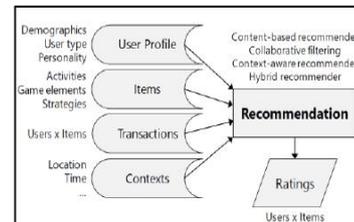


Fig.4: Recommender system for personalized gamification [27]

The framework specifies the inputs, outputs, and processes that make up the recommender system's major components. User profiles, items to be rated, interactions between items and individuals to be evaluated, and finally the context, such as location or environment, are the components of inputs. The output consists of the ratings that the recommender system will predict. Depending on the situation or application, the procedure uses the techniques and algorithms that the recommender system uses. By tailoring gamification elements to each user's preferences, this framework helps to increase user

motivation. Additionally, this framework helps researchers and designers clarify the key elements of recommender systems connected to gamified systems.

A method proposed by [28] to present an adaptive approach to gamification that suggests game elements that fit a player's profile and meet user preferences. The Hexad model of player types was used to build player profiles in this model. Before a gamified experience starts, a Hexad questionnaire proposed by [17] and validated by [11] [23] is used to set up the player profile. The profile changes over time based on how users interact with it. Based on how users interact with it, it can suggest game design elements that match user preferences. The suggested approach was expanded upon by the research's original authors in an additional study [29], which included new inputs including activity completion and a case study in which the system was tested on actual users.

III. RESEARCH METHODOLOGY

A. Research Objective

In order to explore the most recent adaptive models and the key components that need to be taken into account when designing an adaptive gamification approach, the study's main goal is to review the efforts that have been made to adapt gamification in accordance with learners' preferences. This includes identifying the adaptation models, which model of user types have been adopted, as well as the different types of user profiles that have been used.

B. Research Questions

This study provides an answer to the primary research question, which is: What current efforts have been made to adapt gamification models? and responds to the subsequent research questions, namely: What user type models have adaptive approaches adopted? What kinds of user profiles do adaptive approaches use? What factors should be considered while creating personalized gamification?

C. Searching Procedure

To answer research questions, this study searches for adaptive gamification approaches in e-learning environments in recent scholarly papers that are available on Google Scholar, ACM Digital Library, IEEE Xplore, Science Direct, Springer Link, Web of Science, Education Resources Information Center (ERIC), ResearchGate, ProQuest, Academia, Springer and Scopus databases. The keywords "gamification", "adaptive gamification", "personalized gamification", "tailored gamification" are used to retrieve these research papers. The output was filtered based on inclusion and exclusion criteria.

D. Inclusion and Exclusion Criteria

The articles that were written in English and related to adaptive gamification approaches in an e-learning context were selected as inclusion criteria. On the other hand, articles that were written in languages other than English, related to other scopes, white papers, and duplicate articles were excluded.

IV. RESULT AND DISCUSSION

The process of adapting gamification to user preferences is known as adaptive gamification. By employing the same gamification elements for all user types in a gamified technology, traditional gamification design has taken a one-size-fits-all approach. Due to the fact that every player has different playing motivations and preferences, traditional gamification often fails [30] [14]. Therefore, an alternate strategy to address this issue is adaptive gamification based on learners' preferences [4].

There are two forms of adaptive gaming: static and dynamic. Static adaptation is the strategy that is most often adopted. The static adaptive technique uses a static player profile to customize gamification and captures player type data prior to the experience. On the other hand, a dynamic adaptive technique that adapts in real time to user behavior and interactions [31] uses player profiles that modify throughout the duration of an experience. Users may be directly questioned using questionnaires. However, data-driven creations may be made by observing and interpreting user interactions. Additionally, the two previously described techniques may be combined. The user model may be stereotyped, static, or dynamic. Static, when data is just collected once and is not updated. Dynamic when the data is regularly updated. When inferred from certain common characteristics among user groups, stereotypes are created [14].

To answer research questions about adaptive gamification models, table I presents comparisons among adaptive gamification studies according to types of user profiles and models of user types that adopt:

TABLE I: COMPARISON AMONG ADAPTIVE MODELS

No.	Ref.	Adaptation Model	Types of users profile	Models of User type
1.	[4] [24]	Linear model relies on matrix factorization.	static	BrainHex
2.	[15] [25]	tailoring gamified educational system	static	BrainHex
3.	[26]	propose generic gamified adaptive model	static	BrainHex
4.	[27]	Recommender system	n/a	n/a
5.	[28]	gamified adaptive method	Static/Dynamic	Hexad
6.	[29]	dynamic adaptive method	Static/Dynamic	Hexad

According to literature research and existing models of adaptive gamification, there are interesting factors and characteristics to consider when designing personalized gamification. Here is further information about these components and elements:

5th College of science International Conference on Recent Trends in Information Technology (CSCTIT 2022), AL-Mustansiriyah University, Baghdad-Iraq

A. Models of user type:

In addition to their preferences for gamification components, the majority of research focused on user models, more especially user typologies [14] [13] [4]. User typologies are therefore one of the key elements to take into account when building adaptive gamification. The findings of the literature already in existence supported the need of taking player profiles into account when creating gamification systems [14].

The findings of the literature research show that the Hexad user type is more relevant to creating gamification since Hexad was built specifically to handle gamification [32]. As an alternative to the questionnaire scale that was developed by [17] and confirmed by [34] [23], new research by [33] uses game-like apps to predict player types.

We may draw the conclusion that gamification tailored in accordance with the Hexad model tends to increase motivation and learner engagement [35], which is supported by another research [36]. In contrast, other user kinds like BrainHex were developed to meet different gaming player types. The Big Five is a different user type that was developed to address personality attributes [27].

B. Types of user profile

User profiles come in static and dynamic types. When information is gathered via a player-type questionnaire prior to the beginning of the experience, the user profile remains static. Dynamic user profiles are those where information changes over time while participating in a gamified experience depending on user activity like interactions [29].

C. Motivation strategies:

One of the key elements that must be taken into account while building gamification interventions is motivational strategies [32]. The majority of research [37] concentrated on the level of game mechanics, which are sometimes referred to as persuasive or motivating strategies. In order to make gamification principles and motivating techniques clearer, there are numerous frameworks that categorize and arrange gamification features. In order to define the notion of gamification, Werbach and Hunter [38] presented the DMC (Dynamics, Mechanics, and Components) framework. This framework introduces a gamification pyramid that categorizes gamification aspects into three levels. Dynamics, such as emotions, are the most basic and abstract elements that cannot be easily included into a gamification system. In a gamified system, dynamics such as challenges and competition are used to motivate player participation. This process is known as mechanics. Components, like badges and avatars, are the tangible representations of mechanics and dynamics. One of the primary current and future research themes is game components [39].

D. The context:

Based on previous contextualized research, the findings of the literature analysis show that the context influences the motivating effect of game features. Therefore, while creating game features, context should be taken into account [27] [39].

According to research by [32], the context of a gamified system should be taken into account while designing gamification features. The user's behavior, such as taking tests, or the domain, such as education, are both examples of context.

V. CONCLUSION

The process of adapting gamification to user preferences is known as adaptive gamification. By using the same gamification elements for all user types in a gamified technology, traditional gamification design has taken a one-size-fits-all approach. Due to the fact that each player has unique playing motivations and preferences, this strategy frequently fails. Therefore, an alternative strategy to solve this problem is adaptive gamification based on student preferences. This study's goal is to outline efforts for adaptive gamification strategies in e-learning that tend to customize gamification elements in accordance with learner preferences.

According to literature reviews and existing models of adaptive gamification, there are intriguing elements and considerations to consider when developing personalized gamification. According to the results of the currently published literature, the player profile should be the first consideration when developing gamification systems. A user's profile might be static or dynamic. The user typology model is the second element to consider. Most research focused on user models, particularly user typologies like the Hexad user type and user preferences for gamification elements. The findings of the literature review indicated that this user type is most relevant to producing gamification because Hexad was created specifically to handle it. Utilizing motivational strategies is the third factor to take into account. Game mechanics, sometimes referred to as persuasive or motivational methods, are an important factor to consider while creating gamification treatments. The context of the gamified system, such as the domain or type of user activity, should be taken into account when developing game elements.

The outcome of this study highlighted the Hexad model, which is the most well-liked user typology model, as well as various static and dynamic user profile types utilized in adaptive gamification strategies.

REFERENCES

- [1] S. , Deterding, D. , Dixon, R. , Khaled, and L. Nacke, "From Game Design Elements to Gamefulness: Defining 'Gamification,'" in *Proceedings of the 15th International Academic MindTrek Conference Envisioning Future Media Environments.*, 2011, p. 341.
- [2] J. Hamari, "Gamification," in *The Blackwell Encyclopedia of Sociology*, Oxford, UK: John Wiley & Sons, Ltd, 2019, pp. 1–3. doi: 10.1002/9781405165518.wboos1321.
- [3] İ. Yıldız, E. Topçu, and S. Kaymakci, "The effect of gamification on motivation in the education of pre-service social studies teachers," *Think Skills Creat*, vol. 42, Dec. 2021, doi: 10.1016/j.tsc.2021.100907.
- [4] E. Lavoué, B. Monterrat, M. Desmarais, S. George, and É. Lavoué, "Adaptive Gamification for Learning Environments," *IEEE Transactions on Learning Technologies*, Institute of Electrical and Electronics Engineers, vol. 12, no. 1, 2019, doi: 10.1109/TLT.2018.2823710f.
- [5] A. C. T. Klock, I. Gasparini, and M. S. Pimenta, "User-centered gamification for e-learning systems: A quantitative and qualitative analysis of its application," *Interact Comput*, vol. 31, no. 5, pp. 425–445, Feb. 2020, doi: 10.1093/iwc/iwz028.

5th College of science International Conference on Recent Trends in Information Technology (CSCTIT 2022), AL-Mustansiriyah University, Baghdad-Iraq

- [6] R. N. Landers and M. B. Armstrong, "Enhancing instructional outcomes with gamification: An empirical test of the Technology-Enhanced Training Effectiveness Model," *Comput Human Behav*, vol. 71, pp. 499-507, Jun. 2017, doi: 10.1016/j.chb.2015.07.031.
- [7] M. A. Hassan, U. Habiba, F. Majeed, and M. Shoaib, "Adaptive gamification in e-learning based on students' learning styles," *Interactive Learning Environments*, vol. 29, no. 4, pp. 545-565, 2021, doi: 10.1080/10494820.2019.1588745.
- [8] C. E. Lopez and C. S. Tucker, "The effects of player type on performance: A gamification case study," *Comput Human Behav*, vol. 91, pp. 333-345, Feb. 2019, doi: 10.1016/j.chb.2018.10.005.
- [9] T. Jagušt, I. Botički, and H. J. So, "Examining competitive, collaborative and adaptive gamification in young learners' math learning," *Comput Educ*, vol. 125, pp. 444-457, Oct. 2018, doi: 10.1016/j.compedu.2018.06.022.
- [10] G. F. Tondello, R. Orji, and L. E. Nacke, "Recommender systems for personalized gamification," in *UMAP 2017 - Adjunct Publication of the 25th Conference on User Modeling, Adaptation and Personalization*, Jul. 2017, pp. 425-430, doi: 10.1145/3099023.3099114.
- [11] G. F. Tondello, R. R. Wehbe, L. Diamond, M. Busch, A. Marczewski, and L. E. Nacke, "The gamification user types Hexad scale," in *CHI PLAY 2016 - Proceedings of the 2016 Annual Symposium on Computer-Human Interaction in Play*, Oct. 2016, pp. 229-243, doi: 10.1145/2967934.2968082.
- [12] J. Koivisto and J. Hamari, "The rise of motivational information systems: A review of gamification research," *International Journal of Information Management*, vol. 45, Elsevier Ltd, pp. 191-210, Apr. 01, 2019, doi: 10.1016/j.ijinfomgt.2018.10.013.
- [13] W. Oliveira *et al.*, "Does tailoring gamified educational systems matter? The impact on students' flow experience," in *Proceedings of the Annual Hawaii International Conference on System Sciences*, 2020, vol. 2020-January, pp. 1226-1235, doi: 10.24251/hicss.2020.152.
- [14] A. C. T. Klock, I. Gasparini, M. S. Pimenta, and J. Hamari, "Tailored gamification: A review of literature," *International Journal of Human Computer Studies*, vol. 144, Dec. 2020, doi: 10.1016/j.ijhcs.2020.102495.
- [15] W. Oliveira, J. Vassileva, W. Oliveira dos Santos, and I. Ibert Bittencourt, "Gamification Design to Tailor Gamified Educational Systems Based on Gamer Types," in *SBGames 2018*, 2018. [Online]. Available: <https://goo.gl/NS6PCd>.
- [16] A. Mora, D. Riera, C. Gonzalez, and J. Amedo-Moreno, "A Literature Review of Gamification Design Frameworks," in *VS-Games 2015 - 7th International Conference on Games and Virtual Worlds for Serious Applications*, Oct. 2015, doi: 10.1109/VS-GAMES.2015.7295760.
- [17] A. Marczewski, "EVENNINJA.MONKEYS.LIKE.TO.PLAY.UNICORN.EDITION Gamification, Game Thinking and Motivational Design," *CreateSpace Independent Publishing Platform*, 65-80, 240-290, ., 2015. <https://www.gamified.uk/user-types/>
- [18] L. E. Nacke, C. Bateman, and R. L. Mandryk, "LNCS 6972 - BrainHex: Preliminary Results from a Neurobiological Gamer Typology Survey," 2011. [Online]. Available: www.bramhex.com
- [19] Lewis R. Goldberg, "The Development of Markers for the BigFive factor Structure," *The American Psychological Association, Inc.*, 1992.
- [20] R. M. Ryan and E. L. Deci, "Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being," *American Psychologist*, vol. 55, no. 1, pp. 68-78, 2000, doi: 10.1037/0003-066X.55.1.68.
- [21] R. Orji, G. F. Tondello, and L. E. Nacke, "Personalizing persuasive strategies in gameful systems to gamification user types," in *Conference on Human Factors in Computing Systems - Proceedings*, Apr. 2018, vol. 2018-April, doi: 10.1145/3173574.3174009.
- [22] D. Holmes, D. Charles, P. Morrow, S. McClean, and S. McDonough, "Rehabilitation Game Model for Personalised Exercise," in *Proceedings - 2015 International Conference on Interactive Technologies and Games, ITAG 2015*, Feb. 2015, pp. 41-48, doi: 10.1109/ITAG.2015.11.
- [23] G. F. Tondello, A. Mora, A. Marczewski, and L. E. Nacke, "Empirical validation of the Gamification User Types Hexad scale in English and Spanish," *International Journal of Human Computer Studies*, vol. 127, pp. 95-111, Jul. 2019, doi: 10.1016/j.ijhcs.2018.10.002.
- [24] B. Monterrat, M. Desmarais, E. Lavoué, and S. George, "A Player Model for Adaptive Gamification in Learning Environments," *AIED 2015, Jun 2015, Madrid, Spain*, pp. 297-306, hal01165497, pp. 297-306, 2015. [Online]. Available: <https://hal.archives-ouvertes.fr/hal-01165497>
- [25] W. Oliveira *et al.*, "The effects of personalized gamification on students' flow experience, motivation, and enjoyment," *Smart Learning Environments*, vol. 9, no. 1, Dec. 2022, doi: 10.1186/s40561-022-00194-x.
- [26] B. Monterrat, É. Lavoué, and S. George, "Adaptation of Gaming Features for Motivating Learners," *Simul Gaming*, vol. 48, no. 5, pp. 625-656, Oct. 2017, doi: 10.1177/1046878117712632.
- [27] G. F. Tondello, R. Orji, and L. E. Nacke, "Recommender systems for personalized gamification," in *UMAP 2017 - Adjunct Publication of the 25th Conference on User Modeling, Adaptation and Personalization*, Jul. 2017, pp. 425-430, doi: 10.1145/3099023.3099114.
- [28] I. Rodriguez, A. Puig, and A. Rodriguez, "We Are Not the Same Either Playing: A Proposal for Adaptive Gamification," in *Frontiers in Artificial Intelligence and Applications*, Oct. 2021, vol. 339, pp. 185-194, doi: 10.3233/FAIA210133.
- [29] I. Rodriguez, A. Puig, and Á. Rodriguez, "Towards Adaptive Gamification: A Method Using Dynamic Player Profile and a Case Study," *Applied Sciences (Switzerland)*, vol. 12, no. 1, Jan. 2022, doi: 10.3390/app12010486.
- [30] H. Akasaki *et al.*, "One size does not fit all: Applying the right game concepts for the right persons to encourage non-game activities," in *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, 2016, vol. 9735, pp. 103-114, doi: 10.1007/978-3-319-40397-7_11.
- [31] H. Stuart, A. Serna, J.-C. Marty, E. Lavoué, S. Halifax, and J. Moulin Lyon, "Adaptive gamification in education: A literature review of current trends and developments," in *European Conference on Technology Enhanced Learning (EC-TEL)*, 2019, pp. 294-307. [Online]. Available: <https://hal.archives-ouvertes.fr/hal-02185634>
- [32] S. Halifax, A. Serna, J. C. Marty, G. Lavoué, and E. Lavoué, "Factors to consider for tailored gamification," in *CHI PLAY 2019 - Proceedings of the Annual Symposium on Computer-Human Interaction in Play*, Oct. 2019, pp. 559-572, doi: 10.1145/3311350.3347167.
- [33] M. Altmeyer, G. F. Tondello, A. Krüger, and L. E. Nacke, "HexArcade: Predicting Hexad User Types by Using Gameful Applications," in *CHI PLAY 2020 - Proceedings of the Annual Symposium on Computer-Human Interaction in Play*, Nov. 2020, pp. 219-230, doi: 10.1145/3410404.3414232.
- [34] G. F. Tondello, R. R. Wehbe, L. Diamond, M. Busch, A. Marczewski, and L. E. Nacke, "The gamification user types Hexad scale," in *CHI PLAY 2016 - Proceedings of the 2016 Annual Symposium on Computer-Human Interaction in Play*, Oct. 2016, pp. 229-243, doi: 10.1145/2967934.2968082.
- [35] S. Halifax, E. Lavoué, and A. Serna, "To tailor or not to tailor gamification? An analysis of the impact of tailored game elements on learners' behaviours and motivation," in *21th International Conference on Artificial Intelligence in Education*, 2020, pp. 216-227. [Online]. Available: <https://hal.archives-ouvertes.fr/hal-02573200>
- [36] A. Mora, G. F. Tondello, L. E. Nacke, and J. Amedo-Moreno, "Effect of personalized gameful design on student engagement," in *IEEE Global Engineering Education Conference, EDUCON*, May 2018, vol. 2018-April, pp. 1925-1933, doi: 10.1109/EDUCON.2018.8363471.
- [37] R. Orji, J. Vassileva, and R. L. Mandryk, "Modeling the efficacy of persuasive strategies for different gamer types in serious games for health," *User Model User-adapt Interact*, vol. 24, no. 5, pp. 453-498, Oct. 2014, doi: 10.1007/s11257-014-9149-8.
- [38] K. Werbach and Dan Hunter, *For the win: How game thinking can revolutionize your business*. Wharton Digital Press, 2012.
- [39] A. Behl, N. Jayawardena, V. Pereira, N. Islam, M. del Giudice, and J. Choudrie, "Gamification and e-learning for young learners: A systematic literature review, bibliometric analysis, and future research agenda," *Technol Forecast Soc Change*, vol. 176, Mar. 2022, doi: 10.1016/j.techfore.2021.121445.

الملخص

يطلق مصطلح "التلعيب" على استخدام عناصر تصميم اللعبة مثل الشارات ولوحات المتصدرين في بيئات غير متعلقة باللعبة مثل بيئة التعلم الإلكتروني. ان نهج التلعيب التقليدي الذي يتجاهل التفضيلات والسمات الشخصية للمتعلمين يميل للفشل بسبب عدم قدرته على تكيف عناصر التلعيب لتناسب تفضيلات المتعلمين. يعمل التلعيب التكيفي على تخصيص التجارب بناء على ملفات تعريف المستخدمين على حل هذه المشكلة. لذا يتطلب تطوير إستراتيجية تلعيب شاملة وقابلة للتكيف تأخذ في الاعتبار ملفات تعريف المستخدمين وتفضيلاتهم.

في هذه الأطروحة تم اقتراح إستراتيجية لتحديد نوع مجموعة المستخدمين وتفضيلاتهم. تعتمد الإستراتيجية المقترحة على طريقة تحليل المصفوفة لتحديد نوع مجموعة المستخدمين وتفضيلاتهم تجاه عناصر التلعيب. تهدف هذه الإستراتيجية إلى تحسين دافعية المتعلمين والتزامهم في بيئة التعلم الإلكتروني.

تم إنشاء ملف تعريف المستخدم باستخدام استبيان خاص يدعى (Hexad). تم استخدام البرنامج الاحصائي (SPSS) لتحديد (أنواع المستخدمين السائدة) ضمن المجموعة المشاركة بالإضافة إلى (نوع المستخدم الرئيسي) لكل مشارك. تم استخدام برمجة بايثون لتحديد (عناصر التلعيب) التي يفضلها المشاركون اعتماداً على نوع المستخدم المهيم لديهم.

أظهرت الإستراتيجية المقترحة أن نوع المستخدم "المنجزين" ونوع المستخدم "اللاعبين" كانوا أكثر المتعلمين شيوعاً. أما ميزة التلعيب الذي حصل على أعلى تصنيف هو "التحديات" مما يشير الى انها الميزة الأكثر تحفيزاً لمجموعة المتعلمين.

تم استخدام منصة التعلم الإلكتروني المدعومة بالتلعيب (EdApp) لاختبار الإستراتيجية المقترحة في تجربة واقعية من خلال دمج ميزات التلعيب المستخرجة من نتائج الإستراتيجية المقترحة لتلبية تفضيلات الطلاب.

وفقاً لنتائج هذا البحث، فإن التلعيب التكيفي بناءً على تفضيلات المستخدم يعمل على تحسين مشاركة الطلاب والتزامهم. هذه هي الأطروحة الأولى في العراق التي تكيف أسلوب التلعيب مع تفضيلات الطلاب، مما يجعلها إضافة نوعية في هذا المجال.



جمهورية العراق
وزارة التعليم العالي والبحث العلمي
جامعة بابل
كلية تكنولوجيا المعلومات
قسم البرمجيات

تكييف الألعاب لتحسين أداء المتعلمين بالاعتماد على تفضيلاتهم

اطروحة مقدمة الى
مجلس كلية تكنولوجيا المعلومات- جامعة بابل كجزء من متطلبات نيل
درجة الدكتوراة فلسفة في تكنولوجيا المعلومات / البرمجيات

من قبل

ضياء عبدالحسين دراج ذرب

بإشراف

الأستاذ الدكتور المهندس ستار بدر سدخان