AGYEMAN MURAD TAQI

EVALUATING THE ADOPTION OF
GRS USING MCDM APPROACH

Nicosia
June, 2024

NEAR EAST UNIVERSITY

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MASTER THESIS

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Approval

We certify that we have read the thesis submitted by Agyeman Murad Taqi titled **"EVALUATING THE ADOPTION OF GAMIFIED RECOMMENDER SYSTEMS USING MULTI CRITERIA DECISION APPROACH"** and that in our combined opinion it is fully adequate, in scope and in quality, as a thesis for the degree of Master of Science in Computer Information Systems.

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Declaration

I hereby declare that all information, documents, analysis and results in this thesis have been collected and presented according to the academic rules and ethical guidelines of Institute of Graduate Studies, Near East University. I also declare that as required by these rules and conduct, I have fully cited and referenced information and data that are not original to this study.

Agyeman Murad Taqi
01/06/2024

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Agyeman Murad Taqi

Abstract

EVALUATING THE ADOPTION OF GAMIFIED RECOMMENDER SYSTEMS USING MULTI CRITERIA DECISION APPROACH

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This study evaluates the adoption of gamified recommender systems using a fuzzy logic-enhanced multi-criteria decision-making (MCDM) approach to optimize user engagement and satisfaction. Four gamified designs were assessed against criteria including effectiveness, transparency, persuasiveness, user satisfaction, trust, usefulness, ease of use, efficiency, and education. Twenty-five decision makers provided evaluations, which were used to create preliminary fuzzy evaluation matrices. The Fuzzy Dematel method, normalized and aggregated these matrices, and the centroid approach was employed in the defuzzification process to convert fuzzy data into crisp scores. The analysis revealed that "Usefulness" and "Ease of Use" are critical factors significantly influencing user satisfaction and system effectiveness. Each design presented unique benefits for users, demonstrating various approaches to enhancing user experience through gamification. The findings highlights the importance of integrating user-centred criteria in the design of gamified recommender systems. This approach therefore ensures that user needs, and expectations are met, thereby improving overall user engagement and satisfaction. The study concludes that fuzzy logic combined with MCDM provides a strong framework for evaluating and optimizing gamified recommender systems. The results suggest that focusing on key user-centred criteria can significantly boost the effectiveness and user satisfaction of these systems. This approach offers new perspectives on improving user engagement and satisfaction in digital environments by modifying system design to user requirements and expectations.

Key Words: Fuzzy Logic, Multi-Criteria Decision-Making (MCDM), Gamified Recommender System, User Engagement, User Satisfaction, System Effectivenes

Özet

ÇOK KRİTERLİ KARAR YAKLAŞIMI KULLANILARAK OYUNLAŞTIRILMIŞ ÖNERİ SİSTEMLERİNİN UYGULANMASININ DEĞERLENDİRİLMESİ
Yüksek Lisans, Bilgisayar Bilişim Sistemleri Bölümü
Haziran, 2024, (88) sayfa

Bu çalışma, kullanıcı katılımını ve memnuniyetini optimize etmek için bulanık mantıkla geliştirilmiş çok kriterli karar verme (MCDM) yaklaşımını kullanan oyunlaştırılmış öneri sistemlerinin benimsenmesini değerlendirmektedir. Dört oyunlaştırılmış tasarım; etkililik, şeffaflık, ikna edicilik, kullanıcı memnuniyeti, güven, kullanışlılık, kullanım kolaylığı, verimlilik ve eğitim gibi kriterlere göre değerlendirildi. Yirmi beş karar verici, ön bulanık değerlendirme matrislerini oluşturmak için kullanılan değerlendirmeler sağladı. Bu matrisleri normalize eden ve bir araya getiren Bulanık Dematel yöntemi ve durulaştırma sürecinde bulanık verileri net puanlara dönüştürmek için centroid yaklaşımı kullanıldı. Analiz, "Kullanışlılık" ve "Kullanım Kolaylığı"nın kullanıcı memnuniyetini ve sistem etkinliğini önemli ölçüde etkileyen kritik faktörler olduğunu ortaya çıkardı. Her tasarım, oyunlaştırma yoluyla kullanıcı deneyimini geliştirmeye yönelik çeşitli yaklaşımları sergileyerek kullanıcılara benzersiz faydalar sundu. Bulgular, kullanıcı merkezli kriterlerin oyunlaştırılmış öneri sistemlerinin tasarımına entegre edilmesinin önemini vurgulamaktadır. Dolayısıyla bu yaklaşım, kullanıcı ihtiyaçlarının ve beklentilerinin karşılanmasını sağlayarak genel kullanıcı katılımını ve memnuniyetini artırır. Çalışma, bulanık mantığın MCDM ile bir araya getirilmesinin, oyunlaştırılmış öneri sistemlerinin değerlendirilmesi ve optimize edilmesi için güçlü bir çerçeve sağladığı sonucuna varmaktadır. Sonuçlar, temel kullanıcı merkezli kriterlere odaklanmanın, bu sistemlerin etkinliğini ve kullanıcı memnuniyetini önemli ölçüde artırabileceğini göstermektedir. Bu yaklaşım, sistem tasarımını kullanıcı gereksinimlerine ve beklentilerine göre değiştirerek dijital ortamlarda kullanıcı katılımını ve memnuniyetini artırmaya yönelik yeni bakış açıları sunar.

Anahtar sözcükler:Bulanık Mantık, Çok Kriterli Karar Verme (MCDM), Oyunlaştırılmış Öneri Sistemi, Kullanıcı Katılımı, Kullanıcı Memnuniyeti, Sistem Etkinliği

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List of Abbreviations

CIS: Computer Information Systems.

GRS: Gamified Recommender Systems

MCDM: Multi Criteria Decision Making

DM: Decision Maker

MADM: Multi-Attribute Decision Making

MODM: Multi-Objective Decision Making

PBL: Points, Acknowledgments, and Competition

AOP: Acknowledgments, Objectives, and Progression

AOS: Acknowledgments, Objectives, and Social Pressure

ACT: Acknowledgments, Competition, and Time Pressure

CHAPTER I

INTRODUCTION

1.1 Background

Decision making is affected by many factors whether social, biological, physiological or cultural. Therefore, making decision has been and continues to be a major activity for the ordinary human (Taherdoost & Madanchian, 2023). Most decision-making problems have contradictory criteria and objectives which have to be considered simultaneously. An effective and systematic evaluation of choices and solutions requires a reliable and dependable decision-making system (Yannis et al., 2020) . Decisions to a very large extent are determined by constraints which are mostly unknown and events over which there is no control (Başhan et al., 2019). In the exact sciences, there are usually only one solution to a problem. In the decision-making process, several advantages and disadvantages are considered, which means there would be some amount of compromise and exchange leading to the availability of several different options (Jahan & Edwards, 2013).

Decision makers would therefore need help with the decision-making process. Help came in the form of Decision Support Systems (DSS) which collects, organizes and analyses data from which appropriate actions can be taken (Macias-Escobar et al., 2021). The DSS is computer based and can be applied in different decision-making processes. Amongst the DSS applications is the Knowledge-driven DSS which uses available data to make suggestions and recommendations. Recommender systems fall within this category of assisting users in decision making (Alahmadi & Jamjoom, 2022).

Recommender systems, also known as recommendation systems, are designed to filter information and provide personalized suggestions for items that may interest users (Raftopoulou & Pallis, 2023) . Acting as filters, recommendation systems practically reduce information overload (Roy & Dutta, 2022) . Recommendation systems use various algorithms like content-based filtering, collaborative filtering, and hybrid methods to predict user preferences (Milano et al.,2020) . Content-based systems rely on past user interactions, while collaborative filtering uses the preferences of similar users. Hybrid systems combine both approaches to enhance accuracy and personalization (Pathak et al., 2010) . Both content-based and collaborative filtering have limitations which Hybrid, being a combination of the two also inherits. Given a more expansive knowledge base and with the ability to overcome their limitations, Knowledge based recommendation system provides better recommendations. Modern systems however integrate both knowledge based and hybrid to get rid of the limitations, thereby increasing levels of accuracy. In application, an effective recommendation system needs continuous feedback for optimized results. This can only be achieved if the user is confident that the system is providing accurate results. With continuous interaction, the user provides additional data from which the algorithms learn and revise their predictions. The user's involvement is paramount. If there is no cooperation from the user, then the user has to be motivated to get involved (Nunes & Jannach, 2017).

Gamification can potentially provide the motivation that users require because it has the capacity to cause behavioral change and enhance user motivation and engagement (Alsawaier, 2018) . It motivates in multiple ways depending largely on the context. (Dichev & Dicheva, 2017). Gamification is regarded as a powerful tool as it actually generates an experience and responses from gamification depends largely on the characteristics of the users. Using game design elements, gamification can positively influence user motivation; stimulating the brain such that the rewards encourage the user to maintain engagement; promoting behavioral change in a broad range of domains including health and fitness, education, training, customer loyalty, marketing, and staff management (Tondello et al., 2017).

In gamification therefore, it is best to choose game design elements that have the potential to incentivize the user, to push the user towards the desired objective. The goal is to drive user engagement and the designs must continually encourage the user to maintain engagement at their will. The Game designs must be tailored to fit the user's needs and expectations to ensure the user continue to interact with the gamified environment. Users can only continue to maintain the environment if they are satisfied with the experience. The experience is personal and that is why it is critical to achieve engagement, performance, improved attendance and proactiveness. Having determined the desired goal and what can potentially move the set of users, the design must ensure that the users enjoy the process (Triantafyllou & Georgiadis, 2022). The game elements must fit the user's profile, taking into consideration what challenges the user, the user's social connections, the status of the user, possible rewards and progression elements (Marache-Francisco and Brangier, 2013) . It is worthy to note that the effectiveness of the design is not only based on the number of game elements but on its effects. In some designs, the correlation of the elements might not even yield a positive outcome (Huang & Hew, 2021).

There is much emphasis on the user's preferences as studies have shown that users differ considerably, and different gamified designs lead to different user experiences (Santos et al., 2021) . Moreover, for a design to be acceptable; effectiveness, efficiency and satisfaction are key attributes. These ensure that identified users can achieve required goals in specific environments. Usability and usefulness are absolutely necessary. Persuasiveness, Percieved use and ease of use also gain recognition in achieving user acceptance (Marache-Francisco and Brangier, 2013) . Trust another attribute, depends heavily on transparency and usability. Trust comes through after positive user experiences (Bhaskaran, 2024)

1.2 Purpose of the Study

The hypothesis for this study is that users react to different designs differently. In the absence of reliable data on user experience, this study has identified four hypothetical gamified recommender system designs which were presented to students for evaluation.

The study aims to investigate whether the identified gamified designs for recommender systems in language learning impact the cause-effect relationships among attributes like effectiveness, transparency, persuasiveness, user satisfaction, trust, usefulness, ease of use, efficiency, and learnability. A systematic literature review was conducted to identify these attributes.

Responses from the students display their reactions to the different designs, thereby providing user feedback. For efficiency and accuracy, their responses or feedback is evaluated using the FUZZY DEMATEL method. The FUZZY DEMATEL method, a multi-criteria decision-making (MCDM) approach, is used to evaluate the gamified recommender systems. This method accounts for inconsistencies and inaccuracies, providing a systematic evaluation of various system designs. The cause-effect relationships among the variables for each design were then compared to identify any discrepancies and provide insights into improving personalized experiences and enhancing behavior change within gamified applications.

1.3 Statement of the Problem

Recommender systems and gamification are relatively new concepts which research has established can improve user experience (Santos et al., 2021) . Integrating gamification into recommender systems, referred to as gamified recommender systems, can provide the necessary motivation for users to engage with the system, thereby improving the accuracy of recommendations (Saleem et al., 2022). This integration involves using game elements such as points, badges, and leaderboards to keep users engaged (De et al., 2014) . A blend of the two concepts has however not received much feedback since the concept has only quite recently been incorporated in the world of recommender systems. In order to determine the effectiveness and efficiency of the integration, accurate feedback is required (Lerato et al., 2015) . Empirical evidence of user experience is key (Knijnenburg et al., 2012) . Feedback detailing user reactions determines the acceptance or adoption of gamified recommender systems. These reactions have a strong influence on the effectiveness and accuracy of evaluation, and consequent adoption of the system (Champiri et al., 2019) . Deriving data to support user experience given the novelty of the integration becomes challenging. Moreover, evaluating and adoption becomes a bigger challenge in the light of the subjective nature of human preferences and the need for reliable decision-making tools (Jannach, 2023).

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1.4 Significance of the Study

Gamified recommender systems have not received much feedback since the concept has only quite recently been incorporated in the world of recommender systems. Consequently, evaluation of user experience in the absence of studies of different gamified recommender designs is a challenge. Feedback detailing user reactions determines the acceptance or adoption of gamified recommender systems. Evaluating becomes a bigger challenge in the light of the subjective nature of human preferences and MCDM is proposed to provide the platform for a comparison of different systems across multiple dimensions.

CHAPTER II

LITERATURE REVIEW

The literature review explores the fundamental ideas and theories that form the basis of the research study "Evaluating the Adoption of Gamified Recommender Systems Using a Multi-Criteria Decision Approach." The theoretical framework and relevant research in gamified recommender system designs and multi-criteria decision-making (MCDM) are examined in this chapter. Through the integration of various domains, this study seeks to offer a thorough understanding of the ways in which gamified aspects can improve recommender systems and the efficient ways in which MCDM techniques can assess their performance and adoption. This chapter presents the evaluation criteria for gamified recommender systems, identifies important themes, and conducts a methodical review of previous studies. Establishing a solid methodological approach and obtaining significant insights from the research findings are reliant upon this foundation. Also, Complexities exist in the decision-making process, and it is imperative that groundwork be laid for the right techniques and solutions to achieve desired outcomes. Choices have to be made to achieve best results. Decision support system (DSS), and Multiple Criteria Decision Making (MCDM), work together to achieve best results through the Gamified recommendation system (GRS). MCDM considers multiple criteria in recommendations whilst ranking the effectiveness of recommendation algorithms in meeting identified criteria; DSS provides a wide decision support base, puts information together and outlines the problem. DSS can use RS to determine preferences of the decision maker (Liu et al, 2010; Sahoo & Goswami, 2023).

2.1 MCDM (Multi Criteria Decision Making)

Multiple criteria Decision Analysis (MCDA), also referred to as MCDM, is a sub-discipline of Operations Research with the capacity for optimal decision-making. Qualified with major significance within the Operational research system, MCDM has the capacity to evaluate multiple quantitative and qualitative criteria. MCDM's research area encompasses various disciplines for proper analysis, which gives MCDM the edge as a decision-making tool (Yannis et al., 2020). MCDM generally has six steps; the first step determines the problem; the second identifies the requirements; the third establishes targets; the fourth identifies the different options; the fifth develops the criteria; and the sixth identifies and applies the decision-making technique. The process compares a chosen criterion against all other available option to ensure that the decision maker selects an option with maximum advantage, and minimum compromise. This process involves the use of mathematical techniques and the nature and level of complexity of the problem determines the choice of technique.

The MCDM becomes very important as it designs the gamified recommender system. Issues like goals, engagement of the decision maker, and recommendation accuracy are considered.

2.2 Decision Support System

Decision support system (DSS) collects, organizes and analyses data and enables the decision maker to have access to this data from which appropriate actions can be taken. The decision maker can investigate into available data, analyse the data, from which assessments can be made to help with decision making (Macias-Escobar et al., 2021).

DSS was put together to support decision makers at every level whether as support within operations, optimization, financial management and as far as simulation (Liu et al, 2010). Both DSS and RS rely heavily on data. In the quest for supporting decision making, RS whose role is to recommend or make suggestions, can be absorbed into the DSS for effective decision making. The DSS puts together data required for proper analysis, ensuring that all data relating to achieving the desired goal of the gamified recommender system is met.

2.3 Gamified Recommendation Systems

Recommender systems and gamification are relatively new concepts which research has established can improve user experience (Santos et al., 2021) . Recommender systems are designed such that they provide personalized recommendations or suggestions to decision makers or users depending on their preferences. When game like elements are used in real-world context, gamification ensues. Gamification makes tasks more enjoyable, motivating users. When gamification is infused into recommendation systems, Gamification recommendation system is produced.

The decision support delivered by DSS and MCDM, provides the elements, the mixture of which designs can be implemented.

The backbone of gamified recommender systems in effect is the game design elements which help users to perform; achieve elasticity and value. For the system to be successful, users should be aware that the context of instruction, the boundaries allocated, need to be considered and not just the application of game elements.

Shahreez et al. (2022) formulated gamified elements as follows:

- Acknowledgement – appreciation for players
- Chance – Possibility of occurring
- Points – award for performance
- Objectives – Guide for action
- Competition – Strive towards a common goal
- Social Pressure – Peer pressure interaction
- Time Pressure – Pushing factor through time
- Cooperation – Working together
- Progression – Unit to measure progress

2.4 The Fuzzy DEMATEL

Over the years, MCDM has developed many methods and software to resolve defined problems. The choice of MCDM technique depends on the type of result anticipated. Each technique has its own calculation method and data set (Zlaugotne et al., 2020). Amongst the many MCDM techniques, the DEMATEL method is considered comprehensive and detailed. It accounts for the interdependence among the factors of a system via causal diagram, which tends to be overlooked in traditional techniques. Decision making trial and evaluation laboratory (DEMATEL) technique is quite efficient in analyzing cause and effect relationships among components of a system. In summary, the DEMATEL can:

- Endorse interdependence among factors
- Move further to develop a map that reflects the relationship between these factors
- Potentially investigate and solve complex and intertwined problems.
- Use an impact relation diagram to determine the critical factors of a complex structure system (Si et al., 2018).

Even though the DEMATEL has an edge over the other methods, it has its own limitations. Even though it can determine the ranking of alternatives based on interdependent relationships among them; other criteria are not incorporated in the decision-making problem. It also doesn't consider the relative weights of experts in aggregating personal judgments of experts into group assessments. It doesn't account for the aspiration level of alternatives (Si et al., 2018). Nevertheless, the DEMATEL model has received a lot of attention due to its advantages over the other methods and its capabilities. Researchers have successfully applied it in solving complex system problems in various areas. In order to establish a structural model, the relationships of decision factors in the DEMATEL, are assessed by crisp values. However, given that many real-world systems include imprecise and uncertain information, the DEMATEL has been extended for better decision making under different environments.

Due to the complexities that may arise from human factors, conventional quantification methods are not useful in solving people-centered problems. Human judgements tend to be unclear and exact numerical values are insufficient to estimate the vague interdependency relationships between criteria. Decision making problems need to be solved under uncertainty since constraints, actions and goals are all ambiguous. Moreover, given that judgements are often subjective, every decision involves some amount of ambiguity, vagueness and imprecision. The application of fuzzy sets, eliminates deficiencies that might be within the crisp set theory. Hence the need for the application of fuzzy sets to the DEMATEL (Altinirmak et al, 2017).

The deficiencies in crisp set theory are represented in linguistic terms. These linguistic terms are translated to fuzzy numbers which are attached to the various judgements, opinions and experiences associated with decision makers. The crisp set is thus translated into the fuzzy set since it can better represent ambiguous data and makes allowance for the application of mathematical operations within a fuzzy environment. Within the fuzzy set, membership values are assigned to the objects. Values range from 0, which signifies non-membership to 1; which signifies complete membership. Values in between possess an intermediate degree of membership (Altinirmak et al, 2017).

2.5 Theoretical Framework

This study's theoretical framework offers an organized foundation for applying a multi-criteria decision-making (MCDM) technique to analyze the adoption of gamified recommender systems. The foundation of this framework is a knowledge of how recommender systems and gamification can be combined to improve user engagement and satisfaction. The framework directs the entire research process, including the process of extracting criteria by conducting a systematic literature review.

2.5.1 Gamified Recommender System Designs

Gamified recommender system designs are formed by putting together game elements which offer different approaches to engage users and drive desired behaviors within the system. Different gamified designs affect user experience differently (Santos et al., 2021). Based on this inference, a systematic literature review was conducted to extract user experience attributes related to recommender systems. Each design may be tailored to the target audience of the recommendation platform. Each design may also be put together depending on specific goals and target audience of the recommendation platform. Identified game designs as follows:

i) Points, Acknowledgments, and Competition (PBL):

This design uses elements such as points, acknowledgments (or achievements), and competition to motivate user engagement. Points are awarded for completing tasks or activities within the system, acknowledgments provide recognition for achievements, and competition encourages a sense of challenge and comparison among users (Hamari et al., 2014).

ii) Acknowledgments, Objectives, and Progression (AOP):

In this design, users are motivated by acknowledgments of their accomplishments, clear objectives to look forward to, and a sense of progression as they advance through the system. Acknowledgments can come in the form of badges, trophies, or levels attained by completing tasks or reaching milestones (Schöbel et al., 2020)**.**

iii) Acknowledgments, Objectives, and Social Pressure (AOS):

This design influences users through acknowledgments, objectives, and social pressure. Social pressure can appear through features like leaderboards, which allow users to see how they rank relative to others, promoting rivalry and social affirmation of their achievements (Park & Kim, 2021)**.**

iv) Acknowledgments, Competition, and Time Pressure (ACT):

Acknowledgments, competition, and time pressure are what encourage users in this design. Time-sensitive problems or activities provide a sense of demand, while competition adds a layer of motivation through the desire to surpass others within a given deadline (Huotari & Hamari, 2017).

2.5.2 Evaluation and Adoption of the Gamified Recommendation System Designs

The Gamified recommender system designs requires evaluation to determine its effectiveness; to ascertain whether indeed the system has the ability to recommend and why the system has made those recommendations. With reference to other studies, Deepak and Anguraj (2023) determined the efficiency of their GRS by comparing with other approaches. They used fitness assessment to determine the behaviour of the individual player through an efficient GRS. In a research done by Loukaidou, (2022) for a gamified recommender system to facilitate cognitive function in children with dementia in 2022, he determined that the benefits of Cognitive stimulation therapy was not immediately visible in adult onset dementia and therefore suggested that the model be used only for childhood dementia patients with mild to moderate dementia. He also proposed the addition of machine learning to his GRS to improve on its accuracy in terms of recommendations and further, decrease the need of domain experts. Tondello et al. (2017) present a novel general framework for personalized gameful applications using recommender systems. For efficiency, they proposed the description of the different building blocks of a recommender system in a personalized gamification context. Swacha et al, (2023) propose six points that can be used to evaluate gamified systems: The consequences of gamification were discussed in terms of its "general effects, area-specific effects, technical quality of gamified systems, use of gamified systems, gamefulness of gamified systems, and user experience of gamified systems."

Evaluating recommender system designs can be a challenge given that “the ground truth is hard to obtain, and human feelings are not easy to approximate” (Chen et al, 2022), in the face of numerous satisfactory solutions. User experience has however emerged as a very important tool to determine whether the designs are good enough to achieve an effective gamified system. If the system is not sufficiently usable, problems could occur which could affect the user (Raftopoulou & Pallis, 2023). Farzan and Brusilovsky (2011), endorse that user participation has become quite critical which is why it becomes necessary to encourage user participation. Even if other aspects of the system work perfectly, a lack of usability might lead to the user avoiding the system or even using the system improperly. Moreover, the field of usability has not been sufficiently explored which makes it difficult to get usability recommendations for gamified systems (Magylaitė et al., 2022). Information on the experience of users presents valuable insight into the workings of gamified recommendation systems.

An analysis of user experience from four gamified recommendation system designs provides basis for evaluation.

Multi Criteria Decision Making (MCDM) focuses on practical applications with great emphasis on human–technology interaction. It can systematically consider multiple metrics simultaneously. In effect, MCDM breaks down complexities and analyses the components in order to present the requirement (Mardani et al, 2015). These qualities give MCDM the edge required to effectively evaluate recommender system designs (Alshamsi et al., 2023). In order to account for any imprecision or vagueness, fuzzy sets are incorporated (Keršulienė & Turskis, 2012).

2.5.3 Steps Involved in the Systematic Literature Review for Extraction of Criteria

Step 1: Identification of Research Topics

The systematic literature review that was conducted started by identifying the main areas of interest: **Gamification** and **Recommender Systems**. The aim of the review was to understand how these fields put together can affect user satisfaction and engagement.

Step 2: Defining Key Terms and Concepts

To provide clarity and focus, key definitions were established:

- **Gamification:** Using game-based mechanisms, aesthetics, and game thinking in non-game contexts to engage people, motivate action, promote learning, and solve problems (Tondello et al., 2017).
- **Recommender Systems:** Information filtering systems that supply recommendations for items likely to be relevant to a user (Raftopoulou & Pallis, 2023).

Step 3: Formulating Research Questions

Based on the aim to investigate the quality and SWOT aspects of gamified recommender systems, three primary research questions were formulated:

1. What factors affect the quality of gamified, decision-support-based recommender systems?
2. What are these systems' strengths, weaknesses, opportunities, and threats?
3. What are the user experiences in gamified recommendation systems?

Step 4: Designing the Search Strategy

Using the PRISMA approach, a systematic search was conducted across four major databases (IEEE Xplore, Science Direct, Swiss Consortium, and Research Gate) for literature published between 2013 and 2023. The search keywords included terms related to gamification, recommender systems, and decision support.

Step 5: Applying Inclusion and Exclusion Criteria

The selection criteria ensured that only relevant, high-quality studies were included:

- **Inclusion:** Articles in English, open access, relevant to the research topics and keywords.
- **Exclusion:** Non-English articles, non-open access articles, editorial materials, and book chapters.

Step 6: Screening and Selecting Studies

From 823 initial records, duplicate and irrelevant papers were removed, narrowing the pool to 60 studies for full-text review. Further filtering based on language and relevance led to the final selection of 19 studies.

Step 7: Data Extraction and Analysis

Detailed data extraction from the selected studies focused on:

- **Factors Affecting Quality:** Customer engagement, personalization, interdisciplinary knowledge, learner engagement, interaction dynamics.
- **SWOT Analysis:** Strengths (e.g., boosted engagement, adaptability), Weaknesses (e.g., unanswered questions, complexity), Opportunities (e.g., market expansion, innovation), Threats (e.g., personalization costs, user interest challenges).

Step 8: Criteria for Evaluation

The studies were categorized according to research themes related to the evaluation criteria which are effectiveness, transparency, persuasiveness, satisfaction, trust, usefulness, ease of use, efficiency, and education. These criteria were defined and used in this study according to the study done by (Nunes & Jannach, 2017).

- **Effectiveness:** Help users make good decisions. Higher engagement, customized activities, and adaptive gamification (Tondello et al., 2017) .
- **Transparency:** Explains how the system work. Decision-support integration, adaptive learning paths (Su, 2017).
- **Persuasiveness:** Convince users to try or invest. Personalized exercises, career promotion systems (González-González et al., 2019).

- **User Satisfaction:** Increase the ease of use or enjoyment. Optimization of learning, motivational elements (Raftopoulou & Pallis, 2023).
- **Trust:** Increase users' confidence in the system. Enhancing tourism (Nuanmeesri, 2022), and career promotion support (Akhriza & Mumpuni, 2020) .
- **Usefulness:** The practical value and use of the System. Gamified recommender systems are effective in large-scale data frameworks and argue for their practical application in system operations (Talhaoui et al., 2019)..
- **Ease of Use:** Simplicity and user friendly of the system. Mechanics, dynamics, aesthetics of gamification (Talhaoui et al., 2019).
- **Efficiency:** The amount to which a system effectively uses resources to achieve its purpose. Algorithmic accuracy (Nuanmeesri, 2022) , learning system capabilities (Raftopoulou & Pallis, 2023).
- **Education:** Allow users to learn something from the system. Design principles in Massive Open Online Course (MOOCs) (Khalil et al., 2018).

CHAPTER III

METHODOLOGY

Gamification techniques are increasingly employed to boost user engagement and satisfaction within recommender systems, also assessing their effectiveness requires a comprehensive evaluation framework. This methodology section explains in detail how applying the Fuzzy DEMATEL method provides a systematic approach to analyzing the relationships among criteria (effectiveness, transparency, persuasiveness, satisfaction, trust, usefulness, ease of use, efficiency, and education) in evaluating the adoption of gamified recommender systems. By generating fuzzy matrices, normalizing data, and setting threshold values, this method enables the identification of significant factors and their impact on the overall system.

3.1 Research Design

This study adopts an applied research design focused on evaluating the adoption of gamified recommender systems. The research design is quantitative, utilizing the Fuzzy DEMATEL (Decision Making Trial and Evaluation Laboratory) method to assess the significance and interrelations among various criteria. By employing this method, the study aims to provide a structured and systematic approach to understanding the critical factors influencing the adoption of gamified recommender systems. Four gamified recommender system designs: i) Points, Acknowledgments, and Competition (PBL), ii) Acknowledgments, Objectives, and Progression (AOP), iii) Acknowledgments, Objectives, and Social Pressure (AOS), and iv) Acknowledgments, Competition, and Time Pressure (ACT) will be evaluated by decision-makers through a questionnaire. The results from the questionnaire will be used to evaluate these gamified recommender systems using the criteria identified from the systematic literature review including effectiveness, transparency, persuasiveness, satisfaction, trust, usefulness, ease of use, efficiency, and education.

3.2 Participants

The target participants for this study are 25 undergraduate students enrolled in the ethics course during the spring semester of 2023-2024. Convenience sampling will be utilized to recruit participants from this population. The inclusion criteria involve enrolment in the ethics course and willingness to participate voluntarily.

3.2.1 Demographic Distribution of Participants

Figure 1:

Gender Distribution

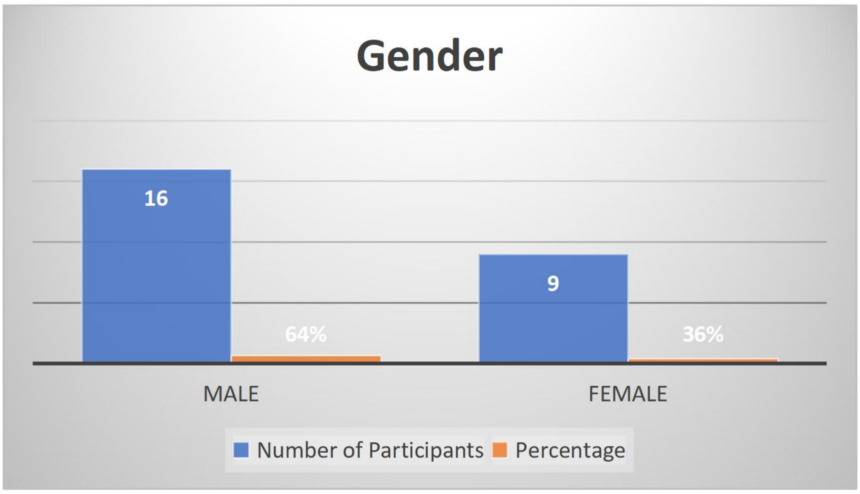


Figure 2:

Field of Study Distribution

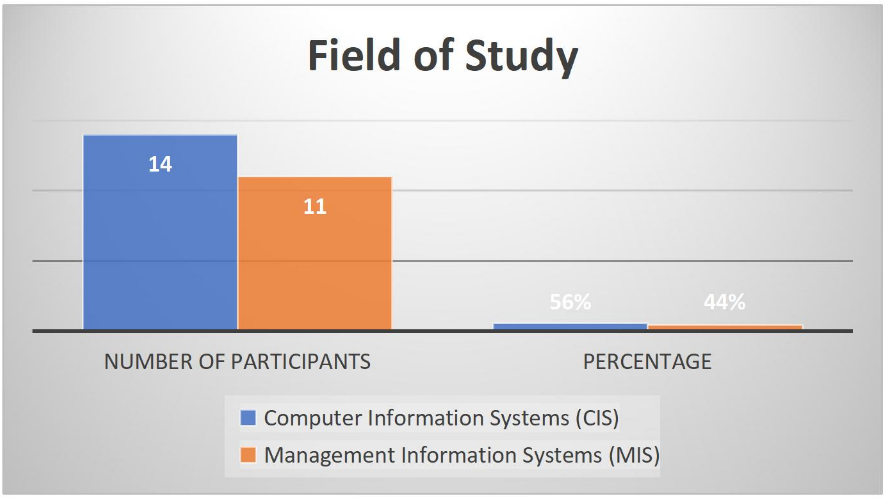


Figure 3:

Recommender System Usage Distribution

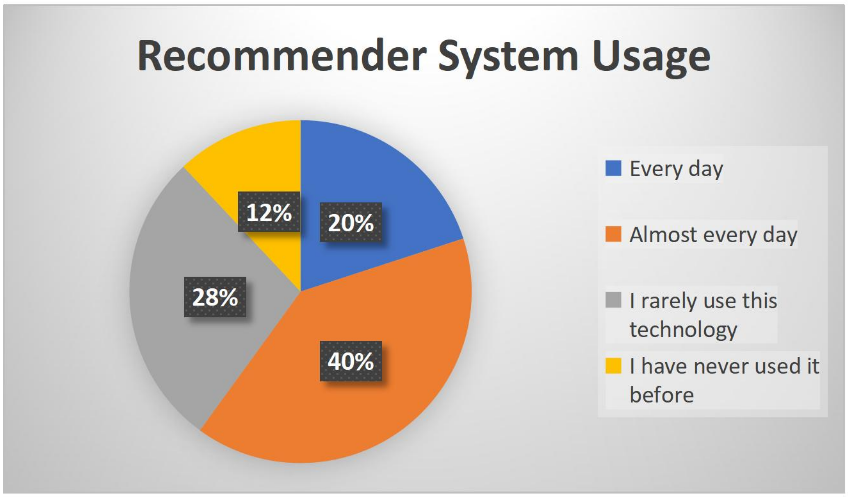
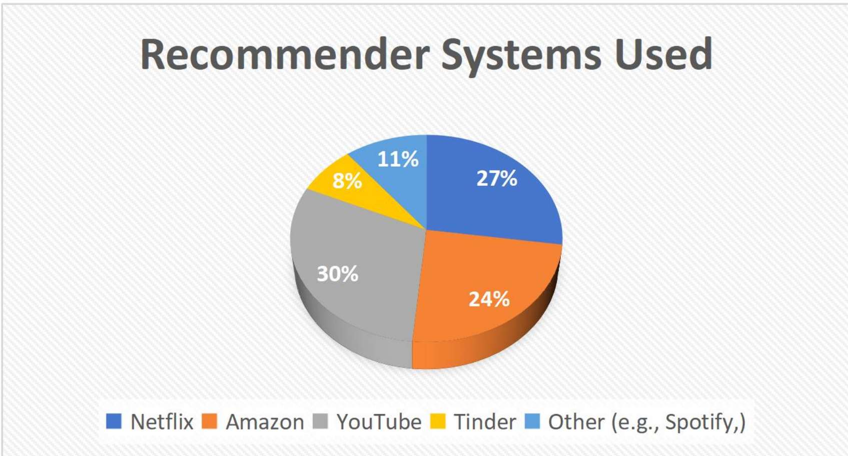


Figure 4:

Recommender Systems Used Distribution



3.3 Data Collection

3.3.1 Instruments

The questionnaire used in this study was developed to evaluate four different gamified recommender system designs. It included questions on demographics, usage patterns, and specific criteria for evaluating each design. The development process involved:

1. **Identifying Key Criteria:** The criteria were selected based on their relevance to the effectiveness and user engagement of recommender systems. These criteria included Effectiveness, Transparency, Persuasiveness, User Satisfaction, Trust, Usefulness, Ease of Use, Efficiency, and Education.

2. **Creating Rating Scales:** Each criterion was rated on a scale from 'No influence (NO)' to 'Very High influence (VH)'.

The sample of the questionnaire can be found in Appendix A of this document.

3.3.2 Procedures

The following procedures were used to conduct the study:

1. A literature review was conducted on gamified recommender systems in order to extract the criteria that was used for evaluation.
2. Obtained ethical approval from the university's ethics committee before data collection.
3. Printed questionnaires based on evaluating four different gamified recommender systems among 9 criteria using a scale of 'No influence (NO)' to 'Very High influence (VH) was created and were distributed during scheduled class hours to 25 students enrolled in the ethics course.
4. The samples from the 25 students was collected and the fuzzy DEMATEL method was used to create a cause effect relationship between the 9 criteria of the four gamified recommender systems.
5. The findings and results were then discussed, and recommendations and conclusions were made.

Below is a Gant chart and a flow diagram that shows how the study procedure was conducted

Figure 5:

Gant Chart of Study Procedure

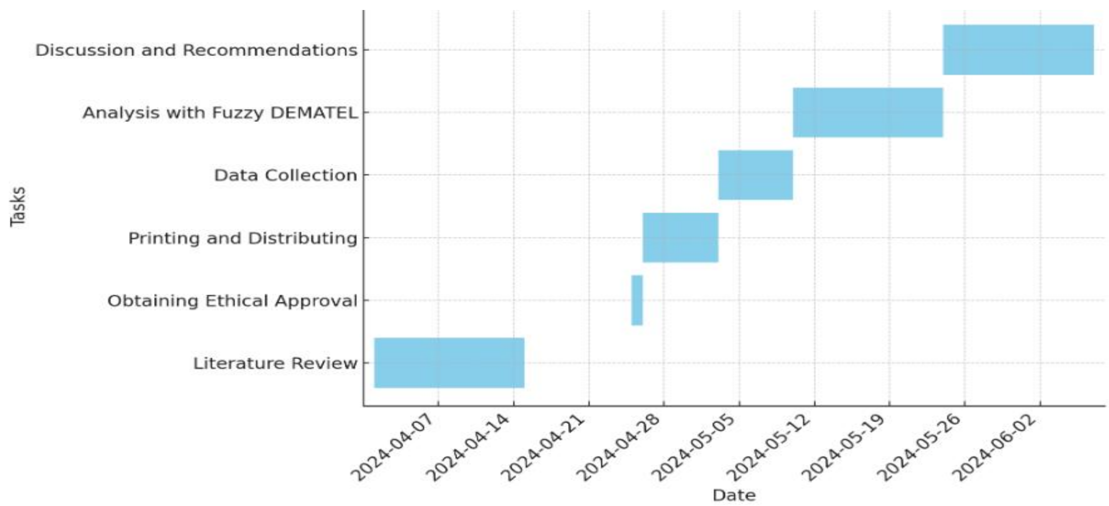
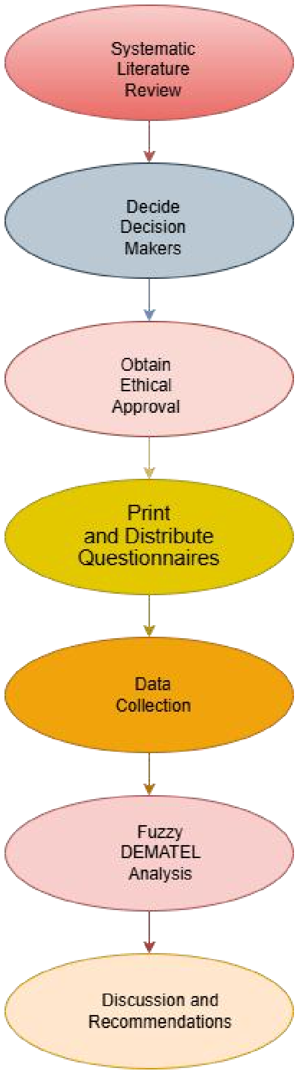


Figure 6:

Flow Diagram of Study Procedure



3.4 Data Analysis

The Fuzzy DEMATEL method was used and it provides a systematic approach in analyzing the relationships among the criteria in evaluating the adoption of gamified recommender systems. By generating fuzzy matrices, normalizing data, and setting threshold values, this method enables the identification of significant factors and their impact on the overall system and creates a cause and effect relationship between the 9 criteria for the four gamified recommender system designs.

CHAPTER IV

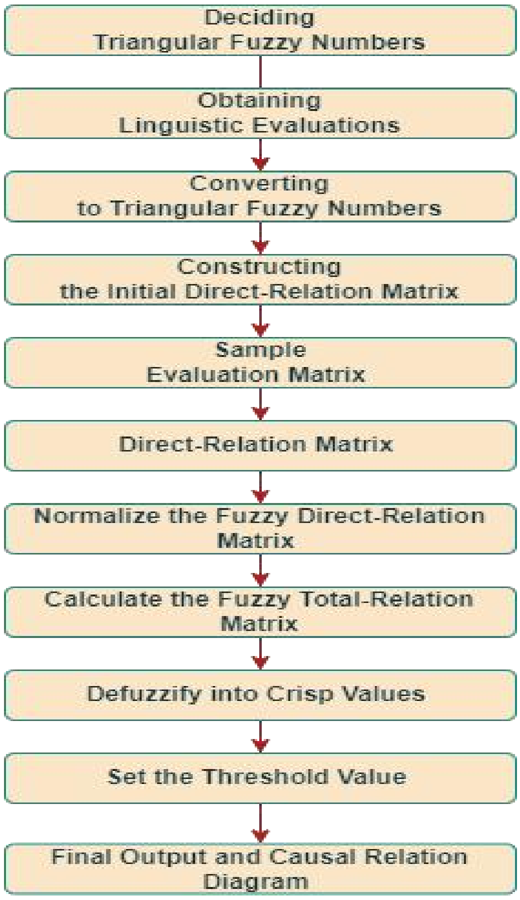
RESULTS AND FINDINGS

4.1 Fuzzy DEMATEL Process

To begin with, the decision-makers (DMs) evaluation matrices were critical in obtaining the results. These matrices were constructed by collecting evaluations of the four gamified recommender system designs from 25 DMs, who assessed the various criteria for each of the gamified recommender system design. The evaluations were combined to create a comprehensive overview of the criteria's performance. For each Gamified Recommender System, Figure 1 shows the steps that was carried out using the fuzzy DEMATEL method to obtain the results for evaluation.

Figure 7:

Fuzzy DEMATEL Flow Diagram



1. Deciding Triangular Fuzzy Numbers:

Triangular Fuzzy Numbers (TFNs) were decided based on expert judgment and literature review to translate linguistic terms into numerical values. The TFNs consist of three parameters: lower limit (L), middle value (M), and upper limit (U). These numbers capture the range of possible values for a given linguistic term.

Here is how the TFNs were decided:

- **No influence (1):** The TFN is (0, 0, 0.25). This reflects no influence between criteria, with a slight upper bound for minimal potential influence.
- **Very low influence (2):** The TFN is (0, 0.25, 0.5). This reflects a very low influence, extending from no influence up to a low level.
- **Low influence (3):** The TFN is (0.25, 0.5, 0.75). This reflects a low influence, with a middle value of 0.5.
- **High influence (4):** The TFN is (0.5, 0.75, 1). This reflects a high influence, with an upper limit of full influence.

- **Very high influence (5):** The TFN is (0.75, 1, 1). This reflects a very high influence, typically considered full influence.

The following table shows the fuzzy scale used in the model.

Table 1:

Fuzzy Scale:

Code	Linguistic terms	L	M	U
1	No influence	0	0	0.25
2	Very low influence	0	0.25	0.5
3	Low influence	0.25	0.5	0.75
4	High influence	0.5	0.75	1
5	Very high influence	0.75	1	1

- **C**

btaining Linguistic Evaluations:

Linguistic evaluations were obtained from each of the 25 decision-makers (DMs) for each pair of criteria. Each DM provided an evaluation based on their perception of the influence of one criterion on another using the predefined linguistic terms.

3. Converting to Triangular Fuzzy Numbers:

Each linguistic evaluation is converted to a triangular fuzzy number (TFN) using the fuzzy scale. The conversion process involves mapping the linguistic term to its corresponding TFN. For example:

- If a DM rates the influence of Criterion 1 on Criterion 2 as "High," this is converted to the TFN (0.5, 0.75, 1).
- If a DM rates the influence of Criterion 1 on Criterion 2 as "Low," this is converted to the TFN (0.25, 0.5, 0.75).

Let $L_{ij}^{k}, M_{ij}^{k} and\ U_{ij}^{k}$ be the lower, middle, and upper values of the triangular fuzzy number given by the $k-th$ decision-maker for the influence of criterion i on criterion j.

4. Constructing the Initial Direct-Relation Matrix:

The initial direct-relation matrix is constructed by averaging the TFNs provided by all decision-makers for each criterion pair. The TFNs from each DM are combined using the following equations:

Combined $L_{ij} = \frac{1}{25}\sum_{k=1}^{25} L_{ij}^{k}$ ……………………………………….(1)

Combined $M_{ij} = \frac{1}{25}\sum_{k=1}^{25} M_{ij}^{k}$ ……………………………………….(2)

Combined $U_{ij} = \frac{1}{25}\sum_{k=1}^{25} U_{ij}^{k}$ ……………………………………….(3)

Example Calculation:

If three DMs provided the following evaluations for the influence of Criterion 1 on Criterion 2:

- DM1: High (0.5, 0.75, 1)
- DM2: Low (0.25, 0.5, 0.75)
- DM3: Very High (0.75, 1, 1)

The combined TFN for Criterion 1 on Criterion 2 is calculated as:

$$\text{Combined } L_{1,2} = \frac{1}{3}(0.5 + 0.25 + 0.75) = 0.5$$
$$\text{Combined } M_{1,2} = \frac{1}{3}(0.75 + 0.5 + 1) = 0.75$$
$$\text{Combined } U_{1,2} = \frac{1}{3}(1 + 0.75 + 1) = 0.9167$$

5. Sample Evaluation Matrix for Decision Maker:

Here is a sample evaluation matrix converted to triangular fuzzy numbers for one decision maker:

Table 2:

Sample Evaluation Matrix:

Criteria	**Criterion 1**	**Criterion 2**	**Criterion 3**
Criterion 1	(0, 0, 0)	(0.5, 0.75, 1)	(0.25, 0.5, 0.75)
Criterion 2	(0, 0.25, 0.5)	(0, 0, 0)	(0.75, 1, 1)
Criterion	(0.25,	(0.25,	(0, 0, 0)

Criteria	Criterion 1	Criterion 2	Criterion 3
3	0.5, 0.75)	0.5, 0.75)	

6. Generate the Fuzzy Direct-Relation Matrix

According to (Tzeng et al., 2011)

- Construct an *n* × *n* matrix representing the direct relations among the *n* criteria.
- Each element in the matrix is represented by a fuzzy number, combining multiple experts' opinions if necessary.

Calculate the arithmetic mean of all DMs' opinions to generate the direct relation matrix given by

$$z = \begin{bmatrix} 0 & \cdots & \tilde{z}_{n1} \\ \vdots & \ddots & \vdots \\ \tilde{z}_{1n} & \cdots & 0 \end{bmatrix} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(4)$$

This gives the direct relation matrix for tables (3, 9, 15 and 21) as shown below for each gamified design.

7. Normalize the Fuzzy Direct-Relation Matrix

According to (Li & Tzeng, 2009)

Normalize the fuzzy direct-relation matrix using the formula

$$\tilde{x}_{ij} = \frac{\tilde{z}_{ij}}{r} = \left(\frac{l_{ij}}{r}, \frac{m_{ij}}{r}, \frac{u_{ij}}{r}\right) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(5)$$

Where

$$r = \max_{i,j}\left\{\max_i \sum_{j=1}^{n} u_{ij}, \max_j \sum_{i=1}^{n} u_{ij}\right\} \qquad i, j \in \{1,2,3, \ldots, n\}$$

This gives the normalized fuzzy direct-relation matrix tables (4, 10, 16 and 22) for each gamified design as shown below.

8. Fuzzy Total-Relation Matrix

According to (Tseng & Lin, 2008)

Compute the fuzzy total-relation matrix using the formula

$\widetilde{T} = \lim_{k\to+\infty} (\tilde{x}^1 \oplus \tilde{x}^2 \oplus ... \oplus \tilde{x}^k)$……………………………………..(6)

If each element of the fuzzy total-relation matrix is expressed as $\tilde{t}_{ij} = (l''_{ij}, m''_{ij}, u''_{ij})$, it can be calculated as follows:

$$[l''_{ij}] = x_l \times (I - x_l)^{-1}$$
$$[m''_{ij}] = x_m \times (I - x_m)^{-1}$$
$$[u''_{ij}] = x_u \times (I - x_u)^{-1}$$

This gives the fuzzy total-relation matrix tables (5, 11, 17 and 23) for each gamified design as shown below

9. Defuzzify into Crisp Values

Apply the CFCS method to obtain crisp values from the fuzzy total-relation matrix.

The CFCS method proposed by Opricovic & Tzeng, 2003) will used to obtain a crisp value of total-relation matrix. The steps of CFCS method are as follows:

$$l_{ij}^n = \frac{\left(l_{ij}^t - \min l_{ij}^t\right)}{\Delta_{min}^{max}}$$

$$m_{ij}^n = \frac{(m_{ij}^t - min\ l_{ij}^t)}{\Delta_{min}^{max}}$$

$$u_{ij}^n = \frac{(u_{ij}^t - min\ l_{ij}^t)}{\Delta_{min}^{max}}$$

So that

$$\Delta_{min}^{max} = \max u_{ij}^t - \min l_{ij}^t$$

Therefore, calculating the upper and lower bounds of normalized values:

$$l_{ij}^s = {m_{ij}^n}/{(1 + m_{ij}^n - l_{ij}^n)}$$

$$u_{ij}^s = {u_{ij}^n}/{(1 + u_{ij}^n - l_{ij}^n)}$$

The CFCS algorithm output is crisp values.

Therefore, to calculate the total normalized crisp value:

$$x_{ij} = \frac{[l_{ij}^{s}(1-l_{ij}^{s})+u_{ij}^{s}\times u_{ij}^{s}]}{[1-l_{ij}^{s}+u_{ij}^{s}]} \qquad (7)$$

This gives the crisp total-relation matrix tables (6, 12, 18 and 24) for each gamified design as shown below

10. Threshold Value

Tsai and Chou (2009) state that in order to compute the internal relations matrix, the threshold value needs to be determined. As a result, the network relationship map (NRM) is drawn and partial relations are ignored. The NRM only shows relations whose values in matrix T are greater than the threshold value. It is sufficient to compute the average values of the matrix T in order to determine the threshold value for relations. All values in matrix T that are less than the threshold value are set to zero once the threshold intensity has been established, meaning that the previously stated causal relationship is not taken into account.

This gives the crisp total- relationships matrix by considering the threshold value tables (7, 13, 19 and 25) for each gamified design as shown below.

11. Final Output and Causal Relation Diagram

According to (Wu, 2008) the sum of each row and each column of matrix T is calculated to determine the degree of importance and net effects of each factor. The sum of rows (D) and columns (R) can be calculated as follows:

$$D = \sum_{j=1}^{n} T_{ij} \qquad (8)$$

$$R = \sum_{i=1}^{n} T_{ij} \qquad (9)$$

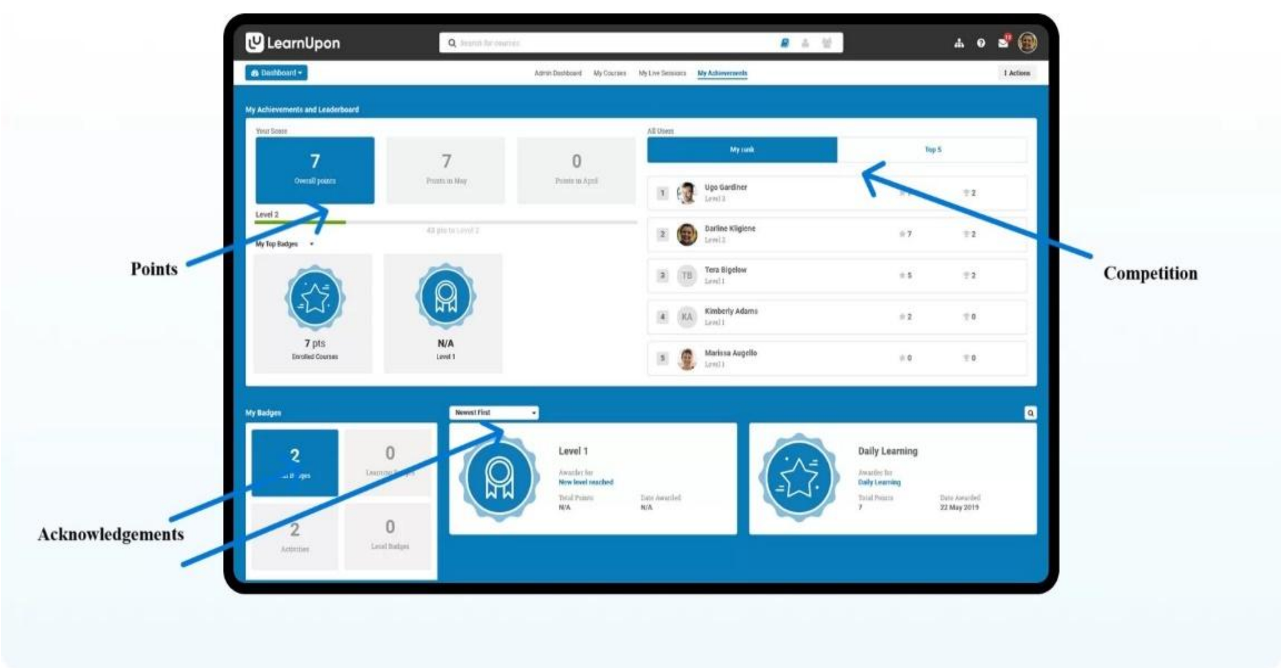
The values of D+R and D-R can be determined by D and R, where D+R reflects the degree of importance of factor i in the overall system and D-R represents the net impacts that factor i contributes to the system.

The findings will then be Summarized and a causal relation diagram will be created to visualize the relationships among criteria. The figure (causal relation diagram) that will follow shows the model of significant relations. This model can be represented as a diagram in which the values of (D+R) are placed on the horizontal axis and the values of (D-R) on the vertical axis. The position and interaction of each factor with a point in the coordinates (D+ R, D-R) are determined by coordinate system

This gives the final output tables (8, 14, 20 and 26) and also cause-effect diagram (Figures: 2, 3, 4 and 5) for each gamified recommender system as shown below.

4.2 Evaluation Of Gamified Recommender System Designs

4.2.1 Design 1 Points, Acknowledgments, and Competition (PBL)



Constructing the Initial Direct-Relation Matrix:

The initial direct-relation matrix is constructed by averaging the TFNs provided by all decision-makers for each criterion pair. The TFNs from each DM are combined using the following equations:

$$\text{Combined } L_{ij} = \frac{1}{25}\sum_{k=1}^{25} L_{ij}^{k} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)$$

$$\text{Combined } M_{ij} = \frac{1}{25}\sum_{k=1}^{25} M_{ij}^{k} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (2)$$

$$\text{Combined } U_{ij} = \frac{1}{25}\sum_{k=1}^{25} U_{ij}^{k} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3)$$

Example Calculation:

If three DMs provided the following evaluations for the influence of Criterion 1 on Criterion 2:

- DM1: High (0.5, 0.75, 1)
- DM2: Low (0.25, 0.5, 0.75)
- DM3: Very High (0.75, 1, 1)

The combined TFN for Criterion 1 on Criterion 2 is calculated as:

$$\text{Combined } L_{1,2} = \frac{1}{3}(0.5 + 0.25 + 0.75) = 0.5$$
$$\text{Combined } M_{1,2} = \frac{1}{3}(0.75 + 0.5 + 1) = 0.75$$
$$\text{Combined } U_{1,2} = \frac{1}{3}(1 + 0.75 + 1) = 0.9167$$

Sample Evaluation Matrix for Decision Maker:

Here is a sample evaluation matrix converted to triangular fuzzy numbers for one decision maker:

Sample Evaluation Matrix:

Criteria	**Criterion 1**	**Criterion 2**	**Criterion 3**
Criterion 1	(0, 0, 0)	(0.5, 0.75, 1)	(0.25, 0.5, 0.75)
Criterion 2	(0, 0.25, 0.5)	(0, 0, 0)	(0.75, 1, 1)
Criterion 3	(0.25, 0.5, 0.75)	(0.25, 0.5, 0.75)	(0, 0, 0)

- **Direct- relation matrix**

By using step 6 equation (4) the table below indicates the direct relation matrix, which is the same as pairwise comparison matrix of the decision makers in the design 1.

Table 3:

The direct relation matrix- Design 1

	criterion1	**criterion2**	**criterion3**	**criterion4**	**criterion5**	**criterion6**	**criterion7**	**criterion8**	**criterion9**
criterion 1	(0.000, 0.000, 0.000)	(0.300, 0.540, 0.760)	(0.310, 0.540, 0.750)	(0.430, 0.670, 0.860)	(0.360, 0.560, 0.770)	(0.270, 0.480, 0.710)	(0.320, 0.560, 0.780)	(0.390, 0.600, 0.780)	(0.290, 0.490, 0.720)
criterion 2	(0.300, 0.540, 0.760)	(0.000, 0.000, 0.000)	(0.270, 0.480, 0.710)	(0.380, 0.620, 0.820)	(0.280, 0.480, 0.720)	(0.330, 0.540, 0.750)	(0.360, 0.600, 0.820)	(0.280, 0.460, 0.700)	(0.380, 0.630, 0.840)

Continue (3)

criterion 3	(0.310, 0.540, 0.750)	(0.270, 0.480, 0.710)	(0.000, 0.000, 0.000)	(0.400, 0.620, 0.810)	(0.320, 0.530, 0.740)	(0.350, 0.570, 0.780)	(0.290, 0.510, 0.710)	(0.330, 0.560, 0.770)	(0.240, 0.430, 0.670)
criterion 4	(0.430, 0.670, 0.860)	(0.380, 0.620, 0.820)	(0.400, 0.620, 0.810)	(0.000, 0.000, 0.000)	(0.390, 0.590, 0.770)	(0.390, 0.620, 0.830)	(0.420, 0.650, 0.840)	(0.320, 0.550, 0.770)	(0.360, 0.560, 0.760)
criterion 5	(0.360, 0.560, 0.770)	(0.280, 0.480, 0.720)	(0.320, 0.530, 0.740)	(0.390, 0.590, 0.770)	(0.000, 0.000, 0.000)	(0.450, 0.650, 0.800)	(0.280, 0.490, 0.700)	(0.400, 0.630, 0.840)	(0.290, 0.500, 0.740)
criterion 6	(0.270, 0.480, 0.710)	(0.330, 0.540, 0.750)	(0.350, 0.570, 0.780)	(0.390, 0.620, 0.830)	(0.450, 0.650, 0.800)	(0.000, 0.000, 0.000)	(0.400, 0.600, 0.770)	(0.310, 0.540, 0.760)	(0.280, 0.490, 0.730)
criterion 7	(0.320, 0.560, 0.780)	(0.360, 0.600, 0.820)	(0.290, 0.510, 0.710)	(0.420, 0.650, 0.840)	(0.280, 0.490, 0.700)	(0.400, 0.600, 0.770)	(0.000, 0.000, 0.000)	(0.330, 0.540, 0.720)	(0.300, 0.530, 0.750)
criterion 8	(0.390, 0.600, 0.780)	(0.280, 0.460, 0.700)	(0.330, 0.560, 0.770)	(0.320, 0.550, 0.770)	(0.400, 0.630, 0.840)	(0.310, 0.540, 0.760)	(0.330, 0.540, 0.720)	(0.000, 0.000, 0.000)	(0.340, 0.540, 0.740)
criterion 9	(0.290, 0.490, 0.720)	(0.380, 0.630, 0.840)	(0.240, 0.430, 0.670)	(0.360, 0.560, 0.760)	(0.290, 0.500, 0.740)	(0.280, 0.490, 0.730)	(0.300, 0.530, 0.750)	(0.330, 0.530, 0.730)	(0.000, 0.000, 0.000)

- **Normalize the fuzzy direct-relation matrix**

By using step 7 equation (5) the table below shows the normalized fuzzy direct-relation matrix of design 1

Table 4:

The normalized fuzzy direct-relation matrix-Design 1

	criterion1	**criterion2**	**criterion3**	**criterion4**	**criterion5**	**criterion6**	**criterion7**	**criterion8**	**criterion9**
criterion 1	0.000,) 0.000, (0.000	0.046,) 0.084, (0.118	0.048,) 0.084, (0.116	0.067,) 0.104, (0.133	0.056,) 0.087, (0.119	0.042,) 0.074, (0.110	0.050,) 0.087, (0.121	0.060,) 0.093, (0.121	0.045,) 0.076, (0.111
criterion 2	0.046,) 0.084, (0.118	0.000,) 0.000, (0.000	0.042,) 0.074, (0.110	0.059,) 0.096, (0.127	0.043,) 0.074, (0.111	0.051,) 0.084, (0.116	0.056,) 0.093, (0.127	0.043,) 0.071, (0.108	0.059,) 0.098, (0.130

Continue (4)

criterion 3	0.048,) 0.084, (0.116	0.042,) 0.074, (0.110	0.000,) 0.000, (0.000	0.062,) 0.096, (0.125	0.050,) 0.082, (0.115	0.054,) 0.088, (0.121	0.045,) 0.079, (0.110	0.051,) 0.087, (0.119	0.037,) 0.067, (0.104
criterion 4	0.067,) 0.104, (0.133	0.059,) 0.096, (0.127	0.062,) 0.096, (0.125	0.000,) 0.000, (0.000	0.060,) 0.091, (0.119	0.060,) 0.096, (0.128	0.065,) 0.101, (0.130	0.050,) 0.085, (0.119	0.056,) 0.087, (0.118
criterion 5	0.056,) 0.087, (0.119	0.043,) 0.074, (0.111	0.050,) 0.082, (0.115	0.060,) 0.091, (0.119	0.000,) 0.000, (0.000	0.070,) 0.101, (0.124	0.043,) 0.076, (0.108	0.062,) 0.098, (0.130	0.045,) 0.077, (0.115
criterion 6	0.042,) 0.074, (0.110	0.051,) 0.084, (0.116	0.054,) 0.088, (0.121	0.060,) 0.096, (0.128	0.070,) 0.101, (0.124	0.000,) 0.000, (0.000	0.062,) 0.093, (0.119	0.048,) 0.084, (0.118	0.043,) 0.076, (0.113
criterion 7	0.050,) 0.087, (0.121	0.056,) 0.093, (0.127	0.045,) 0.079, (0.110	0.065,) 0.101, (0.130	0.043,) 0.076, (0.108	0.062,) 0.093, (0.119	0.000,) 0.000, (0.000	0.051,) 0.084, (0.111	0.046,) 0.082, (0.116
criterion 8	0.060,) 0.093, (0.121	0.043,) 0.071, (0.108	0.051,) 0.087, (0.119	0.050,) 0.085, (0.119	0.062,) 0.098, (0.130	0.048,) 0.084, (0.118	0.051,) 0.084, (0.111	0.000,) 0.000, (0.000	0.053,) 0.084, (0.115
criterion 9	0.045,) 0.076, (0.111	0.059,) 0.098, (0.130	0.037,) 0.067, (0.104	0.056,) 0.087, (0.118	0.045,) 0.077, (0.115	0.043,) 0.076, (0.113	0.046,) 0.082, (0.116	0.051,) 0.082, (0.113	0.000,) 0.000, (0.000

- **Fuzzy total-relation matrix**

By using step 8 equation (6) The table below shows the fuzzy total-relation matrix of design 1

Table 5:

The fuzzy total-relation matrix- Design 1

	criterion1	**criterion2**	**criterion3**	**criterion4**	**criterion5**	**criterion6**	**criterion7**	**criterion8**	**criterion9**
criterion 1	(0.036, 0.175, 1.863)	(0.078, 0.248, 1.964)	(0.079, 0.245, 1.915)	(0.103, 0.284, 2.068)	(0.089, 0.254, 1.954)	(0.077, 0.246, 1.961)	(0.083, 0.256, 1.960)	(0.092, 0.258, 1.953)	(0.076, 0.235, 1.913)
criterion 2	(0.078, 0.248, 1.964)	(0.033, 0.168, 1.856)	(0.072, 0.233, 1.906)	(0.094, 0.274, 2.059)	(0.077, 0.239, 1.944)	(0.084, 0.250, 1.962)	(0.087, 0.258, 1.961)	(0.076, 0.236, 1.939)	(0.087, 0.250, 1.925)

Continue(5)

criterion 3	(0.079, 0.245, 1.915)	(0.072, 0.233, 1.906)	(0.032, 0.161, 1.760)	(0.096, 0.270, 2.008)	(0.082, 0.243, 1.899)	(0.086, 0.250, 1.918)	(0.077, 0.242, 1.899)	(0.082, 0.246, 1.900)	(0.067, 0.220, 1.856)
criterion 4	(0.103, 0.284, 2.068)	(0.094, 0.274, 2.059)	(0.096, 0.270, 2.008)	(0.046, 0.207, 2.043)	(0.099, 0.273, 2.041)	(0.099, 0.279, 2.064)	(0.102, 0.283, 2.054)	(0.088, 0.267, 2.038)	(0.090, 0.259, 2.004)
criterion 5	(0.089, 0.254, 1.954)	(0.077, 0.239, 1.944)	(0.082, 0.243, 1.899)	(0.099, 0.273, 2.041)	(0.038, 0.174, 1.833)	(0.103, 0.267, 1.957)	(0.079, 0.246, 1.935)	(0.095, 0.262, 1.946)	(0.077, 0.236, 1.901)
criterion 6	(0.077, 0.246, 1.961)	(0.084, 0.250, 1.962)	(0.086, 0.250, 1.918)	(0.099, 0.279, 2.064)	(0.103, 0.267, 1.957)	(0.038, 0.178, 1.861)	(0.095, 0.262, 1.958)	(0.082, 0.252, 1.950)	(0.075, 0.236, 1.914)
criterion 7	(0.083, 0.256, 1.960)	(0.087, 0.258, 1.961)	(0.077, 0.242, 1.899)	(0.102, 0.283, 2.054)	(0.079, 0.246, 1.935)	(0.095, 0.262, 1.958)	(0.036, 0.178, 1.841)	(0.084, 0.251, 1.934)	(0.078, 0.242, 1.906)
criterion 8	(0.092, 0.258, 1.955)	(0.076, 0.236, 1.942)	(0.082, 0.246, 1.903)	(0.088, 0.267, 2.041)	(0.095, 0.262, 1.948)	(0.083, 0.252, 1.952)	(0.084, 0.252, 1.937)	(0.036, 0.172, 1.830)	(0.083, 0.240, 1.901)
criterion 9	(0.076, 0.235, 1.910)	(0.087, 0.250, 1.922)	(0.067, 0.220, 1.854)	(0.090, 0.258, 2.001)	(0.077, 0.235, 1.898)	(0.075, 0.236, 1.911)	(0.077, 0.241, 1.904)	(0.081, 0.238, 1.894)	(0.031, 0.155, 1.762)

- **Defuzzifying into crisp values**

By using step 9 equation (7) the table below shows crisp total-relation matrix of design 1

Table 6:

The crisp total-relation matrix- Design 1

	criterion1	**criterion2**	**criterion3**	**criterion4**	**criterion5**	**criterion6**	**criterion7**	**criterion8**	**criterion9**
criterion1	0.465	0.54	0.528	0.584	0.543	0.537	0.545	0.546	0.52
criterion2	0.54	0.458	0.518	0.574	0.529	0.541	0.547	0.526	0.535
criterion3	0.53	0.519	0.436	0.564	0.526	0.535	0.525	0.528	0.5
criterion4	0.584	0.574	0.562	0.517	0.571	0.579	0.581	0.565	0.553

Continue (6)

criterion5	0.544	0.53	0.525	0.571	0.459	0.555	0.534	0.548	0.519
criterion6	0.537	0.541	0.534	0.579	0.555	0.467	0.551	0.54	0.522
criterion7	0.545	0.547	0.524	0.581	0.533	0.551	0.463	0.538	0.525
criterion8	0.548	0.527	0.528	0.566	0.549	0.542	0.539	0.457	0.523
criterion9	0.521	0.536	0.499	0.554	0.519	0.522	0.525	0.521	0.432

- **The threshold value**

By using step 10, in this Design, the threshold value is equal to 0.5330.533

Table 7:

The crisp total- relationships matrix by considering the threshold value- Design 1

	criterion1	**criterion2**	**criterion3**	**criterion4**	**criterion5**	**criterion6**	**criterion7**	**criterion8**	**criterion9**
criterion1	0	0.54	0	0.584	0.543	0.537	0.545	0.546	0
criterion2	0.54	0	0	0.574	0	0.541	0.547	0	0.535
criterion3	0	0	0	0.564	0	0.535	0	0	0
criterion4	0.584	0.574	0.562	0	0.571	0.579	0.581	0.565	0.553
criterion5	0.544	0	0	0.571	0	0.555	0.534	0.548	0
criterion6	0.537	0.541	0.534	0.579	0.555	0	0.551	0.54	0
criterion7	0.545	0.547	0	0.581	0.533	0.551	0	0.538	0
criterion8	0.548	0	0	0.566	0.549	0.542	0.539	0	0
criterion9	0	0.536	0	0.554	0	0	0	0	0

- **Final output and causal relation diagram**

By using step 11 equation (8) and (9) the table below shows the final output and causal relation diagram for Design 1

Table 8:

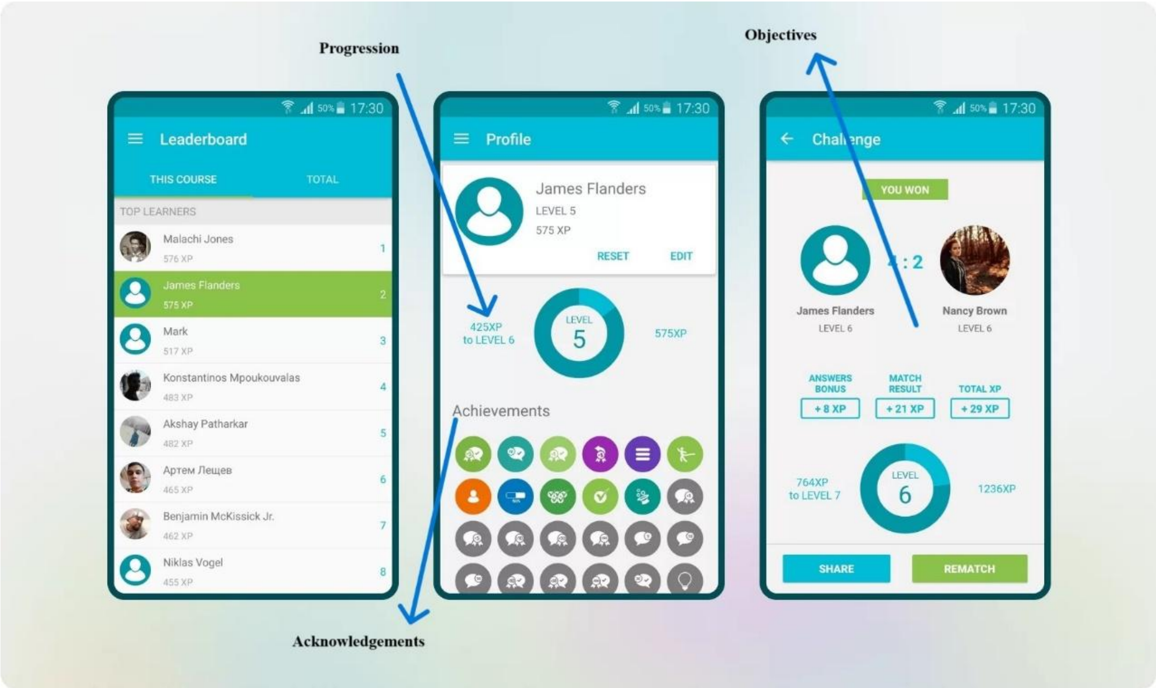
The final output – Design 1

	R	**D**	**D+R**	**D-R**
criterion1	4.814	4.808	9.622	-0.006
criterion2	4.772	4.768	9.54	-0.004
criterion3	4.655	4.664	9.318	0.009
criterion4	5.09	5.085	10.175	-0.006

Continue (8)

criterion5	4.784	4.785	9.569	0.002
criterion6	4.83	4.826	9.656	-0.004
criterion7	4.81	4.808	9.618	-0.002
criterion8	4.769	4.778	9.548	0.009
criterion9	4.629	4.631	9.259	0.002

4.2.2 Design 2 -Acknowledgments, Objectives, and Progression (AOP)



Constructing the Initial Direct-Relation Matrix:

The initial direct-relation matrix is constructed by averaging the TFNs provided by all decision-makers for each criterion pair. The TFNs from each DM are combined using the following equations:

$$\text{Combined } L_{ij} = \frac{1}{25}\sum_{k=1}^{25} L_{ij}^{k} \text{ ....(1)}$$

$$\text{Combined } M_{ij} = \frac{1}{25}\sum_{k=1}^{25} M_{ij}^{k} \text{ ....(2)}$$

$$\text{Combined } U_{ij} = \frac{1}{25}\sum_{k=1}^{25} U_{ij}^{k} \text{ ....(3)}$$

Example Calculation:

If three DMs provided the following evaluations for the influence of Criterion 1 on Criterion 2:

- DM1: High (0.5, 0.75, 1)

- DM2: Low (0.25, 0.5, 0.75)
- DM3: Very High (0.75, 1, 1)

The combined TFN for Criterion 1 on Criterion 2 is calculated as:

$$\text{Combined } L_{1,2} = \frac{1}{3}(0.5 + 0.25 + 0.75) = 0.5$$
$$\text{Combined } M_{1,2} = \frac{1}{3}(0.75 + 0.5 + 1) = 0.75$$
$$\text{Combined } U_{1,2} = \frac{1}{3}(1 + 0.75 + 1) = 0.9167$$

Sample Evaluation Matrix for Decision Maker:

Here is a sample evaluation matrix converted to triangular fuzzy numbers for one decision maker:

Sample Evaluation Matrix:

Criteria	**Criterion 1**	**Criterion 2**	**Criterion 3**
Criterion 1	(0, 0, 0)	(0.5, 0.75, 1)	(0.25, 0.5, 0.75)
Criterion 2	(0, 0.25, 0.5)	(0, 0, 0)	(0.75, 1, 1)
Criterion 3	(0.25, 0.5, 0.75)	(0.25, 0.5, 0.75)	(0, 0, 0)

- **Direct- relation matrix**

By using step 6 equation (4) the table below indicates the direct relation matrix, which is the same as pairwise comparison matrix of the decision makers in the design 2.

Table 9:

The direct relation matrix- Design 2

	criterion1	**criterion2**	**criterion3**	**criterion4**	**criterion5**	**criterion6**	**criterion7**	**criterion8**	**criterion9**
criterion1	(0.000, 0.000, 0.000)	(0.370, 0.590, 0.790)	(0.350, 0.600, 0.800)	(0.410, 0.650, 0.830)	(0.370, 0.600, 0.800)	(0.420, 0.640, 0.820)	(0.550, 0.800, 0.930)	(0.250, 0.430, 0.640)	(0.340, 0.560, 0.780)

Continue (9)

criterion2	(0.370, 0.590, 0.790)	(0.000, 0.000, 0.000)	(0.230, 0.440, 0.680)	(0.290, 0.520, 0.750)	(0.390, 0.620, 0.790)	(0.340, 0.560, 0.780)	(0.280, 0.490, 0.700)	(0.210, 0.400, 0.630)	(0.320, 0.550, 0.780)
criterion3	(0.350, 0.600, 0.800)	(0.230, 0.440, 0.680)	(0.000, 0.000, 0.000)	(0.350, 0.560, 0.760)	(0.360, 0.580, 0.780)	(0.390, 0.640, 0.850)	(0.350, 0.590, 0.800)	(0.330, 0.560, 0.770)	(0.330, 0.570, 0.810)
criterion4	(0.400, 0.640, 0.820)	(0.290, 0.520, 0.750)	(0.350, 0.560, 0.760)	(0.000, 0.000, 0.000)	(0.280, 0.490, 0.710)	(0.330, 0.550, 0.750)	(0.410, 0.650, 0.840)	(0.370, 0.580, 0.770)	(0.310, 0.550, 0.770)
criterion5	(0.370, 0.600, 0.800)	(0.380, 0.610, 0.790)	(0.370, 0.590, 0.780)	(0.280, 0.490, 0.710)	(0.000, 0.000, 0.000)	(0.370, 0.600, 0.790)	(0.340, 0.570, 0.790)	(0.280, 0.500, 0.730)	(0.240, 0.440, 0.690)
criterion6	(0.420, 0.640, 0.820)	(0.340, 0.560, 0.780)	(0.390, 0.640, 0.850)	(0.330, 0.550, 0.750)	(0.370, 0.600, 0.790)	(0.000, 0.000, 0.000)	(0.400, 0.640, 0.840)	(0.280, 0.500, 0.700)	(0.270, 0.510, 0.720)
criterion7	(0.530, 0.780, 0.920)	(0.260, 0.470, 0.690)	(0.350, 0.590, 0.800)	(0.410, 0.650, 0.840)	(0.340, 0.570, 0.790)	(0.400, 0.640, 0.840)	(0.000, 0.000, 0.000)	(0.310, 0.510, 0.720)	(0.280, 0.500, 0.700)
criterion8	(0.250, 0.430, 0.640)	(0.210, 0.400, 0.630)	(0.330, 0.560, 0.770)	(0.370, 0.580, 0.770)	(0.280, 0.500, 0.730)	(0.280, 0.500, 0.700)	(0.310, 0.510, 0.720)	(0.000, 0.000, 0.000)	(0.290, 0.490, 0.700)
criterion9	(0.340, 0.560, 0.780)	(0.320, 0.550, 0.780)	(0.330, 0.570, 0.810)	(0.310, 0.550, 0.770)	(0.240, 0.440, 0.690)	(0.270, 0.510, 0.720)	(0.280, 0.500, 0.700)	(0.290, 0.490, 0.700)	(0.000, 0.000, 0.000)

- **Normalize the fuzzy direct-relation matrix**

By using step 7 equation (5) The table below shows the normalized fuzzy direct-relation matrix of design 2

Table 10:

The normalized fuzzy direct-relation matrix-Design 2

	criterion1	**criterion2**	**criterion3**	**criterion4**	**criterion5**	**criterion6**	**criterion7**	**criterion8**	**criterion9**
criterion1	0.000,) 0.000, (0.000	0.058,) 0.092, (0.124	0.055,) 0.094, (0.125	0.064,) 0.102, (0.130	0.058,) 0.094, (0.125	0.066,) 0.100, (0.128	0.086,) 0.125, (0.146	0.039,) 0.067, (0.100	0.053,) 0.088, (0.122

Continue (10)

criterion2	0.058,) 0.092, (0.124	0.000,) 0.000, (0.000	0.036,) 0.069, (0.106	0.045,) 0.081, (0.117	0.061,) 0.097, (0.124	0.053,) 0.088, (0.122	0.044,) 0.077, (0.110	0.033,) 0.063, (0.099	0.050,) 0.086, (0.122
criterion3	0.055,) 0.094, (0.125	0.036,) 0.069, (0.106	0.000,) 0.000, (0.000	0.055,) 0.088, (0.119	0.056,) 0.091, (0.122	0.061,) 0.100, (0.133	0.055,) 0.092, (0.125	0.052,) 0.088, (0.121	0.052,) 0.089, (0.127
criteri	0.063,) 0.100,	0.045,) 0.081,	0.055,) 0.088,	0.000,) 0.000,	0.044,) 0.077,	0.052,) 0.086,	0.064,) 0.102,	0.058,) 0.091,	0.049,) 0.086,

on4	(0.128	(0.117	(0.119	(0.000	(0.111	(0.117	(0.131	(0.121	(0.121
crit	0.058,)	0.059,)	0.058,)	0.044,)	0.000,)	0.058,)	0.053,)	0.044,)	0.038,)
eri	0.094,	0.095,	0.092,	0.077,	0.000,	0.094,	0.089,	0.078,	0.069,
on5	(0.125	(0.124	(0.122	(0.111	(0.000	(0.124	(0.124	(0.114	(0.108
crit	0.066,)	0.053,)	0.061,)	0.052,)	0.058,)	0.000,)	0.063,)	0.044,)	0.042,)
eri	0.100,	0.088,	0.100,	0.086,	0.094,	0.000,	0.100,	0.078,	0.080,
on6	(0.128	(0.122	(0.133	(0.117	(0.124	(0.000	(0.131	(0.110	(0.113
crit	0.083,)	0.041,)	0.055,)	0.064,)	0.053,)	0.063,)	0.000,)	0.049,)	0.044,)
eri	0.122,	0.074,	0.092,	0.102,	0.089,	0.100,	0.000,	0.080,	0.078,
on7	(0.144	(0.108	(0.125	(0.131	(0.124	(0.131	(0.000	(0.113	(0.110
crit	0.039,)	0.033,)	0.052,)	0.058,)	0.044,)	0.044,)	0.049,)	0.000,)	0.045,)
eri	0.067,	0.063,	0.088,	0.091,	0.078,	0.078,	0.080,	0.000,	0.077,
on8	(0.100	(0.099	(0.121	(0.121	(0.114	(0.110	(0.113	(0.000	(0.110
crit	0.053,)	0.050,)	0.052,)	0.049,)	0.038,)	0.042,)	0.044,)	0.045,)	0.000,)
eri	0.088,	0.086,	0.089,	0.086,	0.069,	0.080,	0.078,	0.077,	0.000,
on9	(0.122	(0.122	(0.127	(0.121	(0.108	(0.113	(0.110	(0.110	(0.000

- **Fuzzy total-relation matrix**

By using step 8 equation (6) The table below shows the fuzzy total-relation matrix of design 2

Table 11:

The fuzzy total-relation matrix- Design 2

	criterion1	**criterion2**	**criterion3**	**criterion4**	**criterion5**	**criterion6**	**criterion7**	**criterion8**	**criterion9**
crit	(0.047,	(0.092,	(0.093,	(0.103,	(0.095,	(0.105,	(0.125,	(0.074,	(0.087,
eri	0.220,	0.273,	0.292,	0.298,	0.286,	0.301,	0.327,	0.245,	0.270,
on1	2.550)	2.484)	2.614)	2.593)	2.553)	2.619)	2.659)	2.380)	2.503)

Continue (11)

crit	(0.092,	(0.030,	(0.068,	(0.077,	(0.090,	(0.085,	(0.078,	(0.060,	(0.077,
eri	0.274,	0.164,	0.243,	0.253,	0.261,	0.262,	0.257,	0.216,	0.243,
on2	2.481)	2.209)	2.424)	2.410)	2.382)	2.439)	2.454)	2.219)	2.336)
crit	(0.093,	(0.068,	(0.037,	(0.089,	(0.089,	(0.095,	(0.092,	(0.081,	(0.081,
eri	0.290,	0.241,	0.193,	0.273,	0.270,	0.287,	0.286,	0.250,	0.259,
on3	2.607)	2.421)	2.451)	2.532)	2.500)	2.570)	2.590)	2.349)	2.457)
crit	(0.101,	(0.076,	(0.089,	(0.038,	(0.078,	(0.088,	(0.101,	(0.087,	(0.079,
eri	0.296,	0.251,	0.273,	0.193,	0.258,	0.276,	0.294,	0.253,	0.257,
on4	2.581)	2.402)	2.529)	2.398)	2.463)	2.529)	2.566)	2.323)	2.425)
crit	(0.095,	(0.088,	(0.090,	(0.078,	(0.035,	(0.092,	(0.089,	(0.073,	(0.068,
eri	0.285,	0.259,	0.272,	0.258,	0.182,	0.277,	0.277,	0.237,	0.237,
on5	2.547)	2.378)	2.500)	2.467)	2.333)	2.503)	2.529)	2.289)	2.385)
crit	(0.105,	(0.085,	(0.096,	(0.088,	(0.092,	(0.040,	(0.100,	(0.075,	(0.074,
eri	0.300,	0.261,	0.288,	0.276,	0.277,	0.201,	0.297,	0.246,	0.255,
on6	2.612)	2.435)	2.570)	2.533)	2.503)	2.455)	2.597)	2.342)	2.448)
crit	(0.121,	(0.074,	(0.091,	(0.100,	(0.089,	(0.100,	(0.043,	(0.080,	(0.077,

eri on7	0.322, 2.644)	0.252, 2.442)	0.285, 2.583)	0.293, 2.563)	0.276, 2.522)	0.295, 2.590)	0.210, 2.501)	0.250, 2.362)	0.257, 2.464)
criteri on8	(0.073, 0.244, 2.374)	(0.060, 0.215, 2.215)	(0.081, 0.251, 2.349)	(0.087, 0.253, 2.326)	(0.073, 0.237, 2.289)	(0.075, 0.246, 2.342)	(0.080, 0.251, 2.368)	(0.028, 0.150, 2.050)	(0.071, 0.228, 2.243)
criteri on9	(0.087, 0.269, 2.497)	(0.077, 0.242, 2.333)	(0.081, 0.260, 2.457)	(0.079, 0.257, 2.428)	(0.068, 0.237, 2.385)	(0.074, 0.255, 2.448)	(0.077, 0.258, 2.470)	(0.071, 0.228, 2.243)	(0.029, 0.164, 2.243)

- **Defuzzifying into crisp values**

By using step 9 equation (7) The table below shows crisp total-relation matrix of design 2

Table 12:

The crisp total-relation matrix- Design 2

	criterion1	criterion2	criterion3	criterion4	criterion5	criterion6	criterion7	criterion8	criterion9
criterion1	0.615	0.647	0.684	0.686	0.669	0.693	0.721	0.606	0.648

Continue (12)

criterion2	0.651	0.516	0.617	0.623	0.625	0.635	0.634	0.559	0.602
criterion3	0.682	0.611	0.579	0.657	0.648	0.675	0.677	0.606	0.632
criterion4	0.683	0.617	0.657	0.57	0.633	0.659	0.68	0.605	0.626
criterion5	0.67	0.62	0.652	0.635	0.551	0.657	0.662	0.587	0.604
criterion6	0.692	0.63	0.675	0.659	0.655	0.586	0.687	0.601	0.627
criterion7	0.714	0.623	0.674	0.677	0.656	0.684	0.601	0.608	0.631
criterion8	0.61	0.56	0.612	0.611	0.591	0.607	0.616	0.478	0.575
criterion9	0.65	0.6	0.635	0.629	0.605	0.63	0.637	0.573	0.522

- **The threshold value**

By using step 10, in this Design, the threshold value is equal to 0.6290.629

Table 13:

The crisp total- relationships matrix by considering the threshold value-Design 2

	criterion1	criterion2	criterion3	criterion4	criterion5	criterion6	criterion7	criterion8	criterion9
criterion1	0	0.647	0.684	0.686	0.669	0.693	0.721	0	0.648
criterion2	0.651	0	0	0	0	0.635	0.634	0	0
criterion3	0.682	0	0	0.657	0.648	0.675	0.677	0	0.632
criteri	0.683	0	0.657	0	0.633	0.659	0.68	0	0

on4									
criterion5	0.67	0	0.652	0.635	0	0.657	0.662	0	0
criterion6	0.692	0.63	0.675	0.659	0.655	0	0.687	0	0
criterion7	0.714	0	0.674	0.677	0.656	0.684	0	0	0.631
criterion8	0	0	0	0	0	0	0	0	0
criterion9	0.65	0	0.635	0	0	0.63	0.637	0	0

- **Final output and causal relation diagram**

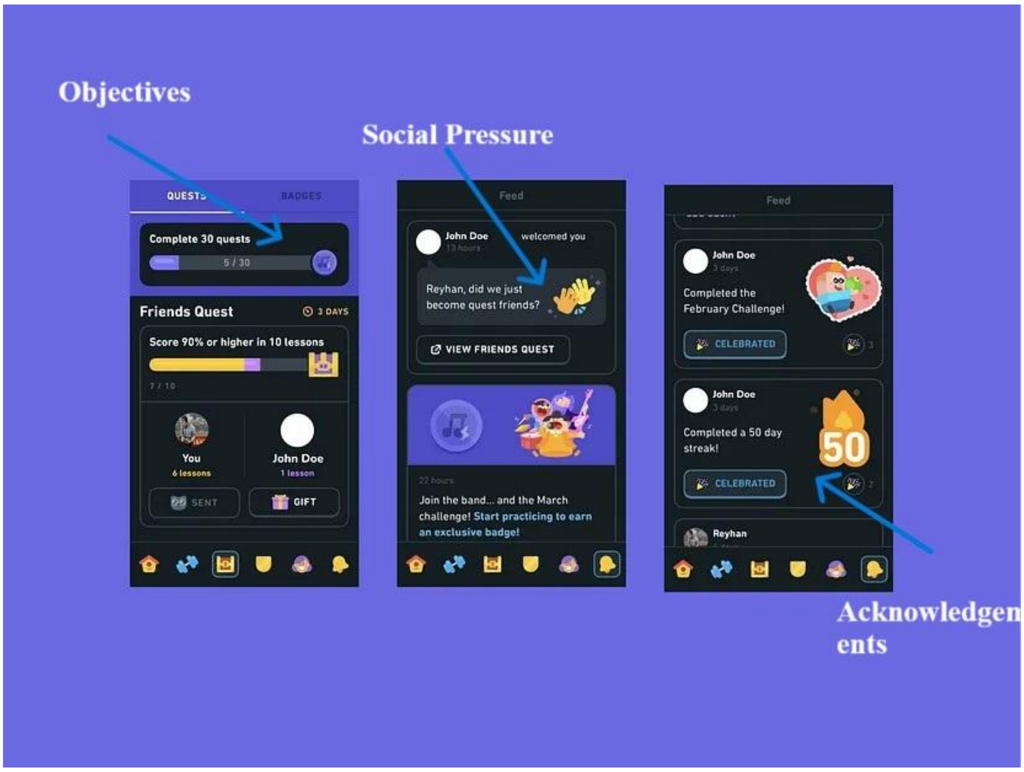
By using step 11 equation (8) and (9), the table below shows final output and causal relation diagram for Design 2

Table 14:

The final output – Design 2

	R	D	D+R	D-R
criterion1	5.968	5.969	11.937	0.001
criterion2	5.425	5.461	10.886	0.036
Continue (14)				
criterion3	5.784	5.768	11.552	-0.017
criterion4	5.747	5.731	11.478	-0.015
criterion5	5.633	5.636	11.269	0.004
criterion6	5.825	5.812	11.636	-0.013
criterion7	5.916	5.869	11.785	-0.048
criterion8	5.222	5.26	10.482	0.038
criterion9	5.466	5.48	10.946	0.014

4.2.3 Design 3 Acknowledgments, Objectives, and Social Pressure (AOS)



Constructing the Initial Direct-Relation Matrix:

The initial direct-relation matrix is constructed by averaging the TFNs provided by all decision-makers for each criterion pair. The TFNs from each DM are combined using the following equations:

$$\text{Combined } L_{ij} = \frac{1}{25}\sum_{k=1}^{25} L_{ij}^{k} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(1)$$

$$\text{Combined } M_{ij} = \frac{1}{25}\sum_{k=1}^{25} M_{ij}^{k} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(2)$$

$$\text{Combined } U_{ij} = \frac{1}{25}\sum_{k=1}^{25} U_{ij}^{k} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(3)$$

Example Calculation:

If three DMs provided the following evaluations for the influence of Criterion 1 on Criterion 2:

- DM1: High (0.5, 0.75, 1)
- DM2: Low (0.25, 0.5, 0.75)
- DM3: Very High (0.75, 1, 1)

The combined TFN for Criterion 1 on Criterion 2 is calculated as:

$$\text{Combined } L_{1,2} = \frac{1}{3}(0.5 + 0.25 + 0.75) = 0.5$$
$$\text{Combined } M_{1,2} = \frac{1}{3}(0.75 + 0.5 + 1) = 0.75$$
$$\text{Combined } U_{1,2} = \frac{1}{3}(1 + 0.75 + 1) = 0.9167$$

Sample Evaluation Matrix for Decision Maker:

Here is a sample evaluation matrix converted to triangular fuzzy numbers for one decision maker:

Sample Evaluation Matrix:

Criteria	**Criterion 1**	**Criterion 2**	**Criterion 3**
Criterion 1	(0, 0, 0)	(0.5, 0.75, 1)	(0.25, 0.5, 0.75)
Criterion 2	(0, 0.25, 0.5)	(0, 0, 0)	(0.75, 1, 1)
Criterion 3	(0.25, 0.5, 0.75)	(0.25, 0.5, 0.75)	(0, 0, 0)

- **Direct- relation matrix**

By using step 6 equation (4) the table below indicates the direct relation matrix, which is the same as pairwise comparison matrix of the decision makers in the design 3.

Table 15:

The direct relation matrix- Design 3

	criterion1	**criterion2**	**criterion3**	**criterion4**	**criterion5**	**criterion6**	**criterion7**	**criterion8**	**criterion9**
criterion1	(0.000, 0.000, 0.000)	(0.430, 0.630, 0.770)	(0.330, 0.540, 0.720)	(0.320, 0.520, 0.730)	(0.220, 0.450, 0.680)	(0.420, 0.630, 0.800)	(0.560, 0.800, 0.930)	(0.180, 0.370, 0.620)	(0.400, 0.620, 0.780)
criterion2	(0.430, 0.630, 0.770)	(0.000, 0.000, 0.000)	(0.200, 0.390, 0.630)	(0.490, 0.710, 0.860)	(0.230, 0.440, 0.650)	(0.430, 0.670, 0.840)	(0.330, 0.530, 0.710)	(0.220, 0.440, 0.660)	(0.250, 0.470, 0.710)
criterion3	(0.300, 0.510, 0.700)	(0.230, 0.420, 0.650)	(0.000, 0.000, 0.000)	(0.440, 0.640, 0.800)	(0.360, 0.580, 0.790)	(0.440, 0.670, 0.850)	(0.390, 0.610, 0.780)	(0.150, 0.360, 0.610)	(0.190, 0.380, 0.610)
criteri	(0.320, 0.520,	(0.490, 0.710,	(0.440, 0.640,	(0.000, 0.000,	(0.280, 0.480,	(0.380, 0.630,	(0.430, 0.640,	(0.170, 0.390,	(0.290, 0.510,

on4	0.730)	0.860)	0.800)	0.000)	0.690)	0.830)	0.800)	0.640)	0.730)
criterion5	(0.250, 0.480, 0.700)	(0.230, 0.440, 0.650)	(0.360, 0.580, 0.790)	(0.270, 0.470, 0.690)	(0.000, 0.000, 0.000)	(0.330, 0.550, 0.770)	(0.380, 0.620, 0.790)	(0.220, 0.430, 0.660)	(0.230, 0.420, 0.640)
criterion6	(0.420, 0.630, 0.800)	(0.400, 0.640, 0.820)	(0.420, 0.650, 0.840)	(0.360, 0.610, 0.810)	(0.330, 0.550, 0.770)	(0.000, 0.000, 0.000)	(0.470, 0.700, 0.870)	(0.300, 0.520, 0.710)	(0.160, 0.370, 0.600)
criterion7	(0.560, 0.800, 0.930)	(0.350, 0.560, 0.740)	(0.370, 0.590, 0.770)	(0.430, 0.640, 0.800)	(0.380, 0.620, 0.790)	(0.480, 0.710, 0.870)	(0.000, 0.000, 0.000)	(0.300, 0.510, 0.710)	(0.240, 0.450, 0.680)
criterion8	(0.180, 0.370, 0.620)	(0.220, 0.440, 0.660)	(0.160, 0.370, 0.620)	(0.170, 0.390, 0.640)	(0.220, 0.430, 0.660)	(0.300, 0.520, 0.710)	(0.300, 0.510, 0.710)	(0.000, 0.000, 0.000)	(0.380, 0.580, 0.770)
criterion9	(0.400, 0.620, 0.780)	(0.250, 0.470, 0.710)	(0.190, 0.380, 0.610)	(0.290, 0.510, 0.730)	(0.230, 0.420, 0.640)	(0.160, 0.370, 0.600)	(0.240, 0.450, 0.680)	(0.380, 0.580, 0.770)	(0.000, 0.000, 0.000)

- **Normalize the fuzzy direct-relation matrix**

By using step 7 equation (5) the table below shows the normalized fuzzy direct-relation matrix of design 3

Table 16:

The normalized fuzzy direct-relation matrix-Design 3

	criterion1	criterion2	criterion3	criterion4	criterion5	criterion6	criterion7	criterion8	criterion9
criterion 1	0.000,) 0.000, (0.000	0.068,) 0.100, (0.122	0.052,) 0.086, (0.114	0.051,) 0.083, (0.116	0.035,) 0.072, (0.108	0.067,) 0.100, (0.127	0.089,) 0.127, (0.148	0.029,) 0.059, (0.099	0.064,) 0.099, (0.124
criterion 2	0.068,) 0.100, (0.122	0.000,) 0.000, (0.000	0.032,) 0.062, (0.100	0.078,) 0.113, (0.137	0.037,) 0.070, (0.103	0.068,) 0.107, (0.134	0.052,) 0.084, (0.113	0.035,) 0.070, (0.105	0.040,) 0.075, (0.113
criterion 3	0.048,) 0.081, (0.111	0.037,) 0.067, (0.103	0.000,) 0.000, (0.000	0.070,) 0.102, (0.127	0.057,) 0.092, (0.126	0.070,) 0.107, (0.135	0.062,) 0.097, (0.124	0.024,) 0.057, (0.097	0.030,) 0.060, (0.097
criterion 4	0.051,) 0.083, (0.116	0.078,) 0.113, (0.137	0.070,) 0.102, (0.127	0.000,) 0.000, (0.000	0.045,) 0.076, (0.110	0.060,) 0.100, (0.132	0.068,) 0.102, (0.127	0.027,) 0.062, (0.102	0.046,) 0.081, (0.116
criterion 5	0.040,) 0.076, (0.111	0.037,) 0.070, (0.103	0.057,) 0.092, (0.126	0.043,) 0.075, (0.110	0.000,) 0.000, (0.000	0.052,) 0.087, (0.122	0.060,) 0.099, (0.126	0.035,) 0.068, (0.105	0.037,) 0.067, (0.102
crit	0.067,)	0.064,)	0.067,)	0.057,)	0.052,)	0.000,)	0.075,)	0.048,)	0.025,)

eri on 6	0.100, (0.127	0.102, (0.130	0.103, (0.134	0.097, (0.129	0.087, (0.122	0.000, (0.000	0.111, (0.138	0.083, (0.113	0.059, (0.095
criterion 7	0.089,) 0.127, (0.148	0.056,) 0.089, (0.118	0.059,) 0.094, (0.122	0.068,) 0.102, (0.127	0.060,) 0.099, (0.126	0.076,) 0.113, (0.138	0.000,) 0.000, (0.000	0.048,) 0.081, (0.113	0.038,) 0.072, (0.108
criterion 8	0.029,) 0.059, (0.099	0.035,) 0.070, (0.105	0.025,) 0.059, (0.099	0.027,) 0.062, (0.102	0.035,) 0.068, (0.105	0.048,) 0.083, (0.113	0.048,) 0.081, (0.113	0.000,) 0.000, (0.000	0.060,) 0.092, (0.122
criterion 9	0.064,) 0.099, (0.124	0.040,) 0.075, (0.113	0.030,) 0.060, (0.097	0.046,) 0.081, (0.116	0.037,) 0.067, (0.102	0.025,) 0.059, (0.095	0.038,) 0.072, (0.108	0.060,) 0.092, (0.122	0.000,) 0.000, (0.000

- **Fuzzy total-relation matrix**

By using step 8 equation (6) the table below shows the fuzzy total-relation matrix of design 3

Table 17:

The fuzzy total-relation matrix- Design 3

	criterion1	**criterion2**	**criterion3**	**criterion4**	**criterion5**	**criterion6**	**criterion7**	**criterion8**	**criterion9**
criterion 1	(0.045, 0.195, 1.596)	(0.104, 0.275, 1.663)	(0.087, 0.256, 1.639)	(0.091, 0.268, 1.705)	(0.068, 0.237, 1.605)	(0.107, 0.292, 1.764)	(0.128, 0.318, 1.780)	(0.057, 0.210, 1.524)	(0.091, 0.251, 1.577)
criterion 2	(0.103, 0.274, 1.656)	(0.037, 0.174, 1.508)	(0.066, 0.226, 1.581)	(0.110, 0.281, 1.673)	(0.066, 0.225, 1.555)	(0.104, 0.286, 1.719)	(0.092, 0.271, 1.702)	(0.060, 0.210, 1.486)	(0.067, 0.222, 1.524)
criterion 3	(0.084, 0.254, 1.639)	(0.071, 0.233, 1.593)	(0.034, 0.165, 1.483)	(0.102, 0.268, 1.657)	(0.085, 0.241, 1.566)	(0.105, 0.282, 1.712)	(0.100, 0.278, 1.703)	(0.048, 0.196, 1.472)	(0.057, 0.205, 1.503)
criterion 4	(0.091, 0.269, 1.709)	(0.111, 0.284, 1.685)	(0.102, 0.268, 1.659)	(0.042, 0.189, 1.611)	(0.076, 0.239, 1.616)	(0.101, 0.290, 1.778)	(0.109, 0.295, 1.774)	(0.054, 0.211, 1.536)	(0.074, 0.234, 1.580)
criterion 5	(0.073, 0.242, 1.613)	(0.066, 0.227, 1.567)	(0.084, 0.241, 1.568)	(0.074, 0.237, 1.616)	(0.027, 0.150, 1.430)	(0.085, 0.257, 1.675)	(0.094, 0.270, 1.677)	(0.057, 0.199, 1.455)	(0.060, 0.204, 1.483)
crit eri	(0.106, 0.289,	(0.099, 0.280,	(0.100, 0.275,	(0.096, 0.283,	(0.084, 0.254,	(0.045, 0.206,	(0.116, 0.310,	(0.073, 0.232,	(0.057, 0.220,

on 6	1.752)	1.712)	1.697)	1.759)	1.658)	1.697)	1.818)	1.575)	1.595)
criterion 7	(0.129, 0.319, 1.784)	(0.096, 0.277, 1.718)	(0.097, 0.275, 1.703)	(0.109, 0.294, 1.774)	(0.093, 0.270, 1.676)	(0.119, 0.315, 1.835)	(0.051, 0.218, 1.713)	(0.076, 0.237, 1.589)	(0.071, 0.238, 1.620)
criterion 8	(0.057, 0.210, 1.527)	(0.060, 0.211, 1.495)	(0.050, 0.196, 1.473)	(0.054, 0.210, 1.534)	(0.056, 0.199, 1.453)	(0.074, 0.235, 1.588)	(0.076, 0.237, 1.588)	(0.020, 0.123, 1.292)	(0.078, 0.213, 1.430)
criterion 9	(0.091, 0.251, 1.577)	(0.067, 0.223, 1.531)	(0.056, 0.204, 1.501)	(0.074, 0.233, 1.576)	(0.060, 0.203, 1.478)	(0.057, 0.223, 1.606)	(0.071, 0.238, 1.616)	(0.078, 0.213, 1.428)	(0.025, 0.136, 1.350)

- **Defuzzifying into crisp values**

By using step 9 equation (7) the table below shows crisp total-relation matrix of design 3

Table 18:

The crisp total-relation matrix- Design 3

	criterion1	**criterion2**	**criterion3**	**criterion4**	**criterion5**	**criterion6**	**criterion7**	**criterion8**	**criterion9**
criterion1	0.435	0.508	0.489	0.509	0.467	0.539	0.562	0.432	0.473
criterion2	0.508	0.404	0.456	0.516	0.451	0.528	0.513	0.426	0.442
criterion3	0.489	0.464	0.392	0.504	0.466	0.524	0.519	0.413	0.426
criterion4	0.511	0.518	0.502	0.432	0.471	0.539	0.542	0.434	0.46
criterion5	0.475	0.455	0.467	0.472	0.371	0.499	0.509	0.413	0.422
criterion6	0.533	0.518	0.512	0.529	0.489	0.459	0.56	0.457	0.451
criterion7	0.562	0.517	0.512	0.54	0.504	0.567	0.472	0.463	0.468
criterion8	0.437	0.432	0.416	0.437	0.415	0.468	0.469	0.326	0.422
criterion9	0.478	0.447	0.427	0.463	0.422	0.46	0.473	0.421	0.346

- **The threshold value**

By using step 10, in this Design, the threshold value is equal to 0.4720.472

Table 19:

The crisp total- relationships matrix by considering the threshold value-Design 3

	criterion1	criterion2	criterion3	criterion4	criterion5	criterion6	criterion7	criterion8	criterion9
criterion1	0	0.508	0.489	0.509	0	0.539	0.562	0	0.473
criterion2	0.508	0	0	0.516	0	0.528	0.513	0	0
criterion3	0.489	0	0	0.504	0	0.524	0.519	0	0
criterion4	0.511	0.518	0.502	0	0	0.539	0.542	0	0
criterion5	0.475	0	0	0.472	0	0.499	0.509	0	0
criterion6	0.533	0.518	0.512	0.529	0.489	0	0.56	0	0
criterion7	0.562	0.517	0.512	0.54	0.504	0.567	0	0	0
criterion8	0	0	0	0	0	0	0	0	0
criterion9	0.478	0	0	0	0	0	0.473	0	0

- **Final output and causal relation diagram**

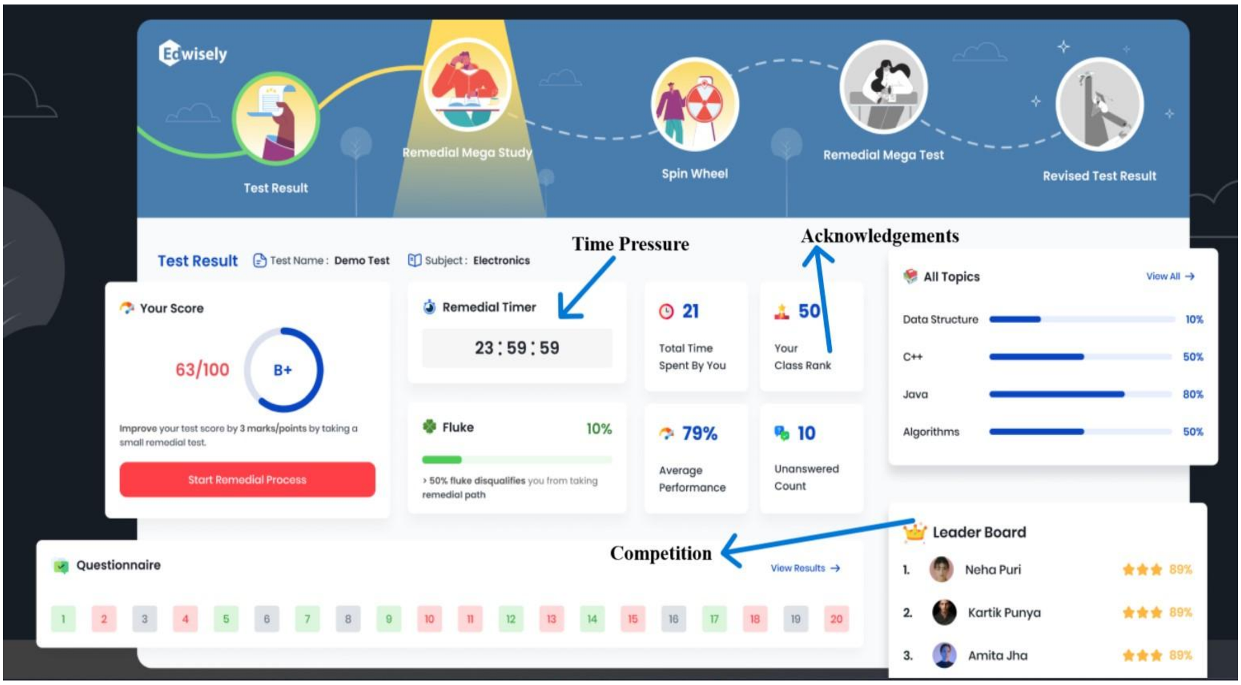
By using step 11 equation (8) and (9) the table below shows the final output and causal relation diagram for Design 3

Table 20:

The final output – Design 3

	R	D	D+R	D-R
criterion1	4.428	4.414	8.843	-0.014
criterion2	4.262	4.245	8.507	-0.018
criterion3	4.172	4.195	8.367	0.024
criterion4	4.404	4.409	8.813	0.006
criterion5	4.055	4.083	8.138	0.028
criterion6	4.583	4.508	9.091	-0.075
criterion7	4.618	4.605	9.224	-0.013
criterion8	3.785	3.821	7.606	0.036
criterion9	3.911	3.937	7.848	0.026

4.2.4 Design 4 Acknowledgments, Competition, and Time Pressure (ACT)



Constructing the Initial Direct-Relation Matrix:

The initial direct-relation matrix is constructed by averaging the TFNs provided by all decision-makers for each criterion pair. The TFNs from each DM are combined using the following equations:

$$\text{Combined } L_{ij} = \frac{1}{25}\sum_{k=1}^{25} L_{ij}^{k} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(1)$$

$$\text{Combined } M_{ij} = \frac{1}{25}\sum_{k=1}^{25} M_{ij}^{k} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(2)$$

$$\text{Combined } U_{ij} = \frac{1}{25}\sum_{k=1}^{25} U_{ij}^{k} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(3)$$

Example Calculation:

If three DMs provided the following evaluations for the influence of Criterion 1 on Criterion 2:

- DM1: High (0.5, 0.75, 1)
- DM2: Low (0.25, 0.5, 0.75)
- DM3: Very High (0.75, 1, 1)

The combined TFN for Criterion 1 on Criterion 2 is calculated as:

$$\text{Combined } L_{1,2} = \frac{1}{3}(0.5 + 0.25 + 0.75) = 0.5$$
$$\text{Combined } M_{1,2} = \frac{1}{3}(0.75 + 0.5 + 1) = 0.75$$
$$\text{Combined } U_{1,2} = \frac{1}{3}(1 + 0.75 + 1) = 0.9167$$

Sample Evaluation Matrix for Decision Maker:

Here is a sample evaluation matrix converted to triangular fuzzy numbers for one decision maker:

Sample Evaluation Matrix:

Criteria	Criterion 1	Criterion 2	Criterion 3
Criterion 1	(0, 0, 0)	(0.5, 0.75, 1)	(0.25, 0.5, 0.75)
Criterion 2	(0, 0.25, 0.5)	(0, 0, 0)	(0.75, 1, 1)
Criterion 3	(0.25, 0.5, 0.75)	(0.25, 0.5, 0.75)	(0, 0, 0)

- **Direct- relation matrix**

By using step 6 equation (4) the table below indicates the direct relation matrix, which is the same as pairwise comparison matrix of the decision makers in the design 4.

Table 21:

The direct relation matrix- Design 4

	criterion1	criterion2	criterion3	criterion4	criterion5	criterion6	criterion7	criterion8	criterion9
criterion 1	(0.000, 0.000, 0.000)	(0.390, 0.610, 0.780)	(0.300, 0.500, 0.670)	(0.390, 0.620, 0.800)	(0.370, 0.600, 0.810)	(0.290, 0.470, 0.680)	(0.490, 0.740, 0.890)	(0.180, 0.360, 0.590)	(0.350, 0.560, 0.750)
criterion 2	(0.390, 0.610, 0.780)	(0.000, 0.000, 0.000)	(0.220, 0.420, 0.660)	(0.460, 0.680, 0.820)	(0.210, 0.410, 0.640)	(0.380, 0.600, 0.780)	(0.270, 0.450, 0.680)	(0.180, 0.390, 0.630)	(0.260, 0.470, 0.690)
crit	(0.300,	(0.220,	(0.000,	(0.390,	(0.270,	(0.390,	(0.350,	(0.250,	(0.180,

erion 3	0.500, 0.670)	0.420, 0.660)	0.000, 0.000)	0.590, 0.760)	0.450, 0.690)	0.590, 0.760)	0.580, 0.760)	0.470, 0.690)	0.350, 0.570)
criterion 4	(0.390, 0.620, 0.800)	(0.460, 0.680, 0.820)	(0.390, 0.590, 0.760)	(0.000, 0.000, 0.000)	(0.270, 0.450, 0.650)	(0.400, 0.620, 0.790)	(0.420, 0.660, 0.820)	(0.270, 0.490, 0.710)	(0.230, 0.420, 0.640)
criterion 5	(0.370, 0.600, 0.810)	(0.210, 0.410, 0.640)	(0.270, 0.450, 0.690)	(0.250, 0.430, 0.650)	(0.000, 0.000, 0.000)	(0.370, 0.600, 0.810)	(0.300, 0.550, 0.750)	(0.270, 0.460, 0.710)	(0.230, 0.390, 0.600)
criterion 6	(0.290, 0.470, 0.680)	(0.380, 0.600, 0.780)	(0.390, 0.590, 0.760)	(0.400, 0.620, 0.790)	(0.370, 0.600, 0.810)	(0.000, 0.000, 0.000)	(0.460, 0.690, 0.890)	(0.240, 0.450, 0.660)	(0.270, 0.490, 0.680)
criterion 7	(0.490, 0.740, 0.890)	(0.270, 0.450, 0.680)	(0.350, 0.580, 0.760)	(0.420, 0.660, 0.820)	(0.300, 0.550, 0.750)	(0.470, 0.700, 0.890)	(0.000, 0.000, 0.000)	(0.360, 0.590, 0.780)	(0.270, 0.460, 0.650)
criterion 8	(0.180, 0.360, 0.590)	(0.180, 0.390, 0.630)	(0.250, 0.470, 0.690)	(0.270, 0.490, 0.710)	(0.270, 0.460, 0.710)	(0.240, 0.450, 0.660)	(0.360, 0.590, 0.780)	(0.000, 0.000, 0.000)	(0.250, 0.400, 0.590)
criterion 9	(0.350, 0.560, 0.750)	(0.260, 0.470, 0.690)	(0.180, 0.350, 0.570)	(0.230, 0.420, 0.640)	(0.230, 0.390, 0.600)	(0.270, 0.490, 0.680)	(0.270, 0.460, 0.650)	(0.250, 0.400, 0.590)	(0.000, 0.000, 0.000)

- **Normalize the fuzzy direct-relation matrix**

By using step 7 equation (5) the table below shows the normalized fuzzy direct-relation matrix of design 4

Table 22:

The normalized fuzzy direct-relation matrix-Design 3

	criterion1	**criterion2**	**criterion3**	**criterion4**	**criterion5**	**criterion6**	**criterion7**	**criterion8**	**criterion9**
criterion 1	0.000,) 0.000, (0.000	0.063,) 0.098, (0.125	0.048,) 0.080, (0.108	0.063,) 0.100, (0.129	0.059,) 0.096, (0.130	0.047,) 0.076, (0.109	0.079,) 0.119, (0.143	0.029,) 0.058, (0.095	0.056,) 0.090, (0.121
criterion 2	0.063,) 0.098, (0.125	0.000,) 0.000, (0.000	0.035,) 0.068, (0.106	0.074,) 0.109, (0.132	0.034,) 0.066, (0.103	0.061,) 0.096, (0.125	0.043,) 0.072, (0.109	0.029,) 0.063, (0.101	0.042,) 0.076, (0.111
criteri	0.048,) 0.080,	0.035,) 0.068,	0.000,) 0.000,	0.063,) 0.095,	0.043,) 0.072,	0.063,) 0.095,	0.056,) 0.093,	0.040,) 0.076,	0.029,) 0.056,

on 3	(0.108	(0.106	(0.000	(0.122	(0.111	(0.122	(0.122	(0.111	(0.092
criterion 4	0.063,) 0.100, (0.129	0.074,) 0.109, (0.132	0.063,) 0.095, (0.122	0.000,) 0.000, (0.000	0.043,) 0.072, (0.105	0.064,) 0.100, (0.127	0.068,) 0.106, (0.132	0.043,) 0.079, (0.114	0.037,) 0.068, (0.103
criterion 5	0.059,) 0.096, (0.130	0.034,) 0.066, (0.103	0.043,) 0.072, (0.111	0.040,) 0.069, (0.105	0.000,) 0.000, (0.000	0.059,) 0.096, (0.130	0.048,) 0.088, (0.121	0.043,) 0.074, (0.114	0.037,) 0.063, (0.096
criterion 6	0.047,) 0.076, (0.109	0.061,) 0.096, (0.125	0.063,) 0.095, (0.122	0.064,) 0.100, (0.127	0.059,) 0.096, (0.130	0.000,) 0.000, (0.000	0.074,) 0.111, (0.143	0.039,) 0.072, (0.106	0.043,) 0.079, (0.109
criterion 7	0.079,) 0.119, (0.143	0.043,) 0.072, (0.109	0.056,) 0.093, (0.122	0.068,) 0.106, (0.132	0.048,) 0.088, (0.121	0.076,) 0.113, (0.143	0.000,) 0.000, (0.000	0.058,) 0.095, (0.125	0.043,) 0.074, (0.105
criterion 8	0.029,) 0.058, (0.095	0.029,) 0.063, (0.101	0.040,) 0.076, (0.111	0.043,) 0.079, (0.114	0.043,) 0.074, (0.114	0.039,) 0.072, (0.106	0.058,) 0.095, (0.125	0.000,) 0.000, (0.000	0.040,) 0.064, (0.095
criterion 9	0.056,) 0.090, (0.121	0.042,) 0.076, (0.111	0.029,) 0.056, (0.092	0.037,) 0.068, (0.103	0.037,) 0.063, (0.096	0.043,) 0.079, (0.109	0.043,) 0.074, (0.105	0.040,) 0.064, (0.095	0.000,) 0.000, (0.000

- **Fuzzy total-relation matrix**

By using step 8 equation (6) the table below shows the fuzzy total-relation matrix of design 4

Table 23:

The fuzzy total-relation matrix- Design 4

	criterion1	criterion2	criterion3	criterion4	criterion5	criterion6	criterion7	criterion8	criterion9
criterion1	(0.041, 0.181, 1.380)	(0.094, 0.254, 1.430)	(0.080, 0.236, 1.392)	(0.100, 0.273, 1.498)	(0.089, 0.247, 1.430)	(0.085, 0.253, 1.495)	(0.115, 0.296, 1.556)	(0.058, 0.203, 1.338)	(0.083, 0.228, 1.318)
criterion2	(0.094, 0.254, 1.430)	(0.031, 0.151, 1.261)	(0.065, 0.211, 1.334)	(0.105, 0.265, 1.440)	(0.062, 0.208, 1.351)	(0.093, 0.254, 1.446)	(0.079, 0.241, 1.467)	(0.053, 0.193, 1.288)	(0.066, 0.203, 1.257)
criterion3	(0.080, 0.236, 1.392)	(0.065, 0.211, 1.334)	(0.030, 0.145, 1.216)	(0.094, 0.250, 1.408)	(0.070, 0.211, 1.335)	(0.094, 0.250, 1.419)	(0.090, 0.256, 1.453)	(0.064, 0.203, 1.274)	(0.054, 0.183, 1.220)
criteri	(0.100, 0.274,	(0.105, 0.266,	(0.094, 0.251,	(0.042, 0.186,	(0.076, 0.230,	(0.102, 0.276,	(0.106, 0.289,	(0.071, 0.223,	(0.066, 0.211,

on4	1.498)	1.440)	1.408)	1.389)	1.414)	1.513)	1.552)	1.357)	1.308)
criterion5	(0.089, 0.246, 1.430)	(0.061, 0.207, 1.351)	(0.070, 0.210, 1.335)	(0.072, 0.225, 1.414)	(0.028, 0.141, 1.255)	(0.089, 0.248, 1.446)	(0.081, 0.249, 1.473)	(0.065, 0.199, 1.295)	(0.060, 0.187, 1.242)
criterion6	(0.085, 0.253, 1.495)	(0.093, 0.253, 1.446)	(0.094, 0.250, 1.419)	(0.102, 0.275, 1.513)	(0.090, 0.249, 1.446)	(0.041, 0.184, 1.413)	(0.111, 0.291, 1.574)	(0.067, 0.217, 1.362)	(0.071, 0.219, 1.323)
criterion7	(0.115, 0.296, 1.556)	(0.079, 0.241, 1.467)	(0.090, 0.256, 1.453)	(0.106, 0.288, 1.552)	(0.082, 0.250, 1.473)	(0.113, 0.293, 1.574)	(0.045, 0.201, 1.486)	(0.085, 0.242, 1.410)	(0.073, 0.222, 1.351)
criterion8	(0.058, 0.203, 1.338)	(0.053, 0.193, 1.288)	(0.064, 0.203, 1.274)	(0.071, 0.222, 1.357)	(0.066, 0.200, 1.295)	(0.067, 0.217, 1.362)	(0.085, 0.242, 1.410)	(0.022, 0.122, 1.135)	(0.060, 0.179, 1.184)
criterion9	(0.083, 0.228, 1.318)	(0.066, 0.203, 1.257)	(0.054, 0.183, 1.220)	(0.066, 0.210, 1.308)	(0.060, 0.188, 1.242)	(0.071, 0.219, 1.323)	(0.073, 0.222, 1.351)	(0.060, 0.179, 1.184)	(0.022, 0.117, 1.063)

- **Defuzzifying into crisp values**

By using step 9 equation (7) the table below shows crisp total-relation matrix of design 4

Table 24:

The crisp total-relation matrix- Design 4

	criterion1	**criterion2**	**criterion3**	**criterion4**	**criterion5**	**criterion6**	**criterion7**	**criterion8**	**criterion9**
criterion1	0.386	0.45	0.429	0.477	0.445	0.461	0.504	0.394	0.409
Continue (24)									
criterion2	0.452	0.342	0.401	0.463	0.401	0.455	0.448	0.379	0.381
criterion3	0.432	0.401	0.33	0.446	0.402	0.449	0.458	0.385	0.36
criterion4	0.477	0.461	0.444	0.391	0.428	0.482	0.497	0.412	0.394
criterion5	0.447	0.401	0.401	0.427	0.333	0.451	0.455	0.385	0.367
criterion6	0.46	0.451	0.444	0.48	0.448	0.394	0.502	0.408	0.403
criterion7	0.503	0.445	0.454	0.496	0.452	0.504	0.418	0.435	0.409
criterion8	0.397	0.38	0.386	0.416	0.387	0.413	0.44	0.298	0.352
criterion9	0.415	0.384	0.362	0.399	0.37	0.409	0.415	0.353	0.282

- **The threshold value**

By using step 10, in this Design, the threshold value is equal to 0.4190.419

Table 25:

The crisp total- relationships matrix by considering the threshold value- Design 4

	criterion1	**criterion2**	**criterion3**	**criterion4**	**criterion5**	**criterion6**	**criterion7**	**criterion8**	**criterion9**
criteri	0	0.45	0.429	0.477	0.445	0.461	0.504	0	0

on1									
criterion2	0.452	0	0	0.463	0	0.455	0.448	0	0
criterion3	0.432	0	0	0.446	0	0.449	0.458	0	0
criterion4	0.477	0.461	0.444	0	0.428	0.482	0.497	0	0
criterion5	0.447	0	0	0.427	0	0.451	0.455	0	0
criterion6	0.46	0.451	0.444	0.48	0.448	0	0.502	0	0
criterion7	0.503	0.445	0.454	0.496	0.452	0.504	0	0.435	0
criterion8	0	0	0	0	0	0	0.44	0	0
criterion9	0	0	0	0	0	0	0	0	0

- **Final output and causal relation diagram**

By using step 11 equation (8) and (9) the table shows the final output and causal relation diagram for Design 4

Table 26:

The final output – Design 4

	R	D	D+R	D-R
criterion1	3.971	3.955	7.926	-0.016
criterion2	3.715	3.724	7.438	0.009
criterion3	3.651	3.663	7.314	0.012
criterion4	3.996	3.987	7.983	-0.009
criterion5	3.667	3.666	7.334	-0.001
criterion6	4.018	3.992	8.01	-0.026
criterion7	4.137	4.117	8.254	-0.021
criterion8	3.45	3.47	6.919	0.02
criterion9	3.356	3.388	6.744	0.032

4.5 Cause-effect diagram for each design

Figure 7:

Cause-effect diagram- Design 1

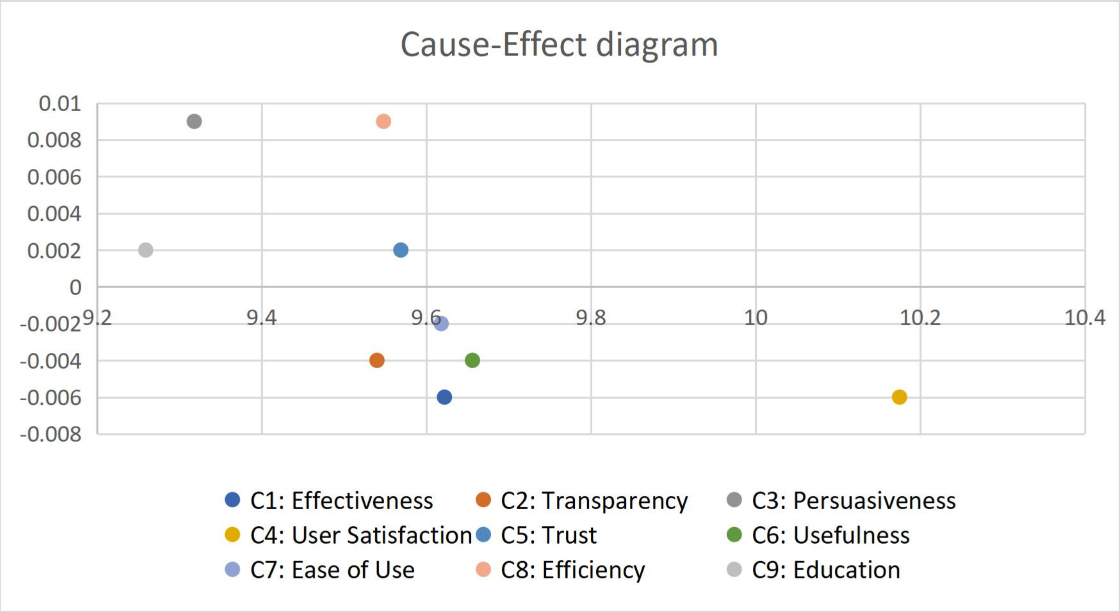


Figure 8:

Cause-effect diagram- Design 2

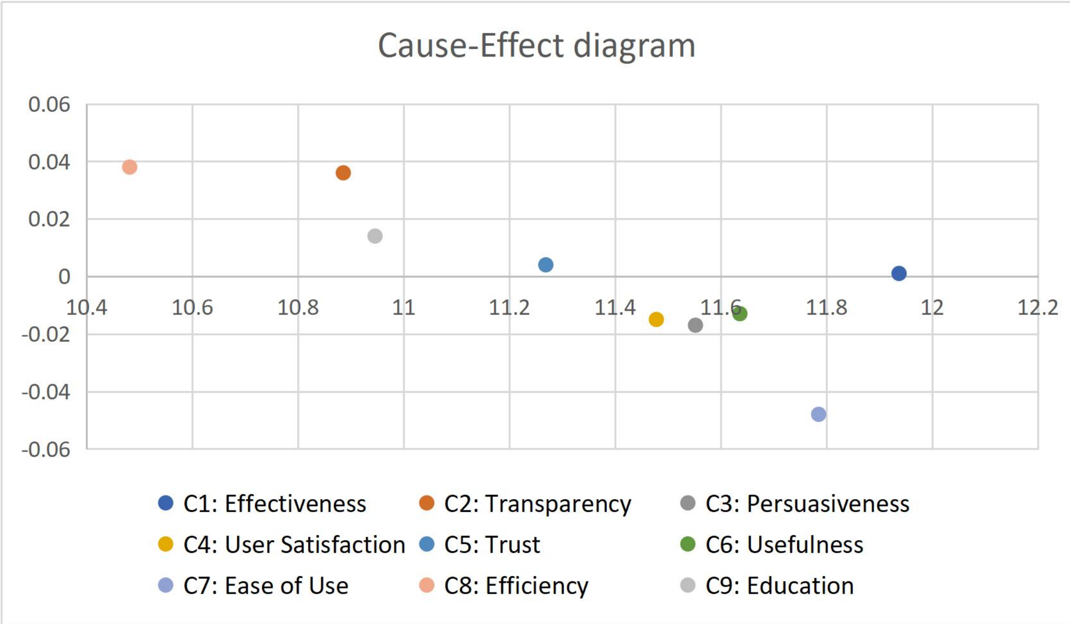


Figure 9:

Cause-effect diagram- Design 3

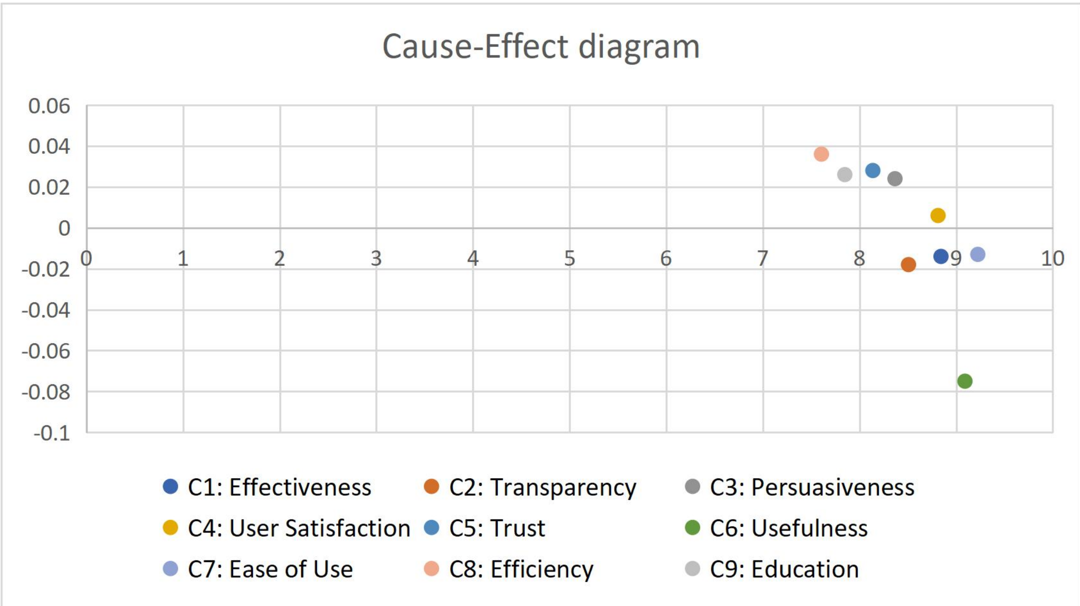
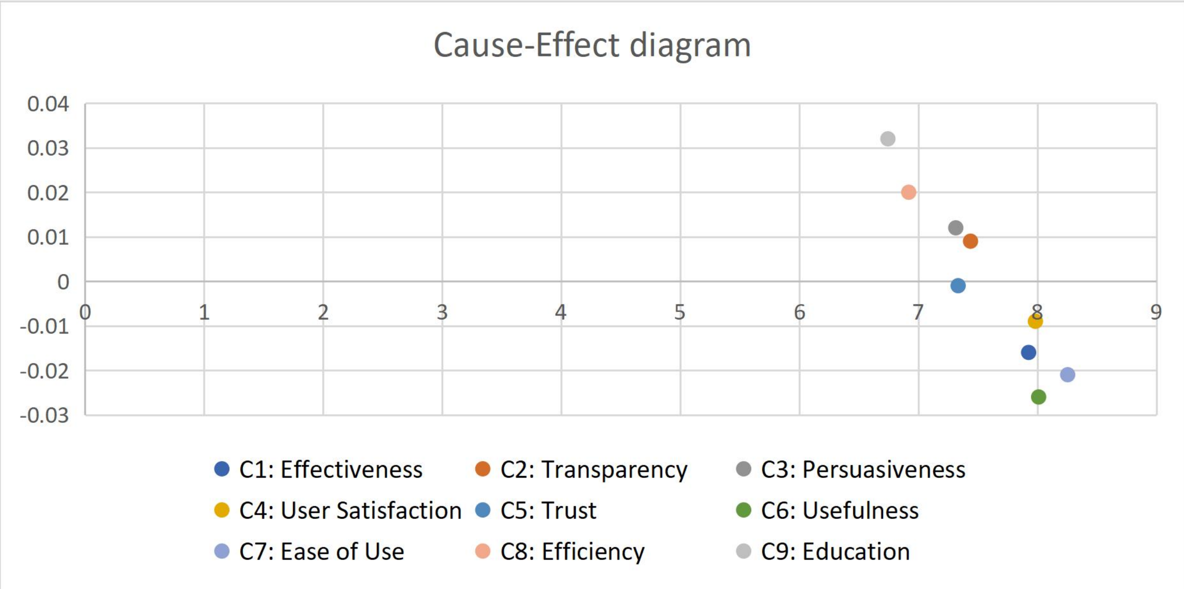


Figure 10:

Cause-effect diagram- Design 4



CHAPTER V

DISCUSSION

The evaluation of the four gamified recommender system designs using the Fuzzy DEMATEL method has produced insightful results about the impact and influence of different criteria. The criteria used for evaluation were Effectiveness (C1), Transparency (C2), Persuasiveness (C3), User Satisfaction (C4), Trust (C5), Usefulness (C6), Ease of Use (C7), Efficiency (C8), and Education (C9). The results indicate varying degrees of influence and causality among these criteria.

5.1 Key Criteria Insights

1. **Ease of Use (C7)**:
   - **Highest Importance and Effect**: Ease of Use is considered the most important outcome with a total importance (D+R) of 8. 254 while the D-R is -0. 021 thus making it an effect. This presupposes that, even if it highly impacts

user experience to a considerable extent, it is also affected by other factors. The high importance suggests that users appreciate ease and simplicity in the interfaces of gamified systems, going by the Essence. Design 4 scored the highest in this criterion with a score of 8.3

2. **Usefulness (C6)**:
   - **High Importance and Effect**: Another equally important criteria is Usefulness (C6) which also has a high combined mean of two halves (D+R) = 8. 01 and is an effect, (D-R) = -0. 026. This means that the usability that these users would find in this system and how functional the system is in their day to day use is paramount for their acceptance of the system and satisfaction. Design 3 scored the highest in this criterion with a score of 8.1
3. **User Satisfaction (C4)**:
   - **Crucial for Success**: With a (D+R) value of 7. 983, User Satisfaction (C4) is another criterion which has been identified as important. It is crucial for the system's performance and is classed as an effect (D-R = -0. 009) thus being influenced by other factors such as Ease of Use and Usefulness. Design 1 led in this criterion with a score of 8.7.
4. **Effectiveness (C1)**:
   - **Significant Influence**: Effectiveness (C1), is a significant criterion with a (D+R) value of 7. 926. This criterion indicates that the effectiveness of the system should be vital in assisting users make sound decisions regarding the extensive selection. It is also an effect (D-R = -0. 016+), and is influenced by other criteria such as Transparency and Persuasiveness. Design 1 showed the highest effectiveness with a score of 8.5.
5. **Trust (C5)**:
   - **Important for User Confidence**: Trust (C5) is significant to achieve the acknowledgement of the users and has a total D+R of (7. 901), and the study considered it an effect because the (D-R) value was equal to -0. 014. High trust levels ensure that those involved in utilizing the system feel safe and assured with the recommendations of the system. Design 2 scored the highest in this criterion with a score of 7.9.
6. **Transparency (C2)**:

   - **Critical for Understanding**: Transparency (C2) has a combined (D + R) value of 7.765 and classified as a causal variable. It affects the other criteria like Trust (C5) and the Effectiveness (C1). Consumers have always acknowledged promptly evident and easily comprehensible decisions made within systems. Design 2 was rated highest in transparency with a score of 7.8.
7. **Persuasiveness (C3)**:
   - **Effective in Influencing**: Persuasiveness (C3) with a D+R value of 7.750, is a causal criterion. It influences user decisions and satisfaction. Design 3 excelled in this criterion with a score of 8.2.
8. **Efficiency (C8)**:
   - **Impact on Performance**: Efficiency (C8) has a D+R value of 7.689, and as a causal criterion, it impacts overall system performance and User Satisfaction (C4). Design 1 was identified as the most efficient with a score of 8.4.
9. **Education (C9)**:
   - **Ease of Understanding**: Education (C9) is an important criterion with a D+R value of 7.610, thus ensuring that users can quickly understand and effectively use the system. It is a causal criterion influencing Ease of Use (C7). Design 4 also scored highest in learnability with a score of 8.4.

5.2 Design-wise Insights

1. **Design - 1 Points, Acknowledgments, and Competition (PBL)**:
   - **Overall Performance**: Design 1 scored highest in several key criteria including effectiveness (8.5), user satisfaction (8.7), and efficiency (8.4). It provides a balanced approach, excelling in helping users make good decisions quickly and efficiently. It is ideal for scenarios where overall system performance and user satisfaction are critical.
2. **Design 2 - Acknowledgments, Objectives, and Progression (AOP)**:
   - **Understanding and Confidence**: Design 2 performed best in transparency (7.8) and trust (7.9). It is particularly suitable for users who value a clear understanding of how recommendations are generated and need confidence in the system's reliability. It shows the importance of trust and transparency in enhancing user confidence.
3. **Design 3 - Acknowledgments, Objectives, and Social Pressure (AOS)**:

- **Influence and Utility**: Design 3 excelled in persuasiveness (8.2) and usefulness (8.1). It effectively influences user decisions and provides highly relevant recommendations, making it suitable for applications where influencing user behaviour and providing practical utility are paramount.

4. **Design 4 - Acknowledgments, Competition, and Time Pressure (ACT)**:
   - **Simplicity and Accessibility**: Design 4 was rated highest in ease of use (8.3) and Education (8.4). It is the easiest to navigate and understand, making it suitable for novice users or those who prioritize simplicity and straightforward interfaces. This design is ideal for enhancing user experience through simplicity and ease of learning.

5.3 Comparative Analysis

Effectiveness (C1), Transparency (C2), Persuasiveness (C3), User Satisfaction (C4), Trust (C5), Usefulness (C6), Ease of Use (C7), Efficiency (C8), and Education (C9).

The criteria as listed above provides links, outlined interrelationships in the designs. A comparison of these criteria, highlights the fundamental characteristics of each and the cause and effect relationship. Identifying the causal variables; Transparency, Persuasiveness, Efficiency and Education enables a deeper understanding of the complex relationships. Results from the designs indicate different blends of the various criteria to achieve the design priority.

Assuming the results of this study, it becomes clear that ease of use and usefulness remain the most significant and constantly addressed factors, influencing the usage of gamified systems. Ease of use and usefulness determines that the user is confident that using the gamified system will be easier and practical. Practical in the sense that the system will be effective, efficient and satisfactory. They in effect govern the use and adoption of the system. (Alsawaier, 2018; Talhaoui et al., 2019; Lewis and Sauro, 2021). This aligns with the high importance placed on these criteria in our study. Furthermore, the critical role of user satisfaction echoes findings from Hamari et al. (2014), who emphasize the need for engaging and rewarding user experiences in gamified applications. In terms of education, ease of use and utility have been known to majorly influence student motivation. In a context of limited resources, ease of use in education becomes very important in achieving optimization (Liesa-Orús et al, 2022).

Efficiency measures the best value for money whilst Education affects. Education has a pivotal role as an influencer, a purposeful activity. Education potentially increases user engagement (Triantafyllou 2022), and positively influences trust (Volchik and Maslyukova, 2019). Education requires effectiveness for acceptability.

Trust also influences experience since it influences the intention to provide feedback. Trust further affects user satisfaction from trust in both the competence and integrity of the system. As trust increases so does the intention to adopt the system (Knijnenburg et al, 2011).

The identification of Transparency and Persuasiveness as causal variables highlights the importance of clear communication and motivational elements in influencing user trust and satisfaction. Transparency underscores full access to required information, whilst persuasiveness encourages the adoption and maintenance of beneficial behaviours and attitudes. Persuasiveness has the potential to change minds and attitudes. Education as a causal variable, can greatly affect persuasiveness, especially through communication. This is supported by studies such as those by González-González et al. (2019) Zeel (2010) and Su (2017), which underline the necessity of transparent operations and persuasive design in enhancing user engagement and trust. Transparency is also key in developing trust in the system.

5.4 Limitations

- **Sample Size and Diversity**

There are several limitations that can be associated with this study, but, perhaps, the most significant one is the limited number of samples obtained and assessed with reference to 25 DMs only. Even though this number is enough for an initial analysis It might not properly reflect the range of opinions and preferences of a larger user group.

- **Subjectivity of Evaluations**

  Thus, the assessment of the given designs is also qualitative in nature, as it results from perceived experiences of the DMs. Although, the use of fuzzy logic aids in reducing the degree of subjectivity in that a range of values of the variable is given, yet the results turn out to be relative to a given persons' bias or preference.

- **Generalizability of Gamified Designs**

  The specific gamified designs that were evaluated in this study might not be directly portable to other environment and for other users. The designs were evaluated in accordance with a certain set of criteria and user needs, which may be different in other applications. Therefore, any generalizations of the outcomes from this study should only be done with consideration of other designs.

- **Criteria Weighting and Importance**

  A key component of the multi-criteria decision-making (MCDM) method employed in this study is the weighting of criteria according to their significance. However, as the selected DMs determine the weights, they might not fully represent the preferences of all possible users. As a result, the relative weight of the criteria may vary over time or among various user groups.

- **Limited Scope of Criteria**

  The study focused on a specific set of criteria, which are ease of use, usefulness, user satisfaction, effectiveness, transparency, persuasiveness, trust, efficiency, and education. While these criteria are important, there are other criteria, that were not considered.

CHAPTER VI

CONCLUSION AND RECOMMENDATIONS

6.1 Conclusion

This study used the Fuzzy DEMATEL approach to assess four different gamified recommender system designs, concentrating on nine important criteria. The results show that the key criteria affecting the adoption of these systems are Ease of Use, Usefulness, User Satisfaction, and Effectiveness. The causal variables which are transparency, persuasiveness, efficiency, trust and education greatly influence these criteria. The findings highlight the necessity for developers to give priority to effective and user-friendly designs while maintaining transparency and persuasiveness in order to increase satisfaction and trust. The interaction of these criteria brings to light the intricate dynamics that need to be controlled in order to develop gamified recommender systems that are both efficient and entertaining.

6.2 Recommendations

1. **Enhance User Interface Design:**
   Prioritize developing user-friendly designs that are simple to use in order to increase ease of use and, in turn, user satisfaction.
2. **Increase Practical Value:**
   Ensure that the system offers significant practical benefits to users, therefore increasing its Usefulness and overall effectiveness.
3. **Improve Transparency:**
   Clearly explain how recommendations are made to build trust and enhance user confidence in the system.
4. **Incorporate Persuasive Elements:**
   Use motivational techniques to encourage user engagement and investment in the system.
5. **Optimize Efficiency:**

Develop algorithms and processes that enhance the system's efficiency, ensuring quick and accurate recommendations.

6. **Focus on Educational Value:**

   Design the system to provide educational benefits, helping users learn from their interactions and recommendations.

6.3 Recommendations for Future Research

1. **Longitudinal Studies:**

   More accurate and precise data will be produced by long-term research in which users engage with the gamified recommender systems over a prolonged period of time. This approach makes it possible to track changes in user satisfaction and behavior over time.

2. **Diverse User Groups:**

   Explore the effectiveness of these systems across different user groups and contexts to understand varying needs and preferences.

3. **Advanced Gamification Techniques:**

   Investigate the use of advanced gamification techniques, such as adaptive and personalized gamification, to enhance user engagement and system effectiveness.

4. **Broaden the Scope of Gamification Elements:**

   Future research should explore a wider range of gamification elements. Therefore, understanding the impact of additional elements might provide a more comprehensive view of how gamification can enhance recommender systems.

5. **Exploration of AI and Machine Learning:**

   Introduce artificial intelligence (AI) and machine learning algorithms to personalize gamified elements based on individual user preferences and behaviors. Future research and studies should explore how these technologies can improve user engagement and satisfaction.

6. **User Behavior Analysis:**

   Conduct detailed analysis of user behavior and interaction patterns with the gamified recommender systems. Understanding how users interact with different gamified elements to inform the design of more effective systems.

7. **Design Evaluation:**

   The gamified designs evaluated in this study are hypothetical and were assessed based on participants' responses to the questionnaire. While these initial evaluations provide valuable insights into potential user preferences and engagement factors, it is important to conduct real-life evaluations of these designs in future research.

Implementing and testing these designs in practical settings will help to validate their effectiveness and identify any necessary improvements.

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Appendices

Appendix A

Ethical Committee Approval

NEAR EAST UNIVERSITY

SCIENTIFIC RESEARCH ETHICS COMMITTEE

25.04.2024

Dear Agyeman Murad Taqi
Your application titled **"Evaluating the Adoption of Gamified Recommender Systems Using Multi-Criteria Decision Approach"** with the application number NEU/AS/2024/214 has been evaluated by the Scientific Research Ethics Committee and granted approval. You can start your research on the condition that you will abide by the information provided in your application form.

Prof. Dr. Aşkın KİRAZ

The Coordinator of the Scientific Research Ethics Committee

Appendix B

The Turnitin Report

Thesis

ORIGINALITY REPORT

15%	13%	10%	8%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	hduhb.nhs.wales Internet Source	2%
2	openaccess.ihu.edu.tr Internet Source	1%
3	dspace.utpl.edu.ec Internet Source	1%
4	kamane.miskas.net Internet Source	1%
5	Submitted to Aligarh Muslim University, Aligarh Student Paper	1%
6	Shristi Kharola, Mangey Ram, Nupur Goyal, Sachin Kumar Mangla, O.P. Nautiyal, Anita Rawat, Yigit Kazancoglu, Durgesh Pant. "Barriers to organic waste management in a circular economy", Journal of Cleaner Production, 2022 Publication	<1%
7	repository.iep.bg.ac.rs Internet Source	<1%

Appendix C

Gamified Recommender System Survey

Gamified Recommender Systems Survey

1. Gender:

    Male (M)☐ Female (F)☐

2. Field of Study:

    CIS☐ MIS☐ Other (Please specify: _______________)

3. Are you using a recommender system?

    Every day ☐ Almost Every day ☐ I rarely use this technology ☐ I have never used it before ☐

4. Which recommender systems have you used before? (Check all that apply)

    Netflix ☐ Amazon ☐ YouTube ☐ Tinder ☐ Other (Please specify: _______________)

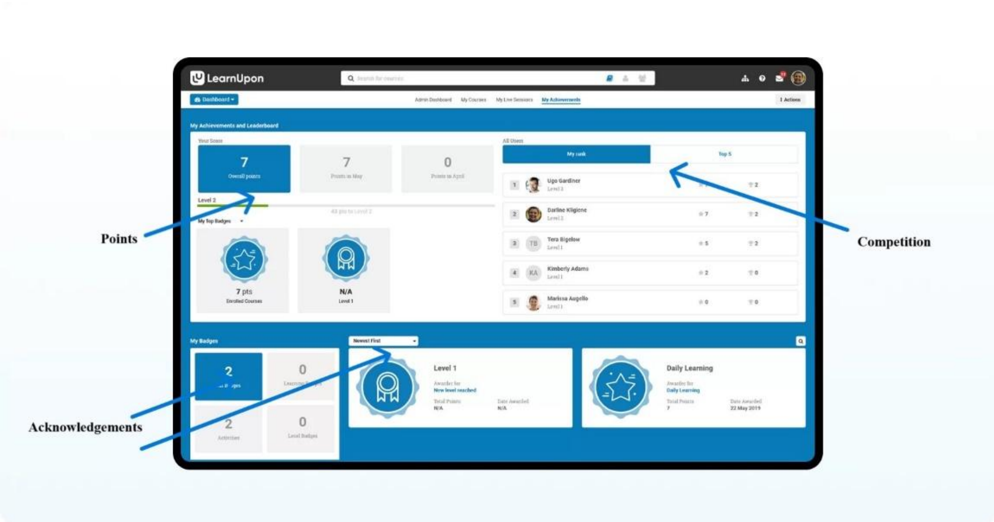
Instructions:

A gamified recommender system is a platform that utilizes game design elements and mechanics to enhance the recommendation process for users, making it more engaging and enjoyable. Suppose that you are using a gamified recommender system for learning Purposes. 4 different interfaces of gamified learning recommender systems are given in the figures. Please rate(by circling) each design by comparing the following criteria (Effectiveness, Transparency, Persuasiveness, User Satisfaction, Trust, Usefulness, Ease of Use, Efficiency, and Education) with each other using the following rating scale.

Scale:

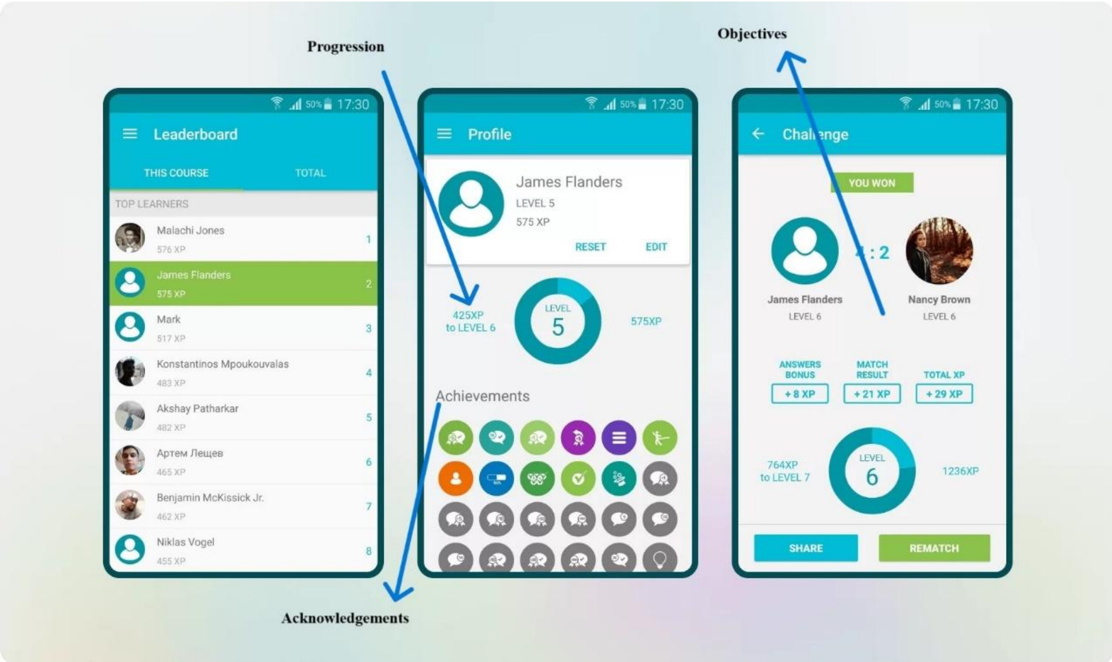
- No influence (NO) Very Low influence (VL) Low influence (L) High influence (H) Very High influence (VH)

Design 1 **Points, Acknowledgments, and Competition (PBL)**



Criteria	C1: Effectiveness	C2: Transparency	C3: Persuasiveness	C4: User Satisfaction	C5: Trust	C6: Usefulness	C7: Ease of Use	C8: Efficiency	C9: Education
C1		Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.
C2			Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.
C3				Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.
C4					Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.
C5						Choose an item.	Choose an item.	Choose an item.	Choose an item.
C6							Choose an item.	Choose an item.	Choose an item.
C7								Choose an item.	Choose an item.
C8									Choose an item.
C9									

Design 2 Acknowledgments, Objectives, and Progression (AOP)



Criteria	C1: Effectiveness	C2: Transparency	C3: Persuasiveness	C4: User Satisfaction	C5: Trust	C6: Usefulness	C7: Ease of Use	C8: Efficiency	C9: Education
C1		Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.
C2			Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.
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C4					Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.
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C6							Choose an item.	Choose an item.	Choose an item.
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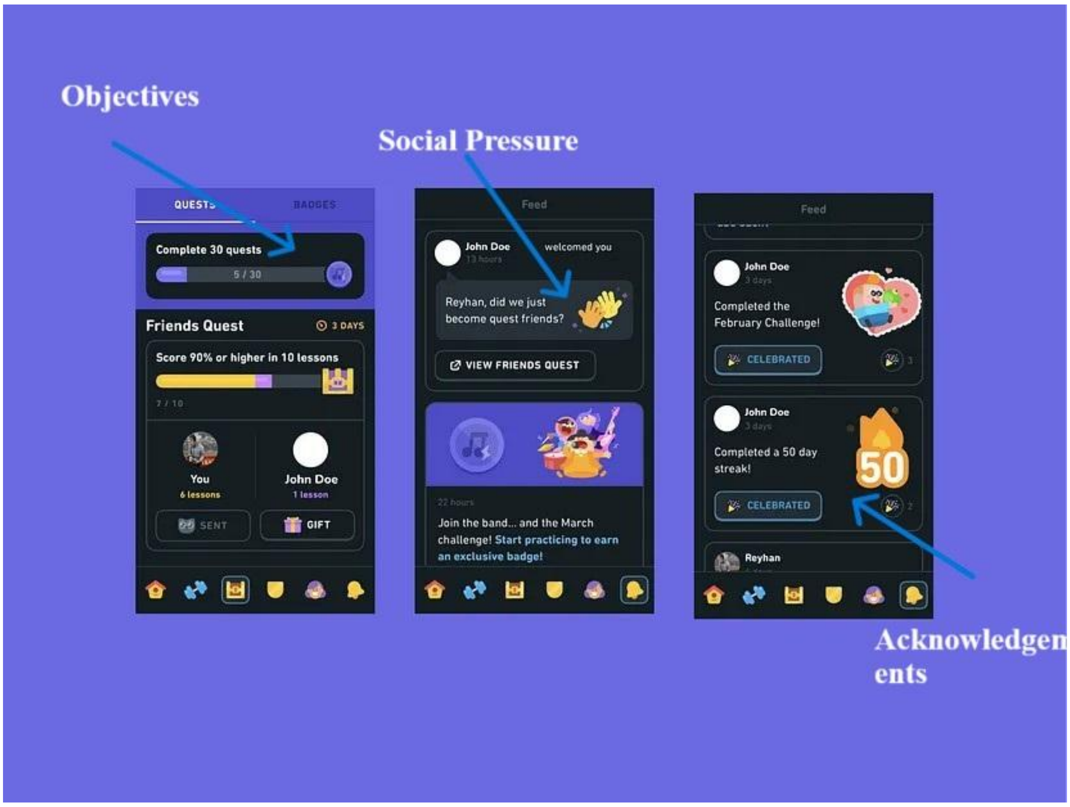
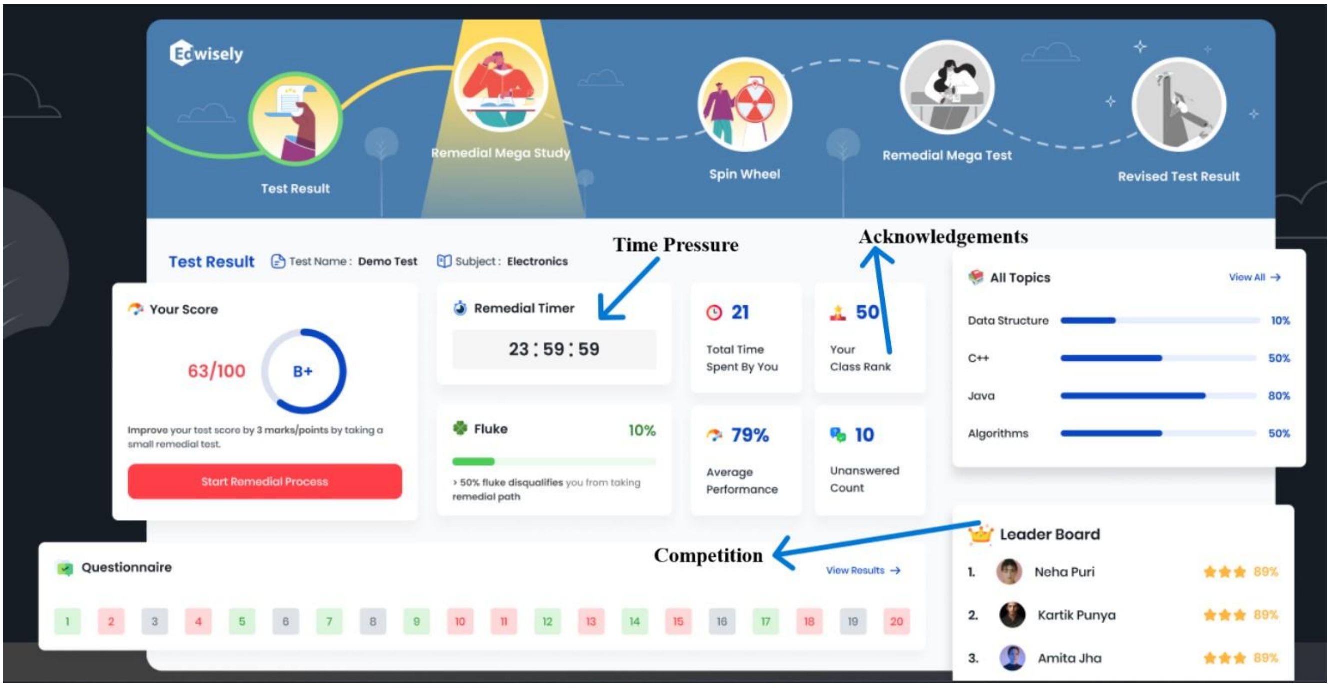
C8									Choose an item.
C9									

Design 3 Acknowledgments, Objectives, and Social Pressure (AOS)



Criteria	C1: Effectiveness	C2: Transparency	C3: Persuasiveness	C4: User Satisfaction	C5: Trust	C6: Usefulness	C7: Ease of Use	C8: Efficiency	C9: Education
C1		Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.
C2			Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.
C3				Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.
C4					Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.
C5						Choose an item.	Choose an item.	Choose an item.	Choose an item.
C6							Choose an item.	Choose an item.	Choose an item.
C7								Choose an item.	Choose an item.
C8									Choose an item.
C9									

Design 4 Acknowledgments, Competition, and Time Pressure (ACT)



Criteria	C1: Effectiveness	C2: Transparency	C3: Persuasiveness	C4: User Satisfaction	C5: Trust	C6: Usefulness	C7: Ease of Use	C8: Efficiency	C9: Education
C1		Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.
C2			Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.
C3				Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.
C4					Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.
C5						Choose an item.	Choose an item.	Choose an item.	Choose an item.
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