The design of 'League of Legends' decision support system for Inexperienced players

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ABSTRACT

Decision Support System(DSS), which assists people in making determinations and judgments by accumulating thorough data, is gaining more and more clout in the world of sports. Recently, it has also had a favorable effect on the developing eSports industry. DSS is the primary enabler for raising players' performance and enabling them to make optimal decisions. This research focuses on the development of DSS for a specific eSports title, 'League of Legends(LoL)'. The major aims of the research are to: 1) Analyze the challenges encountered by inexperienced players during each phase of the game; 2) Identify potential solutions of challenges that could be mitigated by DSS; and 3) Design a prototype of DSS. In this research, usability and system testing are used to assess the efficacy of a web-based system. The paper lays the groundwork for the suggestion of developing effective DSS to improve the capacity of inexperienced players in League of Legends.

KEYWORDS

Esports, decision support systems, inexperienced players, League of Legends, decision-making

1 INTRODUCTION

Decision Support Systems(DSS) are frequently used to guide individuals toward the best choice. They were initially developed to support business managers in making an informed decision by linking raw data and the human decision-making process [3]. A marketing decision support system (MDSS) contains the models to operate "what-if" analyses that foster the integration of a large amount of information and suggest the expected outcomes of each decision [5]. The DSS's application area widened and it started to be frequently used outside of business industry. DSS is acknowledged as an effective tool to help people make the best decision in any industry where human actions have significant impact on results at decisive moments.

With the purpose of decision support, DSS is particularly useful in sports where every moment of decision of the player is related to victory or defeat. In sports, the game doesn't admit to a moment of delay. Making the best choice quickly is the essential strategy. Esports are similar. A real user immersed in an online virtual environment must make decisions every moment to succeed. To reach the ultimate triumph, the proper decisions maximize players' or teams' gains and reduce losses. It is referred to 'snowball' effect in which tiny adjustments can quickly become unstoppable momentum and result in a victory [21]. For inexperienced players, it is critical to become familiar with identifying the most determining component in "snowballing" a team. This research focuses on the inexperienced player, as they are at the stage of growth that requires the most help, from the beginner to the proficient stage. A DSS can help inexperienced players operate the game more strategically. The game contains more than 140 champions [39] and a variety of circumstances might happen depending on several in-game variables such as item usage, position, or role of the champion. As a result, it is a strategic, intricate game that is challenging to learn. The entry point for the main competitive elements of the game is level 30. Therefore, the inexperienced player is defined as a player who has a level below 30 in this paper. Furthermore, the DSS of LoL works differently from a learning system of LoL since DSS goes beyond the capabilities of the learning system. Even though the DSS is involved in the user's learning, they are different since the learning system is used as a procedure to attain the primary purpose of DSS, which is to aid the user's decision-making process. The DSS continuously monitors the user's status, and its changing needs, whereas the learning system does not so through the DSS, the user can effectively reflect for their further decisions.

TScIT 37, July 8, 2022, Enschede, The Netherlands

1.1 Background

The section gives specific insight by proposing the background of the game, 'League of Legends', the decision support system, and the reasons why a DSS for LoL is important for novice players.

1.1.1 League of Legends

League of Legends is a multiplayer online battle arena (MOBA) video game in which two teams of five players compete to destroy the opposing team's base (Nexus) by attacking champions and holding territory [21]. Every phase contains tasks that each player must perform: including as selecting the proper lane, killing minions to increase CS, and gaining gold [18]. CS is a shorthand for 'Creep Score' that represents the number of minions or monster kills you have accomplished during a game. As a team, players must coordinate harmonious combinations of champions to strengthen the team and break the Nexus to secure victory. The game was created in 2009 by Riot Games and has risen to the top of the most-played PC game in the world [31]. There are about 180 million monthly active players in League of legends [35].

League of Legends consists of several stages. At the start, players must select their champion to play with. The champions are classified into 6 categories: assassin, fighter, mage, support, tank, and marksman [21]. Each player must pick their champion based on the features of each champion. This is called pre-game. The map, 'Summoner's Rift' contains 3 lanes, top, middle, and bottom [38]. Players have to tactically choose the lane and operate the game in each position. They have to battle the adversaries in each lane in the main game. To be more specific, there are four main phases that are pre-game, laning, mid-game, and late-game [34]. This paper defines the first stage as a 'Champion selecting phase'. Team fighting, pushing, and tower defense typically take place in the middle and late stages of the game [20]. This research treated mid and late games as a different phase. Therefore, there are a total of three stages for DSS of a game set: 1) Champion selecting, 2) Laning, and 3) Fighting. The champion selecting phase is the first phase in which players identify the composition of the team and determine the role of each player. In the second phase, the champions of both teams decide the lanes, and the main objective is to earn gold and experience(EXP) that can be obtained by killing minions that spawn in each lane, as well as monsters in the jungle [34]. The third phase, the fighting phase is gameplay that alternates between pushes/team fights and farming [20]. The first stage is the most relevant when developing a DSS for inexperienced players since the decisions made in the first stage dictate the overall direction of the operation for the rest of the stages.

1.1.2 Decision Support System

Decision-making process

Decision-making is a process of making a selection from a range of options in order to reach a desired outcome [11]. There are three levels of decisions: structured, unstructured, and semi-structured [12]. Structured decision consists of well-known steps to address issues and find solutions in a fairly simple manner [25]. The unstructured decision involves a few uncertain steps toward the a solution with a substantial risk in the process of decision-making [23]. Semi-structured decision works as a mediator between the two levels, combining human judgment and computerized information [36]. Raymond [1990] proposed that computers can be involved in making a structured decision, humans in unstructured, and DSS is used to improve semi-structured decisions. In LoL, players must make decisions in the event of uncertainty or confusion. They primarily stem from a lack of sufficient understanding of components and adequate strategy. As the stage progresses, the decisions made in one stage affect decisions made in the subsequent stage, so a step-by-step decision-making process is necessary. In this process, semi-structured decisions are implemented by combining unstructured user decisions with structured system decisions.

Decision Support System(DSS)

DSS is an interactive and flexible computerized system that helps decision-makers to make semi-structured decisions by letting them identify further insight into circumstances [37]. It stands out and is different from other systems. Management Information System (MIS) is a broad information system that processes scalable data into information [30]. MIS provides periodic, structured data while the DSS is intended to be an interactive and real-time system that is responsive to information requests and changing needs of users [16]. Additionally, Transaction Processing Systems (TPS) that collect, verify, and modify data are not qualified to be DSS [26]. The main difference is the purpose of the system. TPS is to accelerate and automate the process of the transaction while DSS is intended to speed up and improve the quality of decisions [16]. Moreover, DSS is distinct from the learning system. The main difference between them is the interaction with users. DSS constantly interacts with each user to suggest suitable input that will affect the decision-making process. The learning system provides one-sided information without considering each user so that the user can learn through them, but it is up to the user to make a decision by selecting suitable and helpful information.

Phillips Wren [2010] proposed a DSS architecture shown in Figure 6 in Appendix A.1 that consists relationship between inputs, processing, and outputs. A user interacts with the system and identifies the space of decision. It mainly focuses on improving the effectiveness of the process of decision-making by emphasizing the quantitative analysis of present and future circumstances. The three key characteristics of DSS are 1) Designed in detail to facilitate and speed up the decision-making process, 2) DSS should support rather than automate decision-making, and 3) DSS should respond quickly based on the changing needs [16]. The proposed DSS should satisfy all of these features to improve effectiveness.

1.2 Problem Statement

League of Legends is a challenging game for novice players to master. To improve game performance, they need tools to help them make decisions about the circumstances. However, there are no studies covering the intersection of DSS and eSports although it is able to find research dealing with each topic of the decision-making process, Decision Support System, or League of Legends respectively. Moreover, the tools of DSS that are already built are effective for proficient players but there is currently no adequate level of tools to help inexperienced players generate proper decisions at each stage. It is unavailable to figure out how the DSS for this target group is structured and what role it plays. Therefore, this research focuses on easing the challenges that novice players face by proposing a DSS and evaluating its usefulness.

1.3 Research Questions

The need for a DSS that enhances to make optimal decisions for inexperienced players leads to the following research questions: What is an effective decision support system for inexperienced players to strategically operate the game?

The sub-questions are :

1. What are the challenges for each phase of the game for the inexperienced player?
2. What actions are required for inexperienced players before/during/after the complete game set?
3. How can a DSS aid inexperienced players?
4. How is the proposed DSS evaluated, subjectively by the players, and objectively by gaming performance?

2 THEORETICAL FRAMEWORK

In this part, the framework of theoretical requirements, information and feedback system, and positioning of the DSS based on the Sheridan model are demonstrated [32]. The framework illustrates the structure of potential DSS for target users with the integration of 1) Information system and 2) Feedback system. They should be harmonized so that the novice players may purely understand, learn, and make further decisions. The DSS should continuously affect users' decision-making to have a beneficial effect. Figure 1 of Appendix A.6 explains how the proposed DSS affects the decision-making process. Three steps make up the decision-making process. In the intelligence phase, the decision-maker recognizes the occasions in which a choice must be made, occupied with knowledge from external resources and concerned with assessing the knowledge [33]. In the design phase, the user formulates knowledge to alternative actions and evaluates those. Lastly, in the choice phase, the decision-maker selects the final decision among the alternatives. Particularly, the information system involves in the first and last phases and the feedback system involves in the last two phases. Figure 2 in Appendix A.5 reflects the connection between DSS and the decision-making process of the user in the design of the proposed system. Since the corresponding DSS is typically for after-game, users can view the information and feedback after the game is finished. It encourages users to make optimal decisions for themselves given the numerous scenarios they will encounter during the upcoming match.

2.1 Information System

The core purpose of the information system of DSS is to let users obtain knowledge about game components that can lessen difficulties through a large amount of data. Since the users are uncertain and unfamiliar with the circumstances of in-game components, it is a priority value to learn the overall flow. Without understanding, users cannot fully approach the purpose of tasks and have difficulty accepting the suggested feedback. Data collection and information transformation should be the first steps in the information system. To reach a final stage of turning the information into knowledge, the process of information retrieval, situation analysis, resource evaluation, goal evaluation, and execution are essential [27]. From the KVI (Knowledge Versus Information) viewpoint, data and information are regarded as precursors of knowledge, with the argument that data are transformed into information and information into knowledge [7]. Data refer to isolated observations that can be collected from Riot API. The primary function of the information system is to meaningfully qualify those data in order to produce information. Finally, knowledge is derived from accumulating relevant information [13]. The information offered by the system would work as knowledge for users. The linkage between decision-making and knowledge is a crucial factor to concern. Before making a decision, the users' first objective is to get knowledge through the provided data. The system would assist the user to manufacture new knowledge by manipulating (gathering, modifying, assembling, transforming) the existing knowledge [13]. The functioning of the learning system is intimately tied to the capacity to manipulate knowledge, which serves as the foundation for decision-making processes [13]. A knowledge-based perspective put forth by Holsapple and Whinston [1996] asserted that a decision is an action commitment based on descriptive knowledge. A decision should also be procedural knowledge that involves step-by-step specifications for completing tasks [19]. The user assesses the knowledge acquired through the information system in the intelligence phase of the decision-making process and reflects the outcomes in the choice phase to choose the best possibilities among potential decisions.

2.2 Feedback System

The main purpose of a feedback system is to enable users to receive the recommendations of actions and determine whether they accept the feedback. Players are guided by feedback as they navigate murky circumstances and reacts to the environment's requests [28].

Depending on the level of expertise of an agent, the conscious cognitive level varies, known as the skill, rule, and knowledge-based framework [27]. The term S,R,K (Skill, Rule, and Knowledge-based) refers "degree of conscious control based on the degree of acquaintance with the environment" [28]. The actions are dynamic and parallel because they alternate between the three levels based on the control of consciousness. The skill-based level with the least conscious engagement, works with the smooth execution of highly repetitive and practiced behaviors [2]. Expert LoL players have cognitive awareness that is primarily skill-based and conversant with the game mechanics. The following level, rule-based level differs from the previous level and it requires some conscious attention. Lastly, novice players tend to stay at the knowledge-based level where a completely conscious manner and considerable mental effort are required. The level of cognitive consciousness fluctuates depending on how familiar and skillful the player can cope with the situation. The feedback system of DSS takes the player's level of consciousness into account. The majority of inexperienced players stay at the knowledge-based level since they are frequently put in scenarios that are completely novel and unfamiliar. Therefore, the feedback system provides appropriate nesting feedback, situation diagnosis, recommendation for specific actions, and short- and long-term goals that can be easily grasped by novice players. Once they accept the feedback and acquire the ability to handle specific situations, their conscious cognitive level continuously shifts to a rule or skill-based level where the novice players no longer rely on the DSS to make decisions. Additionally, it's critical to evaluate how well players comprehend and interpret the information offered by the information system in order to give them feedback that is as helpful as possible. The feedback system should tightly connect the information system and the user's understanding, enabling the user to make the optimal decision for the next play based on the knowledge gained.

2.3 Positioning the DSS

According to Sheridan [2000], the work process between humans and machines is separated into stages and levels. Applying the model proposed by Sheridan to DSS, is demonstrated in Figure 3. Feedback on potential situations in the game is determined through 4 stages and 8 levels, with humans participating in the execution of the system to reach the final decision-making phase.

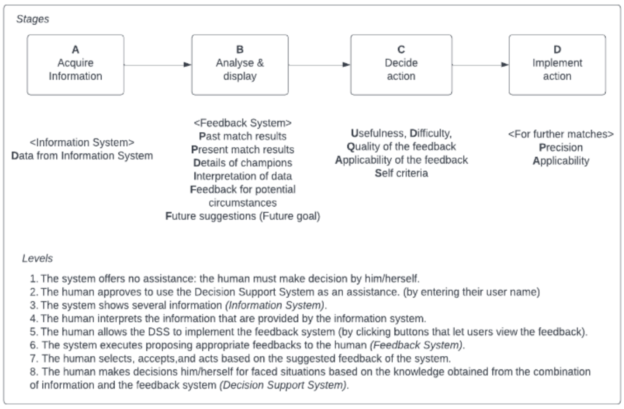

Figure 3. Stages of human and machine processing

Rasmussen [1990] figured out Mohawc's 'Classification system' that focuses on the prototypical decision-making function. The activities involved in decision-making are sequential: 1. Situation analysis, 2. Goal Evaluation, 3. Planning, and 4. Execution. Step 1 contains information observation and diagnosis of the circumstances. Step 2 includes predicting the outcome of the goal and establisihing priorities. The planning of the task procedure is involved in step 3 and the actual execution is included in step 4. Based on each step of activities, the DSS offers feedback on possible conditions, paying particular attention to steps 1, 2, and 3. The feedback system analyses the current state of a circumstance created by the intended user and determines the actions that can be taken. Then, it suggests the expected outcome of the actions. Based on the expectation, the system offers specific details of tasks that users can perform so that players can execute based on the feedback. Additionally, Shute [2008] noted that effective feedback takes the learner's present proficiency level into account. Bangert-Drowns [1991] mentioned that the feedback that outlines how to improve rather than indicating whether it is correct or wrong is more efficient. Taking into account the criteria to provide the best feedback, the feedback should mitigate the difficulty of language, terms, and complexity since the learner of the system is a novice player with minimal knowledge of possible circumstances or game-related terms. In addition, to offer specific solutions to users, the feedback should be handled from strategic, tactical, and operational perspective depending on the level of abstraction of the decisions. The strategic level of feedback contains the problem definition and the purpose. Several scenarios for potential situations are defined at the tactical level. The operational level consists of specific requirements [4].

3 METHODOLOGY

This section concerns the methodology used to answer the research questions and results. To get the answer for the main RQ, the overall steps to get the answers to sub-RQs should be defined first. The general steps of the methods are demonstrated in Figure 4 in Appendix A.4. It follows the DSRM process model [24]. It consists of five activities in nominal sequence. Each step is demonstrated in sections 4.1, 4.2, 4.3, and 4.4 respectively.

3.1 Data Collection Method

The sub-RQ1 addresses the specific challenges that the player encounters while playing the game and the sub-RQ2 focuses on the actions taken before/during/after the game. The data are collected by interviewing people with full experience of LoL, the League of Legends teams 'Esports team Twente' and 'BlueShell', especially players and coaches with more than 5 years of experience in LoL. Since they are knowledgeable experts with a variety of expertise, they can offer guidance from a wide range of perspectives. They also went through the early days as beginners and became proficient players so that they can understand the inexperienced players' point of view as an expert. The interview questions mainly concentrate on getting the answer for the sub RQ1 and RQ2. Thus, the primary goal is to gain a concrete insight about 1) Challenges that players face, 2) Actions required for players for pre, mid, and post-game, and 3) Usefulness of current DSS. Moreover, to approach sub-RQ3 to implement a system, it is essential to figure out the types of data that are accessible for use. With the use of Riot Developer API, it can be used as a tool to collect and extract data [38]. There are three requirements of data collection regarding API, 1) Data about the sequence of events: Analysis of events that happened every minute during the match, 2) In-game match data: Analysis of in-game components, and 3) Data of every player: Analysis of both player and the opponents'. Since the RIOT API satisfies all requirements, it is used as a tool to gather data.

3.2 Requirements

Based on the results of the interviews, the paper focuses on answering the sub-RQ3 with the suggestion of solutions in terms of DSS. With the results of RQ1 and RQ2, the functional and non-functional requirements are provided as agile user stories [22] and are prioritized in accordance with the MoSCoW principle [15]. Data derived through Riot API, functional, and non-functional requirements propose a new version of DSS that can answer RQ3.

3.3 System and Usability Testing

The sub-RQ4 relates to the effectiveness of the proposed system. It is evaluated through system and usability testing. Two inexperienced participants both below level 30 play the identical number of matches, one with assistance from the system and the other without, and then compare the outcomes to determine whether they advance or not. Based on the results and feedback, it is available to identify the usefulness of the system and improve it with points that are indicated by players. The outcome of testing should be measured by 4 points, 1) Speeding up and improving the quality of decisions, 2) Emphasis on present and future circumstances, 3) Supporting rather than automating, and 4) Being Responsive to changing needs.

4. DEVELOPMENT OF SYSTEM

The section illustrates the requirements, design of the actual web-based DSS, and its evaluation through usability and system testing. The code of the final product can be found via https://gitlab.utwente.nl/s2199645/decision-support-system.

4.1 Data Collection Result

4.1.1 Interview

This section is mainly about the first step of the DSRM process. The methods of approaching sub-RQ1 and RQ2 are conducted by interviewing LoL players and a coach from Esports Team Twente and BlueShell. The interview questions vary based on the role of the interviewees since they have different perspectives in the field of the game. For players who have a level above 30 with a lot of experience, the questions concentrate on their experience with the challenges and strategies they had when they were beginners. For a coach, the questions are mostly about ways, tips, and strategies to train players to maximize their ability.

Challenges for each phase

There are a total of three phases in the full game set: 1) Champion selecting, 2) Laning, and 3) Fighting. At each stage, the inexperienced players face difficulties that must be prepared ahead of time. Table 1 describes the possible challenges that novice players may encounter at each stage.

Table 1. Challenges of each phase

Phase	Challenge
1. Champion Selecting	Lack of experience with champions
2. Laning	Lane control (Creep Score control), Wave manipulation
3. Fighting	Vision control, Lack of knowledge with champions

During the champion selecting phase, interviewees pointed out that there are over 150 champions, making it challenging for novice players to distinguish the traits of each champion. Each champion has strong and weak opponents according to roles and skills, but without sufficient understanding, it will be difficult to attack the enemy and defend itself. For the laning phase, interviewees mentioned it is one of the most challenging parts that can learn through numerous numbers of play. In particular, the most fundamental and significant challenge is to hit the minions in time to raise the creep score, which only rises when they are killed. Additionally, it might be difficult to make appropriate choices when the player needs to freeze and push lanes during the laning phase, known as "wave manipulation", because there are numerous scenarios in each lane. In the final phase, a coach stated that inexperience with enemy champions and their own would still be a challenge for the players. Since the skills of each champion are not fully grasped, the novice players are unable to lead the fight to advantage. They identified vision control as another difficulty. Without adequate vision control, players are limited in their ability to see what is happening outside the boundaries of their field of vision.

Actions required for players

Actions required for players based on challenges will be a solution to alleviate difficulties. The actions vary depending on which stage you are in before, during, or after the game set. It can also provide the main source for answering sub-RQ3 to suggest possible solutions in terms of DSS. Table 2 illustrates the required actions according to the stages. It is derived through the interview.

Table 2. Required actions for each stage

	Required Actions
Before	-Communicate with the ally team about the composition of 5 champions (Harmony of AP(Ability Power), AD(Attack Damage) champions/ Determine each player's role and responsibility) -(If you have historically met the opponent team) Investigate more about the opponent team (Strengths and weaknesses) and make it adjustable for our team.
During	-Cooperate/Communicate with the team -Check the role of champions of allies and enemies -Focus on killing minions with the last hit -Place the wards in the proper place at the proper time (Vision control) -Freeze and push the lane at the proper time (Wave manipulation) -Buy items appropriate for the champion (Item usage) -Fight against counters -Attack the counter Nexus
After	-Exchange feedback, mainly about the fighting phase -With the DSS, analyze my match results and my team. -Analyze the features(strength, weakness, tactics) of the opponents -Identify the weakness and strengths of each champion in my team

Usefulness of already-made DSS

The already-made DSS that interviewees actually use are Op.gg [8], METAsrc [9], and U.gg [10]. These are the websites that display the outcomes of user-played matches. Users can get various information such as records of each match, the skills of each champion, recommendation of items, win rate, or pick rate after the game. Players from Esports Team Twente and BlueShell stated that these techniques frequently assist them in the champion selecting phase since they are able to recognize the strengths and weaknesses of the ally team as well as the fighting patterns and tactics of the counter team. With a large amount of data after the game through the DSS, they analyze the data themselves to make improvements for subsequent plays. However, the decisive disadvantage of the existing DSS, noted by the interviewees, is that the majority of already-made DSS require a fundamental understanding of the game in general, and data analysis is left to the player's discretion. For novice players, a large amount of information without the interpretation offered by the already-made DSS is difficult to understand, which restricts their capacity to use the data for decision-making.

4.1.2 Conclusion of data collection

Based on the results of data collection, it is available to get answers for sub RQ1, RQ2, and additional insights for RQ3. Since the existing DSS demands prior knowledge and background information, making it an inefficient tool for novice players, the paper concentrates on implementing a new version of DSS ideal for inexperienced players. The system will primarily focus on mitigating the challenges at each phase by suggesting appropriate actions after the complete set of a match. The suggestion of actions will be created based on the required actions for each stage that are learned from the interviews. Among the three stages(before, during, and after games), the DSS will function as an after-game tool that players may use to seek help after a game set and reflect it into further plays.

4.2 Requirements of the system

This section is mainly about the second step of the DSRM process. Functional requirements can be seen in Table 3. Since the target user is a novice player, offering the heatmap may increase the complexity and confusion of the system. Functionalities of heatmap should be provided once they obtain adequate experience. Thus, the requirement regarding heatmap is not implemented in the final version of DSS.

Nonfunctional Requirements

In terms of non-functional requirements, the primary objective of the system is to improve the perceptions of users by implementing a user-friendly and sufficient level system for the intended user. Even if a system has excellent performance, it cannot be claimed to be a sufficient system if it cannot be used in a user-friendly manner. Especially, since DSS is for novice players, it's important to keep complexity low. The system specifically considers the navigation across web pages, language of feedback, and sufficient description of terminology. The results of whether the system meets the requirements are described in the usability test result section.

Table 3. Functional requirements

Must	-As a user, I can search for the summoner name. -As a user, I can view the brief explanation of my own champion and counter champion as well. (Image, level, name, result of recent match) -As a user, I can view feedback for each counter champion. -As a user, I can view feedback for each phase. -As a user, I can view the match result of my champion and counter champions.
Should	-As a user, I can view the progression of the performance for each component in terms of 5 recent matches. -As a user, I can view the composition of both ally and enemy teams based on roles. -As a user, I can view explanations about each role of the champions. -As a user, I can view the detailed explanation (skills, role, speed) for each champion.
Could	-As a user, I can receive feedback on my progression based on the result of 5 matches. -As a user, I can receive brief feedback about achieving/failing the goal. -As a user, I can view the next goal for each component set by the system.
Won't	-As a user, I can view the heatmap of each champion.

4.3 System Design

This section is mainly about the third and fourth steps of the DSRM process. Subsections 4.3.1, 4.3.2, and 4.3.3 explain the design of the system, and subsection 4.3.4 propose the implementation of a new version of DSS based on the design.

4.3.1 Information System

The information that consists of the proposed DSS can be categorized into 3 groups, 1) My details, 2) Counter team details, and 3) Match results for timeline. They are also classified into 3 categories according to what types of data are necessary for each phase. Each phase requires different groups. In the champion selecting phase, groups 1) and 2) should explain the composition of each team and suggest the ideal combination as feedback. The laning phase requires groups 1) and 3). To let users effectively succeed in the laning, data about the specific skills of the champion and the information on the changes of each in-game element over time are appropriate. Lastly, for the fighting phase, all groups 1), 2), and 3) direct users to acquire the knowledge of the features of champions and identify their progress via the results of the match.

4.3.2 Feedback System

The feedbacks are structured differently for each phase. Potential circumstances under which the system should provide feedback to target users are determined by the results of sub RQ1 and RQ2. The example feedback of the system for the laning phase is demonstrated in Table 4. They consider strategical, tactical, and operational perspectives and are given subject to possible conditions. All feedback for all phases is accessible via https://gitlab.utwente.nl/s2199645/decision-support-system.
Feedback is additionally necessary to describe how a user's in-game components evolve over time. It enables tracking of progress status and identification of weaknesses and strengths.

Table 5 demonstrates the example feedback for ‘my progression’. Other feedback for different situations can be viewed via https://gitlab.utwente.nl/s2199645/decision-support-system.

Table 4. Feedback for each phase

Laning phase	**Condition:** The position of both champions for mine and the opponents’ are the same and my Creep Score OR level is lower than the opponents’
	Feedback: The lane position of yours and the opponents’ are the same. However, your CS is lower than the opponents’. Experience(level) of the early stages of a game is important. From XP(Experience Points), you will progress through levels. Every time you level up, your champion will become stronger. You have to kill as many minions to increase your level and hit minions when they have the last energy. You have to position behind your ally frontlines and hit the opponent’s minions. (Suggestion of the video tutorial of last hit and wave control)

Table 5. Feedback for progression

Condition	Feedback
If the number of Creep Score is decreasing	Your creep score is not improving. You have to hit minions when they have the last energy. If you attack the minions too early, you miss the CS. So use the S key to cancel the attack before the attack is cast and reattack right away. When the minions are inside the tower’s boundary, the tower attacks minions in the order closest to the center of it. You should start last hitting the minions that are close to the center of the tower. You have to kill more ‘siege minions’ since it gives 60-90 gold each. (Suggestion of tutorial for the last hitting, tips of hitting minions, and show pictures of each minion

4.3.3 Prototype

The following section describes the prototype of the new version of DSS based on the information and feedback systems. It is created by Figma and the prototype can be viewed at https://www.figma.com/proto/lTox0wt4iM8X6wykCvR51Z/Decision-Support-system-for-LoL?node-id=0%3A1&scaling=min-zoom&starting-point-node-id=2%3A3.

4.3.4 Technical requirements

The design process for the DSS is described in this section. It is implemented via the Django framework that follows MVC(Model, View, Controller) pattern [6]. It is suitable for both front end and back end. The frontend of DSS has been developed in JavaScript, HTML, and CSS, and the backend has been implemented via Django Python and linked with Riot API. Figure 5 demonstrates the technological architecture of the system. It involves the structure of both the front end and back end of the system.

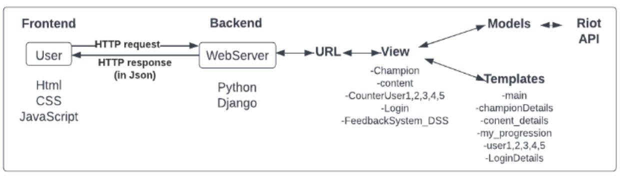

Figure 5. Frontend and backend architecture

4.3.5 Implementation

This section describes how the web-based DSS is actually developed. There are 3 main types of web pages, 1) My progression page, 2) Champion composition page, and 3) Counter champion page. Figures 7,8,9 in Appendix A.2 and https://gitlab.utwente.nl/s2199645/decision-support-system offer screenshots. Page 1) contains the progress of the game component, especially, the kills, deaths, and creep scores of the last 5 matches with graphs. Players can receive feedback on how to raise the creep score, reduce death count, or improve opponent killing skills. The system provides extra goals to stimulate the user based on their present situation. Page 2) lists the composition of champions. The main purpose is to provide information about the champions that players have not yet experienced. Since the challenge of the champion selecting phase is a lack of knowledge of champions, this page seeks to help players gain insight into unfamiliar champions. Page 3) contains the details of the counter champions. Users can view 5 different pages of each opponent and receive feedback for each enemy. The main purpose is to allow players to get the recommendation of actions for each phase. Table 6 explains the goal of each page divided into an information and feedback system that ultimately affects the decision-making process.

Table 6. Goal of each webpage

page	Goal of each page	
	Information System	Feedback System
1)	-Provide progression of each component over time via graph (Number of kills, deaths, creep score)	-Suggest feedback for each circumstance so that players can reflect for further play -Suggest the specific goal for the next game and provide positive/negative feedback –Assist players to decide what to improve for further play
2)	-Focus on smoothing out the difficulties (Lack of knowledge) that players face (Champion names, roles, composition of team)	-Assist players to decide in the champion selecting phase for further play
3)	-Focus on relieving the challenges (Lack of knowledge) of champion selecting phase	-Suggest feedback for each counter champion -Suggest feedback for each phase -Assist players to decide how to cope with each enemy/phase based on the distinct features of enemies/phases (fighting, laning phases)

4.4 Evaluation

A final research question is to evaluate how effective the proposed DSS of LoL is for inexperienced players. A well-developed user interface of DSS can increase productivity and human processing speed (Power, 2016). In this part, it performs the usability and system testing on possible users to show considerations for sub-RQ4 and proposes conclusions based on the test results. This section follows the last step of the DSRM model from methodology.

4.4.1 System Testing & Usability Testing

The main purpose of usability and system testing are to determine how the system affects players to make decisions, and to evaluate whether it is effective in leading the players to improve. It was held by two novice players at levels 8 and 11 respectively. Testing was conducted with one player playing the game with the help from DSS after each match and another player playing without the help. DSS is a post-match tool so that the player with the help of the DSS spent time using it while the other played without any assistance. The tests focused on observing the decisions as well as analyzing the outcome of each player.

4.4.2 Test Result

System Testing
After both players played 15 matches, the difference in the decisions they made every moment became clear. From the first phase, there was a difference in the decisions choosing each champion. Both participants were in the same situation that fellow teammates except for the participants themselves had chosen the AD(Attack Damage) champions. Both players had to decide the champion in the final order. Even in the same situations, their choices were different. With the help of DSS, the player decided to pick the AP (Ability Power) champion based on feedback, while the other selected the AD champion, causing an imbalance in the team's champion role. The specific circumstances for each player are shown in Figures 10, 11 in Appendix A.3. Screenshots are derived from the pages of web-based DSS. The two player's different decision-making styles were clear even in the laning phase, which eventually resulted in differences in their final performances. The DSS primarily concentrates on assisting players to kill many minions. The player with the system focused on acquiring tactics of killing minions while minimizing the champion's health. On the other hand, the player without help attacked minions without a strategy, draining a lot of champion health and significantly reducing accuracy. The difference in the players' decisions was revealed in the difference in the degree of improvement, as Figures 12, 13 in Appendix A.3. The number of minions killed (CS) by the player with DSS showed a gradual growth, while the other showed no improvement and the maximum number of kills even did not exceed 55. The criterion for judging whether players have developed a good strategy in the fighting phase is to compare the number of kills and deaths of each player. The number of kills gradually increased and that of deaths decreased in the graph of players with DSS, but for the other, the performance of the fighting phase didn't improve as shown in Figures 14, 15 in Appendix A.3.

Usability Testing
The usability testing mainly focused on determining whether the interface is easy to use without any guidance and the degree of complexity is proper to the level of users. The following remarks are derived from observation and feedback of usability testing from participants. 1) The system is easy to navigate and browse with buttons that direct to the other pages. 2) The tooltip for certain terms lets the novice players get further insight by getting extra explanations. 3) The graphs enable the user to identify the state of the user at first glance. Additionally, it can view every single graph of kill, death, and CS on the progression page. 4) The language used for the feedback is written in an approachable style. 5) Overall, the simple and concise design of the system makes the inexperienced player easily understand the process.

4.4.3 Conclusion of testing

Through the outcomes of the testing, it is feasible to evaluate how the proposed DSS aids in better decision-making, identify the phase that is most helpful, and figure out parts that need improvement. In each phase, there are clear differences in decision-making between the two players under the same situations, proving that the DSS has a decisive influence on the user's decision. Moreover, based on the remarks from participants, the feedback highlights the current state of the user and suggests a future goal so that they can easily grasp the present and future circumstances. Additionally, the feedback and information are responsive based on the changing role of users' champions. Therefore, the proposed DSS helps users make better decisions.

8. DISCUSSION AND CONCLUSION

This study focuses on collecting data, creating the theoretical framework, implementing the DSS, and evaluating the system through testing. This section summarizes the overall outcome of each section and suggests the direction of future research. Firstly, the study gathered information on the challenges that inexperienced players had during each phase through interviews. From the point of view of seasoned players and a coach, lack of experience with champions, wave manipulation, and vision control are the challenges for novice players. Actions required by players before, during, and after the game to overcome the difficulties of each stage can provide additional insight into possible solutions. The result of the interviews answers RQ1 and RQ2. Secondly, the study identified the theoretical framework and the development of the DSS that lessens the challenges. With the full provision of the information system, the feedback system serves as a tool for interpreting that information. It tries to tie the user's understanding to the decision-making process for each phase by offering strategic, tactical, and operational input on each opponent. The theoretical framework and implementation of the system answer RQ3. Thirdly, proposed DSS aids players in the decision-making process since the usability and system testing showed positive results. The participants were faced with the same situation, but each player made a different choice. The player assisted by the DSS showed significant achievements in every phases, while the other did not. The number of CS, kills gradually increased and that of deaths decreased for the former player, whereas the results for the latter player showed the opposite results. The test results answer the RQ4. Overall, the answers to sub-questions ultimately lead to answering the main RQ. The efficient DSS for novice players mitigates the challenges in each phase, offers appropriate information, and suggests strategic, tactical, and operational feedback. With the DSS's assistance, inexperienced players can strategically operate the game.

Future research should focus on assisting players by suggesting real-time feedback. Since the DSS for this research is for after-game, players can apply the strategy for the next game. DSS for during-game that continuously suggests live feedback while they are playing can be a novel way to help the unskilled players to reflect directly on the play. Based on behavioral changes of players, the live suggestions of actions and varying levels of feedback are given to players so they may flexibly react to the new situations. Moreover, by incorporating more people in the interview process, the methodology of data collection can be improved so that the quantitative data can give precise insight into the development of the system. Additionally, since the novice player who was at the knowledge level wasn't improving for every match, it cannot be guaranteed that their cognitive consciousness shifts to the skill-based level, which is the highest level in the Rasmussen model. Thus, in order to fully satisfy the model, future research should provide feedback with increasing difficulty to match the degree to which the player advances through repeated playing.

In conclusion, this research proposes a web-based DSS, especially for inexperienced players, that combines an information and feedback system to lessen their challenges. The academic and practical value is to let novice player craft its own strategy with the help of DSS. Even though the research shows positive results through testing, this research is the starting point for creating a tool that assists players to make optimal decisions in every moment of circumstances.

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A.2 Appendix A.2

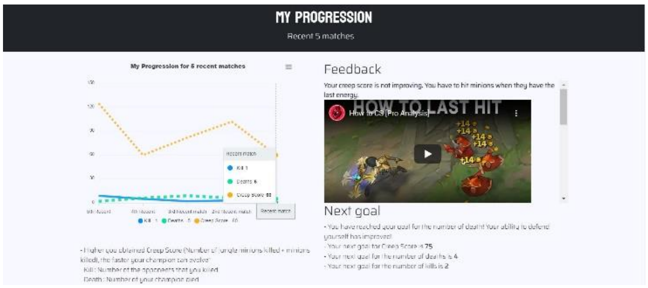

Figure 7. My progression page

Figure 9. Counter champion page

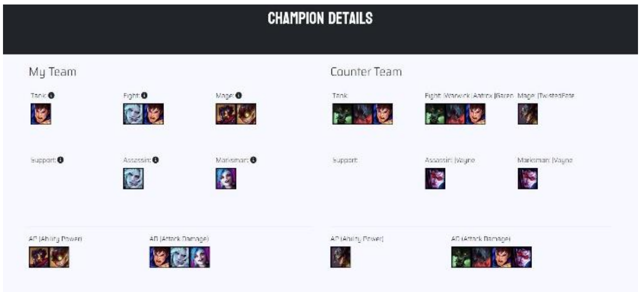

Figure 8. Champion composition page

A.1 Appendix A.1

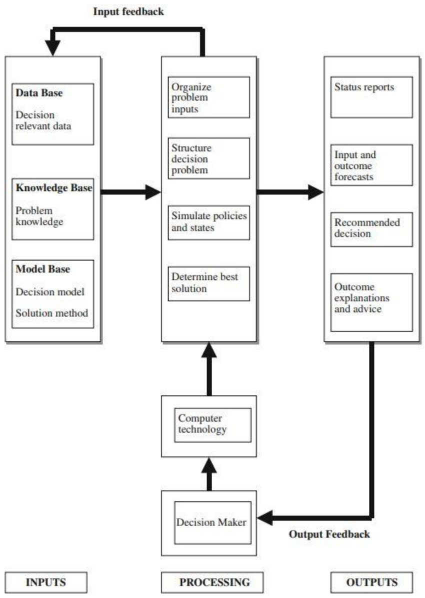

Figure 6. DSS Architecture

A.6 Appendix A.6

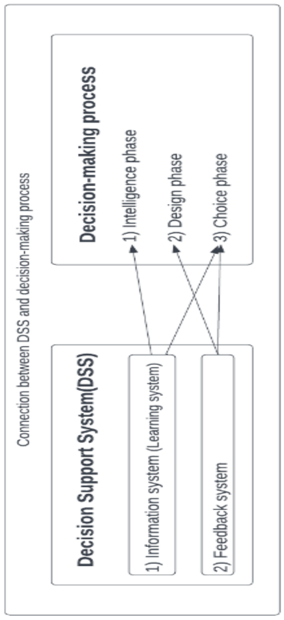

Figure 1. Structure of DSS

A.3 Appendix A.3

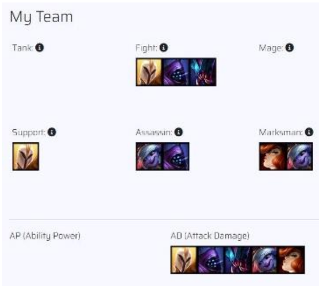

Figure 10. Player without help of DSS

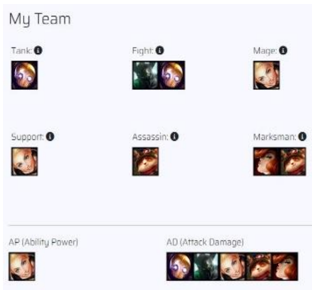

Figure 11. Player with help of DSS

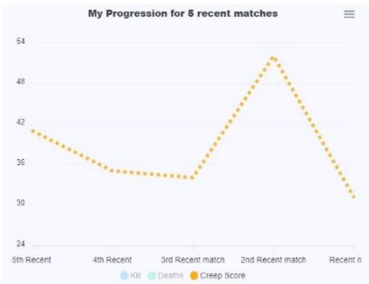

Figure 12. Player without help of DSS

Figure 13. Player with help of DSS

Figure 14. Player without help of DSS

Figure 15. Player with help of DSS

A.4 Appendix A.4

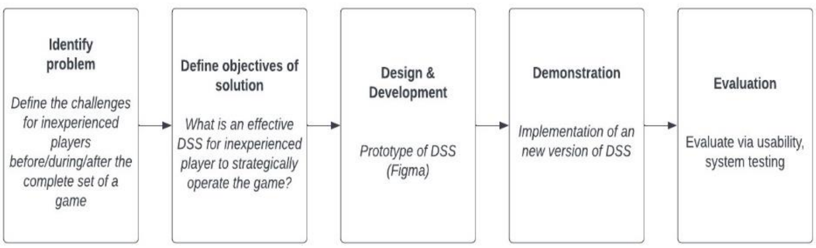

Figure 4. DSRM process model

A.5 Appendix A.5

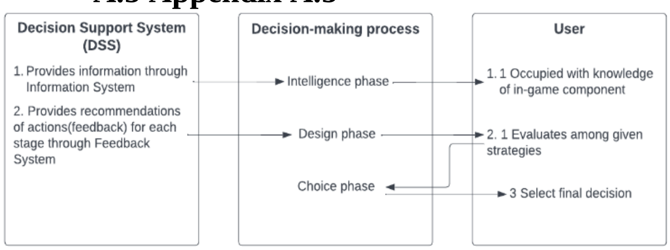

Figure 2. Decision-making process between DSS and user