Usage of Decision-Making and Reasoning Information in Adaptation for Intelligent Systems

A systematic literature review

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Abstract

Various types of user data such as heart rate, age, eye tracking data, body mass index, conversational data and more can be used to model a user. Intelligent systems can user these models to recognize and adapt. For example, by recognizing if someone is bored or scared while playing games based on a model of their engagement and using that to adapt the difficulty of a game [1]. However, this survey will focus on modelling user decision-making and reasoning. It will thus answer the question: "How do intelligent systems acquire and use user data to model decision-making and reasoning, and how are these models applied for recognition and adaptation?"

To answer these questions, a systematic literature review was conducted. Using the key concepts **Intelligent Systems**, **Recognition**, **Adaptation**, **User Modelling**, and **Human Decision-Making and Reasoning**, queries have been formulated for 4 different databases. Papers have been screened and extracted using the PRISMA guidelines [2], resulting in the usage of 52 articles.

The results reveal that intelligent systems are dominated by recommender systems. They use user preferences to recommend items in all sorts of domains. These user preferences can be modelled using other models such as user demographics, behaviour, emotions and characteristics.

Besides making the decision-making process easier and thereby improving user experience, they also deal with other challenges such as fairness, privacy, usability and prediction accuracy.

While being less prevalent, other intelligent systems such as decision support systems, assistance systems and social robots sometimes serve even more important purposes and have the potential of solving diverse problems. However, their underutilization suggests an opportunity for research in this area.

1 Introduction

User modelling is becoming increasingly prevalent. A combination of more user data and advances in artificial intelligence makes it easier to model users in more detail [3]. An example of this is the use of physiological data like heart rate, blood pressure, temperature, and more to model user engagement while playing games [1]. This model can then be used for recognition. It does this by predicting whether a user is bored or anxious. That information can subsequently be used to adapt. In this case, by changing the level of difficulty of the game. This helps keep users engaged and gives them a better experience while playing games.

Modelling a cognitive-affective process like this and using it for recognition and adaptation in intelligent systems can solve many problems. In this research, decision-making and reasoning will be modelled, and the aim is to learn about different ways intelligent systems can recognize and adapt using these models.

Decision-making is the process of selecting the best choice out of two or more possible choices [4]. This also includes identifying possible choices. Decision-making can be influenced by multiple factors, both conscious and unconscious [5]. Examples of these are emotions, cognitive biases and social influences [6–8]. All these factors can thus aid in modelling decision-making.

There are already several papers written on user modelling. For example, a comprehensive survey written on user modelling which explores the data being gathered, the modelling and even a very brief part about the applications of the models [3]. However, this does not involve modelling users their decision-making.

Surveys that do model decision-making also exist. For example, a review covering modelling user behaviour and decision-making [9]. However, this does not focus on using these for recognition and adaptation purposes in intelligent systems.

Therefore, this remains an unexplored field. This survey therefore aims to cover modelling users' decision making and reasoning and using this information for recognition and adaptation in intelligent systems.

To gain more insight into this, the following questions will be answered.

- SQ1: What user data has been used to model decision-making, and how is decision-making represented in this model?
- SQ2: How have these models been used by intelligent systems for recognition and adaptation?
- SQ3: What is the objective of the adaptation of the Intelligent System?
- SQ4: Are there any patterns observable in the Intelligent Systems and their objectives?
- SQ5: In which application domains are the intelligent systems used?
- SQ6: What challenges exist in recent developments?

This paper thus aims to answer the question: "How do intelligent systems acquire and use user data to model decision-making and reasoning, and how are these models applied for recognition and adaptation?"

The aim of this paper is that by addressing the current manners in which intelligent systems work and by addressing their objectives, new ideas can be generated about what other problems could be solved using similar techniques.

After the introduction, related work will follow in chapter 2. This will be followed by chapter 3 which will cover the methodology. This chapter will contain information on how the research was performed. Thereafter, the results will be provided in chapter 4.

The results will commence with section 4.1 covering the data and user modelling. This will be followed by section 4.2 focusing on recognition & adaptation of intelligent systems. After this, the application domains will follow in section 4.3 and to conclude this chapter will be section 4.4 addressing the challenges of intelligent systems.

Following the results will be chapter 5 focusing on responsible research. After this, the discussion will be delivered in chapter 6 and thereafter, chapter 7 will finalize the paper by providing the conclusion and future work.

2 Related Work

In this chapter, related work will be identified and discussed to place this research in perspective with others and identify what it has in common, but also what sets it apart.

Reviews have been written on user modelling. One of these focuses on data mining and machine learning techniques [10]. It addresses data mining techniques that can be used to model users. It does thus not look into adaptation for an intelligent system, nor does it focus on the modelling itself. Another survey that does focus on user modelling, provides an overview of collecting data and user modelling itself [3]. This review even looks into some of the applications of the models. However, this is very limited because it only addresses 3 applications and neither does it model decision-making.

Reviews that do focus on modelling decision-making also exist. For example, a review that models human behaviour and decision-making [9]. This review does model decision-making, in order to mimic human behaviour. It does this to facilitate humans and AI agents to work together. So, while it does focus on modelling it does not focus on using these for recognition and adaptation purposes in intelligent systems.

However, there are other reviews that do focus on recognition and adaptation in intelligent systems. However, they do not provide an overview of the different manners in which this can be done and merely focus on one. For example, one of the papers covers behavioural modelling and using this for recognition and adaptation in recommender systems [11]. However, this does not cover different types of intelligent systems.

In conclusion, papers that focus on user modelling and adaptation in intelligent systems are rare and do not go in depth on the latter. Reviews that additionally model decision-making only cover user modelling or only focuses on one kind of intelligent system. An overview of this could thus broaden the field by providing information about all kinds of intelligent systems using models of users their decision-making.

3 Methodology

This research has followed a systematic literature review. For an outline, an explanation of a systematic literature review, a book has been followed [12]. Additionally, the review follows the PRISMA guidelines [2].

This chapter will start by naming and explaining the exclusion & feasibility criteria in section 3,1. After this, the used databases will be named, and the scope will be described in section 3.2. Section 3.3, which covers the search strategy will follow this. This section will address key concepts, search terms, and how they have been used. Section 3.4 covers the paper screening and selection procedure. After this, section 2.5 explains the systematic data extraction procedure. Finally, section 2.6 will cover PRISMA and how this has been incorporated to ensure transparency and reproducibility.

3.1 Exclusion & Feasibility Criteria

Exclusion criteria are criteria on which papers should be excluded for data extraction [12]. Exclusion criteria can explain specific content-related things a paper must or must not contain. This makes sure the papers found are relevant. The specific criteria used for this research and motivation can be found in Table 4 in appendix A.

Feasibility criteria are also used to exclude papers. However, these are used to make the amount of data used smaller. Given more time, these criteria would not have been used. The research only takes 10 weeks, and to make that feasible, feasibility criteria are implemented. The feasibility criteria can be found in table 5 in appendix A.

3.2 Databases

In this section, the databases used will be named and the scope of these databases will be described in table 1. Scopus[1], Web of Science[2], IEEE Xplore[3] and ACM Digital Library[4] have been used for this research, and on 24 May 2025, the queries were entered. These queries can be found in appendix B. In section 2.3, an explanation about its structure and search terms is provided.

Database	Scope
Scopus	Broad range of scientific papers
Web of Science	Large multi-disciplinary database
IEEE Xplore	Includes papers by the Institute of Electrical and Electronics Engineers
ACM Digital Library	Publications of the Association of Computing Machinery

Table 1: Databases and descriptions

3.3 Search Strategy

This research looked into the modelling of human decision making for adaptation in Intelligent Systems. To build a query that covers this and can provide papers that help answer the research question and sub questions, key concepts were identified. The identified concepts are **Intelligent Systems**, **Human Decision Making & Reasoning**, and **User Modelling**. Intelligent systems can be divided into **Recognition** and **Adaptation**.

User Modelling means using raw data and structuring it into a model. Intelligent systems are systems that both recognize and adapt. A system that recognizes is a system that uses this user model to predict something about the users' decision-making. A system that adapts uses this prediction to act in some way, shape, or form. However, simply providing the prediction does not suffice. In the example of a recommender system, predicting decision-making for all items and then recommending one item does suffice. Human Decision-Making is the act of making a choice and Reasoning means explaining this choice with underlying justifications.

For all these core concepts, multiple search terms were identified. This ensures that the core concept is addressed at least once. It can also be a synonym or a specific example of the core concept. The core concepts and their search terms can be found in table 2.

These search terms were then used to create queries. The search terms are connected with OR, so that at least one of them is contained in the abstract or title of the paper. The key concepts are connected with AND since all of them need to be contained in the paper at least once. These 4 different queries for the 4 databases discussed in section 2.2 can be found in Appendix B.

[1] `https://www.scopus.com`
[2] `https://www.webofscience.com`
[3] `https://ieeexplore.ieee.org`
[4] `https://dl.acm.org`

Core Concept	Search Terms
User Modelling	user modeling, user profil*, user model, cognitive model*, affective model*, student model*, persona model*, patient model*, player model*, employee model*
Human Decision-Making & Reasoning	decision making, decision-making, human decision, decision support
Intelligent Systems	intelligent system, adaptive system, support system, recommender system
Recognition	recogni*, detect*, sens*, perce*, observ*, identif*, classif*, monitor*, track*, analy*
Adaptation	adapt*, act, feedback, respon*, interact*, personali*, react*, updat*, modif*, adjust*, tailor*, customi*

Table 2: Core Concepts and corresponding Search Terms

3.4 Screening Papers

The resulting papers are taken from all databases. These excluded the papers that were filled in using database filters. These database filters can be found in appendix B and were used to apply the exclusion criteria. This resulted in 163 papers. The titles and abstracts of these have been screened to see if they are irrelevant and will then be excluded. This is done based on the exclusion criteria from section 2.1. If after reading the title and abstract, the researcher was certain that one of the exclusion criteria was applied, it was excluded. After this process, 69 papers were excluded and 94 papers were left. The specific criterion why a paper has been left out has not been noted, since this would have taken long and due to time constraints, was infeasible. All of these papers have been retrieved and will be used for data extraction.

3.5 Data Extraction

For data extraction, specific questions have been identified of what has to be extracted from the data to answer the sub questions. In table 3, the specific questions can be found and for which sub question(s) the information is necessary.

For all these 94 papers, an attempt will be made to answer them. If the paper still does not meet one exclusion criterion, it can still be excluded. This data will be collected in a table. The rows will represent the papers and the columns will represent the questions.

#	Question	Subquestion
1	What user data has been used to model decision-making?	SQ1
2	How is decision-making represented in the model?	SQ1
3	What does the Intelligent System do with the model?	SQ2
4	How does the Intelligent System adapt?	SQ2
5	What is the objective of the adaptation of the Intelligent System?	SQ3, SQ4
6	In which application domain(s) is the intelligent system used?	SQ5
7	What additional challenges does the intelligent system encounter?	SQ6

Table 3: Data extraction questions and sub questions they answer

The first question looks for raw forms of user data. Examples of these are heart rate, review data, and answers to survey questions. The second question looks at how this data is structured. This could be user preferences, personality, and also more specific, such as confidence level. The third question looks at where this model is used. Whether it is predicting how much a user likes an item or what choices they are most likely to make while driving in specific situations. The fourth question looks at how the intelligent system adapts. This could be to recommend specific items or to warn the driver if it predicts that the user will decide to do something dangerous. The sixth question is what this adaptation will yield. In the case of the recommender system, it can be user experience, and in the case of the car detection system, it is probably safety. Questions 6 and 7 should be self-explanatory.

3.6 PRISMA

During this research, the PRISMA guidelines were used [2]. These guidelines provide a systematic manner of conducting literature reviews, ensuring transparency and reproducibility. They include a checklist with 27-items checklist covering parts such as eligibility criteria, information sources, search strategy, selection process, and data collection process. During the previously explained steps of the systematic literature review, the diagram was filled in and can be found in figure 1 in appendix C. It shows the papers found per database. Keep in mind that query filters were already used for this phase. Then it displays the number of different articles found by subtracting duplicates (n = 163). Then it gives the number of papers excluded after screening the titles and abstracts (n = 94), and the papers that were not excluded (n = 69). After this, it gives the number of papers retrieved (n = 94) and finally the papers that were excluded during data extraction (n = 42) and their reasons. This then results in the number of papers used for this research (n = 52).

4 Results

In this chapter, the results are provided. These were gathered by extracting data from the selected papers [13–64]. This chapter starts by discussing the different models used for recognition in section 4.1. It provides examples of user data used in these models. Following this, will be section 4.2. This section will focus on the recognition and adaptation of intelligent systems. Section 4.3 covers the domains in which intelligent systems operate and lastly, section 4.4 covers the challenges of intelligent systems.

4.1 Data and User Modelling

In this section, the different ways users are modelled will be discussed. It will also touch on what forms of user data were used to create these models. Together, these models represent user decision-making. Intelligent systems use more of these models for recognition purposes. Table 6 in appendix D, shows the different user models and the papers in which they are modelled.

User Preferences is the most used model with 45 usages contributing to 87% of the papers. It captures what users like and dislike. Data such as clicks, ratings and listening histories [13,19,26] can be used to model user preferences. While being less prominent, **User Interests** were modelled in 6 papers. This model captures a user their level of interest in specific items and is modelled using similar data user preferences uses [34]. **User Behaviour**

model both online and offline behaviour of and was user in 18 papers. Examples of data used to model user behaviour are eye tracking data, clicks, listening history, and physical data collected during physical activities [19,34,37,40]. Additionally, **User Needs** models what a user desires with 5 papers using this model.

The following models cover the identity of a user. **User Demographics** were used in 6 papers that contain basic statistical data on a user, such as their age, education level and gender [14]. **User Characteristics** are stable traits of the users and was modelled 14 times. Questionnaires, social media profiles and conversational data can be used to model user characteristics [17,24,36]. **User Skills** are stable abilities the user possesses, used in 3 of the articles.

Socio-emotional factors can also play a role in decision-making. **User Relations & Social Influence** models the user connections and how they influence the user. It was used in 5 papers. A questionnaire measuring social anxiety, social media network data and user similarity are forms of data used to model it [24,29,46]. **User Emotions** were used in 3 instances. They can be modelled using questionnaires, physiological data and physical data [29,59].

Some models are only found once and are more niche. Examples of these are **User Motivation**, **User Satisfaction** and **User Engagement**, **User Perception**.

4.2 Recognition & Adaptation of Intelligent Systems

In this chapter, the various ways that intelligent systems recognize and adapt will be described and explained. These Intelligent Systems include Recommender Systems which will be covered by section 4.2.1 Systems. After this, Decision Support Systems will be described in section 4.2.2. Thereafter, assistance systems will follow in section 4.2.3 and social robots will conclude the chapter in section 4.3.4. Which papers include which type of intelligent systems can be found in table 7 in appendix D.

4.2.1 Recommender Systems

Recommender systems mainly use user preferences. As seen in figure 2 in appendix E , 41 of the 45 recommender systems use these user preferences. In addition, user characteristics and user behaviour are used quite often. A wide range of other user models is also used. The recommender system thus uses a variety of user models. Recommender systems estimate the rating that a user would give to many different items. Based on these predictions, the system recommends the items with the highest estimated ratings. For example, a system that uses customer preferences to predict how much a user likes specific hawker stalls [33]. Hawker stalls are places where people can get food. There are usually a lot of these stalls close together, so finding the perfect one can be difficult. The recommender system solves this problem.

A variant of this is the group recommender system [29,57]. Usually a user relationship & social influence model is used in combination with other user data in combination with preferences. They predict user ratings for all users in the group and recommend the items that are preferred by the group.

4.2.2 Decision Support Systems

Decision support systems usually take both user preferences and user behaviour as can be seen in figure 3 in appendix E. A diverse group of other models is also used in combination with these [23,34,62]. It uses all of this to predict user ratings and adapts by giving advice. For example, by giving advice about which contraceptives fit a user [23]. It does not just recommend contraceptives, it provides advice on what to look for in contraceptives. Another example is a system that predicts user ratings of mobile health-based interventions. It uses this to advice a schedule of interventions and a way of monitoring these [34].

Another example is a group decision support system [16]. It models user preferences and use them to predict user ratings. These are then used by the intelligent system to find conflicts in a group. These conflicts are then communicated through to the user responsible for making the decision.

Another variant is the decision support system that does not model user preferences, it models user behaviour and predicts behavioural decision-making in evacuations [25]. This information of multiple users is used to adapt the evacuation strategy.

4.2.3 Assistance Systems

Assistance systems can use various types of behavioural data, combined with user characteristics and user perception, as can be seen in figure 4 in appendix E [21,40]. They predict user behaviour to assist the user while performing a task. Two examples will be provided.

The first uses a behavioural model of a driver [21]. It uses this to predict the real-time driving decision of the driver. These predictions can then be used to warn the driver or assist them.

The second uses vision data to predict the real-time performance of a pilot [40]. This can help the pilot by providing alerts or automating parts that the pilot performs poorly.

4.2.4 Social Robots

A Social Robot can user various types of behavioural data combined with user needs as can be seen in 5 in appendix E. The robot uses this to predict the intentions of the user. The social robots can use this information to adapt by personalizing the robots' behaviour. For example, if it detects that the user is uncomfortable with the robot, the robot will move away a bit further [31]. Another example is the robot learning that two users like to sit together in a room. It adapts by informing one of the users if the other is sitting in that room alone [31]. Social robots do all of this to provide a sociable experience for the user.

4.3 Application Domains of Intelligent Systems

In this chapter, the application domains will be discussed and what intelligent systems operate in these domains. The domain in which intelligent systems belong can be found in table 8 in appendix D. The domains discussed will be food & health in section 4.3.1, mobility, transportation & safety in section 4.3.2, media in section 4.3.3, education & sport in section 4.3.4 and finally consumer products & services in 4.3.5.

4.3.1 Consumer Services & Products

In this domain, products and services that consumers can buy will be explored. Examples of these are restaurants, apartments, activities and all sorts of products. This is the largest domain, with 19 papers covering it.

As can be seen in 6 in E, all but one of the intelligent systems operating in this domain are recommender systems. In most cases, recommender systems are used to improve the decision-making process. For example, by recommending all sorts of products [13, 19]. However, it can also recommend very niche and specific items such as ceramic products [51]. In addition, restaurants, food stalls, apartments, touristic attractions and general points of interest (POI), can all be recommended using recommender systems [22, 33, 54–56].

However, decision support systems can also be of use. Especially when one person has to make a decision for the group. A decision support system can inform the decision-maker about conflicts that might arise when selecting a restaurant [16]. Making an informed group decision can be very challenging and this system can aid in keeping everyone content with the final decision.

4.3.2 Food & Health

This domain focuses on food, cooking, nutrition and health in general. When looking at food & health, recommender systems are very prominent. As seen in figure 7 in appendix E. For example, a recommender system that recommends surprising recipes [49] to let people discover recipes they would not regularly make, but do like. There are also food recommender systems that focus on nutrition and health. They take into account both user preferences and healthiness of food. [14, 20, 44]. These have as a goal to nudge users into better eating habits.

A social robot also operates in this domain, adapting its behaviour based on the users' decision-making. It, for example, brings users together that the robot thinks would like to be together [31]. It tries to provide a social experience for the elderly. This can significantly improve their health.

Decision support systems also try to improve health. First, by giving advice on contraceptives to help users make informed decisions [23]. Secondly, by scheduling mobile health interventions to help people improve all sorts of health problems [34]. Lastly, by advising users about medical services [62]. This helps them in the decision-making process by making a decision both informed and efficiently.

4.3.3 Media

The domain of media focuses on movies, music and news. The only intelligent systems that are used in this domain are recommender systems. In this domain, recommender systems are often utilized to help users find content they like. There are recommender systems that recommend music artists [30], music songs using an emotional model [59] and news items using user engagement [64]. By recommending content that the user likes, the user will have a better experience. Additionally, artists and movies can get more recognition and media sites and apps will make more profit when users eventually spend more time on their app or site.

4.3.4 Education & Sport

The domain of education & sport focuses on improving mentally and physically. This is only done by using recommender systems. Some of these focus on finding e-learning content that users find interesting [41, 61]. Another system recommends educational programs using user skills, characteristics and interests [17]. This can help in making a very important decision more efficiently and more accurately. In addition, while playing sports, recommender systems can help out. User skills can be used to recommend exercises. In the case of sport climbing, it can be used to recommend climbing routes [38]. When playing basketball, training activities can be recommended. The objective of both is to find activities and locations that are challenging, but not too complicated. This helps improve performance while keeping the user engaged [60].

4.3.5 Mobility, Transportation & Safety

The domain of mobility, transportation & safety focuses on transporting humans in a safe manner. For example, by utilizing the assistance system. These are the most dominant, with 50% of all intelligent systems being assistance systems as can be seen in figure 8 in appendix E. These can warn the user or assist them during a dangerous situation while driving or flying [21] [40]. It does this to prevent accidents and make the roads and sky safer.

Similarly, a recommender system has the same objective. By recommending in-vehicle functionalities, it aims to prevent distractions while driving [48].

Safety can also be improved in other ways. That is, using a decision support system to predict user behaviour during evacuation situations [25]. It uses this information to adapt the evacuation plan and informs authorities.

4.4 Challenges of Intelligent Systems

In this chapter, the challenges of intelligent systems will be discussed and the manner in which recent studies have tried to overcome these. In table 9 in appendix D, the challenges can be found and in which paper they are referenced.

4.4.1 Prediction Accuracy

Often, papers focus on improving the performance of these intelligent systems. This is the most prevalent challenge with 36 papers addressing it. They aim to improve the accuracy for recognition, as comparable systems lack accuracy [15]. Two different ways of accomplishing this often come back. These can be found in table 10 in appendix D. All types of intelligent systems address this challenge, as can be seen in figure 9 in appendix E

The first is by using more forms of user data, 23 papers use this technique as can be seen in figure. By also modelling different parts of the user than their preferences, interests, behaviour and demographics, the model becomes more accurate. Adding models such as user characteristics, relationships & influences, emotions and needs can help improve this accuracy [22, 29, 51].

The second way to improve the accuracy is to apply specific or new algorithms that similar systems did not use [15]. Examples of these are papers using an Ant Colony Optimization algorithm, other evolutionary algorithms and an extension of a Top-N algorithm to increase the accuracy of the predictions [27, 41, 55]

4.4.2 Biases, Fairness & Explainability

Biases, fairness & explaininibility is also mentioned quite frequently, 8 papers cover it. Multiple systems address fairness [29, 37, 60, 63]. One of the papers uses user demographics which can cause biases. It analyses these biases and uses bias mitigation strategies to ensure fairness [37]. One of the papers incorporates explainability by using explainable AI. The system can explain why it recommended certain items that ensure transparency [42].

4.4.3 Interface and Usability

The interface of these intelligent systems is certainly also an important part and a challenge found in 5 papers. With 4 of these papers being recommender systems and 1 a decision support system as can be seen in figure 10 in appendix E.

Some papers focus on their interface. For instance, a research that conducted a usability study of their recommender system [38]. However, many systems take this for granted.

4.4.4 Privacy & Security

Only 3 papers address the issue of privacy & security. All of these papers are recommender systems.

Some of the papers focussed on the privacy and security of their systems. For example, by designing a privacy-preserving data platform [42].

4.4.5 Data Collection

Before modelling, the data must also be collected. This can be challenging. This challenge is addressed twice, in both cases, by papers using recommender systems.

Two papers address this challenge and attempt to overcome it. They do this by developing a tool to collect data. One of these implemented a telegram bot that uses a career guidance test to collect user data [17]. The other paper created a questionnaire with the intention of modelling meta-intents [32]. However, data collection is usually not talked about in detail, even though it is a crucial part of user modelling and can be very complicated.

5 Responsible Research

When conducting research, the results are important, but they must be collected in a responsible manner. Ethics, reproducibility, and the prevention of biases are important aspects to consider. Section 5.1 covers reproducibility and the efforts made to ensure reproducibility in this research. Section 5.2 will explain the measures taken to prevent biases and proof integrity. Finally, section 5.3 covers the ethics of a literature review like this.

5.1 Reproducibility

The methodology was described in great detail and according to the PRISMA guidelines [2]. The databases, queries, time of the query, and filters are recorded for reproducibility purposes. A detailed explanation of the methodology should suffice. The exclusion criteria can be used to see which papers were excluded. The final papers can be found in the references. Due to the time constraint, during the abstract and title screening phase, the titles and reasons for their exclusion were not recorded. This could be done to further improve the reproducibility.

5.2 Preventing Biases

The systematic approach of this literature review, combined with following the PRISMA guidelines [2] mitigates bias when looking for articles. This systematic process ensures a comprehensive and unbiased search for the relevant literature. In particular, when creating a search query after conducting comprehensive background research. This aids in creating a broad and unbiased search query in contrast to a non-systematic approach in which previous knowledge biases the search query.

Due to time constraints, papers before 2021 have been excluded, and since technology changes over time, this creates a slight temporal bias in the results. This study thus acknowledges that only research from after 2020 is used, which should be taken into account when reading the paper.

5.3 Ethics

Although ethics do not play a direct role in conducting a literature survey, the primary research used in this study may contain ethical implications. A key observation is that not many papers address ethical implications. However, some address these ethical issues. For example, a research that conducts research using elderly participants. They address ethics and the rights of the elderly and prevent dehumanization [60] during their research.

Not all papers address this and do not always specify how they treat the participants and handle their data. This lack of transparency in primary research indicates a broader issue in the field, where ethical considerations are not always addressed.

6 Discussion

This chapter will discuss both the limitations of the studies and the results. The limitations and results of feasibility criteria will be discussed in section 5.1. The results will be discussed in section 5.2

6.1 Limitations

For feasibility purposes, only articles published after 2020 were used for this research. This might also affect the results, since technology and in this case, intelligent systems and user modelling have changed a lot over the years [3]. Only taking results from the last 5 years will influence the results. However, because these results usually build further upon previous work, the intelligent systems are most likely more accurate and serve more purposes than the previous iterations. Since the results only spanned 5 years, decided was to not include trends in the results. Researching how the usage of intelligent systems has changed is less relevant when only 5 years can be taken into account. Not using this feasibility constraint and investigating trends could gain additional results, which this study is missing.

6.2 Result discussion

This section focuses on the key findings of the results and the implications of this will be discussed.

A key finding is the high amount of papers modelling user preference. This is probably associated to the dominance of recommender systems. 85% of all the intelligent systems found are recommender systems. These optimize decision-making in a manner that is humanly impossible. Searching through vast search spaced while containing information on the user solves this problem and with it having usages in all of the application domains makes it very dominant.

Other models such as user characteristics, user behaviour and user demographics also appear quite frequently. This is mainly because they are used in order to model user preferences while still being relatively easy to model with less specialized data such as age, listing history or social media profile data. Additionally, user interests are only used in recommender systems. They are very similar to user preferences and work in combination or as a replacement of them.

These more specific user models, such as user emotions and user relationships & social influence usually use more complicated data types such as physiological data or questionnaires measuring social anxiety. This data is more complicated to collect, but also provides a lot of insight about the user that other systems might not have. This is usually used in recommender systems to make recommendations more accurate.

Decision support systems have been found similar to recommender systems, but help in more important decisions that should be informed decisions. By advising, using domain knowledge, user knowledge and with knowledge about the possible decisions to be made, the system can aid in making these decisions more informed and more efficiently.

Although being less dominant, assistance systems and social robots tell us that recommender systems are not the only intelligent systems that model decision-making. Real-time intelligent systems that model behavioural decision-making like this can serve important objectives such as safety and social well-being.

Another key finding is the relationship between these systems and application domains. As mentioned above, recommender systems operate in all domains and are very prominent in consumer services and products. They are even the only system operating in the education & sport, media and the undefined domain. Many recommender systems exist without a real purpose, rather than recommending which explains the undefined domain and helps in relatively low-stakes decisions such as consumer products & services and media. An exception of this is the usage of nudging. Recommender systems can be used to nudge users into better eating patterns, for example, by using a combination of user models and information on food nutrition. Although this case is very meaningful, choosing what food to eat is not necessarily an important decision. While decision support systems always deal with important decisions, by operating mainly in the health sector where the stakes are usually higher.

All assistance systems operate in the transport domain and have as objective safety and social robots operate in the food & health domain. Thus, these have high stakes and can help serve very meaningful objectives.

Additionally, recommender systems seem to focus a lot at improving performance and also attention is provided in dealing with biases and privacy & security issues. Especially a lot of focus is put into improving the prediction accuracy, by improving algorithms or using additional user models. Human decision-making is a complicated process and is affected by all sorts of factors, such as emotion and social relationships. Using this to model can therefore aid in increasing the prediction accuracy. The focus of these challenges is less present in the other intelligent systems. They focus more on achieving their main objective than on additional challenges. Some papers also address explainability which provides more transparency when recommending. This can help to prove fairness and provides additional information on the recommendation, making it more trustworthy. In addition, security was sometimes taken into account. A lot of user data means a great risk of disrupting people their privacy and finally, the usability has been a challenge which should be considered. Without a clear interface, user experience decreases and the effectiveness of the complete systems is compromised.

In general, recommender systems are becoming more specialized, focusing on all sorts of domains and addressing a range of challenges while serving diverse objectives. While other intelligent systems rarely model decision-making to recognize and adapt. However, if they do, they can solve complicated problems and help users in meaningful ways.

7 Conclusions and Future Work

This study aimed to explore how intelligent systems model human decision-making and reasoning using user data, and how these models are then used for recognition and adaptation by conducting a systematic literature review.

The results revealed that user preferences are the most commonly modelled aspect of decision-making. This is a result of the prominence of the recommender systems between the other intelligent systems. This suggests that ease of decision-making and user experience currently drives the field in a wide range of domains, especially in the domains of consumer products & services, media and food & health. To increase performance of these systems, additional user models such as user characteristics, user behaviour and user needs are used in combination the development of new algorithms.

More complex forms of decision-making such as emotion and social influence, are used less often, though they can aid significantly in making a more accurate model of decision-making.

Moreover, real-time intelligent systems, such as social robots and assistance systems are underutilized while they can serve important purposes. This highlights the need for more research into other intelligent systems.

Even recommender systems can benefit from more research. They have to deal with challenges such as fairness, explainability, security and usability.

For **Future Work**, several directions could be explored. A survey could be conducted that additionally uses papers from before 2021. This could look at the development over the years and could look at trends. Another possibility for future work is developing new intelligent systems that are not recommender systems. This could be, for example, an assistance system or social robot. However, it could also be something entirely new. Lastly, future work could focus on expanding user models. By expanding upon these models, decision-making can be modelled in more precision which can improve accuracy of recommender systems.

8 Usage of LLMs

LLMs have been used during this research. It has been used to reformat queries, to provide feedback on the writing style and to find synonyms. In appendix F, this will be explained.

A Exclusion & Feasibility Criteria

B Queries

In this appendix, the queries and their corresponding filters can be found in the order Scopus, Web of Science, IEEE Xplore, and ACM Digital Library.

#	Exclusion Criterion	Motivation
1	Exclude surveys and reviews.	Surveys and reviews summarize existing research. Only primary research will be used, because the research is trying to find out what intelligent systems are currently doing.
2	Exclude papers that are not in English.	This course regulations of course CSE3000 require this.
3	Exclude papers that do not use user data. This is data about individual users.	Focus of the paper.
4	Exclude papers that do not model decision-making in some way, shape, or form.	Focus of the paper.
5	Exclude papers that do not include an intelligent system that uses this model and adapts is some way shape or form	Focus of the paper.

Table 4: Exclusion criteria and motivation

#	Feasibility Criterion	Motivation
1	Exclude papers published before 2020.	To make sure the number of papers included is not too large, and papers are still relevant. It does this while biasing minimally.

Table 5: Feasibility criteria and motivation

B.1 Scopus

(TITLE-ABS-KEY("intelligent system" OR "adaptive system" OR "support system" OR "recommender system")) AND (TITLE-ABS-KEY("recogni*" OR "detect*" OR "sens*" OR "perce*" OR "observ*" OR "identif*" OR "classif*" OR "monitor*" OR "track*" OR "analy*")) AND (TITLE-ABS-KEY("adapt*" OR "act" OR "feedback" OR "respon*" OR "interact*" OR "personali*" OR "react*" OR "updat*" OR "modif*" OR "adjust*" OR "tailor*" OR "customi*")) AND (TITLE-ABS-KEY("user modeling" OR "user profil*" OR "user model" OR "cognitive model*" OR "affective model*" OR "student model*" OR "persona model*" OR "patient model*" OR "player model*" OR "employee model*")) AND (TITLE-ABS-KEY("decision making" OR "decision-making" OR "decision support" OR "human decision"))

Filters

- Year: 2021, 2022, 2023, 2024, 2025
- Language: English
- Document type: Article, Conference Paper

B.2 Web of Science

TS=("intelligent system" OR "adaptive system" OR "support system" OR "recommender system") AND TS=(recogni* OR detect* OR sens* OR perce* OR observ* OR identif* OR classif* OR monitor* OR track* OR analy*) AND TS=(adapt* OR act OR feedback OR respon* OR interact* OR personali* OR react* OR updat* OR modif* OR adjust* OR tailor* OR customi*) AND TS=("user modeling" OR "user profil*" OR "user model" OR "cognitive model*" OR "affective model*" OR "student model*" OR "persona model*" OR "patient model*" OR "player model*" OR "employee model*") AND TS=("decision making" OR "decision-making" OR "decision support" OR "human decision")

Filters

- Publication Years: 2021, 2022, 2023, 2024, 2025
- Languages: English
- Document types: Article, Proceeding Paper

B.3 IEEE Xplore

("All Metadata":"intelligent system" OR "All Metadata":"adaptive system" OR "All Metadata":"support system" OR "All Metadata":"recommender system") AND ("All Metadata":"recogni*" OR "All Metadata":"detect" OR "All Metadata":"sens*" OR "All Metadata":"perceive" OR "All Metadata":"observe" OR "All Metadata":"identif*" OR "All Metadata":"classif*" OR "All Metadata":"monitor" OR "All Metadata":"track" OR "All Metadata":"analy*") AND ("All Metadata":"adapt" OR "All Metadata":"act" OR "All Metadata":"feedback" OR "All Metadata":"respon*" OR "All Metadata":"interact" OR "All Metadata":"personali*" OR "All Metadata":"react" OR "All Metadata":"update" OR "All Metadata":"modif*" OR "All Metadata":"adjust" OR "All Metadata":"tailor" OR "All Metadata":"customi*") AND ("All Metadata":"user modeling" OR "All Metadata":"user profile" OR "All Metadata":"user model" OR "All Metadata":"cognitive model" OR "All Metadata":"affective model" OR "All Metadata":"student model" OR "All Metadata":"persona model" OR "All Metadata":"patient model" OR "All Metadata":"player model" OR "All Metadata":"employee model") AND ("All Metadata":"decision making" OR "All Metadata":"decision-making" OR "All Metadata":"decision support" OR "All Metadata":"human decision")

Filters

- Year: 2021 - 2024

B.4 ACM Digital Library

[[Abstract: "intelligent system"] OR [Abstract: "adaptive system"] OR [Abstract: "support system"] OR [Abstract: "recommender system"]] AND [[All: recogni*] OR [All: detect*]

OR [All: sens*] OR [All: perce*] OR [All: observ*] OR [All: identif*] OR [All: classif*] OR [All: monitor*] OR [All: track*] OR [All: analy*]] AND [[All: adapt*] OR [All: act] OR [All: feedback] OR [All: respon*] OR [All: interact*] OR [All: personali*] OR [All: react*] OR [All: updat*] OR [All: modif*] OR [All: adjust*] OR [All: tailor*] OR [All: customi*]] AND [[All: "user modeling"] OR [All: "user profil*"] OR [All: "user model"] OR [All: "cognitive model*"] OR [All: "affective model*"] OR [All: "student model*"] OR [All: "persona model*"] OR [All: "patient model*"] OR [All: "player model*"] OR [All: "employee model*"]] AND [[All: "decision making"] OR [All: "decision-making"] OR [All: "decision support"] OR [All: "human decision"]]

Filters

- Publication Date: Past 5 years

C Prisma Flow Diagram

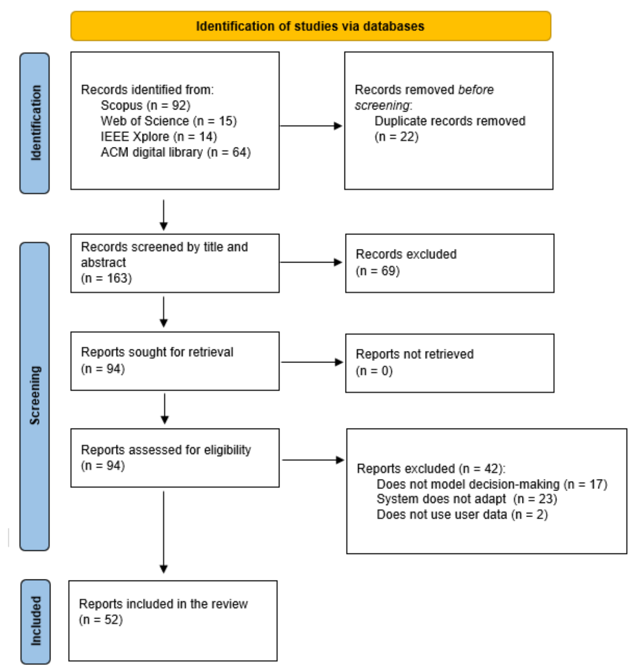

Figure 1: PRISMA Flow Diagram

D Main Results

Models	Number of Papers	Papers
User Preferences	45	[13–16, 18, 20, 22–24, 26–30, 32–36, 38, 39, 41–64]
User Behaviour	18	[18, 19, 24, 25, 30–36, 40–42, 51, 52, 59, 62]
User Characteristics	14	[15, 17, 20–25, 29, 35, 36, 42, 51, 60]
User Demographics	6	[14, 23, 32, 37, 52, 56]
User Interests	6	[17, 19, 28, 35, 42, 61]
User Relations & Social Influence	5	[24, 29, 30, 46, 57]
User Needs	5	[23, 31, 51, 52, 60]
User Emotions	3	[25, 29, 59]
User Skills	3	[17, 38, 60]
User Motivation	1	[34]
User Satisfaction	1	[64]
User Engagement	1	[33]
User Perception	1	[21]

Table 6: User Models and Corresponding Papers

Intelligent Systems	Number of Papers	Papers
Recommender Systems	44	[13–15, 17–20, 22, 24, 26–30, 32, 33, 35–39, 41–61, 63, 64]
Decision Support Systems	5	[16, 23, 25, 34, 62]
Assistance Systems	2	[21, 40]
Social Robots	1	[31]

Table 7: Intelligent Systems and Corresponding Papers

Domains	Number of Papers	Papers
Consumer Services & Products	19	[13, 15, 16, 19, 22, 28, 33, 35, 39, 45–47, 51–56, 63]
Food & Health	10	[14, 20, 23, 31, 34, 42, 44, 49, 58, 62]
Media	8	[26, 27, 30, 36, 37, 50, 59, 64]
Undefined	6	[18, 24, 29, 32, 43, 57]
Education & Sport	5	[17, 38, 41, 60, 61]
Mobility, Transportation & Safety	4	[21, 25, 40, 48]

Table 8: Domains and Corresponding Papers

Challenges	**Number of Papers**	**Papers**
Prediction Accuracy	36	[15–31, 33–36, 39, 41–43, 45, 46, 50–52, 55–57, 59, 60, 64]
Biases, Fairness & Explainability	8	[29, 36, 37, 42, 53, 60, 61, 63]
Interface and Usability	5	[23, 38, 53–55]
Privacy & Security	3	[42, 60, 63]
Data Collection	2	[17, 32]

Table 9: Challenges and Corresponding Papers

Solutions	**Number of Papers**	**Papers**
Uses Additional User Models	23	[15, 17, 20–25, 29–31, 33–36, 42, 46, 51, 52, 57, 59, 60, 64]
Uses Specific or New Algorithms	18	[16, 18, 19, 22, 23, 26–28, 30, 39, 41, 43, 45, 46, 50, 55–57]

Table 10: Solutions and Corresponding Papers

E Additional Results

In this appendix, the additional results can be found. These use main results to find patterns.

E.1 Relation between Intelligent Systems and User Models

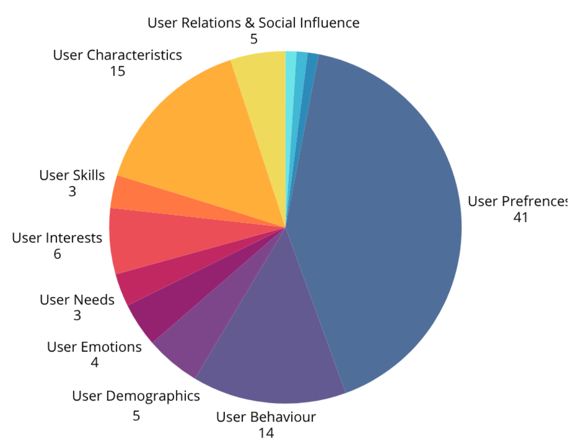

Figure 2: Usage of User Models in Recommender Systems

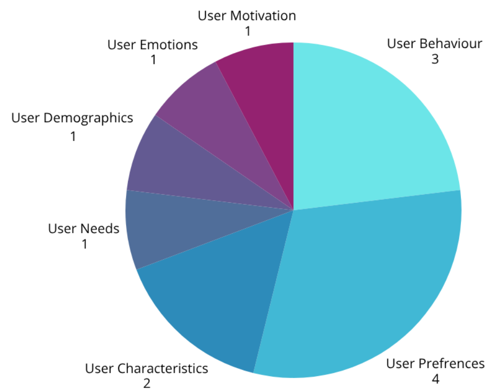

Figure 3: Usage of User Models in Decision Support Systems

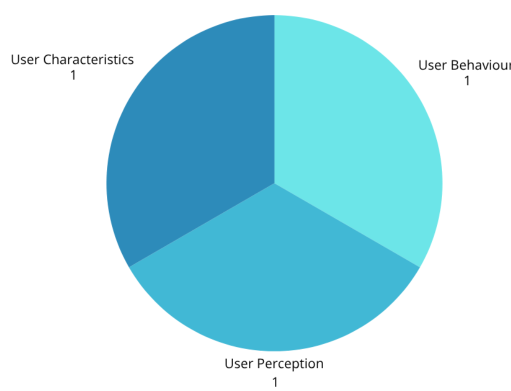

Figure 4: Usage of User Models in Assistance Systems

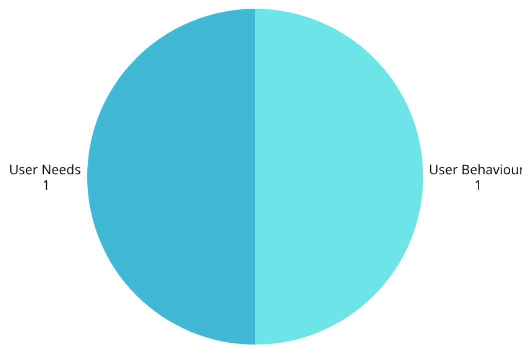

Figure 5: Usage of User Models in Social Robots

E.2 Relation between Application Domains and Intelligent Systems

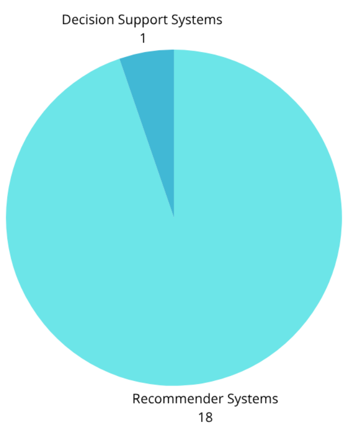

Figure 6: Intelligent Systems in the Consumer Services & Products Domain

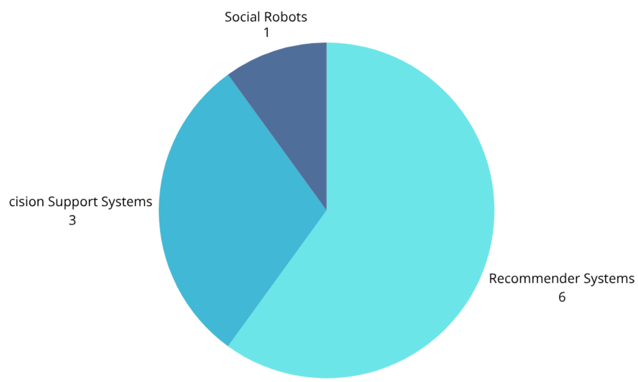

Figure 7: Intelligent Systems in the Food & Health Domain

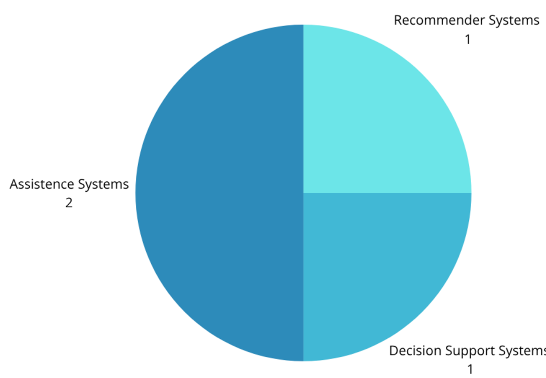

Figure 8: Intelligent Domains in the Mobility, Transportation & Safety Domain

E.3 Relation between Challenges and Intelligent Systems

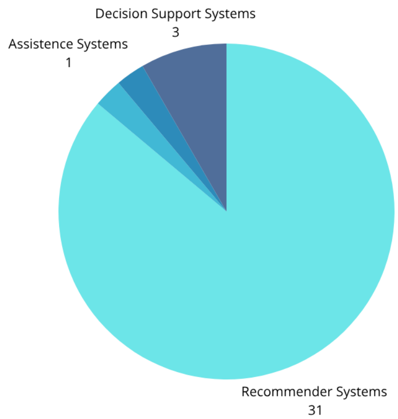

Figure 9: Intelligent Domains addressing Prediction Accuracy

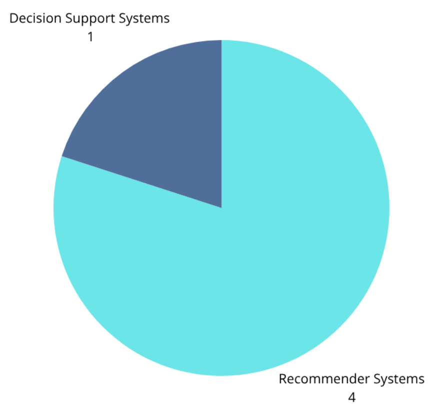

Figure 10: Intelligent Domains addressing Interface and Usability

F Explanation of Usage of LLMs

LLMs have been used for three purposes. These purposes will be discussed and example prompts will be provided.

The first usage for using LLMs was for reformatting queries to be used in other databases. The first query was created without the use of LLMs and the other ones were reformatted. These queries have then been checked on completeness.

The prompt used was: "Could you reformat this Scopus query to a IEEE Xplore query?". The Scopus query was pasted after the question.

The second usage was asking for feedback on writing style. The researcher wanted feedback on his writing style while not having the LLM incorporate this feedback.

The prompt used was: "Could you provide me with feedback on the writing style? There is no need to change the text". The part requested for feedback was paster right after.

Lastly, when having a problem to come up with the right word LLMs were used using two prompts:

- "Could you think of synonyms for (here follows the requested word)?"
- "Could you replace the dots for a word that fits the sentence?'

In the last situation a sentence was provided where a word was replaced with .... The words never changed the content. They were merely in function of improving the writing style.

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