Manchester Metropolitan University

**Department of Computing and Mathematics**

**M.Sc. in Artificial Intelligence**

**KBS COURSEWORK**

**Mortgage Decision Making Expert System**

***Module: KNOWLEDGE REASONING AND REPRESENTATION***

***Semester 1: 2022/2023***

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## Abstract

The housing market not only serves as a medium for individuals to purchase a home, but also as an opportunity for investors to generate income. In Greater Manchester, the rise in house prices by 330% in the last 20 years has made investing in the housing market a profitable enterprise. Considering this, an expert system has been developed to assist millions of people, particularly international students, and young professionals, in fulfilling their dream of owning a home. The Knowledge based system aims to establish who is eligible for a mortgage by developing the expert system that uses Forward Chaining Predicate Logic to determine the final decision on any mortgage application (Elngar & Chowdhury, 2022). The system considers the applicant's credibility in terms of their ability to repay the mortgage and the availability of mortgage options for them. The system was tested, validated, and received feedback from peers and an AI Mortgage Risk Model Manager at the Royal Bank of Canada (RBC), Somto Muotoe, to improve its accuracy and efficiency. This system is expected to make the process of obtaining a mortgage more inclusive and innovative, and help more people achieve their goal of homeownership without being constrained by traditional mortgage requirements (Harvey, 2022).

## Chapter 1.0 Introduction

An expert system for mortgage assessments is a computer program that holds knowledge and mimics the analytical and decision-making skills of a human expert. It will be tailored towards young professionals, who often struggle with the high costs of monthly rents and lack of savings for a down payment. The system will consider factors such as employment status, criminal history, income level and the growth of the real estate market in Greater Manchester. It will be an all-encompassing system that will be a game changer in the mortgage assessment market, providing valuable assistance to young professionals in securing a home (Xu & Li, 2020).

## 1.1 Knowledge Representation and Its Types

Knowledge representation involves more than just storing data in a database. It enables machines to learn and take actions based on that stored knowledge (Bernd Bayerlein, 2022).

### 1.1.1 Types of Knowledge

- **Declarative**: Concepts, Facts, and Objects.
- **Structural:** Relationships between concepts and objects.
- **Procedural:** Rules, Strategies and Procedures.
- **Meta:** Knowledge about other types of knowledge
- **Heuristic:** Expert knowledge from a specific field or subject.

### 1.1.2 Cycle of Knowledge

- **Perception:** Retrieving data from the environment and defining how to respond when any sense is detected.
- **Learning:** Involves using the data gathered by the perception component to improve the AI's performance
- **Knowledge Representation and Reasoning**: Focusing on understanding and building intelligent behaviour in the AI and making automated reasoning procedures available.
- **Planning and Execution**: Analysing the knowledge representation and reasoning component to create a plan, and then executing that plan.

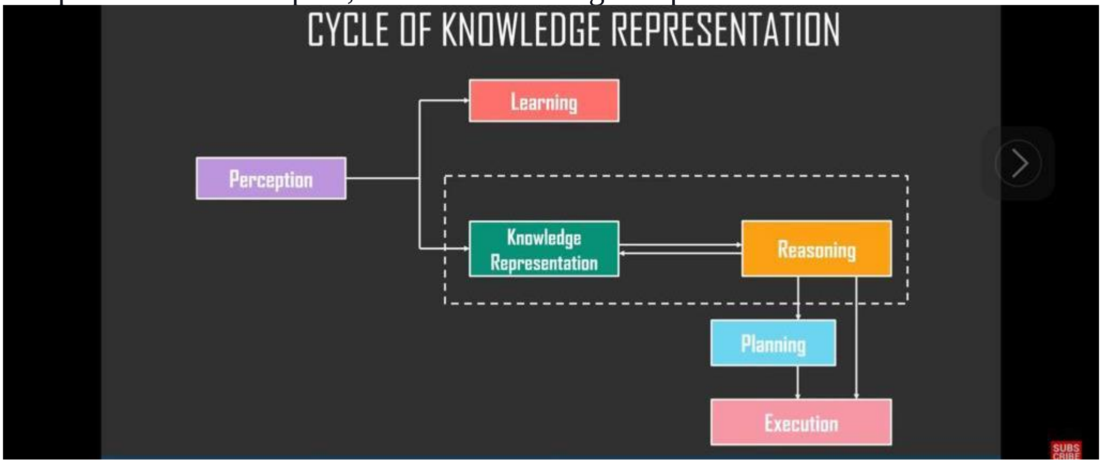


*Fig 1: Cycle of knowledge Representation*

### 1.1.3 KBS Examples and Techniques of Knowledge Representation

1. **Logical Representation**: These KBS that uses specific rules and no ambiguity to order conclusions based on conditions and communication rules, with precise syntax and semantics for sound inference. These KBS are also used for building chatbots using forward and backward chaining (Pandey, 2022).

**Advantages and disadvantages of Logical Representation**

| A**dvantages** | **Disadvantages** |
|---|---|
| • Perfect for performing Logical reasoning | • They have some restrictions and are challenging to work with. |
| • Foundation for the programming languages | • The technique is not very natural, and inference may not be very efficient |

***Table 1: Advantages-and-disadvantages-of-Logical-Representation (Pandey, 2022).***

2. **Semantic Networks Representation**: An alternative method for representing knowledge in graph form, using nodes and arcs, which are used in image recognition software (Baker & Farah, 2021).

**Advantages and disadvantages of Semantics Networks Representation**

| **Advantages** | **Disadvantages** |
|---|---|
| • They are a natural representation of knowledge. | • They take more computational time at runtime |
| • They convey meaning in a transparent manner | • They do not have any equivalent quantifier, therefore sometimes inadequate. |
| • They are easy and simple to understand | • They are not intelligent as they depend on the creator of the system. |

***Table 1.1: Advantages-and-disadvantages-of Semantics-Networks-Representation (Baker & Farah, 2021).***

3. **Frame Representation:** These data structure in knowledge-based systems organizes knowledge into stereotypical situations, consisting of attributes, values, slots, and slot values. These types of KBS are used in search algorithms like Google Drive (Nebel, n.d.).

**Advantages and disadvantages of Frame Representation**

| **Advantages** | **Disadvantages** |
|---|---|
| • It makes the programming easier by grouping the related data. | • In Frame system inference, the processing is somewhat difficult |

| | |
|---|---|
| • Frame representation is easy to understand and visualize. | • Also, it has a very generalized approach |
| • Also, it is easy to include default data and search for missing values. | |
| • It is very easy to add slots for new attributes and relations. | |

*Table 1.2 Advantages-and disadvantages-of-Frame-Representation (Nebel, n.d.).*

4. **Production Rules**: In this rule-based system, the agent checks for conditions and applies the production rule with the corresponding action if the condition is met. This process is known as the recognition-act cycle (D.S.Yeung & C.C.Tsang, n.d.).

**Advantages and disadvantages of Production Rules Representation**

| **Advantages** | **Disadvantages** |
|---|---|
| • The production rules are expressed in natural language | • Its learning capabilities are non-existent and do not store the result of the problem for future use |
| • These rules are extremely modular and can easily be modified or removed | • They are inefficient because many rules are activated during unnecessary execution. |

***Table 1.3:** Advantages-and-disadvantages-of-Production-Rules-Representation (D.S.Yeung & C.C.Tsang, n.d.).*

## Chapter 2.0 Why build an Expert System?

Banks and credit facilities are interested in using expert systems for mortgage loans because they can handle the growing labour cost and process standardization. These systems are also believed to be less prone to bias and can help comply with regulations in some jurisdictions. These systems can also simplify the process of granting loans by providing instant resources and tools to branch employees and can make decisions on behalf of the bank employees, regardless of their knowledge of the screening procedure. It can handle the lower interest rate loans which are open to lower-income families and low-cost properties, by providing instant resources and tools aiding them in processing an application correctly (Mario Romao, 2019).

### 2.1 Stakeholders

Description of Stakeholders: Applicant, Home-seller/Agency, Credit Facility and Government

**a. Agency and Credit Facility**: Mortgage lenders are financial institutions that offer home loans and have specific guidelines to verify creditworthiness and ability to repay. Understanding these guidelines can be challenging, particularly for self-employed applicants.

**b. Property Seller and Agency:** Real estate agents and brokers are licensed professionals who facilitate property transactions between buyers and sellers. They earn commission based on the sale price of the property and their income increases with each successful transaction. They may also need to follow regulations and laws set by the government and work with senior colleagues licensed in the same jurisdiction (G.Donald Jud, 2016).

**c. Government Policy:** Legislation can have a major impact on property prices and demand. Government policies such as subsidies, deductions, and tax credits can temporarily alter the real estate market direction to boost the economy. Being aware of these policies can help buyers and sellers make informed decisions, and not fall prey to FOMO (fear of missing out) or false trends. For example, in 2009, the United States government offered a tax credit for first-time homebuyers to boost home sales and 2.3 million people took advantage of it, however, it's important to note that such policies are temporary and not to be taken as a normal trend (FHA, 2009).

**d. Applicant:** Purchasing a home can be a complicated and lengthy process but with the right knowledge and system, it can be easier for the applicant. A deposit of at least 5% of the property price is usually required by the seller and the rest of the amount can be obtained as a loan from a financial institution. A bigger deposit can help to lower the interest rate and increase the willingness of the financial institution to grant the loan (Sproson, 2022).

**Things to note by the applicant**

1. Catchment Areas for Schools: Manchester is an example with MMU, UOM and multiple colleges. Here, the rate of houses is bound to be higher.
2. Transport links: The closer the property is to good transportation network, the higher the price of the property in most regions.

3. Local Infrastructure and Flood zones: Checking this information is worth it in the long run to avoid issues that are pathetic.
4. Crime Rate: Especially when raising children, this should be looked at from police.uk.

## 2.2 Approach Knowledge Gathering and Sources

- Interviewed a Mortgage Expert at Royal Bank of Canada (RBC) AI Model Manager, Somto Muotoe. (Please, watch the video by clicking the link)

RBC has a big presence in the United Kingdom and being one of the biggest bank in the world, the expertise of one of their finest mortgage risk assessment managers is being collected in a one on one interview submitted with this report (RBC, 2021).

- Real estate agency websites: I combed through dozens of websites to determine prices of houses in different regions.
- Government Real Estate Tax Regulations: This is gotten from Gov.uk
- Credit Organisation/Expert System Owner's Specification: To determine the requirements such as credit score, income statement, criminal records to approve or decline a mortgage loan for ultimate success of the organisation. Some rules will be gotten from 2022 Forbes' top credit mortgage lenders with high success rate to fine tune my rules. Lastly, actions to be taken on defaulted and successful loans to upgrade the system

## 2.3 Rule-based systems requirements:

Requirements for an ideal decision-making mortgage support system

| **Attribute** | **Ideal solution** |
|---|---|
| Explainability | High |
| Accuracy | High |
| Noisy Data Tolerance | Moderate |
| Sparse Data Tolerance | Moderate |
| Tolerance for complexity | High |
| Speedy Response | Moderate |
| Flexibility | High |
| Embeddability | High |

*Table 2.0: Requirements-for-an-ideal-decision-making-system-for-mortgage-support*

**Chapter 3.0** **Justification of Design**

The tables below show the tabular representation of the factors considered in designing the KBS.

- Employment Type: shows how much security you have i.e. earning risk.

| Status | Definition |
|---|---|
| Unemployed | This set of people carry the maximum risk |
| Benefit | People leaving on government benefit |
| Self Employed | Mild risk due to self-governed income |
| Employed | Stable and confident people with prospect |
| Employed and Self-Employed | They can assess almost any amount. |

*Table 3.0: Employment Type*

- Credit Score: shows how great you are in managing your finances, will the applicant pay back?

We will be using the Equifax Credit Score Gauge

| Score | Band |
|---|---|
| 0—438 | Very Poor |
| 439—530 | Poor |
| 531—670 | Good |
| 671—810 | Very Good |
| 811—1000 | Excellent |

*Table 3.1: Equifax-Credit-Score( (Gary Hemming , n.d.)*

- Income level: shows how comfortable you are with mortgage repayment

| Amount Range | Band |
|---|---|
| Under £25,000 | Not very comfortable |
| Between £25,000 and £40,000 | Comfortable Earner |
| Over £40,000 | Affluent and Comfortable Borrower |

*Table 3.2: Income-Level*

- Criminal History: shows how upright/dependable you are, a window to the applicant's character

| | |
|---|---|
| Yes | Has a warning, court order, restriction e.t.c |
| No | Law abiding citizen with Good Character |

*Table 3.3: Criminal-History*

With all these we gauge our decision in three levels namely:

1. Ineligible: This decision points to a very weak applicant credibility
2. Under £40,000: This is the least possible approval for fair repayment credibility

3. Between £40,000 - £80,000: This decision is made for accountable and confident earners
4. Over £80,000: The uncapped amount for a highly credible applicant.

### 3.1 Structure Of The Expert System

Unemployed: People with no Jobs

| **Employment Status** | **Credit Score** | **Annual Income (X)** | **Criminal History** | **Mortgage Offer** |
|---|---|---|---|---|
| **Unemployed** | 0—438 | X <= £25,000 | Yes or No | Ineligible |
| | | £25k < X >= £40k | | |
| | | £40K < X | | |
| | 439 – 530 | X <= £25,000 | Yes or No | |
| | | £25k < X >= £40k | | |
| | | £40k < X | | |
| | 531 – 670 | X <= £25,000 | Yes or No | |
| | | £25k < X >= £40k | | |
| | | £40k < X | | |
| | 671 – 810 | X <= £25,000 | Yes or No | |
| | | £25k < X >= £40k | | |
| | | £40k < X | | |
| | 811 – 1,000 | X <= £25,000 | Yes or No | |
| | | £25k < X >= £40k | | |
| | | £40k < X | | |

***Table 3.4.1: Unemployed-People***

Benefit: People leaving on only governmental support

| **Employment Status** | **Credit Score** | **Annual Income (X)** | **Criminal History** | **Mortgage Offer** |
|---|---|---|---|---|
| **Benefit** | 0—438 | X <= £25,000 | Yes or No | Ineligible |
| | | £25k < X >= £40k | | |
| | | £40K < X | | |

| | | | | |
|---|---|---|---|---|
| | 439 – 530 | X <= £25,000 | Yes or No | |
| | | £25k < X >= £40k | | |
| | | £40k < X | | |
| | 531 – 670 | X <= £25,000 | Yes or No | |
| | | £25k < X >= £40k | | |
| | | £40k < X | | |
| | 671 – 810 | X <= £25,000 | Yes or No | |
| | | £25k < X >= £40k | | |
| | | £40k < X | | |
| | 811 – 1,000 | X <= £25,000 | Yes or No | |
| | | £25k < X >= £40k | | |
| | | £40k < X | | |

***Table 3.4.2: People-Leaving-on-Benefit***

Self-Employed: Business Owners

| **Employment Status** | **Credit Score** | **Annual Income (X)** | **Criminal History** | **Mortgage Offer** |
|---|---|---|---|---|
| **Self-Employed** | 0—438 | X <= £25,000 | Yes or No | Ineligible |
| | | £25k < X >= £40k | | |
| | | £40K < X | | |
| | 439 – 530 | X <= £25,000 | Yes or No | |
| | | £25k < X >= £40k | | |
| | | £40k < X | | |
| | 531 – 670 | X <= £25,000 | Yes or No | |
| | | £25k < X >= £40k | | |
| | | £40k < X | Yes | |
| | | | No | Y <= £40,000 |
| | 671 – 810 | X <= £25,000 | Yes or No | Ineligible |
| | | £25k < X >= £40k | Yes | |
| | | | No | Y<=£40,000 |
| | | £40k < X | Yes | Ineligible |

| | | | | |
|---|---|---|---|---|
| | | | No | Y<=£40,000 |
| | 811 – 1,000 | X <= £25,000 | Yes or No | Ineligible |
| | | £25k < X >= £40k | Yes | |
| | | | No | Y<£40,000 |
| | | £40k < X | Yes | Ineligible |
| | | | No | Y<£40,000 |

***Table 3.4.3: Business-Owners***

Employed People

| **Employment Status** | **Credit Score** | **Annual Income (X)** | **Criminal History** | **Mortgage Offer** |
|---|---|---|---|---|
| **Employed** | 0—438 | X <= £25,000 | Yes or No | Ineligible |
| | | £25k < X >= £40k | | |
| | | £40K < X | | |
| | 439 – 530 | X <= £25,000 | | |
| | | £25k < X >= £40k | Yes | |
| | | | No | Y<=£40,000 |
| | | £40k < X | Yes | Ineligible |
| | | | No | Y<=£40,000 |
| | 531 – 670 | X <= £25,000 | Yes or No | Y<=£40,000 |
| | | £25k < X >= £40k | | £80,000<= Y<= £40,000 |
| | | £40k < X | | |
| | 671 – 810 | X <= £25,000 | Yes or No | £80,000<= Y<= £40,000 |
| | | £25k < X >= £40k | | |
| | | £40k < X | | |
| | 811 – 1,000 | X <= £25,000 | Yes or No | £80,000<= Y<= £40,000 |
| | | £25k < X >= £40k | | |
| | | £40k < X | | |

***Table 3.4.4: Employed-People***

Employed and Self- Employed

| **Employment Status** | **Credit Score** | **Annual Income (X)** | **Criminal History** | **Mortgage Offer** |
|---|---|---|---|---|
| **Self Employed/Employed** | 0—438 | X <= £25,000 | Yes or No | Ineligible |
| | | £25k < X >= £40k | | |
| | | £40K < X | | |
| | 439 – 530 | X <= £25,000 | | |
| | | £25k < X >= £40k | Yes | |
| | | | No | Y<=£40,000 |
| | | £40k < X | Yes | Ineligible |
| | | | No | Y<=£40,000 |
| | 531 – 670 | X <= £25,000 | Yes or No | £40,000<= Y<= £80,000 |
| | | £25k < X >= £40k | | |
| | | £40k < X | | |
| | 671 – 810 | X <= £25,000 | | |
| | | £25k < X >= £40k | | |
| | | £40k < X | | |
| | 811 – 1,000 | X <= £25,000 | | |
| | | £25k < X >= £40k | | |
| | | £40k < X | No | £80,000<Y |

***Table 3.4.5: Business-Owners-who-are-also-employees***

## 3.2 Implementation

From my interview with the expert, he mentioned adding more features to my system to make it more robust like the banks.

### 3.2.1 ABHF (Abiola Home Finance) 2.0: Future Features Roadmap

- Age
- Property Type
- Down Payment
- Location of Property
- Marital Status/Family size
- Higher Mortgage Value

For ABHF 1.0, the system will make assessment based on the code representation for the most important features in mortgage banking.

1. Employment Status: These are represented by numbers, with 5 to 1 being the highest to lowest status respectively as shown below in the code implementation.

```
write('What is your employment status?'),nl,
write('1. Unemployed'),nl,
write('2. Benefit'),nl,
write('3. Self Employed'),nl,
write('4. Employed'),nl,
write('5. Self Employed/Employed'),nl,
write("Please enter '1' to '5'"),nl,
read(ES),nl,
```

***Fig 2: Employment Status Code Snippet***

**3.2.2. Credit Score:** Using one of the biggest credit bureaus as explained in Chapter 3, These are represented by numbers, with 5 to 1 being the Best to Poorest Status respectively as shown below in the code implementation (Lynnette Purda, 2022).

```
write('What is your current credit score?'),nl,
write('1. 0 - 438'),nl,
write('2. 439 - 530'),nl,
write('3. 531 - 670'),nl,
write('4. 671 - 810'),nl,
write('5. 811 - 1000'),nl,
write("Please enter '1' to '5'"),nl,
read(CS),nl,
```

***Fig 3: Credit Score Code Snippet***

**3.3.3. Criminality:** Depending on the person's status in the other features, the code representation for criminal history, 2 and 1 shows if the applicant has no record of crime or not respectively.

```
write('Do you have a criminal record?'),nl,
write('1. yes'),nl,
write('2. no'),nl,
write("Please enter '1' to '2'"),nl,
read(CH),nl,
```

***Fig 4: Criminal History Code Snippet***

**3.3.4. Annual Income:** These are represented by numbers, with 3 to 1 being the Highest to Lowest Income Level respectively as shown below in the code implementation.

```
write('What is your annual income?'),nl,
write('1. Up to £25000'),nl,
write('2. £25000 to £40000'),nl,
write('3. £40000 plus'),nl,
write("Please enter '1' to '3'"),nl,
read(AI),nl,
```

***Fig 5: Income Code Snippet***

**3.3.5. Recommendations:** These are given below as;

- ES = Employment Status
- CS = Credit Score
- AI = Annual Income
- CH = Criminal History
- M = Message to Applicant

```
        recommendation(M, ES, CS, AI, CH),write(M).

recommendation('Congratulations, you qualify for £80K and above ', ES, CS, AI, CH) :- ES = 5, CS = 5, AI = 3, CH = 2.
recommendation('Congratulations, you qualify for 40K to 80K ', ES, CS, AI, CH) :- ES = 5, CS = 5, AI = 2.
recommendation('Congratulations, you qualify for 40K to 80K ', ES, CS, AI, CH) :- ES = 5, CS = 4.

recommendation('Congratulations, you qualify for 40K to 80K ', ES, CS, AI, CH) :- ES = 5, CS = 3.

recommendation('Congratulations, you qualify for at most 40K ', ES, CS, AI, CH) :- ES = 5, CS = 2, AI = 3, CH = 2.

recommendation('Congratulations, you qualify for at most 40K ', ES, CS, AI, CH) :- ES = 5, CS = 2, AI = 2, CH = 2.

recommendation('Congratulations, you qualify for 40K to 80K ', ES, CS, AI, CH) :- ES = 4, CS = 5.

recommendation('Congratulations, you qualify for 40K to 80K ', ES, CS, AI, CH) :- ES = 4, CS = 4.

recommendation('Congratulations, you qualify for at most 40K ', ES, CS, AI, CH) :- ES = 4, CS = 3, AI = 1.

recommendation('Congratulations, you qualify for 40K to 80K ', ES, CS, AI, CH) :- ES = 4, CS = 3.

recommendation('Congratulations, you qualify for at most 40K ', ES, CS, AI, CH) :- ES = 4, CS = 2, AI = 3, CH = 2.

recommendation('Congratulations, you qualify for at most 40K ', ES, CS, AI, CH) :- ES = 4, CS = 2, AI = 2, CH = 2.

recommendation('Congratulations, you qualify for at most 40K ', ES, CS, AI, CH) :- ES = 3, CS = 5, AI = 3, CH = 2.

recommendation('Congratulations, you qualify for at most 40K ', ES, CS, AI, CH) :- ES = 3, CS = 5, AI = 2, CH = 2.

recommendation('Congratulations, you qualify for at most 40K ', ES, CS, AI, CH) :- ES = 3, CS = 4, AI = 3, CH = 2.

recommendation('Congratulations, you qualify for at most 40K ', ES, CS, AI, CH) :- ES = 3, CS = 4, AI = 2, CH = 2.

recommendation('Congratulations, you qualify for at most 40K ', ES, CS, AI, CH) :- ES = 3, CS = 3, AI = 3, CH = 2.
recommendation('We are sorry, you are not eligible at this time ', ES, CS, AI, CH) :- ES = 1.
recommendation('We are sorry, you are not eligible at this time ', ES, CS, AI, CH) :- ES = 2.
```

*Fig 6: Recommendations Code Snippet*

**3.3.6. Welcome and Goodbye Messages**: These section gives the Applicant a feel of home with a great welcoming and goodbye message represented in the code below.

**N.B.** The "style_check(-singleton)" is used to remove the negligible error, showing when I intentionally use a variable.

```
:- discontiguous main_menu_option/1.
:- style_check(-singleton).

start:-
    write('Welcome to Abiola Home Finance, pleased to meet you'),nl,
    write('We are here to help you get a mortgage that fits'),nl,
    menu.
```

*Fig 7: Welcome Message Code Snippet*

```
main_menu_option(2) :-
        write('We hope you change you mind and come back later. For now, enjoy the rest of your day!!').
```

*Fig 8: Goodbye Message Code Snippet*

## Chapter 4.0 Evaluation

### 4.1 Methods

Both quantitative and qualitative methods of evaluation were used.

#### 4.1.1 Techniques of Evaluation includes

a. **Formative:** I sort out help from Dr Annabel Latham, KBS Expert on several occasion to understand the ideal knowledge representative for the expert system. Furthermore, an expert AI model banker gave me ideas on how the mortgage model are derived intuitively. All these help in building project which is still undergoing further evaluation as I write this report.

b. **Summative:** At the end of the project, I hosted it on github and selected people of different social class represented test it.

c. **Process:** I am hoping for further feedbacks on features to add and process to optimize, as I am very open to making the system very efficient. This stage will be tested in few months if I get a placement within the banking industry or related field. I am also open to feedbacks from the Lecturer and examiner.

d. **Impact and Outcome Evaluation:** The expert system has a unique feature of “biasness" for younger applicants by placing trust in their potential while still requiring standard requirements from older applicants. The system's success or failure will be evaluated in 3 years after 300 initial users have been onboard and repayment plans are underway, to assess the effectiveness of the "bias" method.

### 4.2 Results

Using forward chaining seems straightforward at first until the knowledge of the mortgage AI model expert from RBC was inquired. I tried to use a weighted approach as shown in the diagram below for

| | | | |
|---|---|---|---|
| Weight | S/E | 4 | +4+4+2-0 – 6 |
| | E | 2 | |
| | S | 2 | +2+1+1+1 – 5 |
| | B | 1 | |
| | U | 0 | |
| Credit | 811—1000 | 8 | |
| | 671—810 | 6 | |
| | 531—670 | 4 | |
| Weight | 439—530 | 2 | |
| | 0—438 | 0 | |
| | | | |
| income | High | 2 | |
| | Medium | 1 | |
| | Low | 0 | |
| Criminal | High | +1 | |
| | Low | -1 | |
| | | | |

*Fig 9: fumbled weighted approach*

each factor considered (ascribing scores to each class) it failed the test as the idea did not consider human character and social life. Using both heuristics and logic gave a perfect representation of human needs and values with respect to the needs of my system.
Out of about 15 people considered for my result, analysis and discussion, every individual's outcome differed based on their scenario and livelihood (Serhad Sarica, 2023).

**Scenario 1**: A mortgage ineligible low-income applicant, with moderate credit score, criminal history and living on benefit.

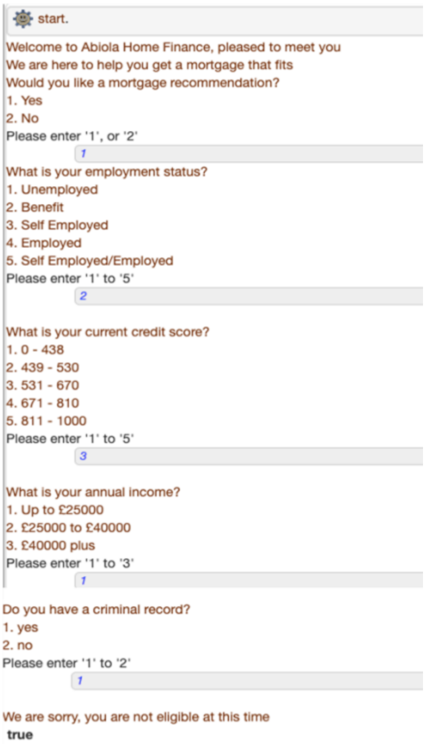


***Fig 10: An Ineligible Applicant***

**Scenario 2:** A £40,000 mortgage capped eligible medium-income business owner, with moderate credit score and zero criminal history.

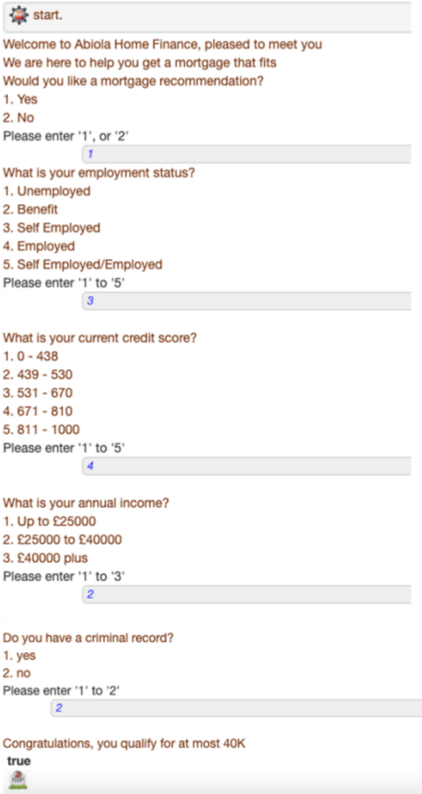


*Fig 11: A £40,000 Capped Mortgage Decision*

**Scenario 3**: An £80,000 capped eligible moderate-income employee, with the moderate credit score, and no criminal history.

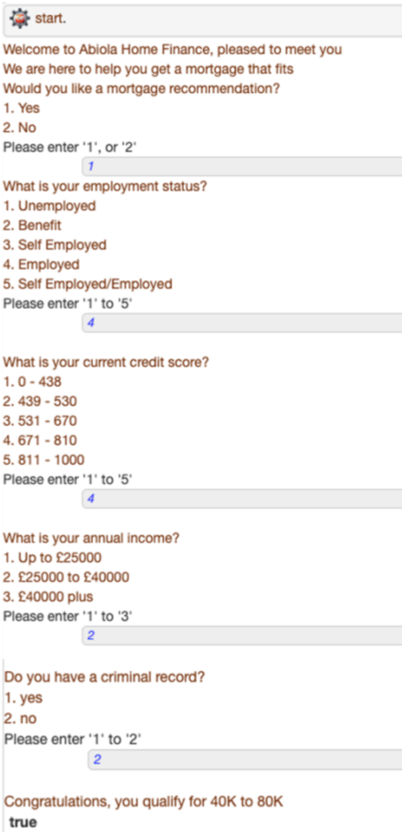


*Fig 12: A £80,000 Capped Mortgage Decision*

**Scenario 4**: A Business Owner with the highest income level, highest credit score, no criminal history and gainfully employed is eligible for an uncapped mortgage (Beyond £80,000).

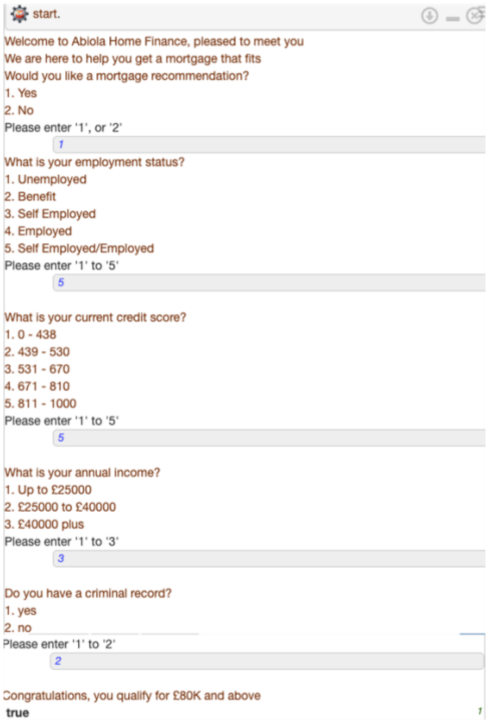


*Fig 13: An Uncapped Mortgage Decision*

## 4.3 Analysis

The table representation of the code shows that only one class of people can assess the highest mortgage range of over £80,000 to prevent unnecessary bad debt. The requirements for assessing standard mortgages differ as the ability to sustain them might not be available to everyone. The project was tested, and two categories of people would have filed complaints if the system was in commercial use.

- The Law-abiding, highest earning, self-employed class: These people have zero criminal records, almost 1,000 credit scores, huge income and still cannot access mortgage beyond £40,000. The explanation is simple, they will need to submit additional verification of their businesses else we will decline amounts beyond our risk aversiveness.
- Any other person who feels the system is unjust: The truth is, no system is 100% perfect. We will give those complaints adequate response and find a way to upgrade the system based on justified reasons.

## Chapter 5.0 Reflection

To be candid, when I started this project, I thought it would be easy considering my deep understanding of the KBS, the subject matter, the plenteous resources available and features to be considered. Surprisingly, I spent countless sleepless nights at the IT Zone section of the library, brainstorming on how to particularly build my knowledge representation tables. I had several calls with my peer, Ebere Ezenwaka and one on one sessions with Israel Amet. Ebere and I went through my codes together less so as Israel had to stay up late with me figuring out how to store my outcomes. I felt lonely at some points even, so I had my friends with me. I reached out to Somto, the AI model manager at RBC, my long-term friend from BSc. He helped me understand the table construction and gave much insight to the use of intuition rather than coded weights representation. That solved 30% of my sleepless nights.

Everything started coming together when I researched mortgage codes on github. There were so many, I picked one and studied it so well that I understood the patterns. I began writing mine. To cut the long story short, my mortgage expert system was born. Believe me, this is not the end as I have learnt a lot and I am still learning about dependent factors that could affect outcomes of mortgage applicants. My KBS Mortgage Expert System 2.0 will have 12 factors, combining predicated logic, heuristics, and numerical-weighted approach to make the project more versatile and robust with little bias.

## 5.1 Conclusion

From ages past, the property market has been a source of livelihood as well as the beginning of a family for many. Extending the opportunity to compete with older citizens for a share in the market is only fair because the younger generation most time contributes to society equally if not more than the elderly. This expert system though not yet perfect helps to give mortgage opportunity to the youths. As time progresses, feature updates will be released, and more feedback worked on to make the KBS great. This project not only helped in creating a new idea but shed lighter on the understanding of the mortgage sector.

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# Appendix

```
:- discontiguous main_menu_option/1.
:- style_check(-singleton).

%This code above removes all the singleton irrelevant errors.

start:-
        write('Welcome to Abiola Home Finance, pleased to meet you'),nl,
  write('We are here to help you get a mortgage that fits'),nl,
  menu.

%The lines above welcomes the applicant by writing out the message for them to choose

menu:-

  write('Would you like a mortgage recommendation?'),nl,
              write('1. Yes'),nl,
        write('2. No'),nl,
        write("Please enter '1', or '2'"),nl,
        read(X),
        main_menu_option(X).

%The menu on line 14 dislays the options 'Yes or no' to the Question on Line 16

main_menu_option(1) :-


              write('What is your employment status?'),nl,
              write('1. Unemployed'),nl,
        write('2. Benefit'),nl,
        write('3. Self Employed'),nl,
        write('4. Employed'),nl,
        write('5. Self Employed/Employed'),nl,
        write("Please enter '1' to '5'"),nl,
        read(ES),nl,

%This section above helps to display all the Employment Status (ES) Options
%and accepting query as ES from 1 to 5

              write('What is your current credit score?'),nl,
        write('1. 0 - 438'),nl,
        write('2. 439 - 530'),nl,
        write('3. 531 - 670'),nl,
        write('4. 671 - 810'),nl,
        write('5. 811 - 1000'),nl,
        write("Please enter '1' to '5'"),nl,
              read(CS),nl,

%This section above helps to display all the Credit Score (CS) Options,
%accepting query from 1 to 5
```

```
			write('What is your annual income?'),nl,
		write('1. Up to £25000'),nl,
		write('2. £25000 to £40000'),nl,
			write('3. £40000 plus'),nl,
		write("Please enter '1' to '3'"),nl,
			read(AI),nl,

%This section above helps to display all the Annual Income (AI) Options,
%accepting inputing from 1 to 3

			write('Do you have a criminal record?'),nl,
		write('1. yes'),nl,
		write('2. no'),nl,
		write("Please enter '1' to '2'"),nl,
			read(CH),nl,

%This section above helps to display all the Criminal History (AI) Options,
%accepts answers to queries by 1 or 2

		recommendation(M, ES, CS, AI, CH),write(M).

%This section above helps to display all the message (M)
%after considering the features stored above.

recommendation('Congratulations, you qualify for £80K and above ', ES, CS, AI, CH) :- ES = 5, CS = 5, AI = 3, CH = 2.

recommendation('Congratulations, you qualify for 40K to 80K ', ES, CS, AI, CH) :- ES = 5, CS = 5, AI = 3, CH = 1.

recommendation('Congratulations, you qualify for 40K to 80K ', ES, CS, AI, CH) :- ES = 5, CS = 5, AI = 2.

recommendation('Congratulations, you qualify for 40K to 80K ', ES, CS, AI, CH) :- ES = 5, CS = 4.

recommendation('Congratulations, you qualify for 40K to 80K ', ES, CS, AI, CH) :- ES = 5, CS = 3.

recommendation('Congratulations, you qualify for at most 40K ', ES, CS, AI, CH) :- ES = 5, CS = 2, AI = 3, CH = 2.

recommendation('Congratulations, you qualify for at most 40K ', ES, CS, AI, CH) :- ES = 5, CS = 2, AI = 2, CH = 2.

recommendation('Congratulations, you qualify for 40K to 80K ', ES, CS, AI, CH) :- ES = 4, CS = 5.

recommendation('Congratulations, you qualify for 40K to 80K ', ES, CS, AI, CH) :- ES = 4, CS = 4.

recommendation('Congratulations, you qualify for at most 40K ', ES, CS, AI, CH) :- ES = 4, CS = 3, AI = 1.
```

recommendation('Congratulations, you qualify for 40K to 80K ', ES, CS, AI, CH) :- ES = 4, CS = 3.

recommendation('Congratulations, you qualify for at most 40K ', ES, CS, AI, CH) :- ES = 4, CS = 2, AI = 3, CH = 2.

recommendation('Congratulations, you qualify for at most 40K ', ES, CS, AI, CH) :- ES = 4, CS = 2, AI = 2, CH = 2.

recommendation('Congratulations, you qualify for at most 40K ', ES, CS, AI, CH) :- ES = 3, CS = 5, AI = 3, CH = 2.

recommendation('Congratulations, you qualify for at most 40K ', ES, CS, AI, CH) :- ES = 3, CS = 5, AI = 2, CH = 2.

recommendation('Congratulations, you qualify for at most 40K ', ES, CS, AI, CH) :- ES = 3, CS = 4, AI = 3, CH = 2.

recommendation('Congratulations, you qualify for at most 40K ', ES, CS, AI, CH) :- ES = 3, CS = 4, AI = 2, CH = 2.

recommendation('Congratulations, you qualify for at most 40K ', ES, CS, AI, CH) :- ES = 3, CS = 3, AI = 3, CH = 2.

recommendation('We are sorry, you are not eligible at this time ', ES, CS, AI, CH) :- ES = 1.

recommendation('We are sorry, you are not eligible at this time ', ES, CS, AI, CH) :- ES = 2.

recommendation('We are sorry, you are not eligible at this time ', ES, CS, AI, CH) :- ES = 3, CS = 1.

recommendation('We are sorry, you are not eligible at this time ', ES, CS, AI, CH) :- ES = 3, CS = 2.

recommendation('We are sorry, you are not eligible at this time ', ES, CS, AI, CH) :- ES = 3, CS = 3, AI = 1.

recommendation('We are sorry, you are not eligible at this time ', ES, CS, AI, CH) :- ES = 3, CS = 3, AI = 2.

recommendation('We are sorry, you are not eligible at this time ', ES, CS, AI, CH) :- ES = 3, CS = 3, AI = 3, CH = 1.

recommendation('We are sorry, you are not eligible at this time ', ES, CS, AI, CH) :- ES = 3, CS = 4, AI = 1.

recommendation('We are sorry, you are not eligible at this time ', ES, CS, AI, CH) :- ES = 3, CS = 4, AI = 2, CH = 1.

recommendation('We are sorry, you are not eligible at this time ', ES, CS, AI, CH) :- ES = 3, CS = 4, AI = 3, CH = 1.

recommendation('We are sorry, you are not eligible at this time ', ES, CS, AI, CH) :- ES = 3, CS = 5, AI = 1.

recommendation('We are sorry, you are not eligible at this time ', ES, CS, AI, CH) :- ES = 3, CS = 5, AI = 2, CH = 1.

recommendation('We are sorry, you are not eligible at this time ', ES, CS, AI, CH) :- ES = 3, CS = 5, AI = 3, CH = 1.

recommendation('We are sorry, you are not eligible at this time ', ES, CS, AI, CH) :- ES = 4, CS = 1.

recommendation('We are sorry, you are not eligible at this time ', ES, CS, AI, CH) :- ES = 4, CS = 2, AI = 1.

recommendation('We are sorry, you are not eligible at this time ', ES, CS, AI, CH) :- ES = 4, CS = 2, AI = 2, CH = 1.

recommendation('We are sorry, you are not eligible at this time ', ES, CS, AI, CH) :- ES = 4, CS = 2, AI = 3, CH = 1.

recommendation('We are sorry, you are not eligible at this time ', ES, CS, AI, CH) :- ES = 5, CS = 1.

recommendation('We are sorry, you are not eligible at this time ', ES, CS, AI, CH) :- ES = 5, CS = 2, AI = 1.

recommendation('We are sorry, you are not eligible at this time ', ES, CS, AI, CH) :- ES = 5, CS = 2, AI = 2, CH = 1.

recommendation('We are sorry, you are not eligible at this time ', ES, CS, AI, CH) :- ES = 5, CS = 2, AI = 3, CH = 1.

%This section above stores all the possible scenarios for all features considered

main_menu_option(2) :-
write('We hope you change you mind and come back later. For now, enjoy the rest of your day!!').

%The secton above displays a farewell message if the applicant changes their mind on getting an assessment.