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TFE22-197 - Social Impact and Social Acceptance. What is the reaction of the Belgian population to alternative fuels and renewable energy?

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Abstract

In a world where people are becoming more and more aware of environmental problems, changes in human energy consumption are inevitable. The transportation sector is currently responsible for about 23% of greenhouse gas emissions in Belgium [1] making it an important sector to a focal point.
To be more precise, this thesis focuses on the Belgian population's social impact and social acceptance of alternative fuels and renewable energy. To centralize research, Brussels and Wallonia were chosen as the target area to determine the level of acceptance of hydrogen cars.
The goal is to develop a model to determine the most interesting policies that give the best social acceptance to a group of people. Furthermore, the objective is to identify a profile type for buyers that would potentially be interested in purchasing a hydrogen car.

Analyzing social acceptance represents a sizable challenge and it is imperative to have a wide range of data to build a model and draw conclusions. Most people remain skeptical about the conventional car as a possible solution to environmental problems and search for an alternative solution. Although most respondents are aware of hydrogen as an energy source, they feel they have inadequate or limited knowledge of this subject. 75% of the population does not believe that hydrogen is a renewable resource although a small majority think that it would go some way to managing environmental problems. There is much confusion about this, and the public would like to be better informed about it. Another critical factor that is crucial if this new technology is accepted, is for relevant and adequate infrastructures to be put in place.

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Introduction

Climate change is becoming a significant issue for many people. COP 26, which was the 2021 United Nations climate change conference, took place at the beginning of November 2021, and the goals set by COP 26 will require considerable change. As a European country, Belgium aims for total carbon neutrality by 2050, with a reduction of 55% in carbon emissions by 2030 [2]. Every sector will have to play its part in reducing pollution if this goal is to be achieved.

For the last few months, fuel prices have continued to rise, and, although most people consider this to be a problem, it could potentially be turned into a favorable situation. If prices continue to increase, it will undoubtedly encourage people to find alternative forms of transport to conventional cars, such as hydrogen or electric vehicles.

In this master thesis, the focus will be on research on hydrogen cars: the goal is to study the social acceptance of this new technology. A machine learning model is developed to predict acceptance within a targeted group of people and identify which policies need to be implemented to improve acceptance depending on the specified group.

The reason why the study is done on hydrogen cars is that the efficiency of electric cars is often questioned: the long time needed to recharge the battery, the limited distance they can travel before recharging, and the problems associated with cold weather for the battery [3]. Furthermore, politicians' opinions on electric cars are not convincing, as explained later, and it seems interesting to find out how the subject is perceived in Belgium.

Hydrogen appears to be an excellent technological choice in the context of development because it could represent near-zero carbon production [4]. The European Commission wants to develop hydrogen technologies to achieve carbon neutrality in 2050. In Europe, 28 countries have already signed to promote hydrogen technologies, and governments will additionally establish additional measures to increase the use of hydrogen [2].

Master Thesis Outline

The first chapter of this thesis is dedicated to setting the context; introducing hydrogen, presenting the global context of hydrogen, and then making a more detailed analysis of Belgium. Then, the research is oriented toward hydrogen cars, and a comparison between hydrogen and electric vehicles is made.

The second chapter is dedicated to machine learning. First, social acceptance is defined, and the study performed is described. Then, the general results are presented. The predictive model is designed to predict people's opinions on hydrogen cars. A second model is performed to verify the relevance of the models used.

In chapter three, the various existing policies are analyzed and compared according to specific characteristics such as the age of those surveyed or where participants live.

To finish, there is a discussion about the work and future work.

Chapter 1

General Context

1 Hydrogen

Hydrogen is the first chemical element, expressed with the letter H symbol on the periodic table. In the typical language, hydrogen is represented by dihydrogen (H_2) in its gaseous form. Hydrogen can be produced in several different ways. The grey hydrogen is made using fossil fuels (with CO_2 emissions), the blue hydrogen is hydrogen developed using carbon capture and storage (emits fewer greenhouse gases than grey hydrogen) and the green hydrogen is created using renewable energies [5].

Green hydrogen appears to provide an excellent solution in the energy transition. As shown in the figure below, clean energies (such as wind and solar power) are used to perform electrolysis in water $2H_2O \rightarrow 2H_2 + O_2$, allowing hydrogen to be produced. After production, the gas can be compressed and transported [5].

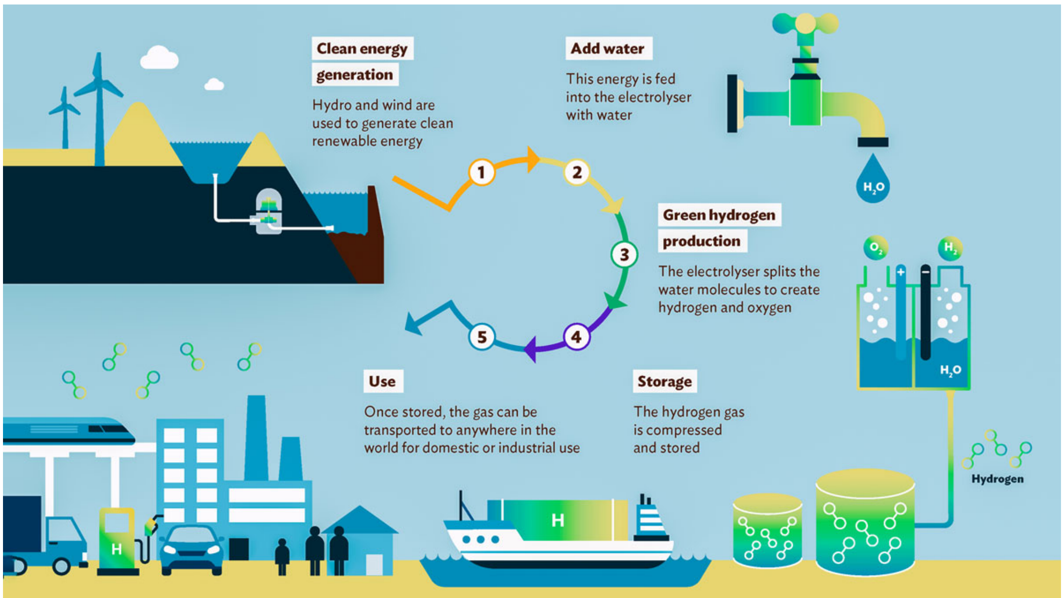

Figure 1.1: Production of green hydrogen [6]

2 Hydrogen in an International Context

As mentioned above, the European Commission has decided on a strategy for green hydrogen and wants it to be used on a large scale by 2030 [2]. But what do other countries think?

In the United Kingdom, the government has defined a hydrogen strategy to reduce natural gas consumption and wants to develop low-carbon hydrogen production by 2030 [7].
In the USA, President Biden has also expressed a desire to develop green hydrogen in collaboration with FCHEA (The Fuel Cell and Hydrogen Energy Association). America believes hydrogen is a part of the energy transition phase [8] and expects hydrogen to represent 14% of energy demand by 2050. Additionally, there is a goal to reduce carbon emissions by 16% and Nitrogen Oxide emissions by 36% [9].
China is another country that has highlighted hydrogen in its five-year plan (2021-2025) and has said that it wants to develop more than 1000 hydrogen stations by 2030 [10].
Russia has developed its hydrogen strategy and aims to become a world leader in hydrogen production and extraction by 2035 [11].

In a nutshell, many countries nowadays need a hydrogen development strategy. A «crowd movement» regarding this new energy is being created worldwide.

2.1 Belgium

Belgian politicians came up with a new hydrogen strategy at the end of 2021, and the Belgian government has deemed hydrogen technology crucial if the country is willing to become carbon neutral by 2050. The European Commission also recognizes the importance of hydrogen, and a collaboration between European countries will be reinforced. Belgium wants to be «a hydrogen imports and transit hub» and intends to continue to be a leader in hydrogen technology [12].

Figure 1.2: Belgium's Hydrogen strategy [12]

Belgium's government has presented the sustainable development goals [13] aside from the United Nations that form the strategy. It is expected that these goals will achieve a more sustainable future worldwide. Six sustainable development goals will be considered:

- Goal 6: clean water and sanitation;
- Goal 7: affordable and clean energy;
- Goal 8: decent work and economic growth;
- Goal 9: industry, innovation, and infrastructure;

- Goal 12: responsible consumption and production;
- Goal 13: climate action;
- Goal 16: peace, justice, and strong institutions;
- Goal 17: partnerships.

As illustrated in *Figure 2*, the Belgian hydrogen strategy considers private means of transport less critical than others. The Belgium government considers that «the battery-electric solution» is the most appropriate option for private cars in this strategy.

Why was this choice made? As set out by a minister's office, different arguments have been put forward:

- «The electric car's efficiency is about 70 to 80%, while that of the hydrogen car is 30 to 35%. Belgium does not have enough renewable sources to meet its demand. In such a context, energy is precious».
  This argument seems to be an economic one. Giving an environmental review is never worth considering a single factor. For example, if the global carbon footprint is considered, hydrogen cars are less consistent than electric ones [14]. An overview is always needed to analyze the various technologies consistently.
- «The adoption of electric vehicles requires a change in our habits but is not insurmountable. New technologies help us greatly (digitalization, battery improvements, fast charging)».
  This second piece of advice will be discussed later, but as already mentioned, many people do not see electric cars as the solution.

Not being convinced by politicians' arguments, it would be interesting to identify with others resources the citizens' acceptance of this technology.

3 Hydrogen Cars

Hydrogen cars use a chemical transformation of dihydrogen and use this transformation as motive power. In the same way as electric cars, this vehicle is part of the family of fuel cell electric vehicles (FCEV) and does not emit greenhouse gases [5].

Many different car brands are now looking to this new technology: including Hyundai, Toyota, BMW, and Jaguar. Other brands have developed this technology for commercial vehicles or trucks rather than for private use vehicles. Therefore, these vehicles are heavier and less suited to running on electricity [15].

The Toyota Mirai (December 2014) [16] was one of the first hydrogen cars launched globally. The car can travel 550 km on a full battery and costs about e78.900. The new version (2021) is cheaper to buy than in 2014 and is more efficient than the earlier model. This last model won the «best alternative energy» award at the AMAM eTrophies on June 2, 2022 [17].

The Korean Company Hyundai has also produced a hydrogen-powered vehicle's second version (Nexo (2022) [18]) to meet growing car demand using the latest fuel-cell technology. It can cover 700 km on a fully charged battery but has the same characteristics as a conventional car.

BMW will join the trend of producing hydrogen cars and launch the iX5 hydrogen car in 2022 [19], a powerful car with similar battery life to the Toyota Mirai.

Since 2014, the market has expanded regarding the number of hydrogen cars available: many different brands are now producing them, and prices are decreasing, making them more attractive.

However, this sector is still competing with electric cars: as said above, the electric car performs better than its hydrogen counterpart, but some points are worth comparing for both types of cars. Hybrid cars will not be considered since the goal is to compare two competing types of cars that can run entirely on renewable energy.

3.1 Comparison between Hydrogen Cars and Electric Ones

The main argument against hydrogen cars is the fact that more modifications are necessary to convert a conventional car to run on hydrogen.
The following figure shows that the electricity generated is directly available in an

electric car's engine, whereas additional steps are necessary when using hydrogen. The electricity must be transformed into hydrogen using electrolysis, and then, the hydrogen must be compressed or liquefied for transportation, which can be converted back into energy. [5].

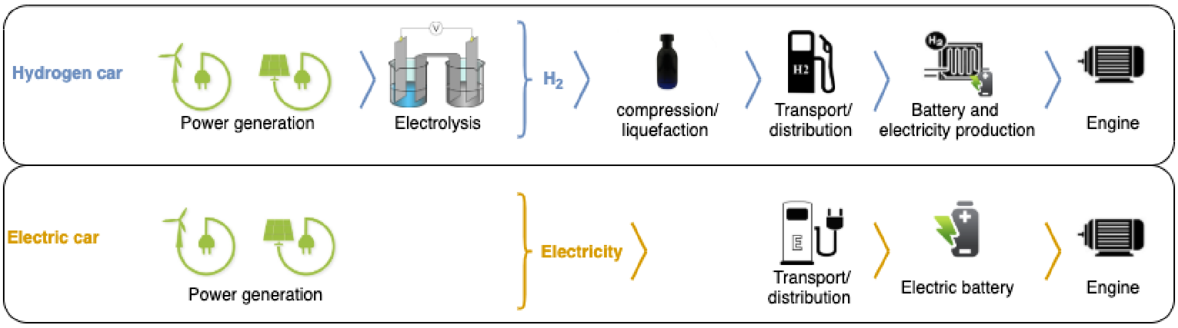

Figure 1.3: Simplified diagram comparing the different stages for electric and hydrogen cars.

Using the energy efficiency factor to compare these two different types of cars, electric cars win hands down as the added steps needed for hydrogen cars cause an energy loss.
Another important measure was to compare the global carbon footprint. This factor is based on the life cycle analysis and all emissions from the manufacturing to the end of life. In this instance, the hydrogen car performed better than the electric one [14].

The population still seems reluctant to convert to electric cars and even if there are numerous advantages to them, many people remain hesitant about accepting them principally due to the time it takes to recharge the battery, their lack of power, and the low number of kilometers possible even with a full battery. In contrast, hydrogen solves these problems and, in addition, the issue of intermittent stalling due to renewable energies.
These properties are carried through to hydrogen cars. However, hydrogen cars have two additional problems: electric shocks and the flammability of the fuel [20].

As is often the case, there is no single solution to a problem, but hydrogen cars fare well in terms of the energy transition.

Chapter 2

Predictive Model of Social Acceptance of Hydrogen Car

1 Definition of Social Acceptance

«Social acceptance is an attitude towards an issue within a group of people» [21].

Many authors have studied social acceptance. The following paragraphs summarize the main ideas obtained in the various articles of Kraeusel J. and Möst D. (2012) [21], Komendantova N. and al. (2021) [22] and Motz A. (2021) [23].

Social acceptance increases with age and education. Older people or people with a higher level of education generally agree to pay 10% more if the energy comes from a renewable source. Another point is that, in general, males have more knowledge about renewable energy than females and are more critical when buying something, whereas women are more concerned and have a better acceptance.

In addition, the residential zone can also affect social acceptance. Last summer saw many environmental disasters, and many people lost their homes. These emergencies trigger reflection, which generally results in better social acceptance.

Another aspect to be considered is energy democracy. Energy democracy is a social movement concerned with energy supply and demand. People want to be involved in reflection on energy policies and expect to participate in the decisions regarding sustainable energy transition. Theoretically, being a part of this change should lead to improved social acceptance.

The way people are informed is also an important factor and can influence decisions. If the information is correctly presented, it can make more people aware and increase social acceptance. On the other hand, a poorly written or researched article negatively influences some people resulting in a reluctance to accept new technology.

2 Survey Analysis

With a clear understanding of social acceptance, a study was conducted from January to April 2022 [24]. The questions in the study were put together using the literature and the *HYACINTH project* [25]. The project aimed to contribute to a deeper understanding of the social acceptance of hydrogen technologies across Europe. The project organizers wanted to study how the citizens would react to new technologies and policies, with a principal focus on hydrogen cars.

This study was intended for the Wallonia and Brussels population as I felt my Dutch knowledge was not good enough to create a study in Flanders and research is known to be more challenging in this region. Moreover, since Belgium is a country with several regional differences, it seemed logical to differentiate between the regions.

This study was composed of three parts. First, there were some demographic questions to identify the profile of survey respondents. Secondly, standard questions were asked about degrees of hydrogen acceptance and how people evaluated its importance compared to other technologies. Lastly, some questions were asked to discover the importance of different characteristics of a hydrogen car for respondents and different policies that they would like to see put in place.

The survey was shared on social networks multiple times to obtain a maximum number of replies. This method increased the chance of having a wide range of respondents who were ill-informed about hydrogen or who could be convinced about this technology. This wide range meant a range of different answers were potentially possible.

2.1 Overall Results

Results were based on a small proportion of the population: more than 300 responses were obtained for Wallonia and Brussels. However, in these results, many demographic differences were demonstrated. It was thought essential to begin by identifying similarities between people. After that, the results more specific to hydrogen cars will be presented.

Unfortunately, as represented in the graphic below, about 60% of the answers come from the province of Liege, making it challenging for the subsequent steps to identify anomalies between areas.

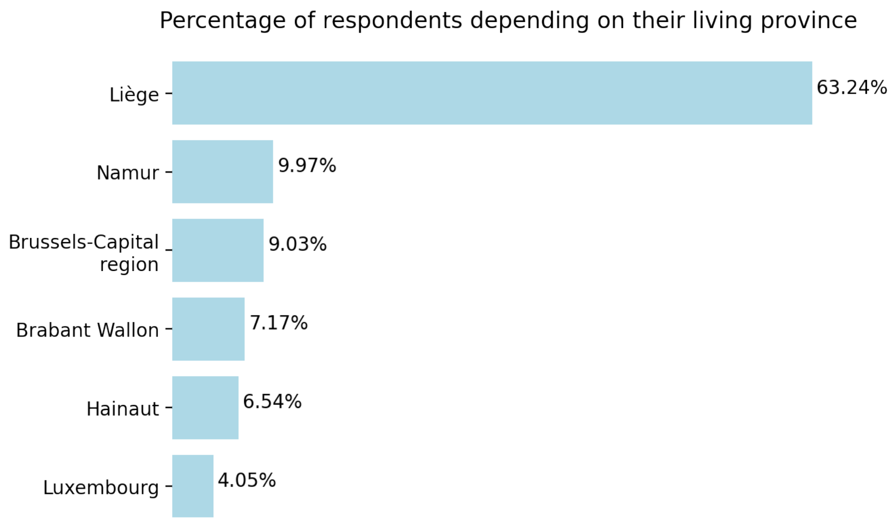

Figure 2.1: Survey - Distribution of respondents between the five provinces of Wallonia and the Brussels-Capital region

When analyzing where participants lived, nearly 40% came from the outskirts or from city center with slightly more than 20% living in the countryside (figure not shown).

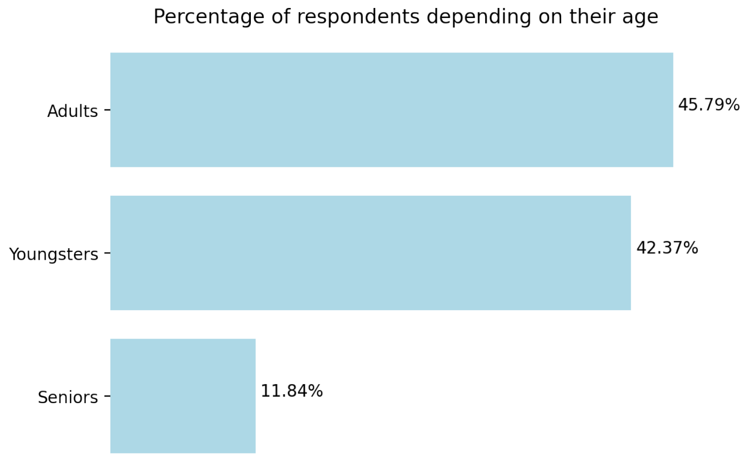

Figure 2.2: Survey - Distribution of respondents among three age groups (youngsters, adults, and seniors)

The participants were sorted into three categories: youngsters between 18 and 25 years old, adults between 26 and 65 years old, and seniors over 65. The distribution of participants was more or less the same for youngsters and adults but was lower for seniors.

2.1.1 Comparison of Different Car Technologies

The following question was to ask people if they believed that hydrogen cars were a better, equal, or worse solution than conventional, hybrid, electric, or natural gas cars.

The results are illustrated in the following figures.

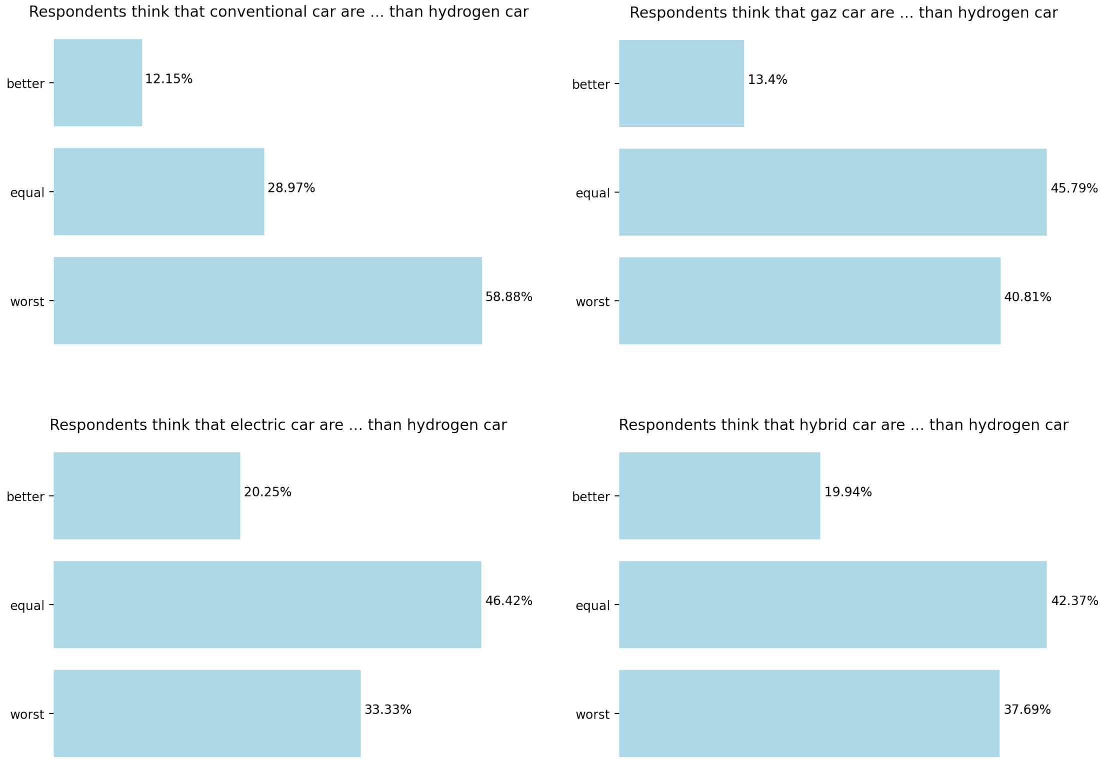

Figure 2.3: Comparison of the appreciation of the different types of cars compared to the hydrogen cars

A large majority of people surveyed believed that conventional cars were a worse option than hydrogen ones, while a minority (12.15%) thought they were better.

When comparing the different car technologies, the opinions were mixed, but the trend was the same for electric and hybrid cars. Slightly less than half considered the technologies equal, with about 35% considering electric or hybrid cars were worse than hydrogen ones. Roughly 20% thought they were better. Gas cars were not considered a viable solution compared to hydrogen cars. Again, half of them felt these two technologies to be equal, with few of them considering gas cars to be better than hydrogen cars...

The current system, dominated by conventional cars, is slowly evolving toward a technology change. However, opinions are strongly mixed, and many people remain confused.

2.1.2 Knowledge of Hydrogen as an Energy Source

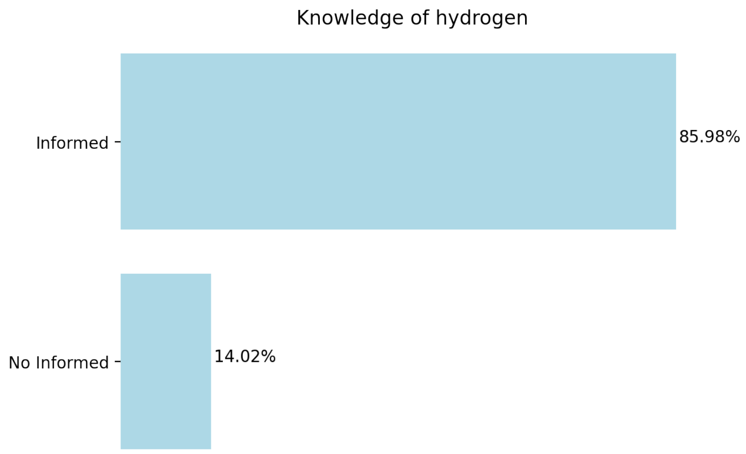

Figure 2.4: Survey - Estimation of the percentage of respondents who are either informed or not informed about hydrogen cars

The first interesting observation came from examining the percentage of people aware of hydrogen as an energy source. A great surprise was that 18% of people were not well-informed on the subject. People living in Brussels seem more informed than in other provinces, while people from Hainaut appeared to be the least knowledgeable about this technology.

A lack of information and communication around the subject of hydrogen was directly perceived in the answers given by participants. Interestingly, over 60% of respondents wanted to be better informed about this technology. It could also be interesting to have a view of their knowledge later.

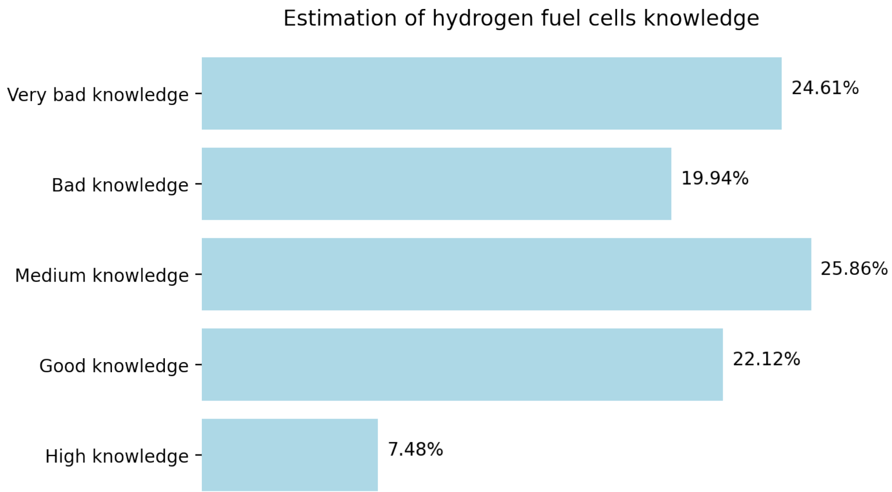

Figure 2.5: Survey - Estimation of the evaluation of respondent's knowledge about hydrogen on five levels

A majority of people felt they had limited knowledge of hydrogen, with only 26% considering themselves to be highly knowledgeable. However, this percentage of knowledge increased when only people working in the environmental sector were considered. Then, this percentage increased to more than 50%. Environmental workers represented 14% of the respondents.

The percentage of respondents considering they had a medium level of knowledge followed the same distribution as environmental workers for the global answers (figure not shown).

About 25% of those surveyed thought they were very ill-informed including one person working in the environmental sector. They were the only participants who described themselves as having a severe lack of knowledge.

2.1.3 Hydrogen: a Possible Solution for Environmental Problems?

This section evaluated the hope of respondents that hydrogen production could be helpful in the ecological transition.

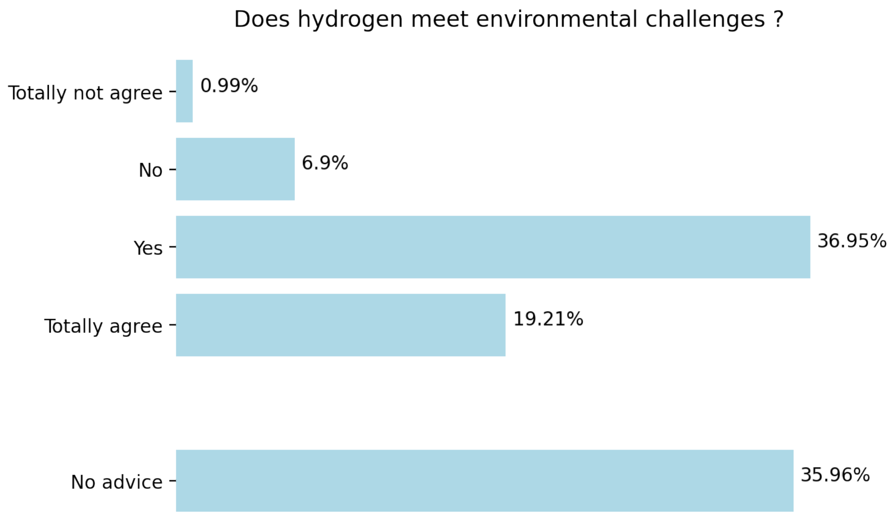

Figure 2.6: Survey - Estimation of the belief in hydrogen to face environmental problems

Most respondents, about 55%, agreed that hydrogen could meet environmental challenges (considering responses either «Yes» or «Totally agree»). Interestingly, very few people do not agree with this statement.

If the results obtained were refined by considering only the workers in this sector (appendix [**A**]), the acceptance obtained becomes greater as about 60% of respondents rated H_2 as a good or very good solution for environmental challenges. Of the remainder, 25% of them had no opinion and only 14% did not agree, although no one totally disagreed with this solution.

Having made these observations, the following step is to predict the acceptance level of hydrogen cars in the Wallonia and Brussels regions. If it possible to predict the acceptance of hydrogen-powered cars within a population group, it can, in theory, make it easier to put the necessary policies in place to increase and support the development of this new technology.

The first step in this process is a machine learning task developed to try and predict to what extent people believe in this technology to meet the environmental challenges currently being faced. After, some description and analysis of policies were carried out to see if the results obtained could be influenced, and to identify a specific «typical population» facing this new technology.

3 A Predictive Model for Opinions about Hydrogen Cars

This section aims to predict to what degree respondents believed hydrogen could solve current environmental problems. To do this, the response variable, containing five categories ranging from « *Totally disagree*» to « *Totally agree*» (score from 1 to 5) was added. Nevertheless, it was decided to reduce the number of categories predicted to three to have a more comprehensive answer.
In this way, the answer to the question: «Do we think that hydrogen cars can help to meet environmental problems?» had a choice of three responses: «Yes» «No advice» and «No».
The following figure illustrates the plan for the next steps described below.

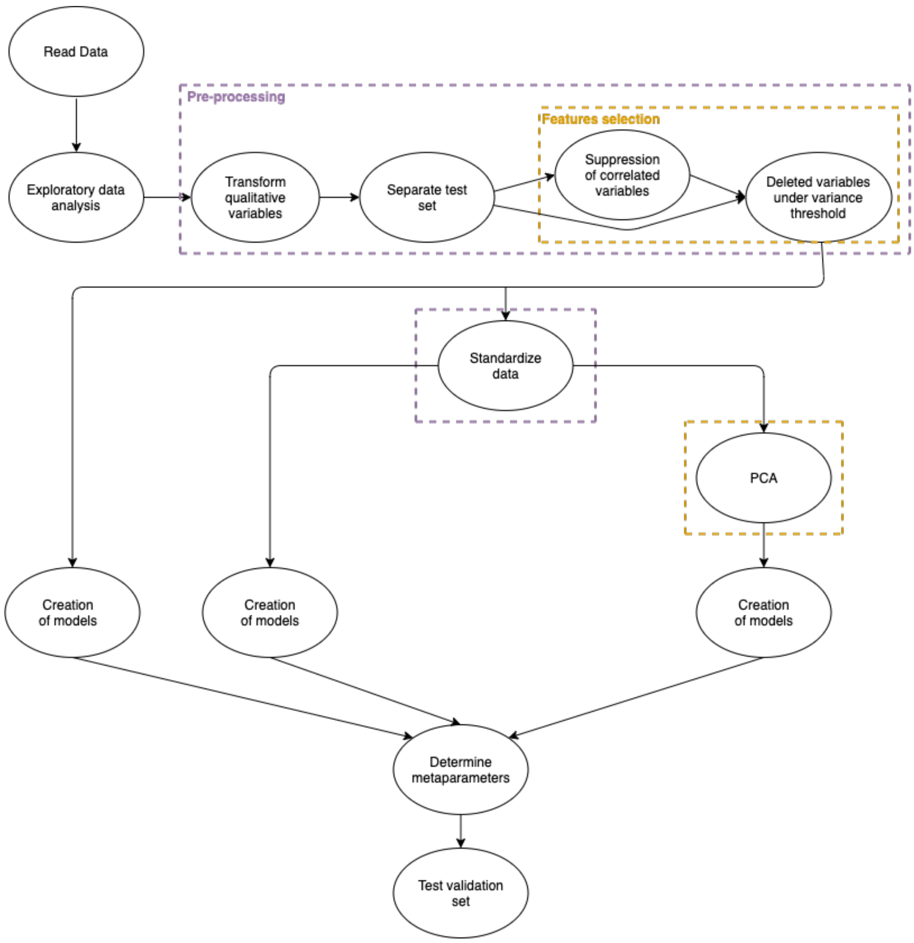

Figure 2.7: Machine learning steps

3.1 Preprocessing Step and Data Visualization

The second step was to enable the given features to be studied, remove any redundant columns, and find a clean dataset to develop suitable models from [26].

3.1.1 Data Visualization

This step used t-distributed stochastic neighbor embedding (t-SNE), using data after the preprocessing done in 3.1.2. This method allowed a non-linear dimensionality reduction technique to visualize high-dimensional data in a low-dimensional space. This made it possible to identify similarities between each of the data points [27].
The data points were plotted on two dimensions using three different families. The axes had no precise signification and simply represented the two dimensions. However, some points that appeared far from their neighbors, such as the red one on the left, could be considered outliers.

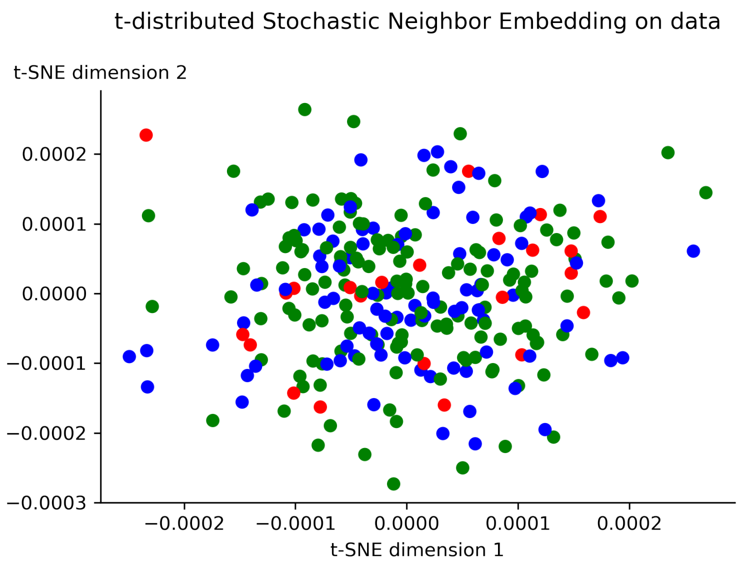

Figure 2.8: ML - Representation of data points from the survey into two dimensions using t-distributed Stochastic Neighbor Embedding

Unfortunately, it was difficult to identify any clusters in this figure, all the colors were mixed, and no similarities could be identified.

3.1.2 Transformation of Qualitative Variables into Quantitative Ones

To use the collected variables in the machine learning task, variables needed to be quantitative, which was not the case. The one-hot encoding method was chosen to give binary variables to obtain usable variables. Variables were converted using the *get_dummies* function in the pandas' library, paying attention to avoid the dummy variable trap [28]. Dummy variable trap arrives when there are more variables than necessary, and when variables are multi-collinear. For example, the *'livingPlace'* had three possible answers: *'in the city center'*, *'in the periphery'*, *'in the countryside'*. Applying a transformation using the *get_dummies* function results in three binary variables; however, only two are necessary.

3.1.3 Test Set

Next, data have to be separated into two sets: one for training and one for testing. The training set is to be used for training models. After the training task, the test set would allow any predictions to be verified at the end of the work. It was decided to make this group from 20% of the original set. The other 80% would serve to train and validate the model.

3.1.4 Features Selection

The next step is to select the features, which would allow the creation of a new and smaller set of features capturing the most relevant information. By including this step, it was expected that the curse of dimensionality would be avoided: using one-hot encoding would enable the number of features to be significantly increased. Different preprocesses were tested and are explained in the following paragraphs.

Preprocess 1 continued the analysis by researching multi-collinearity. To study this, a correlation matrix was plotted (appendix [**B**]). When variables had a value greater than -0.5 or 0.5, they were said to be highly correlated and therefore removed from the dataset [29]. Next, the Variance Threshold function, available in the sklearn library, allowed low-variance features to be removed. In other words, it enabled features that had lower variance than a certain threshold to be deleted.

Preprocess 2 only used the Variance Threshold function for feature selection.

Two different thresholds were denoted for these preprocesses. However, the variance threshold failed to consider the relationship between features. It was important to verify that the variance threshold improved performance compared to the model without preprocessing [30] (the highest score obtained without any preprocessing step was 55%).

3.2 Model Training

Depending on the algorithm used, some preprocessing had to be added before training the model. To explain this in greater detail, the three branches shown in Figure 3.7 will be described.

The same procedure was carried out for each model.
First, the Gridsearch method was used to tune their meta-parameters. This method, available in the sklearn library, facilitated finding the best combination of hyperparameters which gave the highest level of accuracy [31].
Secondly, the K-fold cross-validation method was employed to calculate accuracy. This method separated the data into k sets and calculated the mean accuracy obtained by using two different sets each time; one for the validation set, and the other for the training set. This provided an average of the accuracy despite potential differences in the data sets [32].

3.2.1 First Branch

As shown in the diagram, in the first branch, models were immediately trained. The following models do not need to have standardized data. The models which were tested were decision-tree and random-forest. They were two supervised algorithms, called tree-based machine learning algorithms methods commonly used in machine learning. Random-forest allows for the testing of a large number of random decision-trees. They are used to make a classification task.

3.2.2 Second Branch

In this branch, data needed to be scaled: this enforces feature to hence some mean and variance so there is no dominant variable.

Different models were tested:

– Logistic regression: Logistic regression is a classification problem. It is used to predict binary variables, but this algorithm can be adapted using the *multi_class* parameter with either «*auto*» or «*multinomial*» setting [33].

– SVC is a support vector machine for classification tasks. This method aims to return the «best fit» hyperplane that categorizes the data [34].

– MLPClassifier: This method, called multilayer perceptron, is the simplest neural network. It has three layers: input, hidden, and output layer, and used the backpropagation technique for the training task [35].

– KNeighborsClassifier: The KNN is based on the k nearest neighbors to make predictions, using feature distances to predict new values [36].

3.2.3 Third Branch

In this last branch, the Principal Component Analysis (PCA) method was applied to reduce dimensionality [37]. PCA allows for the reduction of a set of variables by retaining most of the information. Before PCA can be applied, the variables need to be standardized: this can be done using the StandardScaler function.

Plotting the cumulative variance, obtained from the function of the number of components taken, was done to determine the optimal number of components required to use PCA.

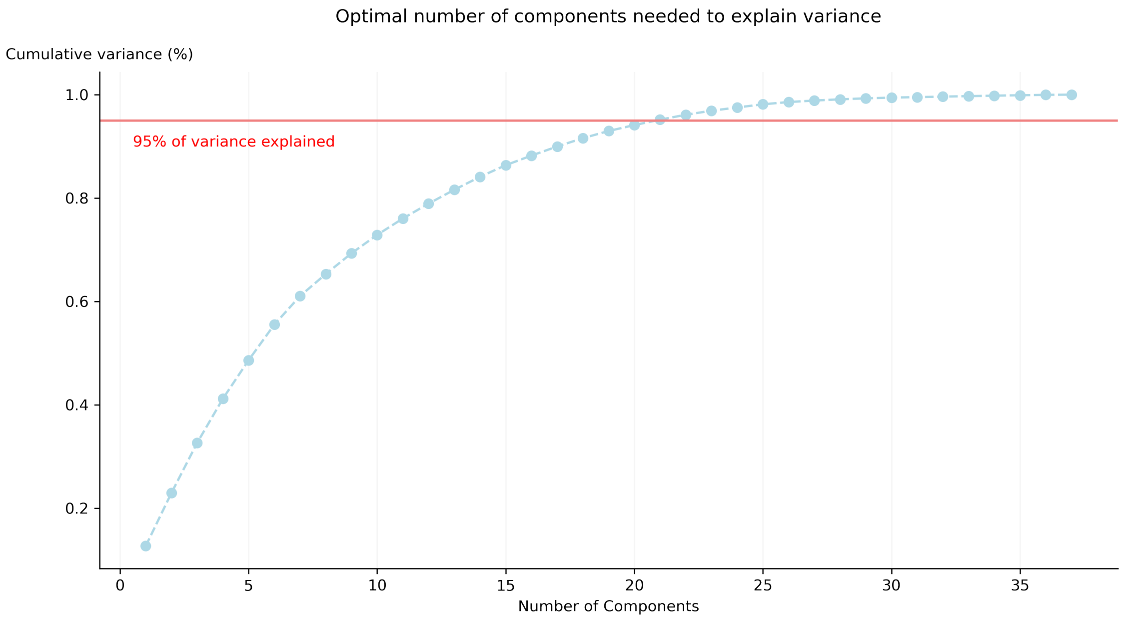

Figure 2.9: ML - Determination of the optimal number for PCA of components enabling a description of the variance at 95%

As shown on the graphic, the cumulative variance converges at twenty-one components, at this stage about 95% of the variance was explained. This was the number of components taken for preprocessing.

3.2.4 Comparison between Different Models

To evaluate models, the score used is the accuracy. It is a metric that is often used to assess model performance. In machine learning, accuracy is a way of determining whether data points are correctly classified or not. This means that accuracy is equal to the number of data points that are correctly classified over all the data points [38].

	Preprocess 1 (thres = 0.05)	Preprocess 1 (thres = 0.1)	Preprocess 2 (thres = 0.05)	Preprocess 2 (thres = 0.1)
DecisionTree	53%	60%	60%	60%
RandomForest	54%	55%	54%	55%
LogisticRegression	55%	56%	52%	53%
SVC	54%	54%	51%	54%
MLPClassifier	50%	52%	48%	51%
KNeighborsClassifier	56%	55%	54%	55%

Tab. 2.1: ML - Accuracy results according to preprocessing for preprocess 1 and 2

	Preprocess 3 (PCA, 21)
DecisionTree	60%
RandomForest	54%
LogisticRegression	54%
SVC	55%
MLPClassifier	54%
KNeighborsClassifier	58%

Tab. 2.2: ML - Accuracy results according to preprocessing for preprocess 3

These tables compare all the models and reveals that Decision Tree had the highest level of accuracy with 60% (for the five different preprocesses). The meta parameters chosen were: *criterion='gini', max_depth=1, min_samples_split=2, splitter='random'*.

3.3 Second Attempt using Feature Crossing

The results obtained were not satisfying as had been hoped for, so it was important to look for a way of improving the prediction. By browsing the literature, the feature crossing method seemed adapted to find a solution to the problem.

Feature crossing is a method that can be applied when no unique line can be found to separate data. This non-linear problem could be solved by applying features crossing [39]. It works by adding new artificial features that come from the features that already exist. This method applies the «reverse» rather than in a normal preprocessing, i.e., it strengthens the correlation between the features.

In particular, two new features were identified which seemed interesting to add:

- *conventional_hybrides_car = conventional_car * hybrides_car*
- *electric_hybrides_car = electric_car * hybrides_car*

After adding these features, the data points were plotted using t-SNE, but no cluster was apparent, so all the models were rerun using the new dataset. Because feature crossing consists in raising the correlation between some features, there was no need to repeat the preprocess 1 step.

In the same way as for the previous attempt, the optimal number of components for PCA in the preprocess 2 was calculated and was found to be equal to 33 (Appendix [**C**]).

	Preprocess 2 (thres 0.05)	Preprocess 2 (thres 0.1)	Preprocess 3 (PCA, 33)
DecisionTree	57%	60%	56%
RandomForest	59%	61%	53%
LogisticRegression	54%	60%	60%
SVC	38%	28%	33%
MLPClassifier	60%	55%	59%
KNeighborsClassifier	56%	65%	55%

Tab. 2.3: ML - Accuracy result depending on the preprocessing using features crossing

This method allows any significant differences in accuracy to be identified. The best parameters for Random Forest Classifier are: *'bootstrap': False, 'criterion': 'gini', 'max_depth': 2, 'min_samples_split': 2, 'n_estimators': 25.*

3.4 Model Chosen and Test Set

Unfortunately, the second method did not result in a significant improvement in accuracy. Using the test set, accuracy was found to be around 56%.

3.5 Observation and Areas for Improvement

The accuracy obtained with the test set was unsatisfactory. A first observation was that the accuracy obtained was equal to the percentage of the majority class, which suggests the accuracy paradox [38]. A second observation was that the model used a small number of variables to make its classification. Depending on the model chosen, one or two variables were selected, less than what would typically be used. Another observation was that the first model used a random splitter, which means that it did not give any better results than a random guess.
It was concluded that the models did not learn from data.

The results could be improved by considering another metric than accuracy. With a class of more than 56%, the problem is unbalanced, and accuracy may not have been the best choice.
F-measure could be a better metric to apply, especially since it was recommended for imbalanced class distribution [40]. This metric did not improve the scores obtained (appendix [**D**]).

Another reflection concerned the collected data. The data collected in this study were, for the most part, transformed into binary variables with only a very few quantitative variables remaining. Adding more numerical variables (for example, collecting some «scores») should undoubtedly have improved the results obtained.

Another improvement that could have made a difference, would have been to ask more general questions about lifestyle habits. This would certainly have given a more profound knowledge of respondents' attitudes towards the environmental challenges facilitating categorization.

The models developed would be tested on another dataset obtained from a second study to verify this point.

4 Is Hydrogen Considered as Renewable Resource?

This model was based on a recent survey carried out by scientists on transportation preferences in Belgium. The goal of this survey was to measure the preference of the Belgian population toward the energy transition in the transportation sector.

Analyzing this second survey would allow testing the machine learning models on a new dataset which would mean that the assumptions from the first study could be verified. The procedure was identical to that used in the first machine learning task, and it was expected that some conclusions would be drawn.

Many of the steps were repetitive, they were not developed in detail as for the first machine learning problem and only interesting results were to be taken.

4.1 Overall Results

In the same way, as for the other survey, this is a rapid description of the population surveyed (graphics are available in appendix [**E**]).

This survey received about 380 answers, but after removing NaN values (deleting rows with many missing responses), 358 values remained.

The age categories were represented by ten-year age groups. Most respondents were about 18 to 34 years old (more than 60% for the two classes together), about 10 percent in the 35-44 and 54-65 groups, and 6% for people over 65 years old.

Gender distribution was balanced with 56.42% of females and 43.58% of males.

The province where each respondent lived was not included but participants came from all over Belgium with about 37% from Wallonia, a small percentage from Brussels, and the remainder from Flanders.

The level of education was predominantly a bachelor's or master's degree (with 35.2% and 37.43% respectively), 17.6% with a high school degree, followed by a doctorate and middle school degree.

4.1.1 Hydrogen as a Renewable Resource?

Respondents were presented with a statement that hydrogen is not renewable energy. About 27% of respondents agreed with the idea for this question, and the other 72% did not agree.

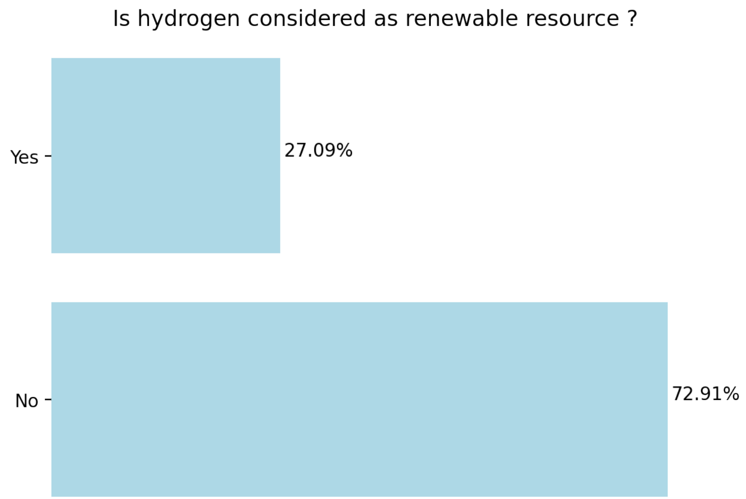

Figure 2.10: Survey 2 - Evaluation of the proportion of surveyed believing that hydrogen is (or is not) a renewable source of energy

The small number of people who regarded hydrogen as renewable energy was surprising. It could have been interesting to evaluate, in the same way, the knowledge of these surveyed about this technology. In parallel to the first survey, the results showed that about 18% of respondents felt they were not informed about this new technology, while 61% of people thought they had some information but would like to be more informed.

It would be interesting to link these different observations together. Even if more than 95% of hydrogen is produced from fossil energy, green (or low-carbon) hydrogen tends to be developed on a larger scale thanks to new renewable energy sources, such as wind or solar energy.

If the information received for these two kinds of energy are taken together, the respondents would consider these energy sources as renewable energies.

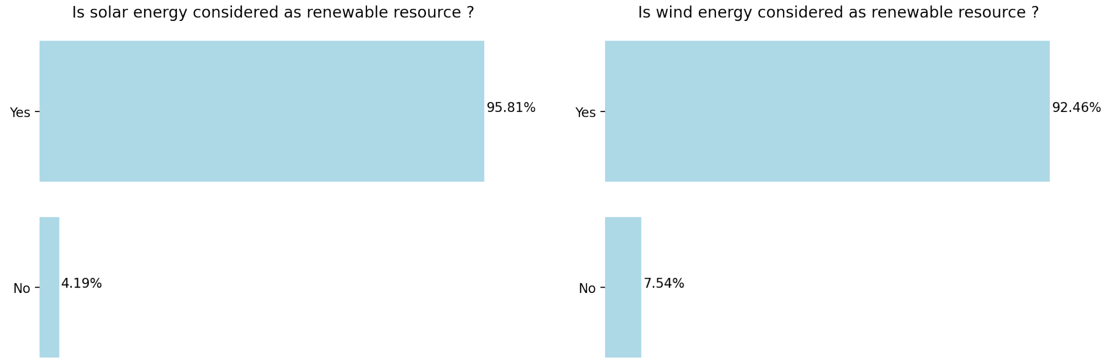

Figure 2.11: Evaluation of the ratio of surveyed believing that solar or wind energy is (or is not) a renewable source of energy

If people were more informed about green hydrogen, they certainly would have a better opinion about hydrogen. Perhaps an explanation was that people consider the general means of hydrogen production, which makes, in effect, hydrogen a non-renewable resource. It could, therefore, be interesting to distinguish between the different types of hydrogen (grey, blue, green).

4.2 Machine Learning Task

The machine learning task is based on the prediction of the answers to the question «Is hydrogen a renewable resource?», which seemed to be a relevant question: in the context of climate change, if people thought of hydrogen as a renewable resource, it could follow that their acceptance of the technology would increase.

As mentioned before, the same process would be used as in the first task.

4.2.1 Data Visualization

The analysis was restarted using the t-SNE method, to see whether any similarities could be already detected between data points. Once again, all data points were mixed, and no apparent similarities were observed.

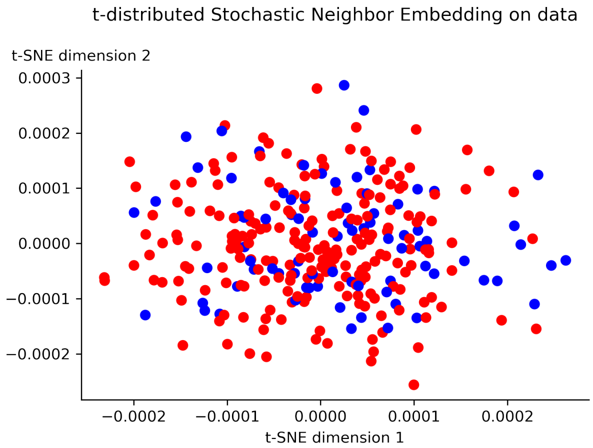

Figure 2.12: Survey 2 - t-SNE distribution

4.2.2 Models

The three same preprocesses were used, and the different models were kept[1]. For the PCA preprocess (appendix [**F**]), an optimal number of components of 123 was found.

	Preprocess 1 (thres 0.05)	Preprocess 1 (thres 0.1)	Preprocess 2 (thres 0.05)	Preprocess 2 (thres 0.1)
DecisionTree	71%	72%	71%	74%
RandomForest	72%	72%	74%	74%
LogisticRegression	63%	66%	64%	64%
MLPClassifier	60%	59%	73%	73%
KNeighborsClassifier	70%	69%	68%	68%

Tab. 2.4: ML2 - Accuracy results according to preprocessing for preprocess 1 and 2

	Preprocess 3 (PCA, 21)
DecisionTree	70%
RandomForest	72%
LogisticRegression	62%
MLPClassifier	58%
KNeighborsClassifier	69%

Tab. 2.5: ML2 - Accuracy results according to preprocessing for preprocess 3

[1]SVC model is omitted due to a sklearn error.

Preprocess 2 gave the highest level of accuracy and was therefore chosen and used with the Random Forest set, and the best meta parameters: *'bootstrap': True, 'criterion': 'gini', 'max_depth': 1, 'min_samples_split': 2, 'n_estimators': 25.*

The accuracy score obtained improved the first machine model.
However, once again, the best accuracy score was equal to the majority class although ultimately this machine performed no better than the first. Moreover, the maximum depth equals 1, which means that the model only used one variable to make its prediction, demonstrating that the model could not learn, confirming the assumptions.
Using the test set on this model, the accuracy score was about 72%.

4.3 Observations

Using the models on another survey gave the same conclusions as in the first machine learning task. Unfortunately, the models did not learn from datasets and no satisfactory results were obtained.

Chapter 3

What is the Point of the Different Policies?

After trying to predict the social acceptance of hydrogen cars, it is then interesting to understand which policies could impact this acceptance.

Energy policy is defined as any scheme in which the government (or any organization) addresses energy growth and usage issues, including energy production, distribution, and consumption [41]. It regroups social, economic, political, and technical skills. The result of a change depends mainly on human behavior, so societal behavior must be considered.

To assist in developing hydrogen car, the respondents answered some questions on a Likert scale about their appreciation of the technical capabilities of this new technology and different policies that they would like to see put in place. This analysis made it possible to determine which of these other points would be important to consider in increasing the levels of social acceptance previously measured.

To calculate the social acceptance, the responses are transformed into numbers: the scale went from 1 for «not at all important» to 5 for «very important». The sum over all surveyed was taken and divided by the number of answers to obtain a mean. After, it was multiplied by 20 to get a percentage. All variables will be explained later.

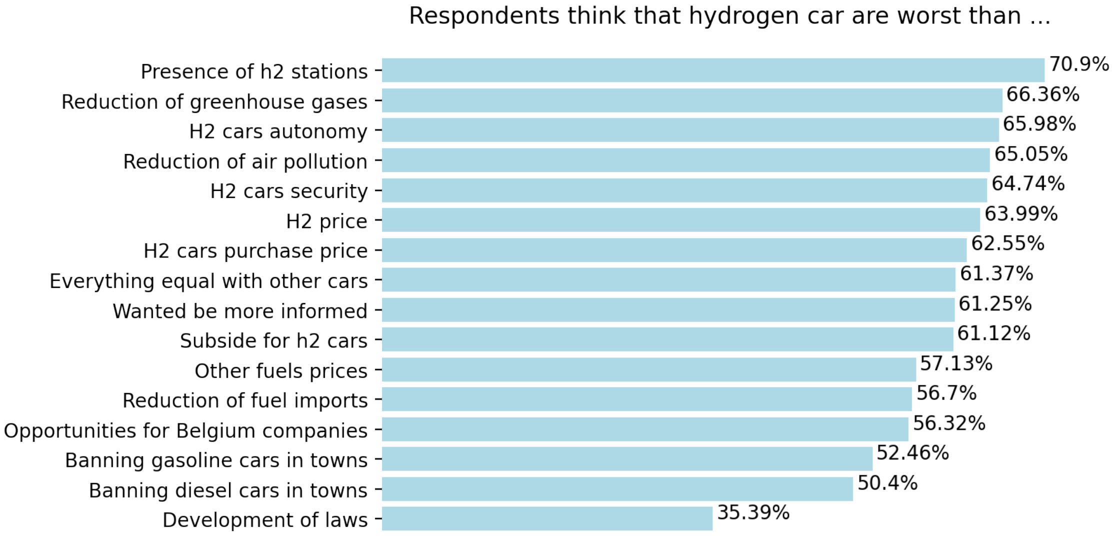

Figure 3.1: Comparison of the importance of different policies and characteristics

The presence of a hydrogen station (*Presence of h2 stations*) was the most important point to consider. This point represents a big challenge for the future of hydrogen because there are very few stations. The H2Benelux [42] gives the different stations present in Europe directly. Currently, Belgium has three operational stations: one in Halle, one in Brussels, and one in Antwerp. Four more stations are in progress. All these new stations have been built by the DATS24 and Colruyt group, in collaboration with WaterstofNet within the H2Benelux project.

The second most important characteristic is the reduction of greenhouse gases (*Reduction of greenhouse gases*) obtained with technological change.

This characteristic is closely followed by the autonomy of the hydrogen car (*H2 cars autonomy*). This is one of the main advantages of hydrogen cars compared to electric cars: the average autonomy of hydrogen cars is generally higher than $500km$, contrary to electric cars, which can only cover around $300km$. Nowadays, some hydrogen cars can travel about $600/700km$, which is equal to conventional cars.

Less significant was the reduction of local air pollution in urban areas (*Reduction of air pollution*), the security associated with the hydrogen car (*H2 cars security*), and the price of hydrogen (*H2 price*).

After, the purchase price of this technology (*H2 cars purchase price*) is a factor. As mentioned previously, the purchase price is high for the moment, but with technological developments, prices will probably go down.

At 60% of importance, there is the fact that hydrogen cars have the same characteristics as other cars (price, autonomy, power, etc.), represented by *Everything equal to other cars* variable. Respondents also wanted to be informed about the subject (*Wanted to be more informed*) and were interested in subsidies (*Subside for h2 cars*).

The lowest importance was given to the development of laws (*Development of laws*). Only 37% of people surveyed said they would be interested in taking part in the reflection on energy policies.

Banning diesel and/or gasoline cars from cities *(Banning diesel cars in towns* and *Banning gasoline cars in towns*) was important to less than 50% of respondents, as was a reduction in fuel imports (*Reduction of fuel imports*), the creation of opportunities for Belgian industries to increase their capacity to provide innovative technologies (*Opportunities for Belgium companies*), and the price of conventional fuels (*Other fuels prices*).

Using these variables, the goal was to highlight which policies/characteristics would be more interesting for some groups of people than others.

1 Comparison of Policies according to Age

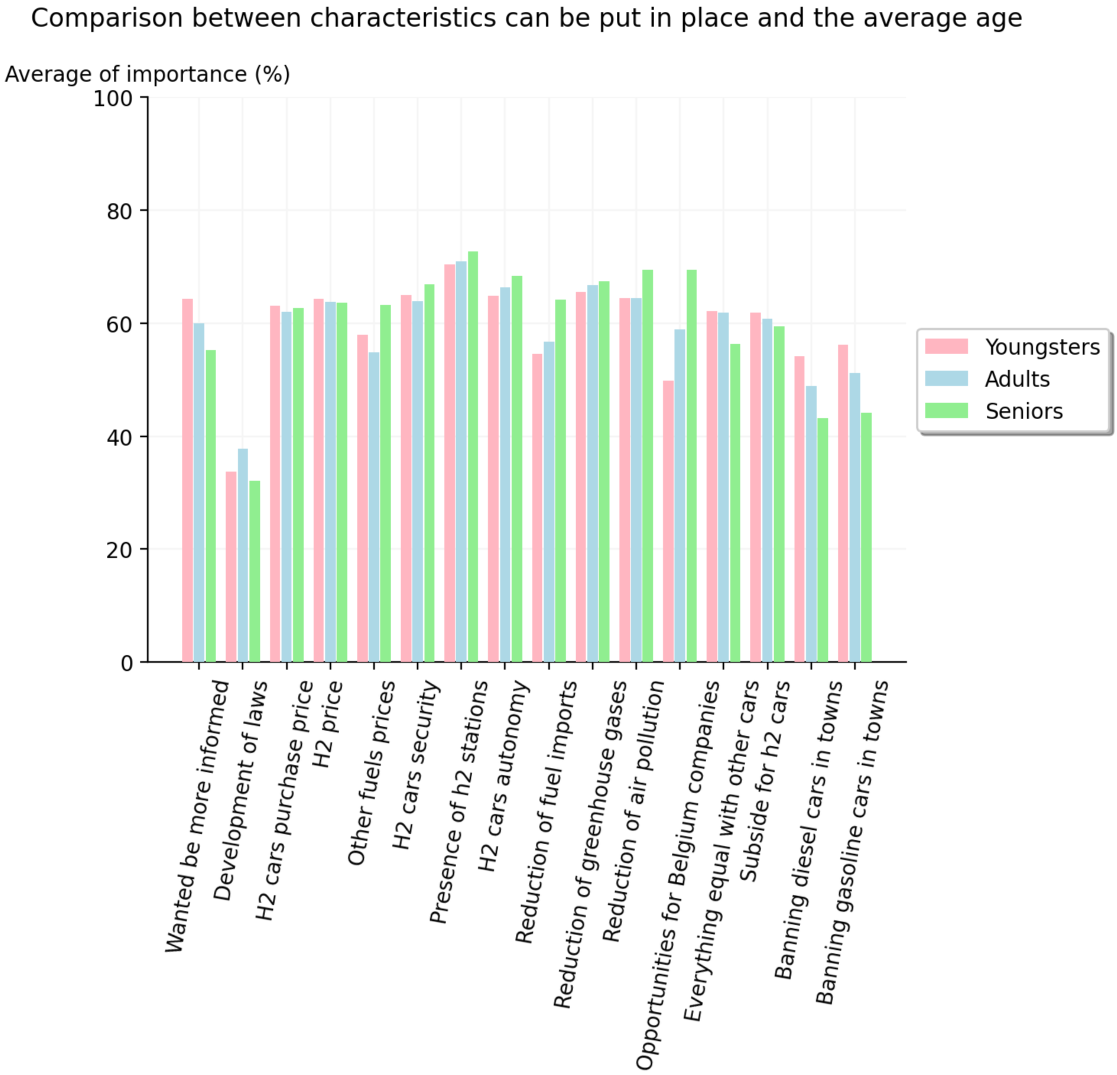

Figure 3.2: Comparison of the importance of the policies according to age

There were no significant differences between the age categories (youngsters, adults, and seniors). Some categories having the largest differences are described in more detail:

Figure 3.3: Comparison of the main differences in policies according to age

The most significant difference in this graphic is for the variable *Belgium_company*, which illustrated that seniors were more attached to Belgian companies than youngsters, with adults falling in between the two groups.

There was also a significant difference of opinion about banning gasoline and diesel cars between the youngsters and seniors' groups. Indeed, young people thought they would be more impacted if diesel or gasoline were forbidden in towns. In the same way, a reduction in imports appeared more important for older adults than for youngsters.

The last point to mention was the importance of the knowledge of the subject for young people. This seemed to be crucial to them in accepting this new technology. More so than for seniors. Adults remained in the middle of the two other groups.

2 Comparison of Policies according to Place of Habitation

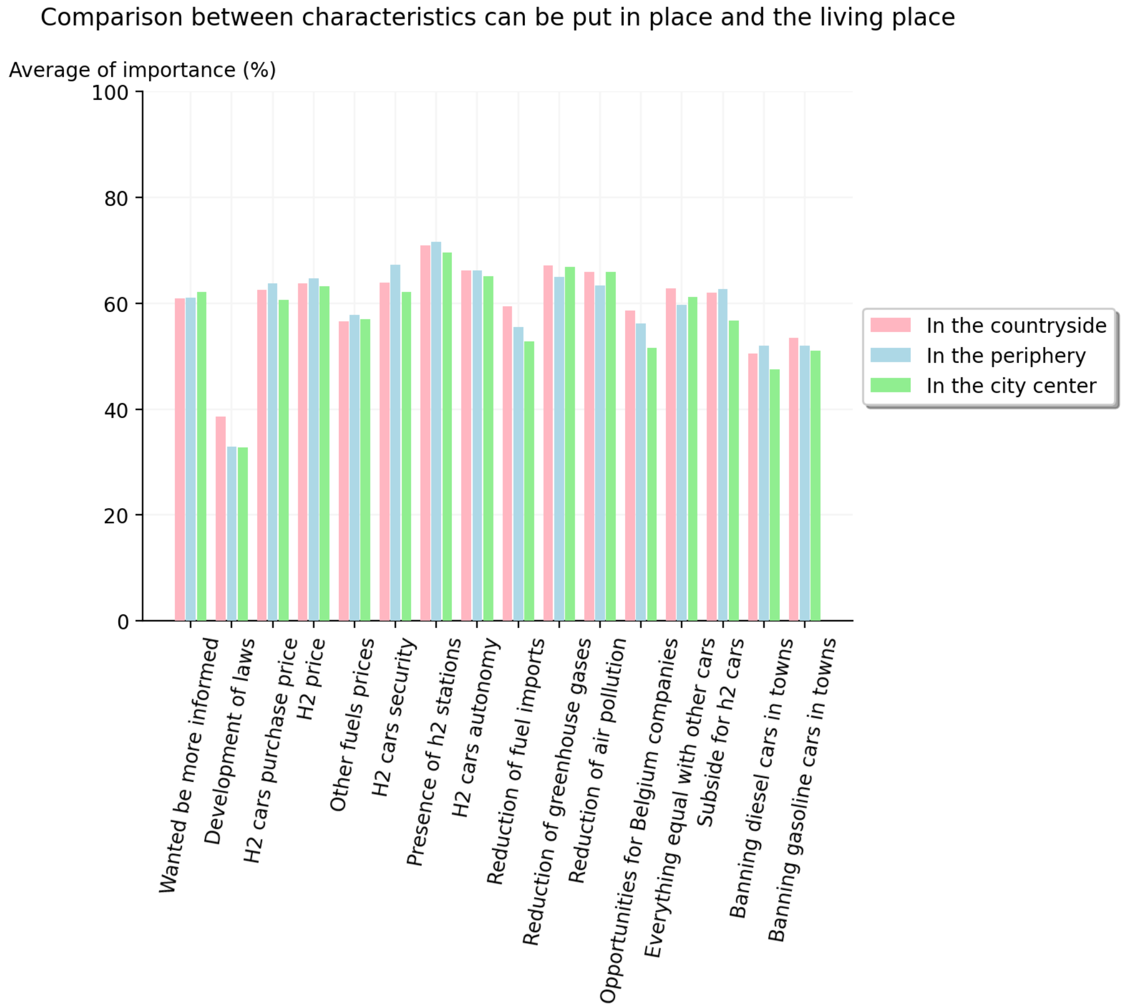

Figure 3.4: Comparison of the importance of the policies according to where participants lived

Again, few differences were observed in this graphic. The principal ones are developed:

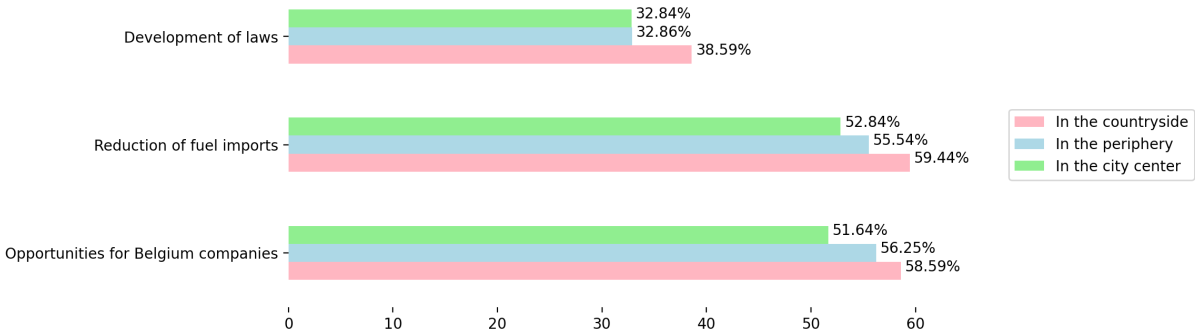

Figure 3.5: Comparison of the main differences in policies according to where participants lived

First, people living in the countryside were more interested in creating laws than the others. The importance of reducing imports seemed to decrease from the countryside to the city center, in the same way as the importance of having more Belgium companies producing hydrogen.

3 Policies Depending on other Demographic Characteristics

Unfortunately, it was challenging to differentiate the importance of some policies from others according to the characteristics of respondents. The two graphics illustrating the most significant differences between policies and some demographic characteristics have been presented.
As the differences were highly insignificant, the decision was not to continue analyzing graphs without significant differences.

Chapter 4

Discussion and Future Work

The field of hydrogen cars, as a new technology, is still too recent and too little is known about it, which makes it far from easy to draw any accurate conclusions. The proposed study did not yield much in the way of desirable outcomes. Predicting the social acceptance of hydrogen cars to solve environmental problems and analyzing some laws increasing this acceptance was not possible.

However, a series of reflections could still be drawn from the results. The questions may have been asked too crudely, without any further explanation on the subject. Seeing how ill-informed people felt they were, it might have been better to add a clearer explanation of hydrogen cars as well as about hydrogen as an energy source.

While it did not impact the second machine learning test, asking generic questions about respondents' habits would still be interesting. It was concluded that more questions should be offered with a score to be awarded, allowing for more quantitative variables. It might also have been interesting to ask more questions about other car technologies (e.g., electric cars, which are direct competitors of hydrogen cars).

A second reflection concerns preprocessing. It might have been interesting to go deeper into the preprocessing by using a more significant number of variable selection techniques to find a subset of variables that would give a better model. Several methods exist, such as «forward selection» or «backward selection» which are sequential approaches allowing variables to be included/excluded one after the other. There is also the LASSO method (Least Absolute Shrinkage and Selection Operator) in which the variables are selected by penalization.

Continuing the focus of this initial work, it could be interesting to continue identifying «typical profiles» for the different technologies and compare the results obtained. It would then be interesting to see if it would be possible to classify the respondents according to their preferred types of cars. Another point would be to identify key criteria allowing this classification and to use them to define/categorize the acceptance of such types of cars.

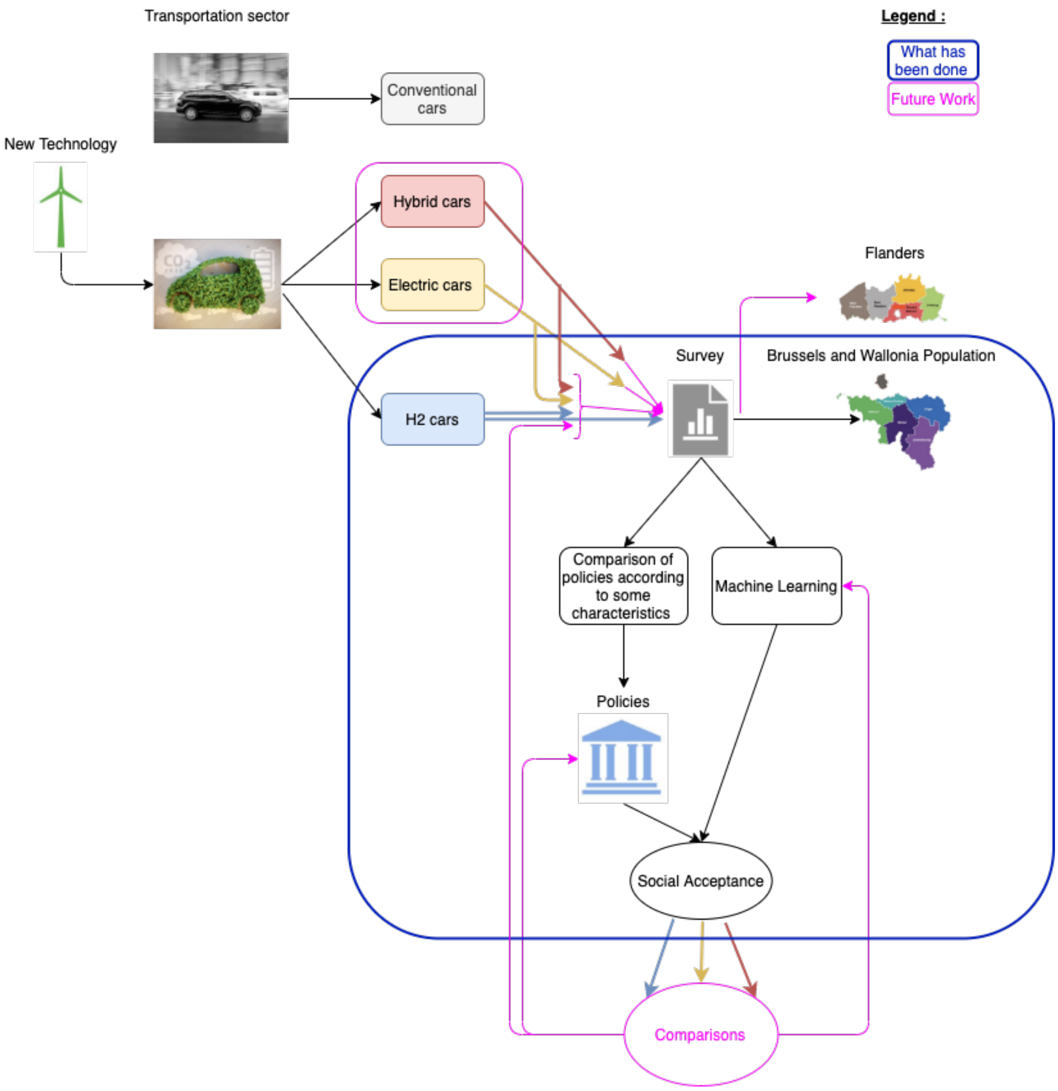

Figure 4.1: Representation of Future Work

Conclusion

Solving environmental problems is a huge challenge and, as demonstrated throughout this thesis, much uncertainty is linked to it.

It became clear that it was highly challenging to conduct a study on the social acceptance of new technology and to predict this social acceptance. Despite the advice found in the literature and a second survey carried out on other bases, no machine learning model worked well. However, the studies meant that a great deal was learned regarding people's ideas about hydrogen cars.

Given the number of respondents who felt they were ill-informed or those who thought they had limited knowledge of this subject, it could be essential to give more opportunities for people to learn about these technologies. One fact that came out of the study was that people did not seem to know that hydrogen can be formed from wind or solar energy and therefore classed as renewable energy. Young people are mainly interested in being more informed about the issue: giving conferences about new technologies or a seminar (open to everyone) could be one way of increasing acceptance.

This age category also seems to be engaging in another type of car if conventional ones are banished from the city center. The development of this policy has already started, especially in Brussels, and has already impacted the way people think. Expanding this ban to other towns could reinforce a commitment to cars other than conventional ones.

The importance of having Belgium companies is mixed depending on the age or place of residence. Seniors and people living in the countryside considered this more important than other groups. Looking at it from an environmental point of view, it would be preferable to create our energy without a need for transformation or other associated impacts. However, as things stand, the government does not believe that Belgium has enough green resources to produce its hydrogen, so this is unlikely to be possible soon.

It came as no surprise that setting up adequate infrastructures that allow new technologies was the most significant concern, followed by a desire to reduce emissions. At present, this is something that needs to be improved for the development of hydrogen: few stations exist in Belgium, even if some projects are already underway.

It would certainly be interesting to conduct a similar study on a larger scale and consider other energy sources. One energy source on its own will not be enough to tackle environmental problems, and people's opinions need to be taken into account even if there will be a divergence of opinion.

It could be interesting to identify the criteria a population group seems to require developing a specific technology more than another in this group.

But it is important to always keep in mind that if we want to reduce our emissions and meet the environmental challenge, we will have to promote sobriety in parallel.

Appendices

A Do respondents from the environmental sector believe that hydrogen can meet environmental challenges?

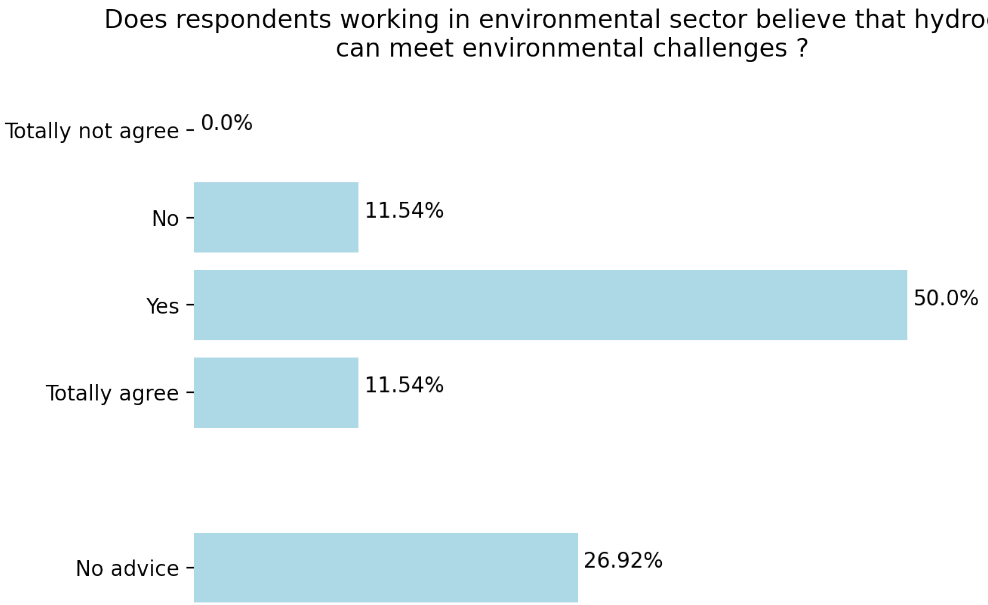

Figure 2: Appendices - Distribution of environmental workers who either believe or do not believe that hydrogen can meet environmental challenges

B Correlation matrix

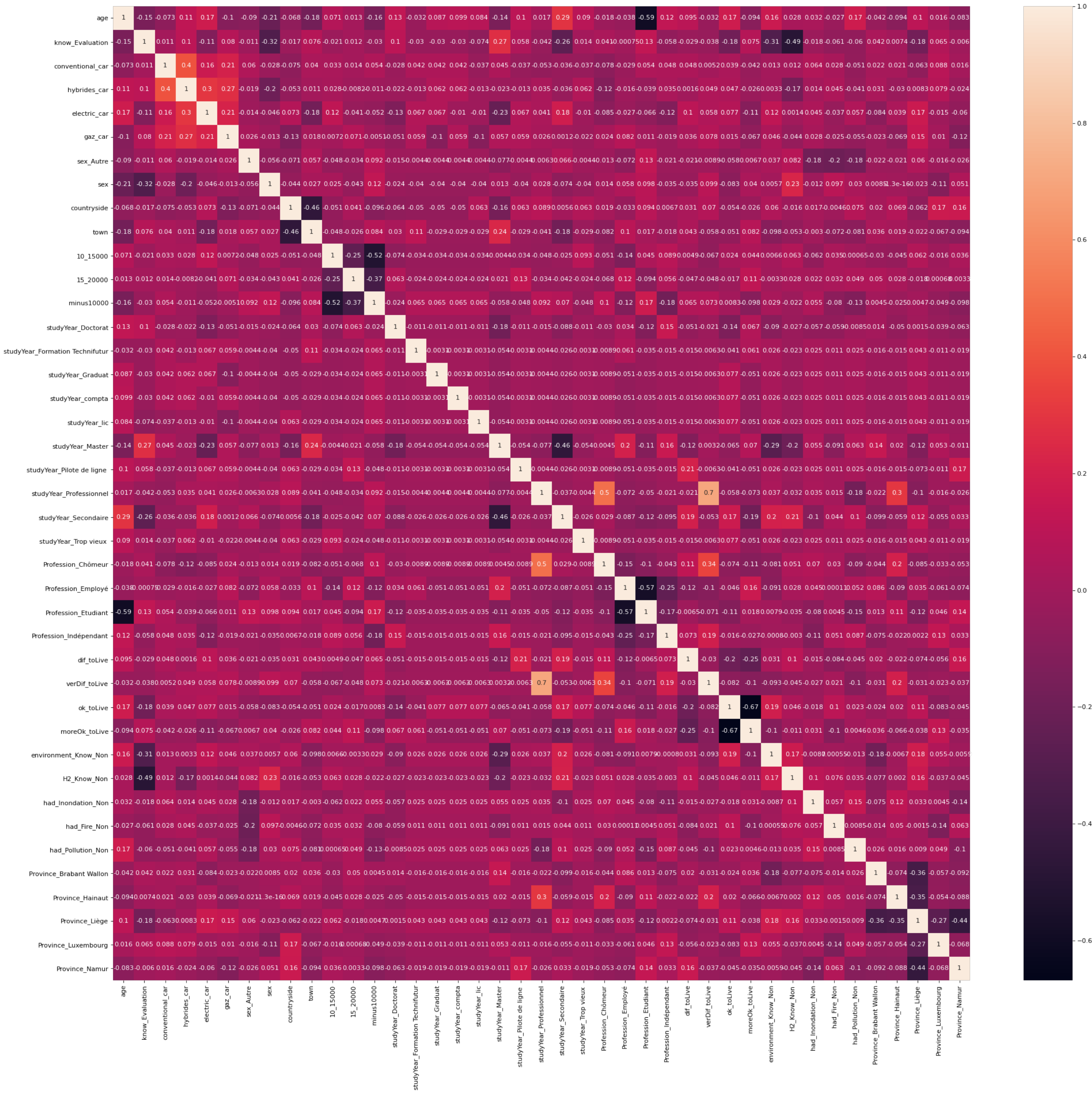

Figure 3: Appendices - Correlation matrix

It is interesting to see the heat map for the correlation matrix.
The correlation matrix is a symmetric matrix. On the diagonal, all elements are equal to 1: it is the correlation of the component itself.
The closer the values are to 1, the stronger the positive correlation, the closer they are to -1, the stronger the negative correlation.

C The optimal number of components for PCA with feature crossing

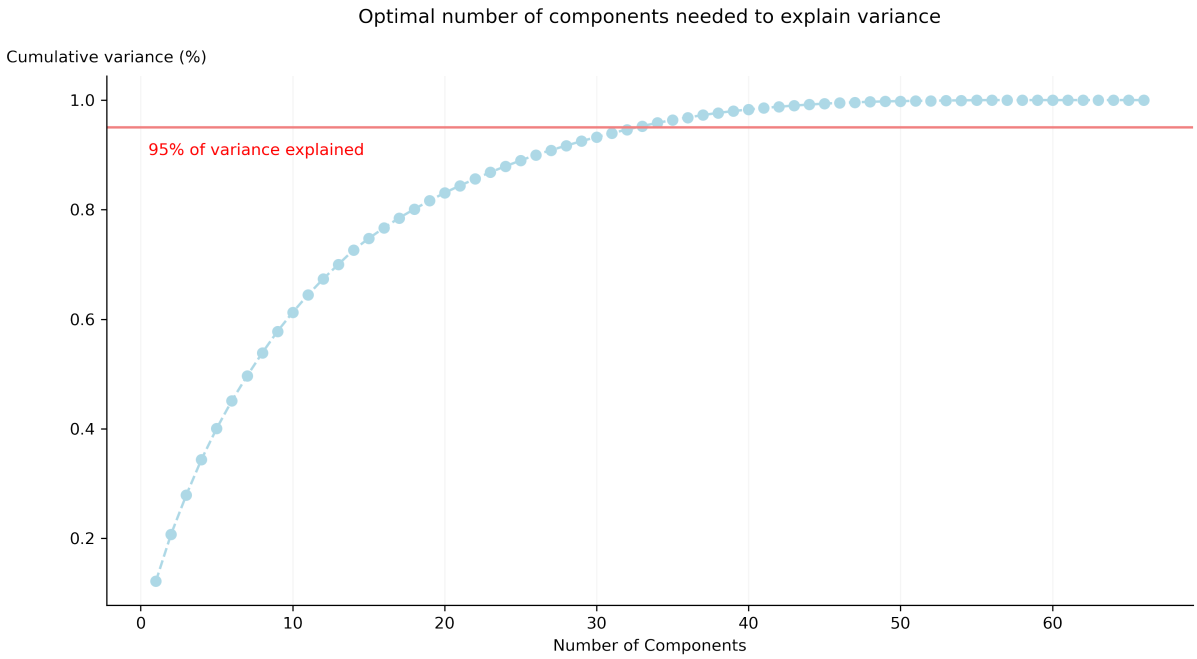

Figure 4: Appendices - Optimal number of components for PCA with feature crossing

D ML - Results using f1-score metric

K Neighbors Classifiers had the highest level in terms of f1-score with 58%. Against this, this method allows any significant differences in scores obtained.

	Preprocess 1 (thres = 0.05)	Preprocess 1 (thres = 0.1)	Preprocess 2 (thres = 0.05)	Preprocess 2 (thres = 0.1)
DecisionTree	51%	44%	44%	52%
RandomForest	53%	51%	39%	39%
LogisticRegression	51%	45%	41%	41%
SVC	50%	49%	38%	34%
MLPClassifier	53%	43%	38%	39%
KNeighborsClassifier	58%	54%	52%	56%

Tab. 1: Appendices - ML - Results according to preprocessing for preprocess 1 and 2 using f1-score

	Preprocess 3 (PCA, 21)
DecisionTree	47%
RandomForest	40%
LogisticRegression	48%
SVC	27%
MLPClassifier	44%
KNeighborsClassifier	53%

Tab. 2: Appendices - ML - Results according to preprocessing for preprocess 3 using f1-score

E Survey 2 - Graphics of overall results

These graphics are the representation of all results described in the report.

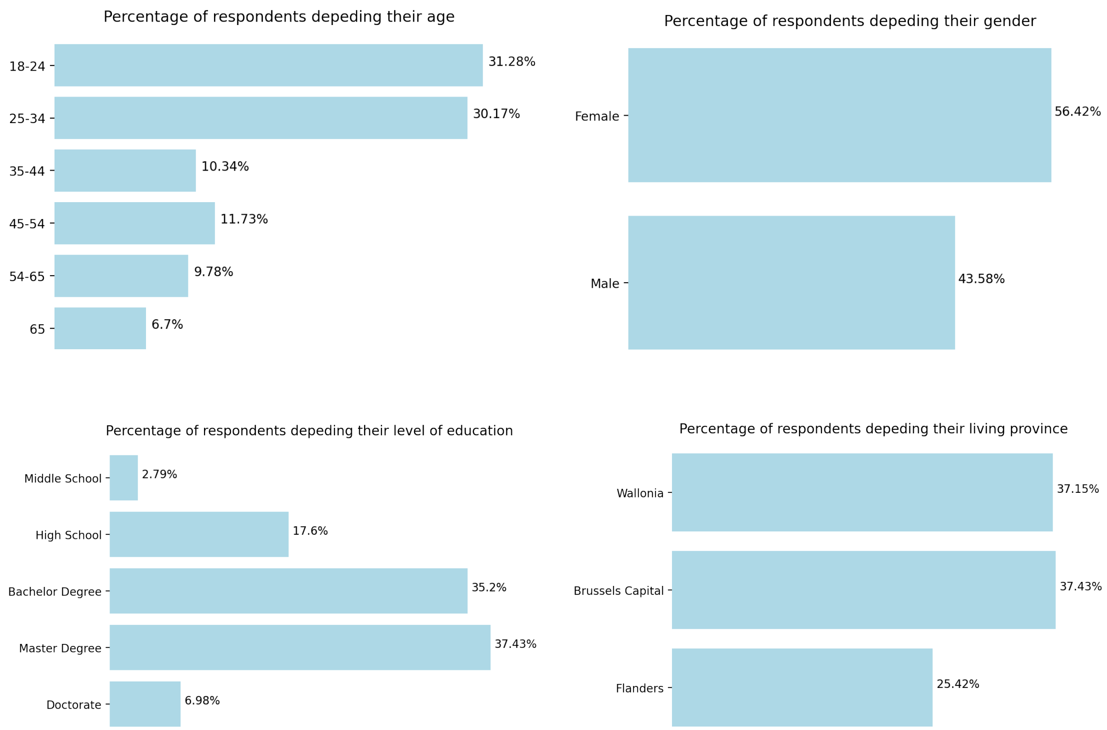

Figure 5: Appendices - Overall results of the second survey

F Survey 2 - The optimal number of components for PCA

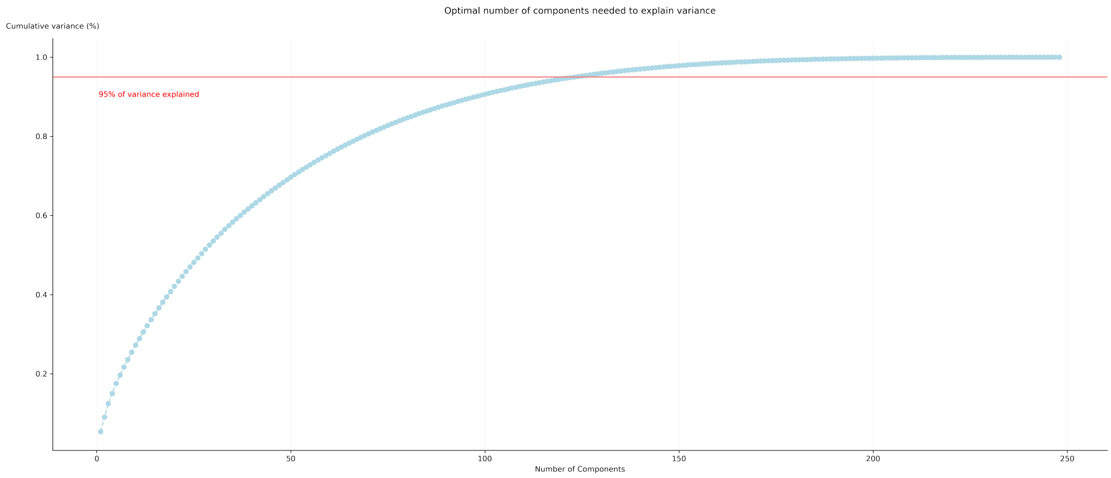

Figure 6: Appendices - Survey 2 - Optimal number of components for PCA

G Link to the Github

Below find a link to further information about the codes (and data) used: https://github.com/DelphMass/TFE22_197.git.

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