Investigating how socioeconomics and access affect planning permission application outcomes for one-off houses in Ireland.

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Abstract

In this project, I investigated how socioeconomic conditions, access to public services and access to infrastructure affect planning permission applications for one-off houses in Ireland. According to the Project Ireland 2040 framework, the government of Ireland aims to maximise employment opportunities, develop rural areas and provide nationwide infrastructure. Using a combination of Planning Application data and 2022 Census data aggregated at the small area level, I used machine learning to train a binary predictor to determine application outcomes. This diagnostic model was intended to highlight inconsistencies between the government's current policies and their long term goals. After experimenting with logistic regression, random forest and neural network algorithms, I designed a gradient boosting model with a strong capability to predict correct outcomes and differentiate between classes. I applied class imbalance handling techniques and hyperparameter tuning before extracting SHapley Additive exPlanations (SHAP) feature importance and interaction values. These metrics explained the influence each feature had on the models predictions. In analysing their values and understanding how the model was trained, I was able to highlight that in spite of the government's prioritisation of rural areas, there is an urgent need for infrastructure and development policy reforms .

1 Introduction

The basis for my project is centred around the Project Ireland 2040 national planning framework issued in 2015 by then Taoiseach Leo Varadkar [1]. It contains guidelines for the Irish government to implement policies to ensure there is enough housing and employment in the country to accommodate projected population growth. The government's main aims are outlined within their National Policy Objectives (NPOs). This includes maximising employment opportunities (Objective 10), developing rural areas (Objective 15) and providing nationwide infrastructure (Objective 18). Given that we are in the midst of a national housing crisis with over 16,000 people currently homeless [2], a record high, it is a fair assessment that these goals are not being achieved. Despite the need for increased accommodation, the rate of planning permission approvals is steadily declining [3]. My research aims to develop a predictive model using machine learning to determine whether one-off houses in Ireland will receive planning permission based on three factors: access to public services, access to infrastructure and the socioeconomic conditions of the area. These are three developmental conditions the government has prioritised as part of its NPOs. It is important to distinguish this will be a diagnostic model that should not be used to determine future outcomes. However the way in which the model is trained can be used to highlight inconsistencies between the government's long-term aspirations and their current policies. Through training a strong predictive model and examining its feature importance and interactions, I will provide a thorough analysis of Irish planning authorities current decision making processes and give advisions for how their policies should be revised going further to more closely align with the Project Ireland 2040 framework.

Research Questions/Tasks:

1. Which of the three factors, socioeconomic conditions, access to infrastructure and access to public services, most significantly determines planning permission application decisions?
2. How do socioeconomic, public service access, and infrastructure factors interact to predict the likelihood of planning permission being granted?
3. Under what combinations of conditions are planning applications most likely to be rejected?

2 Related Work

There have been several implementations of machine learning to enhance planning application processes. Research in Australia has developed a gradient boosting model to predict application assessment times [4]. This is useful for both applicants and authorities as the uncertain and drawn out nature of awaiting verdicts often leads to additional calls and emails from candidates. This increases workload on authorities and creates backlogs of applications. This new technology could provide applicants with a realistic expectation of when they should expect a response and allow councils to work uninterrupted by unnecessary correspondence.

Artificial Intelligence has also been used to automate the detection of common errors within planning forms [5]. Submitting a correct application is a complex task and many are automatically rejected due to incomplete and invalid documents. This ongoing research could further reduce the burden on planning authorities by eliminating manual reviews of inherently redundant applications.

In the United Kingdom, machine learning is already being applied to evaluate planning proposals [6]. The Department for Science, Innovation and Technology has trained a model on satellite imagery of the country's natural habitats to determine the suitability of the land for development. The model's speed, accuracy and objectivity is accelerating the application process and minimising instances of NIMBYism and bias.

Privately-operated Irish website Planner.ie offers a commercial tool providing users with the likelihood of a given site receiving permission approval using AI trained on previous planning data [7]. However, there is no public information about how the model is trained or any formal evaluation metrics. This lack of transparency heavily impacts its worthiness and credibility.

A study into the use of AI in urban planning and development highlighted the risk of perpetuating discrimination against specific areas or groups from previous processes [8]. There has also been evidence of institutionalised policy biases influencing planning outcomes in Ireland [9]. These findings emphasise the value of a diagnostic approach and the dangers of using past application data to determine future decision making.

Overall, several executions provide a strong basis for the capability of machine learning technologies to extract meaningful patterns and make accurate predictions using planning permission data. However, the current state of the art focuses merely on improving the efficiency of the assessment process. There have been no formal scientific or academic proposals to directly predict planning permission application outcomes.

I aim to provide a novel approach and extend the existing literature by not only accurately predicting application verdicts for one-off houses, but also evaluating the most influential features that affect the models performance.

3 Methodology

My methodology incorporated two main data sources. The first was a dataset of all planning permission applications in Ireland since 2012 [10]. I also used 2022 Census data aggregated at the small area level. There are just over 18,000 small areas in Ireland with an average of 300 residents.

I incorporated 8 specific Census datasets to represent my three aforementioned categories [11-18]. For example, for access to public services, I selected a dataset about commuters' means of travel. Generally, we can tell if an area has more public transport options based on the amount of people who use buses, trains or trams to get to school or work.

I then merged these with the planning data to create a new dataset where each row contained information on an application for a one-off house as well as Census data from the small area where the proposed site is located

I initially trained the data on four generic baseline models; Logistic Regression, Random Forest, Gradient Boosting and Neural Networks. I analysed these results and subsequently applied class balancing techniques and hyperparameter tuning to improve performance with an emphasis on AUC (area under curve), recall and F1-score metrics. For the best performing model, I computed SHAP importance and interaction values to interpret the main combinations of features that influence the models output. These values provide a measure of how much each feature pushed the model's predictions up or down. This allowed me to understand the key determinants of planning applications being predicted as approved or denied and provide deeper analysis of whether the government's current policies are reinforcing their long-term objectives.

4 Experimental Setup

I began my experiment by performing necessary transformations to the original source data. I carried out feature extraction and engineering on each of the Census datasets to create a list of meaningful input variables to train my model. For example, I converted the number of people using public transport in an area to the proportion of the local population.

For the Planning Applications data, much of my decision making was informed by domain knowledge, obtained from studying material published by the Planning Commission [19] and the Office of the Planning Regulator [20]. Processing revolved around filtering out invalid applications and those for extensions or multiple units so that only proposals for one-off houses remained. As terminology varied throughout different jurisdictions, I created a binary value for whether an application was accepted or rejected. I deemed any ‘conditional’ cases to be accepted as ultimately the development is to be allowed.

The data didn’t contain the exact GPS location of each site so I applied some textual preprocessing to the addresses and converted them to their latitudinal and longitudinal coordinates using the Photon API [21]. I then lined these points up with a geopackage file of the small area boundaries [22] and merged in the corresponding Census data to each site based on its location. To negate major errors within the API’s conversions (for instance, an address in Blackrock, County Louth being placed in Blackrock, County Dublin), I removed all entries where the planning applications local authority was not the same as its small area.

I further reduced the columns in my new dataset so that only the following input features remained to train my models:

Access to Public Services	**Access to Infrastructure**	**Socioeconomic Conditions**
Commute via personal vehicle	Access to public water supply	Population Density
Commute via public transport	Access to public sewerage system	Employment Rate
Commute via walk/cycle	Has central heating	No Leaving Certificate qualification
Under 30 minutes commute	Has renewable energy source	Third Level Education Degree
30-60 minutes commute		
Over 60 minutes commute		

All features except for population density and employment rate referred to the proportion of the local population who fall into each category. My target variable was a binary value of 1 for accepted applications and 0 for any that were rejected.

I trained my four baseline models with an 80-20 train/test split and default parameter settings. I stratified the data so that both the test and training set contained equal proportions of each class. Although these models achieved a high predictive accuracy, their recall, precision and F1-scores for negative cases were very low.

	Accuracy	AUC	Precision_0	Recall_0	F1_0	Precision_1	Recall_1	F1_1
Logistic Regression	0.870922	0.581903	0.000000	0.000000	0.000000	0.870922	1.000000	0.931008
Random Forest	0.862672	0.665860	0.373272	0.094131	0.150348	0.879138	0.976576	0.925299
XGBoost	0.869422	0.677250	0.453704	0.056944	0.101187	0.876267	0.989838	0.929597
Neural Network	0.870922	0.496571	0.000000	0.000000	0.000000	0.870922	1.000000	0.931008

87% of planning applications are accepted both in my data and according to the Office of the Planning Regulator [23]. This significant class imbalance meant that instances of my models predicting negative cases were extremely rare.

To rectify this, I first trialled Synthetic Minority Oversampling Technique (SMOTE). This method creates synthetic instances of the minority class using linear interpolation. However, I ultimately opted against this as I felt my analysis would hold more weight if based entirely on actual, real-life data points.

	Accuracy	AUC	Precision_0	Recall_0	F1_0	Precision_1	Recall_1	F1_1
Logistic Regression (SMOTE)	0.567839	0.582150	0.162067	0.563045	0.251688	0.897743	0.568550	0.696193
Random Forest (SMOTE)	0.759919	0.662566	0.243056	0.406740	0.304282	0.902325	0.812263	0.854929
XGBoost (SMOTE)	0.721368	0.673104	0.228486	0.487507	0.311144	0.908705	0.756028	0.825365
Neural Network (SMOTE)	0.474912	0.591708	0.154179	0.683905	0.251630	0.904545	0.443937	0.595575

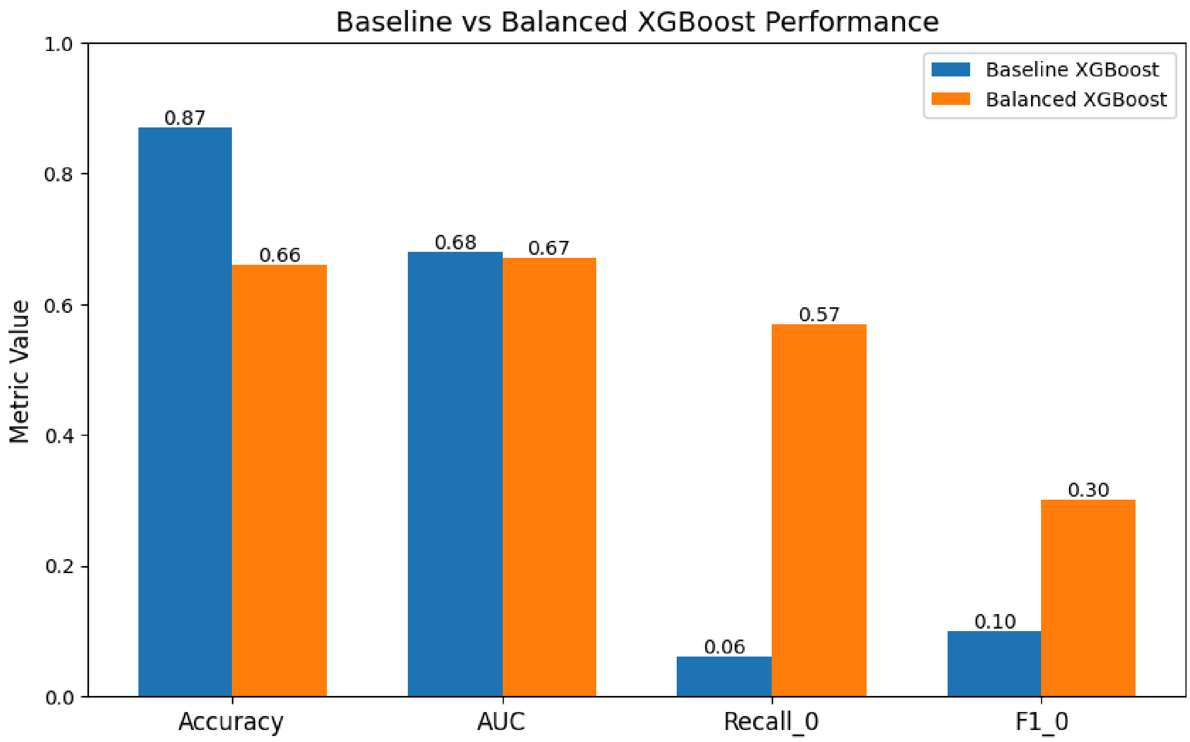
Next, I experimented with randomly undersampling and oversampling the existing data. These approaches equalised the class frequency by either removing positive cases or duplicating negative cases.

	Accuracy	AUC	Precision_0	Recall_0	F1_0	Precision_1	Recall_1	F1_1
Logistic Regression (Undersampling)	0.573764	0.581888	0.161368	0.548518	0.249373	0.896165	0.577506	0.702383
Random Forest (Undersampling)	0.618165	0.645562	0.189801	0.599070	0.288271	0.912669	0.620996	0.739097
XGBoost (Undersampling)	0.604065	0.648749	0.185356	0.608948	0.284203	0.912358	0.603341	0.726349
Neural Network (Undersampling)	0.593190	0.586462	0.165855	0.533992	0.253098	0.897074	0.601963	0.720470

	Accuracy	AUC	Precision_0	Recall_0	F1_0	Precision_1	Recall_1	F1_1
Logistic Regression (Oversampling)	0.568889	0.581648	0.160627	0.553748	0.249020	0.896216	0.571133	0.697665
Random Forest (Oversampling)	0.652216	0.664285	0.203779	0.582801	0.301972	0.914636	0.662504	0.768416
XGBoost (Oversampling)	0.669467	0.672111	0.209055	0.560721	0.304561	0.913273	0.685584	0.783216
Neural Network (Oversampling)	0.585615	0.585820	0.163363	0.536316	0.250441	0.896134	0.592921	0.713656

Eventually, I selected class balancing as the optimal approach for handling the imbalances within my data. When the model makes a mistake on a minority case, it gets punished much more due to weights calculated using the proportional size of the two classes. Although this method resulted in a drop in overall accuracy, the model correctly identified far more rejected applications. This is crucial for my analysis to understand how the model achieved this differentiation and successfully detected both positive and negative cases.

	Accuracy	AUC	Precision_0	Recall_0	F1_0	Precision_1	Recall_1	F1_1
Logistic Regression (Weighted)	0.571364	0.581807	0.161869	0.555491	0.250688	0.896997	0.573717	0.699827
Random Forest (Weighted)	0.708018	0.669046	0.222108	0.504358	0.308403	0.909496	0.738202	0.814945
XGBoost (Weighted)	0.663392	0.671973	0.207938	0.572342	0.305048	0.914379	0.676886	0.777910
Neural Network (Weighted)	0.870922	0.523057	0.000000	0.000000	0.000000	0.870922	1.000000	0.931008



At this point I nominated the single algorithm that I felt held the most predictive power to inform my analysis. I chose the XGBoost model with class balancing applied as it had the strongest combination of AUC score as well as recall and F1 metrics for the negative class. Respectively, these metrics reflect the models ability to differentiate between classes, recognise minority cases and balance the precision-recall relationship.

To further refine the model, I applied GridSearchCV to exhaustively test a list of hyperparameter combinations using cross validation to find the best-performing settings. By optimising parameters such as the learning rate and maximum depth, I was able to maximise the models AUC score.

	Accuracy	AUC	Precision_0	Recall_0	F1_0	Precision_1	Recall_1	F1_1
XGBoost (Tuned)	0.669542	0.675087	0.20973	0.563626	0.305704	0.913757	0.685239	0.783169

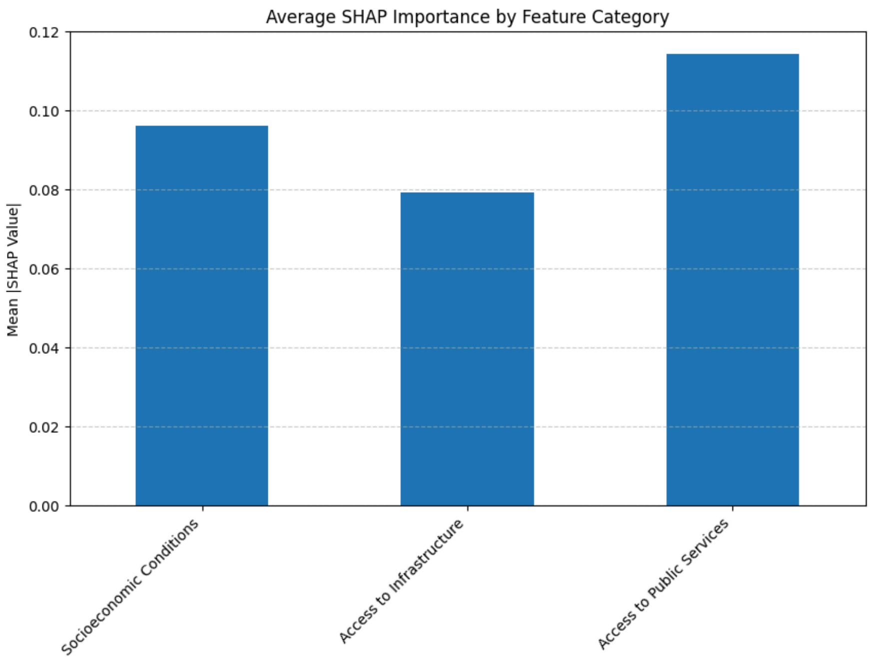
I had now developed a model with strong capabilities to both predict outcomes, differentiate between classes and detect instances of positive and negative cases. Although not perfect, the performance was in line with the accepted gold standard of machine learning implementation in the planning application domain [4], providing a basis for worthy, meaningful analysis. I computed SHAP feature importance and interaction values to understand how the model was making these predictions and which features were driving its decisions. These values and rankings provided the justification for my responses to my original research questions.

5 Results

Research Question 1:

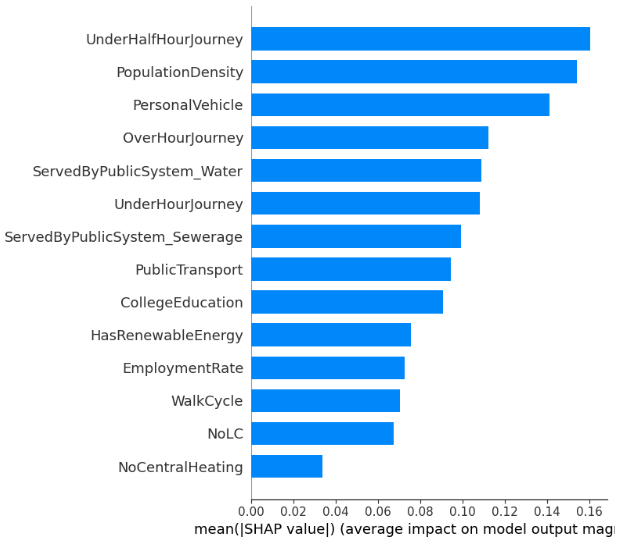
Which of the three factors, socioeconomic conditions, access to infrastructure and access to public services, most significantly determines planning permission application decisions?

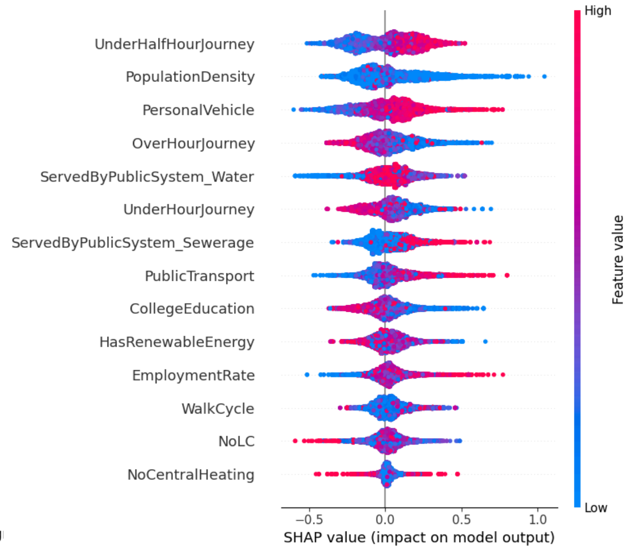
I leveraged SHAP feature importance values to answer my first research question. I compared the absolute mean values of each feature as well as the average absolute mean of each category.



	Mean Abs SHAP
Socioeconomic Conditions	0.096137
Access to Infrastructure	0.079371
Access to Public Services	0.114438

The average SHAP values of the features within each category indicate that access to public services is the most important of the three factors in determining planning permission application outcomes. In second place is the socioeconomic conditions of the area with access to infrastructure deemed the least predictive aspect. However, there is only 0.035 separating the three categories. To learn more about exactly which features are most heavily influencing the model, I extracted the SHAP values at an individual level.





These visualisations show that the main reason behind access to public services being ranked first is the importance the model places on commute time to school and work . These features alone were the first, fourth and sixth most important to the model. The dot plot shows that the majority of people in an area having a shorter commute make it more conducive to planning application approvals. Conversely, areas where commuters are travelling for over 30 or 60 minutes are more likely to be rejected. Other high ranking features such as low population density (2nd), commuting via a personal vehicle (3rd) and, to a lesser extent, low college education levels (9th) suggest that it is rural areas where the majority of people work locally in agriculture and trades that are most often granted permission.

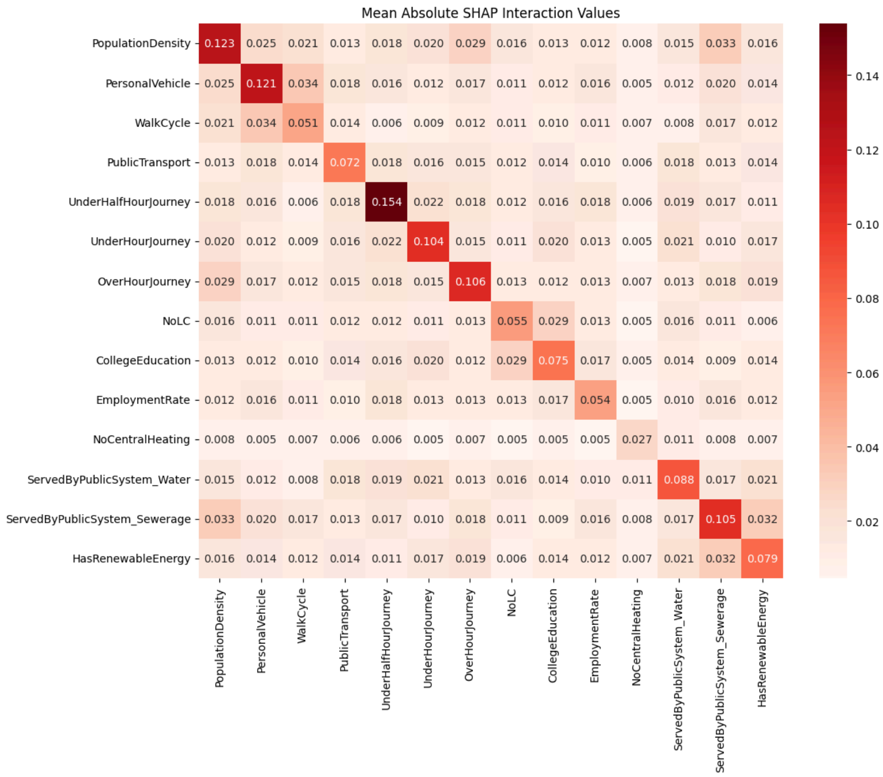
The low rankings of socioeconomic factors such as employment rate (11th) and leaving certificate completion (13th) are encouraging as it suggests there isn't inherent discrimination against unqualified, vulnerable demographics.

Despite access to infrastructures low ranking among the categories, there are still valuable insights to be taken from the individual features. The dot plot strongly displays that, although not the most predictive factors (5th and 7th respectively), areas with poor access to public water and sewerage are more likely to have their proposals dismissed by planning authorities.

Research Question 2:

How do socioeconomic, public service access, and infrastructure factors interact to predict the likelihood of planning permission being granted?

To examine relationships between features within my model, I computed SHAP interaction values, displayed in the following matrix:

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Top 5 interacting feature pairs (mean |SHAP|):
PersonalVehicle ↔ WalkCycle : 0.0340
PopulationDensity ↔ ServedByPublicSystem_Sewerage : 0.0328
ServedByPublicSystem_Sewerage ↔ HasRenewableEnergy : 0.0320
PopulationDensity ↔ OverHourJourney : 0.0287
NoLC ↔ CollegeEducation : 0.0287
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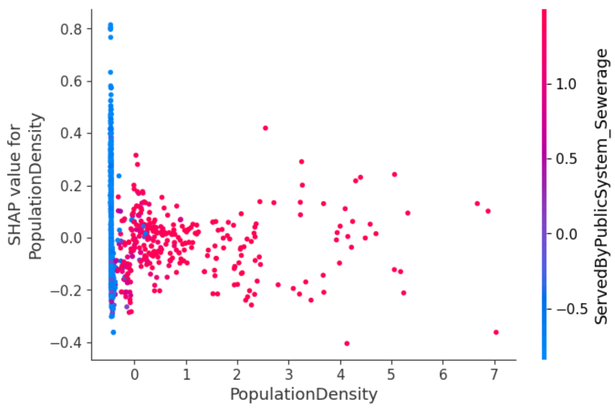
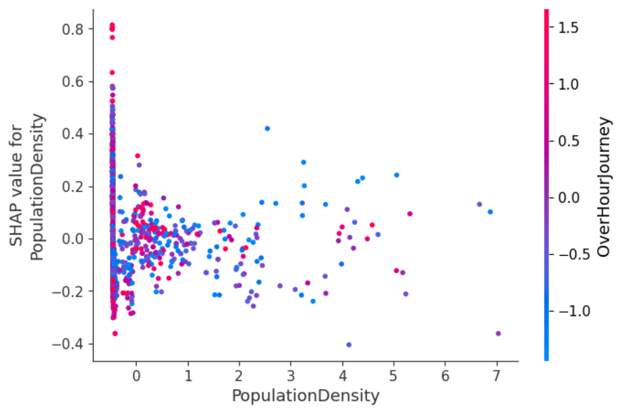
SHAP interaction values describe how strong an effect the value of one feature in a pair has on the other. These pairwise operations can be computationally expensive and slow on such large data. To counteract this, I calculated the values from a random stratified sample of 1000 rows of my test data.

From the top 5 highest interacting pairs, 3 of these (1st - access to public services, 3rd - access to infrastructure and 5th - socioeconomic conditions) are features from the same categories. The other two combine a socioeconomic factor (population density) with access conditions; public sewerage (2nd - access to infrastructure) and over 60 minutes commute time (4th - access to public services).

Several inferences can be made from these scores and rankings to further assert the assumption that rural areas are prioritised in determining planning outcomes. It is evident that population density is an important determinant of how a high or low value of another feature should be interpreted by the model.





The above dependence plot shows that in areas of high population density, long commutes are strong predictors of application refusals and low public sewerage availability points the model towards approvals. However, in less dense areas, these factors actually tend to shift probabilities towards opposite predictions.

More indirect links to the effect of population density can also be extracted from the first and fifth ranked pairs. High levels of personal vehicle use only predict towards application approval if accompanied by low walking and cycling levels. This is reflective of a rural environment rather than a city or town. Low levels of college education in an area also only seem to contribute towards negative case predictions when there is a high proportion of people locally who have completed the Leaving Certificate. Otherwise, it is likely they opted out of these exams to work in manual industries and trades which is very common in less densely populated regions.

The link between sewerage availability and renewable energy shows that even if an area typically relies on the private system, if they have a strong presence of renewable energy sources, the model will use this to influence a positive prediction.

Overall, it appears the most impactful way that features throughout the three categories interact is through the model using socioeconomic conditions to assess whether a site is in a more rural or urban environment. It then uses this information to determine whether various access features should be indicative of a positive or negative case given the population context.

Research Question 3:

Under what combinations of conditions are planning applications most likely to be rejected?

Based on my SHAP analysis in questions 1 and 2, the conditions under which applications are most likely to be rejected are those with high population density and high commute times and also those with low density coupled with poor access to public infrastructure.

The individual feature analysis shows that the model is generally influenced by high population density values to make negative predictions more than any other feature. This is closely followed by commute times over 30 and 60 minutes. Low values for public sewerage and water availability also tend to lead to the model lowering the probability of positive cases.

The SHAP interaction values and plots further show how patterns within these features influence the model's decision making process. The dependency plots show that in highly dense areas, a high proportion of commuters travelling for over an hour becomes a key factor in guiding the model to make negative predictions. Similarly, a lack of public supply systems uniquely becomes a strong indicator of application rejections when paired with low population density.

This is compelling evidence that at both extreme ends of the urbanisation scale, applicants are most unlikely to receive planning permission if they are in a populous, built up region with long travel times to work and school, or in a remote community with minimal access to public sewerage and water supplies.

6 Conclusion & Future Work

My analysis suggests that although the government's current planning policies are striving to achieve National Policy Objective 15 regarding developing rural areas, more needs to be done in terms of maximising employment opportunities (NPO 10) and providing nationwide infrastructure (NPO 18).

It is true that planning authorities are encouraging the building of one-off houses in low population density areas. However, I have highlighted that if an area is remote enough that it does not already have existing public or private access to water and sewerage, applications are very likely to be denied. This behaviour does not align with the government's aspiration to extend these systems to all parts of the country. Going forward, there must be a formal commitment to achieving nationwide coverage.

I also found that the majority of people travelling to school or work in their own vehicle is a strong predictor of an area being admissible for development. This is likely caused by planning permission being granted in areas with a lack of public transport and local employment opportunities that rely heavily on agriculture, tradesmanship and commuting to economically sustain their economy.. Policy changes such as green field site zoning for businesses and increased investment should be implemented to promote more local job creation and entrepreneurship. Expanding more small scale economic centres within satellite communities is essential for the government to control urban sprawl through upcoming periods of population growth.

In conclusion, although the government is adhering to rural development commitments, there are still significant policy changes required to optimise employment and infrastructure development in line with the Project Ireland 2040 framework.

In the future, I would like my current work to be extended by incorporating geographical data through satellite imagery as demonstrated in [6]. This could allow me to identify areas where the land is not fit for development and perhaps offer a more informed analysis with the exclusion of constrained land.

7 Ethical Considerations

All of the data used in this project is publicly available under the Creative Commons Attribution 4.0 International licence [24]. The 2022 Census data used contains no personal information as it is aggregated at the small area level. The planning application contains unique identifiers such as applicant names and addresses. Under the data minimisation terms of GDPR Article 5(1)(c) [25], the names were removed and the exact locations replaced with the Census small area code.

The models created as part of this research must not be used to determine outcomes of future applications. This would only serve to perpetuate and reinforce biases towards specific demographics from previous processes. Instead, the model's behaviour should be examined to highlight patterns of specific social or geographical cohorts facing disadvantages and requiring additional policy support.

Although the original data sources are publicly available, my merged dataset will constitute new processed data. The dataset and the code used to create it will not be published publicly to comply with GDPR Article 5(1)(b) [25] regarding purpose limitation. The data is intended solely for academic research, not to drive unethical, real-world decision making.

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[12] Table 11.3 - Population aged 5 years and over by journey time to work, school or college by Small Areas (Census 2022). (n.d.). https://www.geohive.ie/datasets/8aee10cb3a2d4b768fd751b5ff932e83_0/explore

[13] Table 8.1 - Population aged 15 years and over by principal economic status and sex by Small Areas (Census 2022). (n.d.). https://www.geohive.ie/datasets/c6729d50f8224c75b067a947d6a97f99_0/explore

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