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Elucidating the Predictive Power of Search and Experience Qualities for Pricing of Complex Goods – A Machine Learning-based Study on Real Estate Appraisal

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Information systems have proven their value in facilitating pricing decisions. Still, predicting prices for complex goods remains challenging due to information asymmetries. Beyond Search qualities that sellers can identify ex-ante of a purchase, these goods possess Experience qualities only identifiable ex-post. While research has discussed how information asymmetries cause market failure, it remains unclear what benefits Search and Experience qualities offer for information systems that enable pricing on online markets. In a Machine Learning-based study, we quantify their predictive power for online real estate pricing. We use Geographic Information Systems and Computer Vision to incorporate spatial and image data into a Machine Learning algorithm for price prediction. We find that these secondary use data can transform Experience qualities to Search qualities, increasing the predictive power by up to 15.4%. Our results suggest that secondary use data can provide valuable resources for improving the predictive power of pricing complex goods.

Keywords: information asymmetries, real estate appraisal; SEC theory; Machine Learning; Geographic Information Systems, Computer Vision

Introduction

Pricing decisions play an important role for buyers and sellers involved in sales transactions, since sophisticated pricing decisions can foster competitive advantage [11]. The Information Systems (IS) domain has been investigating pricing strategies in various contexts, like e-commerce and online platforms [53], as well as for understanding, explaining, and predicting prices [11, 29, 53, 67]. For IS research, pricing effects are of interest as they are driven by the discovery and reduction of information asymmetries [20, 25].

Information asymmetries occur when a seller (agent) has more information about a product than a buyer (principal) [64]. Due to the undisclosed information, the agent cannot assess the product's quality fully and thus not rate a price ex-ante to the sale. Following the argumentation by Akerlof [2], information asymmetry can lead to a 'market for lemons', provoking adverse selection for high quality products. These products are pushed out of the market, resulting in a not pareto efficient economy. This effect especially applies to durable goods that are traded on online platforms and cannot be sufficiently described with digital information, while not allowing to touch, feel or experience the product [20].

Until now the field of pricing decisions in IS research mainly bases on well-structured and conventional transaction data [32, 68] from hotel room rentals or used goods trading. These buying transactions often pose low-risk, because on the one hand the objects or services purchased are well-describable and thus have only little information asymmetry, and on the other hand, the price of the object is relatively low.

For goods that are not that easily describable and are subject to individual pricing, the pricing decision is challenging and high-risk due to high information asymmetries. For example, real estate is a product which is described by different qualities ranging from the size to quality and aesthetics [40, 43, 59]. Housing is heterogeneous as each property is non-standardized and has very individual characteristics (e.g. individual interior or exterior design), making it difficult to holistically describe the object [63, 69].

Houses are embedded in a high-dimensional geographical context, in which multiple relationships exist, e.g., the spatial proximity between the house and Points of Interests (POIs) like parks or schools or the dispersion of POIs in the neighborhood [35]. A suitable location considers and balances these multi-dimensional aspects. For example, there are qualities, that can easily be evaluated before the purchase, like the number of rooms. Search, Experience, and Credence (SEC) theory [19, 30, 52], defines these qualities as Search qualities. In contrast, qualities of a good that need to be touched, felt, or experienced are defined as Experience qualities, because they cannot easily be assessed prior to the purchase [52], like noise around the house. Credence attributes are nearly impossible to be evaluated even after the purchase and usage as the data of the counterfactual outcome remain unobserved.

The prediction of house prices is already integrated on online platforms like Zillow, the largest American real estate platform. Zillow provides a unique value proposition with their service Zestimate®, which is claimed to be within 5% of the sale price [73]. Within the domain of IS research, different pricing processes and systems are suggested, including aspects about co-existence of goods [27], automatic pricing [32, 68], pricing strategies and discounts [12, 53, 58], and aspects about information asymmetries [20, 25]. Real estate pricing is more and more extended by variables extracted through GIS [35, 41, 48] and Computer Vision [40, 59]. Since the prediction of house prices holds a high-risk for over- or underestimating prices, a high predictive accuracy is required [40]. While related work focused on improving the predictive performance [5, 38, 40], leveraging different technologies for extracting Experience qualities of goods in the context of high-risk pricing decisions has not been in the focus.

We investigate what the value of using GIS and ML is for pricing products and what predictive performance Search and Experience qualities hold for real estate appraisal. From a data-driven study on predicting prices for 62,641 single family homes located in Philadelphia, PA, we find that extending predictive price models based on Search qualities with Experience qualities reduces the prediction error of our models by 15.4%. Our results indicate that Experience qualities alone cannot outperform a Search quality only model, but a combination of Experience and Search qualities boosts the predictive performance.

Our contribution is three-fold. First, we enhance the theoretical knowledge of pricing decisions in IS. We use the SEC theory to investigate the role of Search and Experience qualities for pricing systems in online housing markets. By combining the SEC Theory and existing pricing systems, we generate knowledge about pricing effects of heterogeneous, complex, physical, high-risk products that are subject to considerable information asymmetries in online markets. Second, on a methodological level, we use secondary-use data in form of location and image data for the pricing process that bear essential information. By using GIS and ML, we extracted Experience qualities, e.g. the noise level, that reduced the information asymmetries. By these means, we quantify the improvement of the predictive accuracy of using Experience qualities and secondary-use data. Third, we go beyond predictive performance and the inner mechanics of the intelligent system and derive practical implications of our real estate pricing system. By including stakeholder positions and theories about livability, we conclude that house pricing systems can reveal insights into the pricing effects on a city or municipality level insights into the pricing effects. For example, the knowledge that crime (captured by various variables) and dirtiness are important variables in the price prediction, can enable city planners or governors to counteract effects like the broken window theory [71] or to uncover early signs of gentrification, increasing a city's or neighborhood's livability for inhabitants [17, 18].

The remainder of this paper is structured as follows: In section 2, we present the scientific background. In section 3, we describe and justify our research approach and present our findings. In section 4, we discuss the results before concluding the paper in section 5.

Scientific Background

Search, Experience, and Credence Qualities

Before buying any kind of good—whether it is a piece of clothing, an elaborate wine, or a house—a potential buyer goes through an internal decision process on whether to make the purchase or not [3]. Such a buying process often involves a contractual arrangement. The relationship between a buyer and a seller can be represented by the Principal Agent Theory, defining a buyer as the principal of a contract and a seller of the good as the agent [64]. Generally, the principal has less information about the qualities of the provided good prior to the purchase or contract conclusion than the agent. A classic example is used cars. Oftentimes a seller has more knowledge about the quality of the car than a buyer resulting in an information asymmetry between the two parties [2].

Since buyers often lack complete information about the different qualities of goods due to information asymmetry or simply because some information like the style is difficult to explicate [52], an essential part of the buyer's decision process is to evaluate if the product can and will satisfy their current needs. To answer this question, a buyer will consider different product qualities to evaluate if it matches her needs and further compare them to rival products. However, product uncertainty remains when some information are not accessible to the buyer [20]. Especially in online markets, the description of goods and their qualities can be challenging, because of the inability to physically experience the product [20]. Thus, certain qualities like the comfort or reliability of a used car cannot be fully evaluated by a buyer prior to the purchase.

Information asymmetry and product uncertainty can lead to a 'market for lemons' [20, 25]. First introduced by Akerlof in 1970, the 'market for lemons' theory states that due to an adverse selection 'lemons' – meaning goods with less quality –

exceed goods with higher quality (‘peaches’), leading to market failure [2]. Thus, ‘lemons’ are sold at the same price as ‘peaches’, although there might be essential differences in quality, and sellers take the products from the market due to insufficient sales prices [2]. The lemon market theory illustrates just how crucial information asymmetry and product uncertainty are for pricing goods, especially for those which have qualities that cannot easily be represented in digital form.

The Search Experience and Credence (SEC) framework can describe the qualities of many objects including products that have heterogeneous characteristics like real estate. Therefore, the SEC framework distinguishes three qualities of goods: Search (S), Experience (E), and Credence (C). Search and Experience qualities were first defined [52] and Credence qualities were added later [19]. Generally, a good or object of purchase can have all three types of qualities, but in different proportions, which makes them either simple or complex goods and allows conclusions about whether the dominant attributes of a good rather match Search, Experience, or Credence qualities [30]. Search qualities are "the most obvious procedure available to the consumer in obtaining information about price or quality" [52, p. 312]. A good can be defined as a Search good if "full information for dominant product attributes can be acquired prior to purchase" [33, p. 196]. Experience qualities are harder to describe and gaining information about these qualities is more costly and difficult than for Search qualities since "full information on dominant attributes cannot be known without direct experience" [33, p. 199]. Thus, customers will more heavily rely on their own or others' product experience and also encounter a higher degree of financial, social, and psychological risk [47]. Today, technology allows for Experience qualities to become describable prior to purchase by changing the nature of the communicable information [33]. Credence goods or qualities "are those which, although worthwhile, cannot be evaluated in normal use. Instead the assessment of their value requires additional costly information" [19, pp. 68-69]. Further, Credence goods “have the characteristic that though consumers can observe the utility they derive from the good ex-post, they cannot judge whether the type or quality of the good they have received is the ex-ante needed one" [22, p. 526]. The SEC theory has been applied and evaluated in several fields over the last decades, e.g., for marketing [24], product evaluations [26], information sources for services [13], and greenhouse gas reporting [16].

We posit that search and experience qualities dominate when it comes to describing real estate. A house includes Search qualities, since attributes like the number of bedrooms, the age, or the type of heating can be specified unambiguously on online real estate platforms. In contrast, important Experience qualities like the real estate’s condition, the surrounding noise level, or the perceived safety cannot be communicated easily without physically experience the object. Since a house is a durable good within a geographical context in most cases a buyer can tell ex-post if the house matches their ex-ante needs. Hence, we posit that Credence qualities play a minor role in describing real estate, which is aligned with the results of Iacobucci [30].

The importance of Experience qualities for describing houses are a key reason for the emergence of information asymmetries in the real estate appraisal processes. Yet, technological advances around big data and analytics make it possible to transform some Experience qualities into Search qualities. For example, modern online mapping services like Google or Bing Maps provide high-resolution satellite, aerial and street view images which enables home buyers to better judge the appearance of a house and its neighborhood. Similarly, open data platforms like data.gov provide rich environmental (e.g., air quality noise levels) and socio-economic (e.g. quantity and quality of schools, crime rates) information about almost any urban area in the United

States. Extracting and integrating this data into real estate appraisal models may reduce information asymmetries and uncertainties.

Real Estate Appraisal

Real estate appraisal is the monetary evaluation of properties or parcels for multiple purposes [43]. Many stakeholders rely on a computer-assisted value estimation for supporting appraisal decisions, including financial institutions for credit assessment and investment estimation [10, 35], for municipalities for calculating property tax [45], and for real estate agents and online platforms for supporting the client's decision process [40, 66]. A recent survey of the National Association of Realtors, found that today online platforms are the main information source during the home buying process: 97% of home buyers use the internet in the search process and 51% of home buyers finding their property online [51]. To decrease information asymmetries online real estate platforms often provide a price estimation in addition to a sellers' bid price. For example, Zillow, the largest American real estate platform, provides a service called Zestimate®, which is claimed to be within 5% of the sale price, 75% of the time [73], with the prediction accuracy being a unique value proposition to the platform.

The predominant approach to predict a price of a house, which is a complex pricing task [34], is based on the Hedonic Pricing Theory. This theory developed by Lancaster and later on refined by Rosen, the overall price of a good is its overall utility [40, 63]. To measure the utility, the good is separated into its characteristics. An additive linear combination of the individual utilities is defining the price. By market observations, the prices (utilities) for the different qualities can be inferred [39, 63]. The classical hedonic model is based on a Linear Regression (LR) because of the interpretability of coefficients and the linear additive characteristic supporting the logic of hedonic pricing. The complexity in the real estate appraisal process comes from the object itself, as housing is not a homogeneous and standardized good [63, 69].

In real estate appraisal two developments happened to improve predictive accuracy: (a) the use of Machine Learning (ML) models (e.g., Random Forest) [35] and (b) the integration of unstructured data, mostly originating from images [40, 50]. By using Convolutional Neural Networks (CNNs), a specific model mainly used in Computer Vision, implicit information about the aesthetics and neighborhood structures can be extracted from different images and used in the prediction model. Image types range from exterior perspectives to satellite images [5, 6]. The gathered additional information improves the predictive performance of real estate models, however, it also reduces interpretability, as complex modeling structures are leveraged to combine classical house attribute and image data in multi-view learning settings [37, 38]. Nevertheless, the predictive performance is an important goal for many stakeholders [66], because real estate appraisal is perceived, due to the high expense, as a high-risk decision.

Enabled by the improving data and analytics capabilities through digitalization [7, 50, 70], additional data sources can be taken into account in appraisal. Using GIS for data analysis has been found to providing richer insights for research by using location-specific data that become available through e.g., open data policies [60]. Notably, many data sources like image or GIS data are often not created with the intention to enable real estate appraisal in the first place, giving them a secondary use. These sources often suite other (multiple) purposes, like geographic noise maps might serve as a basis for city planning or health analyses, e.g., for hearing damage. However, there are also data, which are especially gathered for a specific purpose, e.g. real estate appraisal, like structured data about the size, age, and building materials of a house, creating a primary usage for it.

The extracted information of secondary-use data sources helps to quantify Experience qualities of goods, which has not been possible before [33]. Previously, the evaluation of the price was mostly performed by considering Search qualities only, for a product where, Experience qualities are of importance too. For example, by leverage Information Technology (IT), noise level information could be extracted from noise maps with the help of GIS, while ML algorithms could also make use of visual information from images.

Until now, many real estate papers investigate the predictive performance of different features e.g., the inclusion of exterior images in Liu et al. [44] or the combination of socio-economical, mobility and image data in the research of Kang et al. [31]. While being very successful, their underlying process is often times data-driven by creatively accessing and mining new and previously untapped data sources (secondary-use data). However, current studies often fall short in arguing why certain variables are used in the hedonic model or which Search or Experience quality the data is describing. Consequently, a more theory-driven perspective on the predictive performance of features could help to gain additional knowledge about the field.

Data Analysis

Our research is structured in a five-step process (*Figure 1*). First, we identified, based on a literature review important concepts and variables in real estate appraisal. Based on these results, we performed a survey to classify the variables into Search and Experience qualities. Following, different data sources were acquired to measure the identified variables. Therefore, a dedicated data preparation phase was performed, where data was extracted from GIS and images and cleaned, so that it can be used in the ML based computational experiments in the last step.

[INSERT FIGURE 1 HERE]

Identification of concepts and variables

To predict the price of a house, many different variables are used within the literature. Concepts and constructs can be used to structure these variables [62] representing relevant information for real estate appraisal. 16 concepts can be derived from literature (Figure 2). To be able to group the identified concepts for a more general overview, four meta-concepts for real estate appraisal can be classified: **house**, **location**, **livability**, and **economy**. A level beneath the concepts, constructs can be assigned. A construct is "an operationalisation of a concept in such a way that we can define it by measuring the construct against data" [62, p. 27]. Within literature 69 constructs can be identified bottom-up (Appendix A)[1]. For example, on level 1, within the meta-concept **livability**, there are four concepts on level 2: *mobility*, *safety*, *environmental attributes*, and *educational opportunities*. Here, for example, the concept *environmental attributes* includes the four constructs noise [15, 28, 36, 42], air pollution [42], dirtiness [8], and solar radiation [28, 48] on level 3.

[INSERT FIGURE 2 HERE]

Classification of variables into Search and Experience qualities

To evaluate whether the identified constructs represent either Search or Experience

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[1] https://osf.io/njq9m/?view_only=ca98f39f313e487ebf9de9c615e91df7

qualities[2], we conducted a survey with 16 academics (Ph.D. students, post-docs, and professors) from the field of economics, as they are familiar with SEC theory and in general, are able to apply economic theories appropriately. Our goal was explicitly not to achieve a representative survey, but to rely on experts who understand the theory as a basis to evaluate the constructs of our study. To ensure the participants' understanding of the SEC theory, we included a general description as well as definitions for Search and Experience, and asked them to answer a knowledge assessment. All of the participants answered this question correctly. Except for two persons, all participants have searched for a house or an apartment for property or rent before. To learn more about their current living situation and their preferences, we asked them whether they rent or own property and whether they prefer to live in the city or in a more rural area. Five of the participants currently own property, while 11 live for rent and about 68% of the participants prefer to live in the city area.[3]

We asked the participants to rate each of the constructs on a the following 5-point Likert scale: 1 "Only Search", 2 "Mostly Search", 3 "Search and Experience", 4 "Mostly Experience", and 5 is "Only Experience". We also added the option to give no answer. The structure of the survey can be found in Appendix B.

To aggregate the results of the rating of the constructs, we calculated the mean value for each construct based on the results from our survey. Figure 3 shows the normalized mean values of the constructs. A full version of the results of our survey can be found in Appendix C.

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[2] We excluded Credence qualities from our study, since they cannot be evaluated in normal use and are nearly impossible to verify.

[3] A figure showing the age, gender, and highest educational qualification of the participants can be found in Appendix B.

We normalized the original values, which were in the range between 1 to 5, with a mean of 3, marking the border between Search and Experience qualities. Afterward, we classified constructs that have a negative mean rating as Search and those which have a positive rating as Experience qualities. For example, the construct *total rooms* has the lowest value with -1.625, indicating that this construct is an instance of a Search quality. The construct *perceived safety* has the highest mean value with 1.400, indicating that this construct represents an Experience quality. Overall, 52 constructs were classified as Search qualities and 17 were classified as Experience qualities. Across the 16 concepts, the number of Search and Experience constructs varies. There are some concepts that only include constructs which have been classified as Search, e.g., *size*, *structural attributes*, and *accessibility*. Other concepts include a mix of Search and Experience constructs, e.g., *condition*, *neighborhood qualities*, and *safety*. The only concept including only constructs that have been classified as Experience is *environmental attributes*.

[INSERT FIGURE 3 HERE]

Data acquisition for measuring variables and concepts

Since the identified constructs are multi-dimensional and, thus, "have multiple underlying dimensions, all of which are relevant [...] and [...] must be measured [...] using dedicated variables" [62, p. 28], we proceeded with identifying concrete variables which can be used as predictors in our ML models.

First, we accessed first-use data in form of tabular data containing information about the house, like the number of bedrooms and the size, from the official metadata catalog of the City of Philadelphia [14].

Second, we collected second-use data in the form of spatial data from official open data portals of Philadelphia [14, 54]. These data came in a shapefile format and included location information in the form of coordinates. Consequently, they are not directly ready to use in statistical or ML methods, but first need preprocessing using Geographic Information Systems (GIS). GIS include spatial and attribute data and produce visualizations or data outputs and can provide richer insights for research considering location-specific data [23, 60].

The third data type we collected for our analysis was image data. We used second-use data in the form of street view and first-use data in the form of house images from Bing Maps [46]. We defined house images, as the exterior view of the house visible from the street [6]. Street-view images, on the other hand, showed the street perspective at the location of the house corresponding to a driving position (at a 90-degree angle to the house) [40]. To download the images from Bing Maps, we used the house coordinates and calculated the street direction based on the neighboring houses. We obtained house images at a size of 1024 by 1024 pixels and streetside images at a size of 512 by 512 pixels.

A complete list with the detailed data sources used (e.g. which tables from the Open Data portals) is found in Appendix D.

Data Preparation

The housing characteristics needed preprocessing so that they are usable for ML algorithms. First, in the numerical values we applied winsoring so that extreme values were mapped to the 0.1% percentile for the lower and upper bound. For example, the number of bedrooms variable had before preprocessing 40 occurrences with more than 6 (up to 30 bedrooms). Through the winsorizing, the maximum number of bedrooms were 6. For categorical variables like Zip Code or technical details about the heating configuration, we grouped rare categories (below 25 occurrences) to the value “other”.

Preparation of geospatial data

For the analysis of GIS data, we used the software ArcGIS as well as the Python packages haversine, shapely, and geopandas. Geospatial data can have different types which are point, line, and polygon [23]. To be able to assess the location information from GIS depending on their data type, we applied three different analysis methods with the aim to generate variables ready for ML.

The first was a buffer analysis. A buffer is "an area determined by distances around features and can be applied to points, lines, or polygons to identify areas that fall in or outside the buffer" [23]. This analysis allowed us to count the number of objects (e.g., parks), to determine the length of a line (e.g., bike network) or to calculate the area of objects (e.g., hydrographic areas) within the buffer (*Figure 4*).

[INSERT FIGURE 4 HERE]

The second analysis determined the distance between two points, e.g., between the house and the closest school (Figure 5). This analysis is often used for location selection [23] but can also be applied for determining distances from a fixed point to the surrounding objects and Points of Interest.

The third GIS analysis was overlay, which means to combine two layers to determine for example, overlaying areas [23]. Here, one layer, e.g., the layer containing the houses, can be combined with another layer, which, e.g., comprises the different neighborhoods. Thus, we could determine in which neighborhood the house is located (Figure 5).

[INSERT FIGURE 5 HERE]

Preparation of images

Like GIS data, image data need data preparation to be ready for the analysis. Images being represented as a three-dimensional tensor (height, width, color channels), cannot be analyzed in classical ML models like Linear Regression, Random Forest, or Support Vector Machines, which require tabular or vector input. Either specialized models like multi-view neural networks need to be leveraged for an overall prediction (house price regression), or feature extraction on the image data need to be performed for analysis. We decided to use feature extraction performed by CNNs rather than a complete prediction of the house price, as by extracting specific features like aesthetics or architecture style, we were able to map the features in the SEC theory. In contrast, multi-view neural networks or CNNs regressing the real estate price might have learned multiple concepts in parallel, which are hard to understand and separate, as these are black-box models, leaving their inner decision-making criteria and learned knowledge obfuscated.

Examples for Search data preparation

In the following, we will present examples of constructs from some of the meta-concepts for the categories Search and Experience. A full version of all constructs and the allocated variables can be found in Appendix D.

First, for the category Search, we present three examples of constructs and their corresponding variable selection and analysis.

The first Search construct is *building style* from the meta-concept **house**. The architectural style is an often used variable in related research, indicating by a dummy variable different styles like colonial or conventional [9]. As this information was not included in the structured information about the house, we extracted the style from the exterior image data. We, therefore, trained an *architectural classification model* with the dataset published in [72]. Details about the implementation of our Convolutional Neural Network can be found in Appendix E. We selected 11 different architecture styles for training, ranging from American style via Deconstructivism to Tudor Revival.

With an accuracy of 72% and a F1-score of 0.68, we performed slightly better than the model suggested in the paper. We applied this model to predict the architecture given in the exterior images in our dataset about Philadelphia.

The second construct is *building density* from the meta-concept **location**. Here, we used ArcGIS to determine the sum of the area of buildings in relation to the area of the different neighborhoods. Therefore, we used the house dataset containing the building footprints as polygons, which we then overlayed with the neighborhoods. We cut the areas of the buildings on the borders of the neighborhoods to be able to assign only the parts of the areas that were really inside the neighborhood polygons. The result is the sum of all buildings for each neighborhood. We then divided this sum by the area of the corresponding neighborhood polygon to get a percentage value, which represented the *building density*.

The third construct that has been classified as Search is *distance to airport* and could be found in the meta-concept **livability**. We determined the coordinates of the airport of Philadelphia from Bing Maps. Afterward, we calculated the distance from each house in the dataset to the airport using haversine.

Examples for Experience data preparation

After having presented three Search constructs, we will explain three examples of constructs from the category Experience.

The first Experience construct is *quality* from the meta-concept **house**. The quality variable of the house, in our dataset, was given by the open data about the house. This variable indicated by different grades (e.g., average, above average, excellent), the level of used materials and the workmanship of the house.

The second construct is *perceived safety* and can be found in the meta-concept **livability**. To extract these information, we built a *safetyscore model* based on the Place

Pulse 2 dataset [21], and the work of [49] . In the aforementioned paper, laypeople were asked to decide between two images, which location looks more safe. The votes for the images were transformed using the Trueskill algorithm [21]. Each image finally had a rating between 0 and 10, which we used to train our CNN to predict the score from the image (Appendix E). We filtered the PlacePulse 2 dataset for containing only US cities and excluded images from Philadelphia to prevent information leakage to our collected data about Philadelphia. We used this part of the dataset, to evaluate the performance of the algorithm. The *safetyscore model* had an R^2 of 0.25 and a mean absolute error of 0.93. Example predictions made on our dataset are visible in Figure 6.

[INSERT FIGURE 6 HERE]

The third construct that has been classified as Experience is *noise* from the meta-concept **livability**. We assessed a dataset from the open data portal of Philadelphia containing noise information within a raster format. To get a noise value at each house, we divided the noise dataset into three noise levels according to literature. The first level was less than 55 dB [56], the second was 55 dB to 65 dB, and the last level was over 65 dB [15]. We created three polygons according to these ranges and overlayed the noise layer with the house layer to allocate a noise value to each property.

In Table 1, we highlight descriptive statistics of selected variables. Full details can be found in the Appendix F. The average house has a size of 1140 square feet, and costs 81,302 USD. On average, a high school is 537 meters away from a house. In addition, there are on average 25 grocery stores within an 800 meter buffer around the house.

[INSERT TABLE 1 HERE]

ML Experiments

We collected data for 41 of our 69 constructs since some data, like the financial data, do not provide adequate resolution (as the interest rate is not only dependent on the house but also on the buyer's details, which we cannot access; overall general interest rates being a constant do not add valuable information), or were not available for our analysis area. After having collected the data, we are able to analyze them with ML models.

We tested different ML models on using features representing only Search, only Experience, and Search and Experience qualities. To evaluate the predictive performance, we use a nested cross-validation strategy (Figure 7). Therefore, we first divide the dataset into a spatial-out-of-sample (SooS) test set (unseen houses, unseen neighborhood) containing all houses in the zip codes 19119, 19139, and 19149, resembling a low, medium, high-priced area, and a training set, formed by all other zip codes. On the training set, we applied a nested 5-fold strategy: In the outer loop, we divide repetitive (5-times) the training set into 4/5 of training and 1/5 of validation. The validation set is not shown to the algorithm to be able to estimate the performance on known zip codes (unseen houses, known neighborhoods) later on. For each train-validation split, we train one unique version of the model. The hyperparameters are optimized in the inner loop of the nested cross-validation strategy. Here, the previously train data from the training-validation split are split again repeatedly (by five times) to 4/5 training and 1/5 optimization set to estimate the best hyper-parameter combination by minimizing the root-mean-squared-error (RMSE). Instead of testing a larger parameter grid, we use a Bayesian optimized hyper-parameter search to intelligently select the next best set of parameters. The suggested evaluation strategy allows us to derive five versions of a model, each trained and optimized by 5-fold Bayesian cross-validation, without showing out-of-sample and SooS, preventing leakage and increasing robustness and limiting bias of our performance estimate. We report the average out-of-sample and average SooS performance, including one standard deviation in the prediction metrics RMSE.

We applied the evaluation strategy described above to the following algorithms: LR, Decision Tree (DT), Catboost, and k-nearest-neighbor Regressor (kNN). We decided on those algorithms because the LR is the predominately used model in hedonic pricing, and ML models like DT, Catboost, and kNN promised an increased predictive performance [35, 43, 48, 55, 57, 66]. Instead of a Random Forest, we used a modern boosting approach, namely Catboost, which is skilled in handling many categorical variables [61]. Details about how these algorithms work, and which hyper-parameter were optimized can be found in Appendix G.

[INSERT FIGURE 7 HERE]

Results

In the following paragraphs, we report our results for the out-of-sample validation (Appendix I) and SooS test set (Table 2). For both, we see that although experience variables have some predictive power (as they perform at least 14% better than a naïve model), they result in a higher prediction error (lower performance) compared to Search qualities. Combining Search and Evaluation qualities boosts the predictive accuracy by up to 15.4% compared to search goods only. This holds over different algorithms except for the SooS Decision Tree.

To identify the most important variables for Search, Evaluation, and Search and Evaluation qualities, we calculate a version of feature importance for the Catboost model on the SOOS dataset. The feature importance measures how strong the model relies on that feature during the prediction. Therefore, the corresponding variable *i* is shuffled into a random ordering, and the predictive performance is compared to the original state, where no variable is shuffled by building the ratio.

Thus, a feature importance larger than one means that the model relies on this variable. However, one downside of feature importance is that it cannot measure higher-order concepts than a variable, e.g., constructs and concepts consisting of multiple variables.

Nonetheless, a joint analysis of features is often more valuable for research and practice or necessary because feature importance of single variables gets uninterpretable with many features (hundreds or thousands) [4]. As our analysis aim is about linked feature group rather than individual variables, and we have many variables (157 after preprocessing like dummy encoding), feature importance does not seem to be suitable choice. Therefore, we follow the suggestion of Au et al. [4] and use Group Feature Importance. The groups for the features can either be built computationally, e.g., clustering methods, or as in our case theory-driven (based on the SEC theory). Instead of shuffling single variables, all variables that belong to the group *g* based on a construct or concept are shuffled simultaneously, where the order between the grouped variables remains the same, ensuring the pooled effect is measured (Equation 1). A group feature importance larger than one means that this feature group is important for the model's predictive performance.

$$Feature\ Importance_g = \frac{performance\ evaluation_{g\ permutated}}{performance\ evaluation_{original}},$$

$$g \in Variable\ group, g \subset Variables$$

Equation 1: Group Feature importance.

The most important constructs of search qualities were the average house price in the neighborhood, the squarefeet, distance to miscellaneous amenities, garage, and air condition (Figure 8). The variables related to the concept house and economy, and location.

Essential constructs of experience qualities were crime, dirtiness, and physical state of the house. Thus, these constructs were related to concepts about safety and environmental attributes (both livability) and condition (house) (Figure 9).

Combining search and evaluation qualities led to important constructs of average house price, squarefeet, physical state of the house, garage, and crime (Figure 10), which were already identified as important when used in the search respective experience concept-based models. Consequently, the performance of the real estate appraisal model depends on the house itself, the economic situation, the livability, and location in the neighborhood.

Comparing the feature importance between a model containing only search or experience qualities and a model combining the two, the physical state of the house, the average house price, and the squarefeet gained importance (Figure 11). However, the constructs crime and dirtiness lost importance when used in the model combining search and experience qualities (Figure 11). For the sake of completeness, we provide an analysis of the feature importance of individual variables in Appendix H.

Finally, we test all Search and Experience variables jointly with the group feature importance to get a better understanding regarding the SEC theory (Figure 12). Search qualities are measured twice as important concerning the predictive performance as Experience qualities, making up for the larger part of the model performance. Nevertheless, as Experience qualities have a feature importance larger than one, they contribute to the overall performance. These results support our findings from the out-of-sample, and SooS performance analysis made in Table 2.

[INSERT TABLE 2 HERE]

[INSERT FIGURE 8 HERE]

[INSERT FIGURE 9 HERE]

[INSERT FIGURE 10 HERE]

[INSERT FIGURE 11 HERE]

[INSERT FIGURE 12 HERE]

Discussion

Our goal was to investigate the predictive performance of Search and Experience qualities extracted by GIS and ML. We found that the predictive accuracy for Search qualities had the best performance with an RMSE of 25,364 with the Catboost model in the SOOS set. Furthermore, by leveraging ML and GIS, we were able to transform the Experience qualities into more accessible information. For example, we used noise maps to analyze the noise level at each house or transformed image data of the street into perceived safety scores. However, Experience qualities alone did not perform as well as Search qualities, having the best RMSE of 36,744 in the SooS with the Catboost model. Thus, Experience qualities had a 44% lower performance than Search qualities. When combining both – Search and Experience – the overall best performance was reached. This combination resulted in an RMSE of 21,452 in the Catboost SooS, which is 15.4% better than Search qualities alone. While the results above were evaluated on the rigorous and complex SooS test set (unknown houses, unknown neighborhood), they also hold for the performance evaluation of out-of-sample (unknown houses, known neighborhood). Consequently, there is evidence that experience qualities should be used for real estate appraisal if also search qualities are available because it can improve the predictive accuracy. Up to now, a model using only experience qualities cannot outperform already existing search quality-based models.

Our contribution to the IS discipline is threefold. First, based on the argumentation of Klein [33], we transform through IT Experience qualities, so that these can be gathered and used in a quantitative analysis. The extracted Experience qualities helped to improve the predictive power of the hedonic real estate model, arguably, because information asymmetries can be decreased. A model based only on Search qualities has limited information and thus might not perform well. In particular, the agent (seller), has much more information about the house (Experience qualities) than the principal (buyer), who can only rely on the Search qualities. However, the information asymmetry can be reduced, because the principal, can use technologies like GIS and ML to transform unleveraged Experience qualities, that can be used in a real estate model combining Search and Experience utilities. One example is the noise level, which usually needs to be experienced so that the information can be considered, which is not possible or only manageable with high search costs in the setting of online real estate platforms. Another example is about safety. We used GIS data in form of the number of shootings and a safety score extracted from images, to make safety measurable in data. Our data analysis revealed that this concept is an important quality in real estate appraisal. Arguably, extracting Experience qualities requires GIS to transform spatial data to structured data, as well as ML to extract information out of unstructured image data, both requiring specific knowledge in those field. Nevertheless, it seems worthwhile the effort as the real estate appraisal performance can be improved by a considerable margin (15.4%).

On a more general level, the transformation of the Experience qualities to measurable variables by GIS and ML increased the quality of the application, as the predictive performance was increased. Furthermore, it reduced product uncertainty, as the information about qualities, that are easy to access for the seller (agent), but are not possible to evaluate for the buyer (agent) have been made available. Especially for an online setting (real estate platform), this could help to decrease information asymmetries, because aspects about noise or neighborhood safety need usually be experienced.

Second, we found that the extraction and usage of Search and Experience utilities from secondary-use data enriches the application of real estate appraisal by intriguing aspects. Many of the extracted Experience utilities, like noise level, number of shootings, aesthetics or security score were extracted from GIS and image data sources. We classified these sources as secondary-use data, as they were collected not with the intention to increase the predictive power of real estate appraisal algorithms but were collected for specific applications or in a general-purpose way. It appeals that extending data analysis beyond primary-source data, data collected specifically for the analysis purpose, holds many potentials, not just for real estate appraisal, but also for other applications in Information Systems. We expect that many applications, like for example, service science can be improved when secondary-use data are considered. Especially, as GIS and the location-based exterior and street images can be linked to location, any service that holds a location aspect can leverage such data sources to either improve algorithms or to extract previous unknown knowledge.

Concerning knowledge generation, we used group feature importance and identified the physical state of the house, the size in squarefeet, information about the garage, distance to miscellaneous amenities, and crime as important variables for the performance of the real estate model in Philadelphia. Although the feature importance of crime-related variables decreased when used in a model leveraging both, search and experience qualities, they remain important for the predictive performance. The used Catboost model relied on search qualities like size in squarefeet or the average house price in the neighborhood, as well as experience qualities like crime or physical state. This supports the argumentation of Iaccobucci [30] that real estate holds both Search and Experience qualities. Secondary-use data is a suitable mean to map – mostly Experience – variables, that previously were not possible to be integrated. Further, until now the role of Experience qualities has been underestimated. Though it might be slightly different in other domains, we quantified the effect of Experience characteristics on price prediction. Thus, Experience qualities hold a valuable yet underestimated source of predictive accuracy.

The third contribution is the practical use of our approach for decision-making processes. Improving, or at least maintaining livability is one important part of the job for city planners and governors [18]. While there are various approaches, how to measure livability, using a hedonic pricing model and data about real estate appraisal and their surrounding is one suitable way, as it combines to livability also an economical perspective [17]. The usage of GIS and ML, thus, should not be seen as a tool to predict property prices and conduct research about the importance of concepts like Search and Experience qualities. Following the argumentation of Shmueli and Koppius [65], the role for ML in IS is, among many, the extraction of new variables. These new information can create new knowledge, which is one important use case of ML [1]. In particular, municipalities and city administrative could use such a real estate appraisal system, to gain more knowledge about pricing processes, livability aspects and urban development. Further, GIS should be considered more in IS research, providing richer insights for research by leveraging on location-specific data becoming available through e.g., open data policies [60]. In particular, the inclusion and transformation of secondary-use data, to quantifiable and searchable constructs through GIS and ML, could extend the inclusion of livability factors, which are currently often approximated through easy to gather data [18]. For example, gentrification and decreasing livability are two major issues in many cities around the world. Through applying a real estate appraisal system based on secondary-data and the SEC theory, monitoring and knowledge generation are possible to detect early signs of these phenomena, the results could positively influence many lives.

Conclusion

We encourage other researchers to inspect aspects about the SEC theory in combination with predictive performance in their research fields by characterizing Search and Experience qualities in their data. Research just started to understand the role of these concepts, especially in IS research. As information systems start to get more complex and to integrate more data, the role of primary- and secondary-use data needs further elaboration. The question remains what insights can be gained by using GIS or image data sources in addition to primary-use data. Leveraging additional data sources has not only the potential to increase the predictive power of applications, but to uncover new knowledge by making these data sources accessible.

Practical implications of this research article are including information based on Experience characteristics in real estate models to improve predictive performance, as well as decrease information asymmetries. These aspects are especially valuable for real estate platforms. The extracted knowledge about important variables could appeal to many stakeholders impacted by appraisal, e.g., municipalities, that could identify early signs or drivers of gentrification or quality of life aspects.

Our approach has some limitations. For example, despite our theoretical embedding in the SEC theory, we did not include Credence qualities in our analysis, since it is impossible to determine Credence qualities for real estate appraisal. Further, we only included 16 experts in our survey, which might leave the classification of housing attributes with higher uncertainty compared to large samples. To derive a separation into Search and Experience qualities, we used the mean value for all constructs, which might lead to outliers having a high impact on the result. Moreover, further variables might need to be included in future analyses, e.g., interior images.

In general, it also needs to be clarified, if such appraisal algorithms contribute to pricing effects in the real estate market. Appraisal systems could create self-perpetuating effects, because higher (lower) priced neighborhoods might be more (less) attractive to buyers, leading to higher (lower) prices, creating a vicious cycle.

In this paper, we find that when Search and Experience qualities are combined in a model, the predictive power can be increased by 15.4% compared to using Search qualities alone. We are among the first, to inspect the role of these qualities in predictive research by explicitly using secondary-use data to enrich information from primary use data. Beyond carrying on this work, we posit that integrating Search and Experience qualities, primary- and secondary-use data and ML and GIS in other contexts can add significant value for pricing problems by reducing information asymmetries. We see continuous work in these research fields as a crucial contribution to the IS discipline and call on other researchers to build on our approach to enhance their predictive power.

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Disclosure statement
The authors report there are no competing interests to declare.

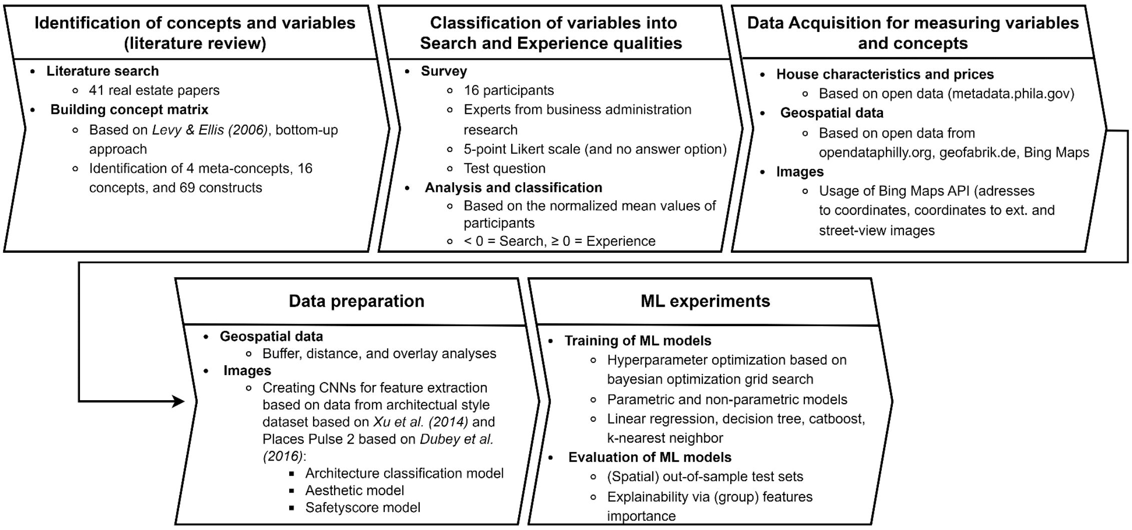

Figure 1: Research process comprising five steps

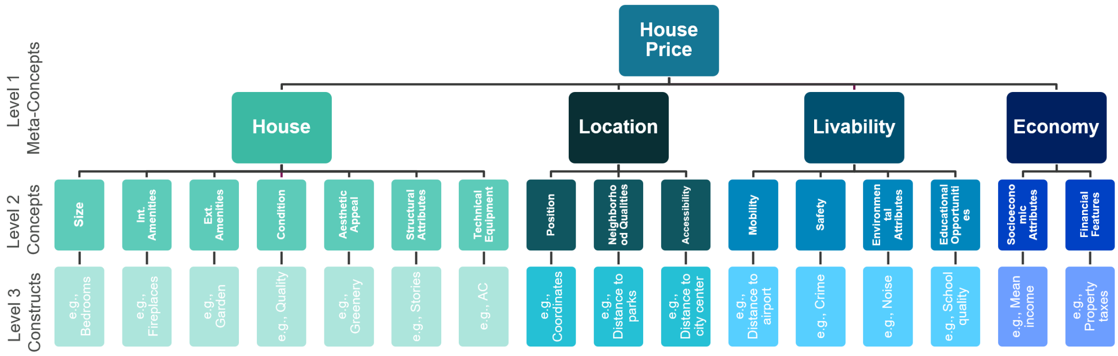

Figure 2: Structure and levels of meta-concepts, concepts and constructs.

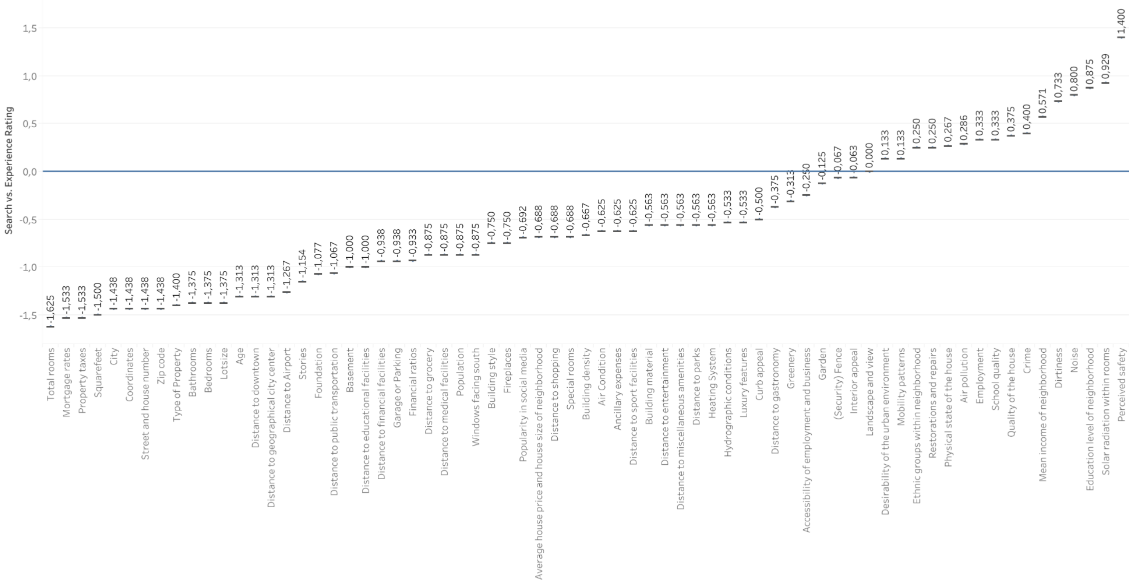

Figure 3: Results of the survey with normalized mean values. Negative values (<0): Search. Positive values (≥0): Experience.

Figure 4: GIS buffer analysis for point (left), line (middle), and polygon (right) objects.

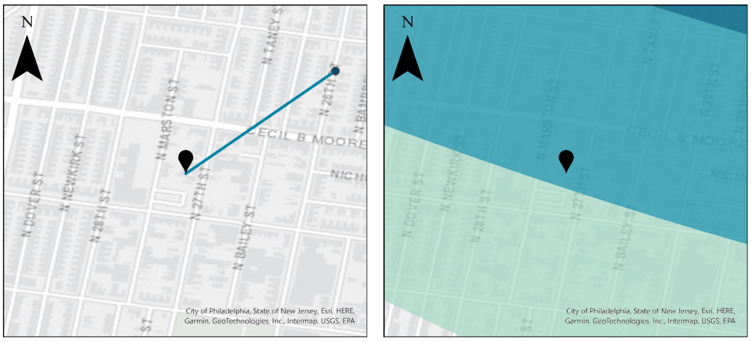

Figure 5: GIS analyses distance (left) and overlay (right).

Figure 6: Example images for the variable 'Perceived safety'. Safety score predicted with our perceived safety estimator based on [21, 49]. The left image depicts an unsafe environment, while the left image depicts a safer environment. We used freely available images for visualization purposes.

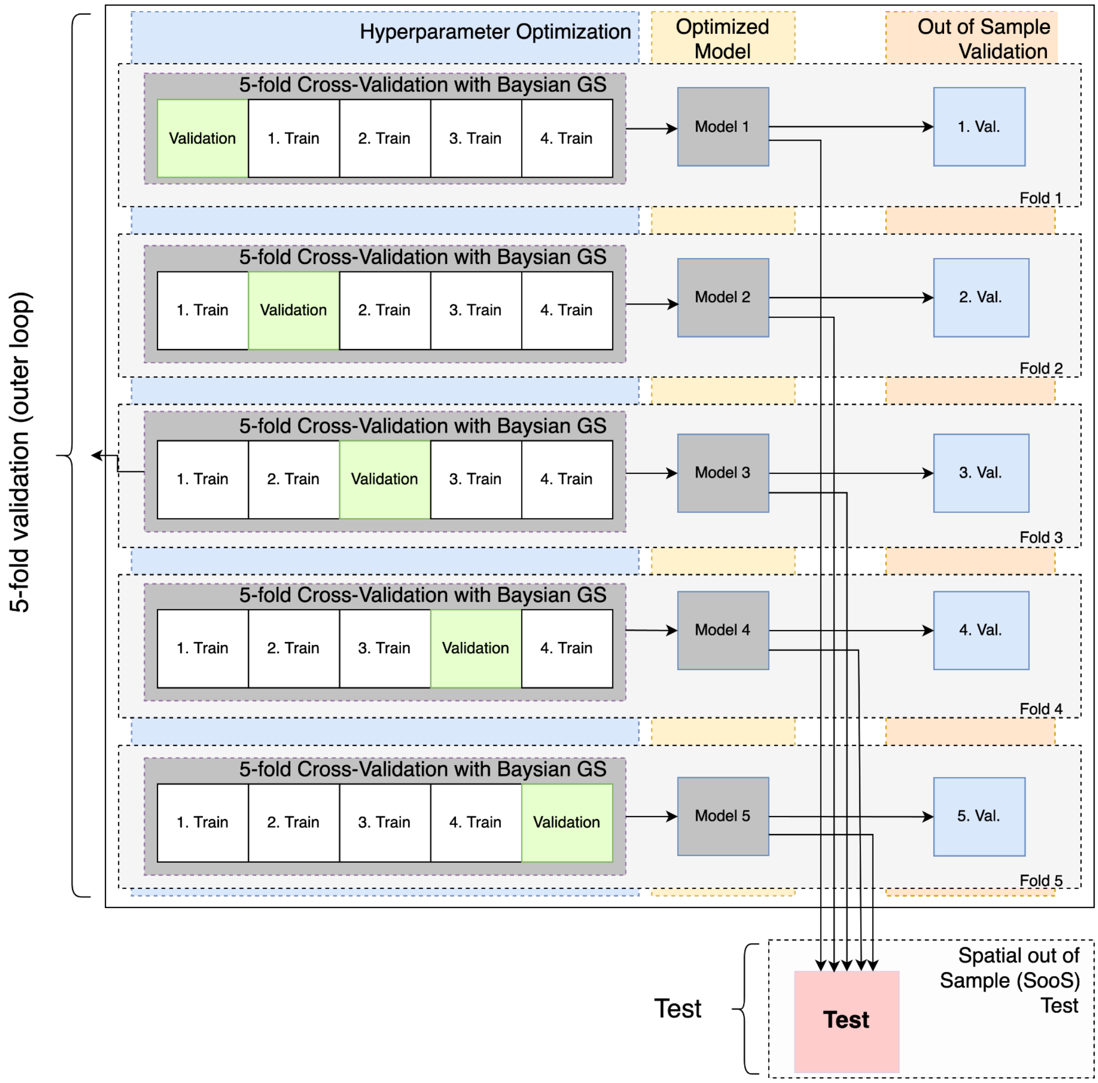

Figure 7: Evaluation strategy. It is a nested five-by-five grid search. Evaluation is performed on out-of-sample validation sets and a Spatial of Sample (SooS) test set. A Bayesian grid search performs hyperparameter optimization.

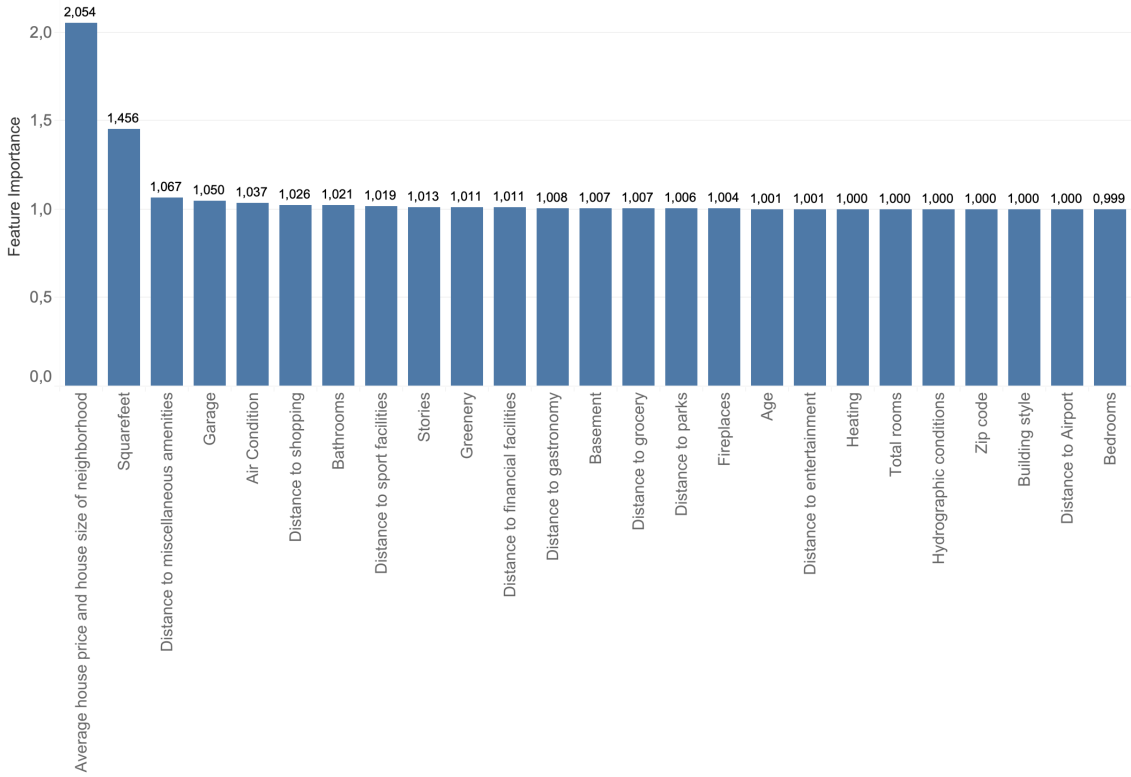

Figure 8: Group feature importance SooS Catboost Search constructs.

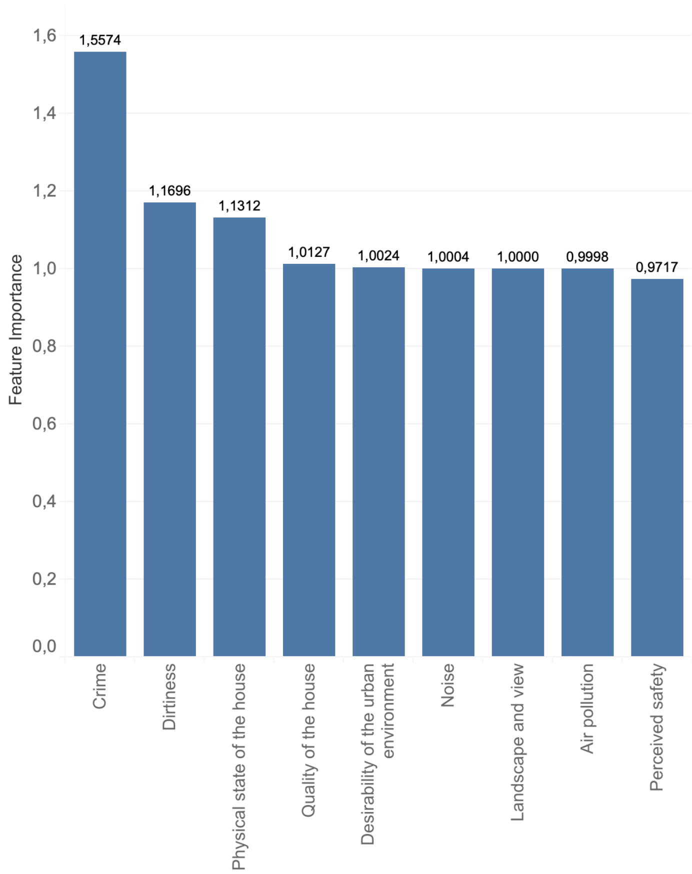

Figure 9: Group feature importance SooS Catboost Experience constructs.

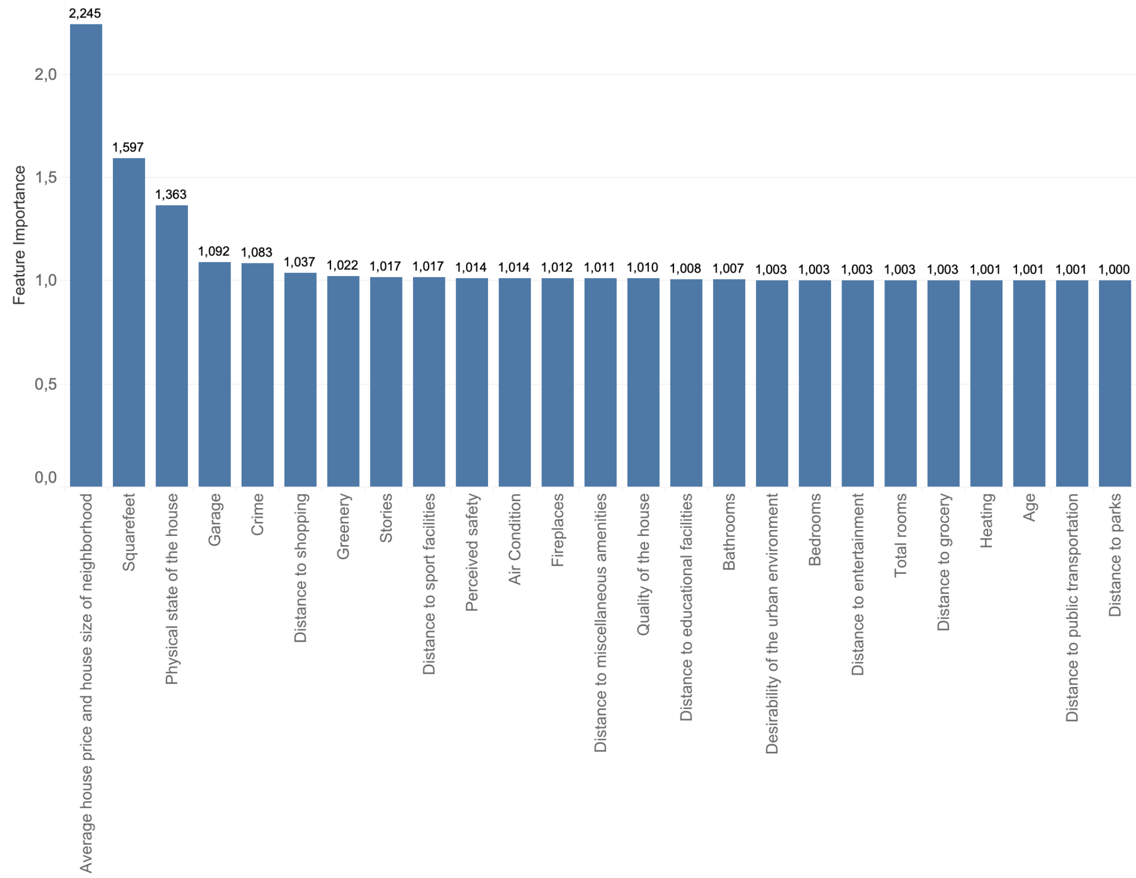

Figure 10: Group feature importance SooS Catboost Search and Evaluation constructs.

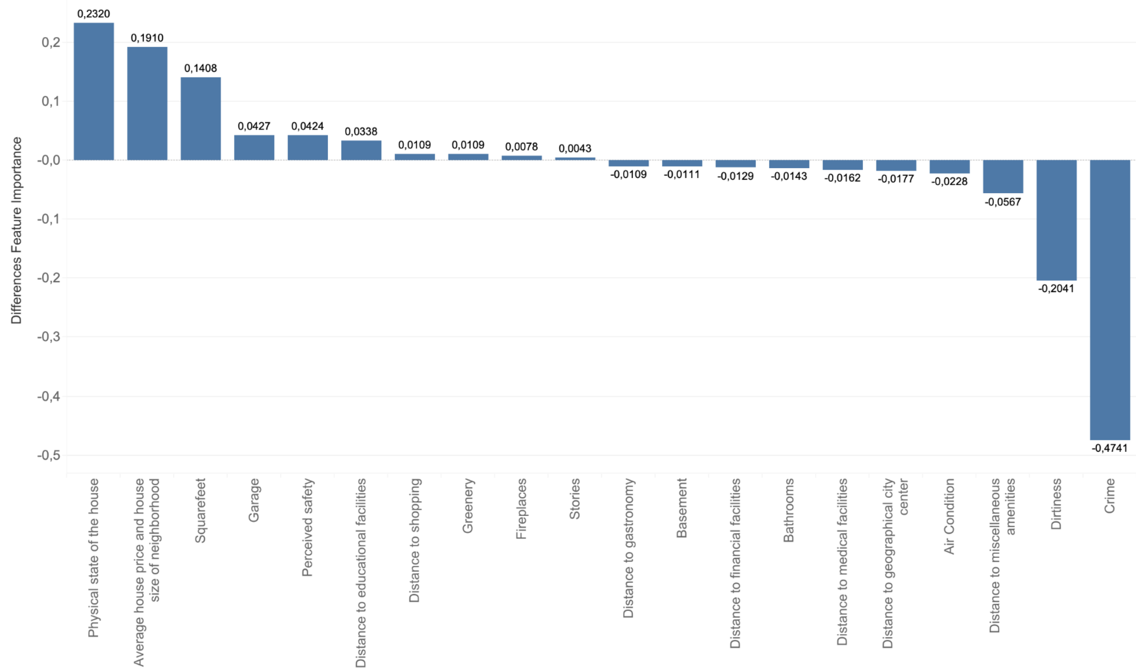

Figure 11: Differences in Feature Importance between search (S) or experience (E) variables in a single model or combined. Delta = importance$_{combined}$ - importance$_{single}$ Highest and lowest ten variables selected. Values smaller than 0 indicate a decrease in import.

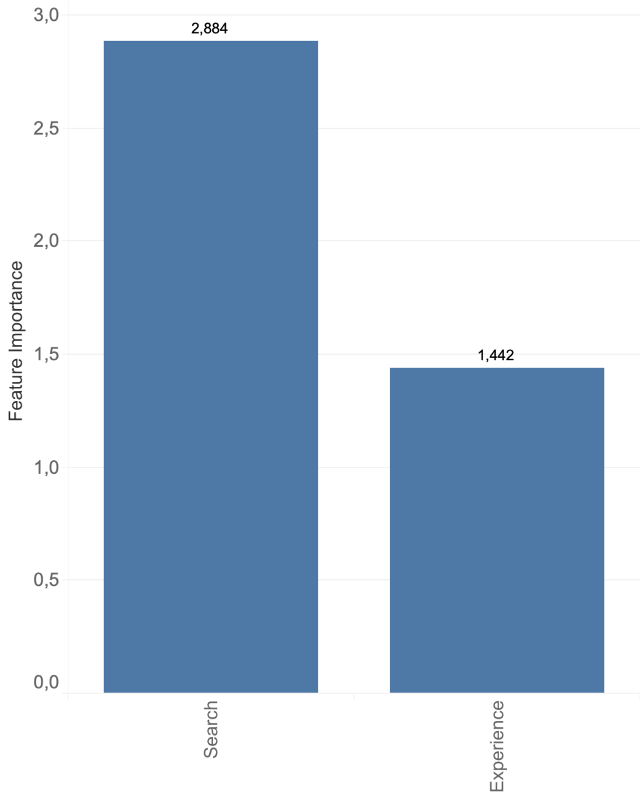

Figure 12:Group Feature Importance for SEC Theory. Search qualities are two times more important in the overall best model than Experience qualities. Nonetheless, as Experience qualities have a Feature Importance larger than 1, they also contribute to the model performance, matching the Out-of-Sample and SooS performance evaluations.

Variable	Min.	Max.	Mean	Standard Dev.
House Price	3,400.00	1,004,300.00	81,302.82	58,554.22
Squarefeet	500.00	7,262.00	1,140.04	275.30
Distance to High School	22.75	2,990.89	537.39	284.70
Number of grocery stores within 800m	3.0	45.0	25.85	6.52

Table 1: Descriptive statistics of selected variables. A complete list is available in Appendix F.

Algorithm	S Variables	E Variables	S & E Variables
LR	42,900± 1,459	38,153 ± 203	33,526 ± 937
LR*	26,087 ± 994	37,608 ± 832	24,759 ± 271
DT	31,306 ± 1,117	47,600 ± 10,652	38,032± 5,669
Catboost	**25,364** ± 2,047	**36,744** ± 7019	**21,452** ± 1,141
kNN	43,173 ± 247	40,869 ± 524	39,016 ± 263

Table 2: Mean and standard deviation in the SooS performance of the different models measured in RMSE. Best performing model printed bold. A naive model predicting the median would result in an RMSE of 55,370 ± 9. *LR = Linear Regression run with recursive feature elimination to improve the predictive performance.