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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

Jennifer Priefer, Jan-Peter Kucklick, Daniel Beverungen and Oliver Müller

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Abstract: Information systems have proven their value in facilitating pricing decisions. Still, predicting prices for complex goods, such as houses, remains challenging due to information asymmetries that obscure their qualities. Beyond search qualities that sellers can identify before a purchase, complex goods also possess experience qualities only identifiable ex-post. While research has discussed how information asymmetries cause market failure, it remains unclear how information systems can account for search and experience qualities of complex goods to enable their pricing in online markets. In a machine learning-based study, we quantify their predictive power for online real estate pricing, using geographic information systems and computer vision to incorporate spatial and image data into price prediction. We find that leveraging these secondary use data can transform some experience qualities into search qualities, increasing predictive power by up to 15.4%. We conclude that spatial and image data can provide valuable resources for improving price predictions for complex goods.

Keywords: information asymmetries; real estate appraisal; SEC theory; machine learning; geographic information systems; computer vision

JEL: C53, D82, R31

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

1. Introduction

Pricing decisions play an important role for buyers and sellers involved in sales transactions, since sophisticated pricing decisions can foster competitive advantage (Breath and Ives 1986). The Information Systems (IS) domain has been investigating pricing strategies in various contexts, including e-commerce and online platforms (Oh and Lucas 2006), as well as their effects for understanding, explaining, and predicting prices (Breath and Ives 1986; Hinz et al. 2011; Oh and Lucas 2006; Soh et al. 2006). For IS research, pricing effects are of interest as they are driven by the discovery and reduction of information asymmetries (Dimoka et al. 2012; Ghose 2009).

Information asymmetries occur when a seller (agent) has more information about a product than a buyer (principal) (Ross 1973). 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 (1978), 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 (Dimoka et al. 2012).

Until now, the field of pricing decisions in IS research mainly bases on well-structured and conventional transaction data (Kisilevich et al. 2013; van Heijst et al. 2008) 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.

However, for goods that are not that easily describable and are subject to individual pricing, the pricing decision remains challenging and high-risk due to considerable information asymmetries. For example, real estate is a product which is described by different qualities ranging from the size to quality and aesthetics (Poursaeed et al. 2018; Limsombunchai 2004; Law et al. 2019). 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 (Rosen 1974; Vanags et al. 2017). 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 (Kok et al. 2017). A suitable location considers and balances these multi-dimensional aspects. Still, there are qualities that can easily be evaluated before the purchase, like the number of rooms in a house.

Search, Experience, and Credence (SEC) theory (Nelson 1970; Iacobucci 1992; Darby and Karni 1973), defines these qualities as search qualities. In contrast, other 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 (Nelson 1970), like noise in the house's neighborhood. Credence attributes are nearly impossible to be evaluated even after the purchase and usage as any data of the counterfactual outcome remain unobserved.

We investigate to what extend unstructured data, like spatial data and images, can represent search and experience qualities of complex goods, increasing the predictive power of pricing on online markets. While our approach focuses on developing a theoretical contribution, we use real estate appraisal as a case to quantify the increase in predictive power. 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 (Zillow Group Inc. 2020). Within the domain of IS research, different pricing processes and systems are suggested, including aspects about co-existence of goods (Hao and Fan 2014), automatic pricing (Kisilevich et al. 2013; van Heijst et al. 2008), pricing strategies and discounts (Phillips et al. 2015; Oh and Lucas 2006; Chiles 2021), and aspects about information asymmetries (Dimoka et al. 2012; Ghose 2009). Real estate pricing is more and more extended by variables extracted through GIS (Kok et al. 2017; Leby and Hashim 2010; Nadai and Lepri 2018) and Computer Vision (Poursaeed et al. 2018; Law et al. 2019). Since the prediction of house prices holds a high-risk for over- or underestimating prices, a high predictive accuracy is required (Law et al. 2019). While related work focused on improving the predictive performance (Kucklick and Müller 2023; Bency et al. 2017), leveraging different technologies for extracting experience qualities of goods in the context of high-risk pricing decisions has not been in the focus.

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 and experience qualities reduces the prediction error by 15.4%. Beyond real estate appraisal, our results indicate that experience qualities alone cannot outperform a search quality model, but a combination of experience and search qualities boosts predictive performance.

Our paper contributes new knowledge on pricing decisions in IS. We use SEC theory to investigate the role of search and experience qualities for price predictions of goods that are subject to considerable information asymmetries due to their heterogeneous, complex, physical, and high-risk properties. We use location and image data to represent search and experience properties, leading to more precise pricing predictions. Managerial implications include recognizing the profound pricing effects on a city or municipality level on house prices. For example, we found that crime and dirtiness are important variables for price predictions, urging city planners and local governments to counteract effects like the broken window theory (Wilson and Kelling 1982) and uncover early signs of gentrification, increasing a city's or neighborhood's livability for inhabitants (D'Acci 2014).

The 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 chapter 4. In section 5, we discuss the results before concluding the paper in section 6.

2. Scientific Background

2.1 Search, Experience, and Credence Qualities

Pricing decisions are fundamental in market transactions, shaping interactions between buyers and sellers. The domain of IS has long investigated pricing strategies in various contexts, including e-commerce, online platforms, and digital markets (Oh and Lucas 2006), and has analyzed how pricing is influenced by information availability and transparency (Breath and Ives 1986; Hinz et al. 2011). A key economic challenge in these transactions is information asymmetry, a phenomenon in which one party in a transaction possesses more or better information about a product than the other (Ross 1973). This imbalance is particularly problematic in markets where product quality is difficult to assess before purchase, leading to inefficiencies in pricing and decision-making. 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 (Andrews and Srinivasan 1995). 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 (Ross 1973). Generally, the principal has less information about the qualities of the provided good prior to the purchase or contract conclusion than the agent (Devos et al. 2011). 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 (Akerlof 1978). This information imbalance forces buyers to rely on imperfect signals—such as branding, warranties, or customer reviews—to infer product quality, often resulting in suboptimal purchasing decisions.

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 (Nelson 1970), 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 their needs and further compare them to rival products. However, product uncertainty remains when some information are not accessible to the buyer (Dimoka et al. 2012). Especially in online markets, the description of goods and their qualities can be challenging, because of the inability to physically experience the product (Dimoka et al. 2012). Thus, certain qualities like the comfort or reliability of a used car cannot be fully evaluated by a buyer prior to the purchase.

One of the most well-known consequences of information asymmetry is adverse selection, a scenario in which lower-quality products dominate the market due to the inability of buyers to differentiate between high- and low-quality goods (Akerlof 1978). Without reliable quality signals, buyers tend to assume an average level of quality and, as a result, are only willing to pay a price that reflects this perceived uncertainty. High-quality sellers, unable to secure a fair price that reflects their product's true value, withdraw from the market, leaving behind only low-quality offerings. This dynamic gradually degrades the overall market quality and can lead to market failure, where transactions cease to occur altogether due to a breakdown in trust.

Information asymmetry and product uncertainty can lead to a 'market for lemons' (Dimoka et al. 2012; Ghose 2009). First introduced by Akerlof in the 1970s, the 'market for lemons' theory provides a framework for understanding how information asymmetry can distort market equilibrium. Using the used car market as a primary example, Akerlof demonstrated that when buyers cannot distinguish between a high-quality used car (a "peach") and a defective one (a "lemon"), they will offer only an average price based on the assumption that there is some probability that they may end up purchasing a low-quality vehicle. However, this average price is often too low to incentivize sellers of high-quality cars to remain in the market. Consequently, more and more high-quality cars are withdrawn from sale, leaving only low-quality cars in circulation, a process that can ultimately result in market collapse.

This principle extends far beyond the used car market and applies directly to real estate transactions, where houses are complex, heterogeneous goods with varying degrees of quality that are difficult to assess before purchase. Real estate markets are particularly vulnerable to information asymmetry due to the inherent opacity of property conditions, neighborhood quality, and external environmental factors (Rosen 1974; Vanags et al. 2017). Unlike consumer goods, where buyers can easily compare attributes such as brand reputation or customer reviews, real estate purchases involve multiple layers of uncertainty that make valuation a highly complex process.

For example, in real estate transactions, sellers have privileged information about a property's structural integrity, history of repairs, and potential defects that are not always disclosed in listing descriptions. Buyers, on the other hand, must rely on incomplete or potentially biased information, including photographs, descriptions, and agent-provided details. This lack of transparency can lead to overvaluation of poor-quality properties and undervaluation of high-quality ones. Sellers of high-quality homes may struggle to obtain fair market value because buyers, wary of purchasing a "lemon," discount prices across the board. As a result, similar to the used car market, adverse selection occurs, pushing high-quality sellers out of the market and reinforcing an inefficient pricing structure. Moreover, the potential application of Goodhart's Law, which suggests that when a measure becomes a target, it ceases to be a good measure, may also offer insights into new market dynamics given the expanded access to information (Goodhart and Goodhart 1984).

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 (Nelson 1970) and Credence qualities were added later (Darby and Karni 1973).

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 (Iacobucci 1992). Search qualities are "the most obvious procedure available to the consumer in obtaining information about price or quality" (Nelson 1970, p. 312). A good can be defined as a Search good if "full information for dominant product attributes can be acquired prior to purchase" (Klein 1998, 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" (Klein 1998, 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 (Mitra et al. 1999). Today, technology allows for

Experience qualities to become describable prior to purchase by changing the nature of the communicable information (Klein 1998). 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" (Darby and Karni 1973, 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" (Dulleck et al. 2011, p. 526). The SEC theory has been applied and evaluated in several fields over the last decades, e.g., for marketing (Ford et al. 1988), product evaluations (Gunasti et al. 2020), information sources for services (Chocarro et al. 2021), and greenhouse gas reporting (Comyns and Figge 2015).

2.2 Appraisal in Online Markets

The concept of appraisal in online markets has evolved alongside the digitalization of commerce, where the necessity to evaluate the trustworthiness and reliability of sellers and products became apparent. Early e-commerce platforms relied on user-generated feedback as a rudimentary mechanism to assess the quality of transactions and mitigate the risks associated with information asymmetry (Resnick et al. 2000). As online marketplaces grew, reputation systems became an essential component of digital transactions, with platforms like eBay pioneering structured rating mechanisms that allowed buyers to provide feedback on sellers. These early systems provided a foundation for the more sophisticated appraisal techniques that followed (Dellarocas 2003).

The evolution of online appraisal methods has been shaped by multiple technological advancements. One of the most enduring approaches is user reviews and ratings, which continue to influence consumer decision-making by providing qualitative insights into seller reliability and product quality (Mudambi and Schuff 2010). Beyond textual feedback, the integration of big data analytics and predictive modeling has significantly transformed the appraisal landscape. Computer-Assisted Mass Appraisal (CAMA) systems, originally developed for property valuation, have been widely adopted in online markets, particularly in real estate, where large datasets and statistical modeling techniques facilitate rapid and scalable valuation processes (McCluskey et al. 2013).

The role of Natural Language Processing (NLP) in appraisal has also expanded through sentiment analysis, which employs ML to extract nuanced insights from user-generated content (Pang et al. 2008). By analyzing patterns in online reviews, these systems provide a more granular understanding of customer satisfaction and perceived product quality, supplementing traditional numerical ratings (Feldman 2013). Another key development in online market appraisal is the emergence of internet price comparison sites (PCS), which enable consumers to evaluate prices across multiple platforms. These tools help reduce information asymmetry by ensuring that buyers have access to real-time pricing data, which in turn influences offline purchasing decisions (Bodur et al. 2015).

The increasing sophistication of trust and reputation systems has further refined the appraisal process. While early reputation models primarily relied on user feedback, modern systems integrate transaction histories, behavioral analytics, and credibility metrics to generate a more comprehensive assessment of seller reliability (Jøsang et al. 2007). These systems use computational approaches to reduce risks like fake reviews and manipulated ratings. However, as these appraisal mechanisms grow more complex, concerns regarding algorithmic fairness and transparency have emerged. Automated decision-making systems often operate as black boxes, making it difficult for users to understand how trust scores and appraisals are determined, raising important questions about accountability in algorithmic decision-making (Diakopoulos 2016).

The Hedonic Pricing Theory developed by Lancaster (1966) and later on refined by Rosen (1974) states that the overall price of a good is its overall utility (Law et al. 2019;

Rosen 1974). 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 (Lancaster 1966; Rosen 1974). 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.

Another transformative development is dynamic pricing, a strategy where ML algorithms continuously adjust prices in response to demand fluctuations, competitor pricing, and market conditions. This real-time appraisal mechanism ensures that pricing remains competitive and reflects market realities, an approach widely utilized in sectors such as e-commerce, hospitality, and ride-sharing services (Chen and Hu 2020). However, while dynamic pricing models optimize revenue strategies, they also raise concerns about price discrimination and fairness, particularly when algorithmic biases lead to unintended disparities among consumers (Barocas and Selbst 2016). Ensuring transparency in algorithmic decision-making is, thus, a pressing issue, as AI-based appraisal mechanisms often make it difficult for users to understand the reasoning behind valuation outcomes (Diakopoulos 2016).

3. Data Analysis

3.1 Real Estate Appraisal

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 (1992).

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.

To analyze what benefits search and experience qualities offer for pricing on online markets, we use the example of real estate appraisal, which is the monetary evaluation of properties or parcels for multiple purposes (Limsombunchai 2004). Many stakeholders rely on a computer-assisted value estimation for supporting appraisal decisions, including financial institutions for credit assessment and investment estimation (Kok et al. 2017; Bourassa et al. 2010), for municipalities for calculating property tax (McCluskey et al. 1997), and for real estate agents and online platforms for supporting the client’s decision process (Law et al. 2019; Sing et al. 2021). 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 (National Association of Realtors 2021). 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 (Zillow Group Inc. 2020), 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 (Koch et al. 2019), is based on the Hedonic Pricing Model. The complexity in the real estate appraisal process comes from the object itself, as housing is not a homogeneous and standardized good (Rosen 1974; Vanags et al. 2017). In real estate appraisal two developments happened to improve predictive accuracy: (a) the use of ML models (e.g., Random Forest) (Kok et al. 2017) and (b) the integration of unstructured data, mostly originating from images (Law et al. 2019; Naser et al. 2021). Recent research has shown that image content can significantly impact pricing in e-commerce, particularly in the real estate market, demonstrating the importance of visual information in property valuation (Naumzik and Feuerriegel 2020). 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 (Bessinger and Jacobs 2016; Bency et al. 2017). 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 (Kucklick and Müller 2023, 2021). Nevertheless, the predictive performance is an important goal for many stakeholders (Sing et al. 2021), 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 (Bharadwaj et al. 2013; Naser et al. 2021; Wei et al. 2022), 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 (Priefer 2023). Furthermore, advanced techniques for mining points-of-interest data can offer valuable insights into urban phenomena, potentially enhancing our understanding of real estate markets in urban contexts (Naumzik et al. 2020). 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 (Klein 1998). 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. (2018) or the combination of socio-economical, mobility and image data in the research of Kang et al. (2021). 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). The effectiveness of DL models for real estate appraisal has become increasingly evident, particularly when dealing with complex, unstructured data types. DL models have shown remarkable success in areas like computer vision and natural language processing, which is particularly relevant for real estate appraisal that involves image analysis and textual descriptions (Kucklick and Müller 2022; Topraklı 2024). For instance, recent studies have demonstrated that DL models can effectively leverage satellite imagery and other visual data to enhance appraisal accuracy (Kucklick et al. 2021; Kucklick and Müller 2022). While the debate on DL's effectiveness for purely tabular data continues, the real estate domain often involves a mix of structured and unstructured data. In this context, DL models shine by their ability to handle multi-modal data inputs, combining traditional property attributes with visual and location-based information (Kucklick et al. 2021). This capability allows for a more comprehensive analysis of property values, capturing nuanced factors that traditional models might miss. Moreover, recent advancements in DL architectures, such as temporal graph networks and meta-transfer learning, have shown promise in addressing challenges specific to real estate appraisal, including data scarcity in smaller markets and the need to model complex spatiotemporal relationships (Grinsztajn et al. 2022). These approaches can potentially outperform traditional methods, especially in scenarios with limited data or when transferring knowledge across different real estate markets. However, it's important to note that the choice of model should be carefully considered based on the specific dataset, the desired level of interpretability, and the available computational resources. While tree-based models offer transparency and ease of understanding, DL models provide the potential for higher accuracy and the ability to directly handle unstructured data, which is increasingly valuable in modern real estate appraisal (Topraklı 2024; Zhao et al. 2019). 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, combined with data processing capabilities of DL, could help to gain additional knowledge about the field and further improve real estate appraisal accuracy.

3.2 Research Process

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.

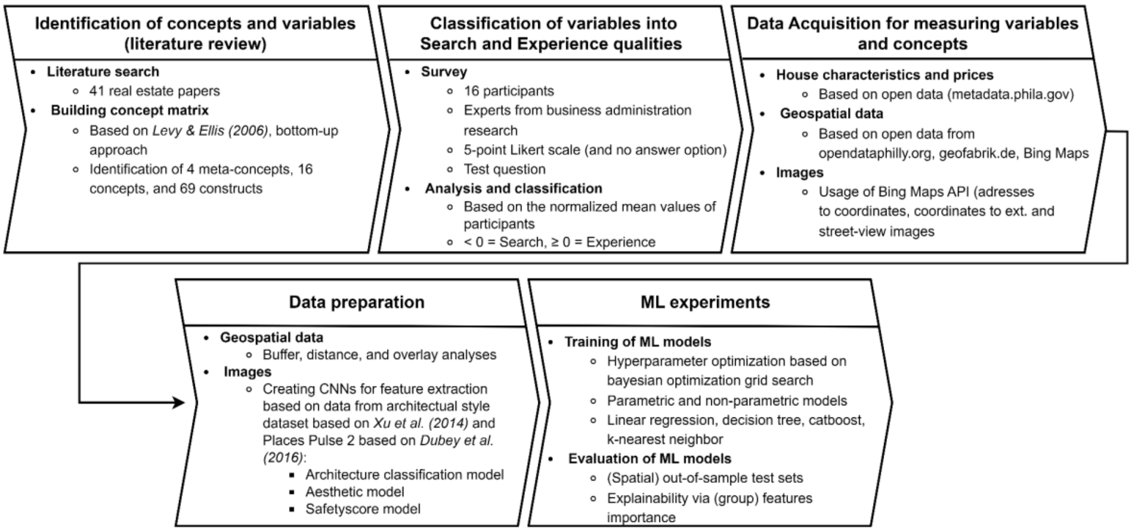

Fig. 1 Research process comprising five steps

3.3 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 (Recker 2021) 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" (Recker 2021, p. 27). Within literature 69 constructs can be identified bottom-up (Online Resource 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 (Cohen and Coughlin 2008; Helbich et al. 2013; Kucklick et al. 2021; Ligus and Peternek 2016), air pollution (Ligus and Peternek 2016), dirtiness (Bin et al. 2020), and solar radiation (Helbich et al. 2013; Nadai and Lepri 2018) on level 3.

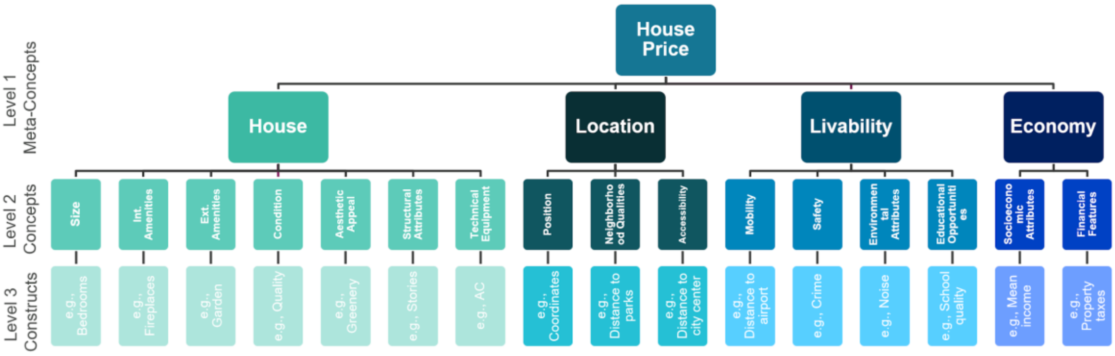

Fig. 2 Structure and levels of meta-concepts, concepts and constructs.

3.4 Classification of variables into Search and Experience qualities

To evaluate whether the identified constructs represent either Search or Experience 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

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[1] Online Resource available upon request from the authors.

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

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 Online Resource 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. Table 1 shows the normalized mean values of the constructs and whether they classify as Search or Experience qualities.

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

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

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*.

3.5 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" (Recker 2021, 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 (2018).

Second, we collected second-use data in the form of spatial data from official open data portals of Philadelphia (OpenDataPhilly 2011; City of Philadelphia 2018). 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 (Farkas et al. 2016; Priefer 2023).

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

(Microsoft Inc. 2020). We defined house images, as the exterior view of the house visible from the street (Bessinger and Jacobs 2016). 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) (Law et al. 2019). 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 Online Resource C.

3.6 Data Preparation

The housing characteristics needed preprocessing so that they are usable for ML algorithms. We used the property assessment data from the City of Philadelphia from the year 2016 and only included residential family homes in our analysis. We check the data for missing values and implausible values for all columns. 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”.

3.6.1 Preparation of geospatial data

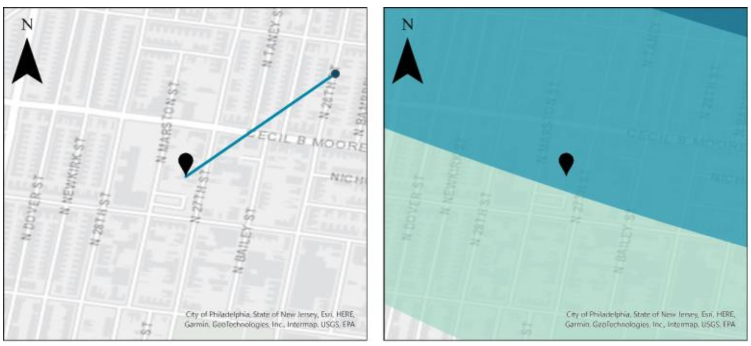
For the analysis of GIS data, we used the software ArcGIS as well as the Python packages haversine, shapely, and geopandas. Geospatial data can have different types which are point, line, and polygon (Farkas et al. 2016). To be able to assess the location information from GIS depending on their data 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” (Farkas et al. 2016). 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 3).

Fig. 3 GIS buffer analysis for point (left), line (middle), and polygon (right) objects

The second analysis determined the distance between two points, e.g., between the house and the closest school (Figure 4). This analysis is often used for location selection (Farkas et al. 2016) 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 (Farkas et al. 2016). 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 4).

Fig. 4 GIS analyses distance (left) and overlay (right)

3.6.2 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.

3.6.3 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 Online Resource C.

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 (Bin et al. 2019). 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 (Xu et al. 2014). Details about the implementation of our Convolutional Neural Network can be found in Online Resource D. 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.

3.6.4 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 (Dubey et al. 2016), and the work of Naik et al. (2014). 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 (Dubey et al. 2016). Each image finally had a rating between 0 and 10, which we used to train our CNN to predict the score from the image (Online Resource D). 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 5.

Fig. 5 Example images for the variable ‘Perceived safety’. Safety score predicted with our perceived safety estimator based on (Dubey et al. 2016; Naik et al. 2014). The left image depicts an unsafe environment, while the left image depicts a safer environment. We used freely available images for visualization purposes.

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 (Park et al. 2018), the second was 55 dB to 65 dB, and the last level was over 65 dB (Cohen and Coughlin 2008). 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.

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 (Table 2). Full descriptive statistics of selected variables can be found in the Online Resource E.

3.7 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 (Online Resource H). 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[4].

We applied the evaluation strategy described above to the following algorithms: LR, Decision Tree (DT), Catboost. We decided on those algorithms because the LR is the predominately used model in hedonic pricing, and ML models like DT and Catboost, promised an increased predictive performance (Phan 2018; Nadai and Lepri 2018; Kok et al. 2017; Limsombunchai 2004; Sing et al. 2021; Park and Bae 2015). We chose a DT as a second baseline model, as it captures by default non-linearities between variables and builds a sweet-spot between interpretability and increased predictive performance. Instead of a Random Forest used in comparative studies, we used a modern boosting approach, namely Catboost, which is skilled in handling many categorical variables (Prokhorenkova et al. 2018) and provides highly accurate predictions . Details about how these algorithms work, and which hyper-parameter were optimized can be found in Online Resource F.

[4] We performed two experiment with a normal scaled and a log-scaled variable. In the log-scaled experiment, we used log-transformed the variable for training, for prediction, we obtained the log-transformed house price values and back transformed the variable to evaluate the RMSE. As results were robust between the two experiments, we use the normal scaled results in the paper.

4. Results

In the following paragraphs, we report our results for the out-of-sample validation and SooS test set (Table 3). 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, explainable artificial intelligence (XAI) was used. While there are many different methods available like Shap (Lundberg et al. 2020; Lundberg and Lee 2017) or Lime (Marco Tulio Ribeiro et al. 2016) to explain tabular data, these methods are designed to measure the influence of a single variable on the prediction. As our goal is to measure the importance of a feature group, we decided to use Group Feature Importance (Au et al. 2022), a special version of feature importance, capable of jointly analyzing features. In general, a feature importance measures how strong the model relies on a feature during the prediction. A feature importance larger than one means that the model relies on this variable One downside of the classical feature importance is that it cannot measure higher-order concepts than a variable, e.g. constructs and concepts consisting of multiple variables. Such an analysis however, is often more valuable for research and practice. Furthermore, sometimes it is even necessary as the analysis of hundreds or thousand variables gets uninterpretable (Au et al. 2022). 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. (2022) 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.

We analyze the feature importance of the best performing model (Catboost). 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 6). 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 7).

Combining search and evaluation qualities led to important constructs of average house price, squarefeet, physical state of the house, garage, and crime (Figure 8), 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 9). However, the constructs crime and dirtiness lost importance when used in the model combining search and experience qualities (Figure 9). For the sake of completeness, we provide an analysis of the feature importance of individual variables in Online Resource G.

Finally, we test all Search and Experience variables jointly with the group feature importance to get a better understanding regarding the SEC theory (Figure 10). 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.

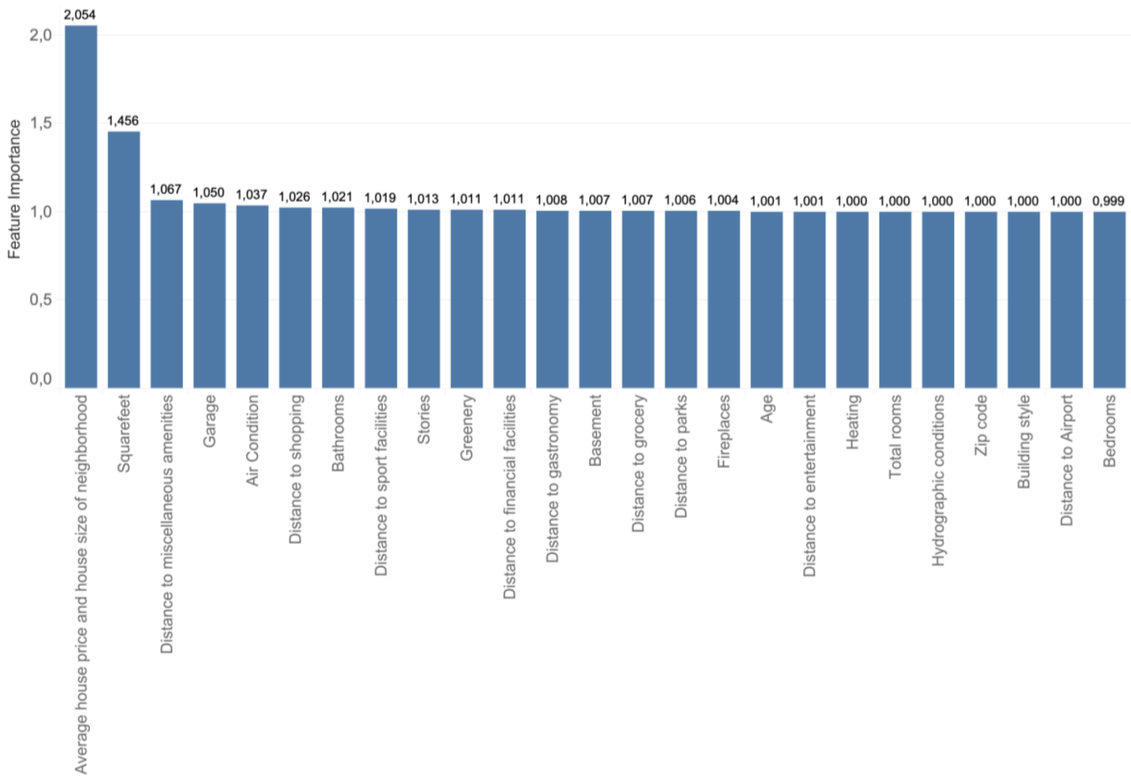


Fig. 6 Group feature importance SooS Catboost Search constructs.

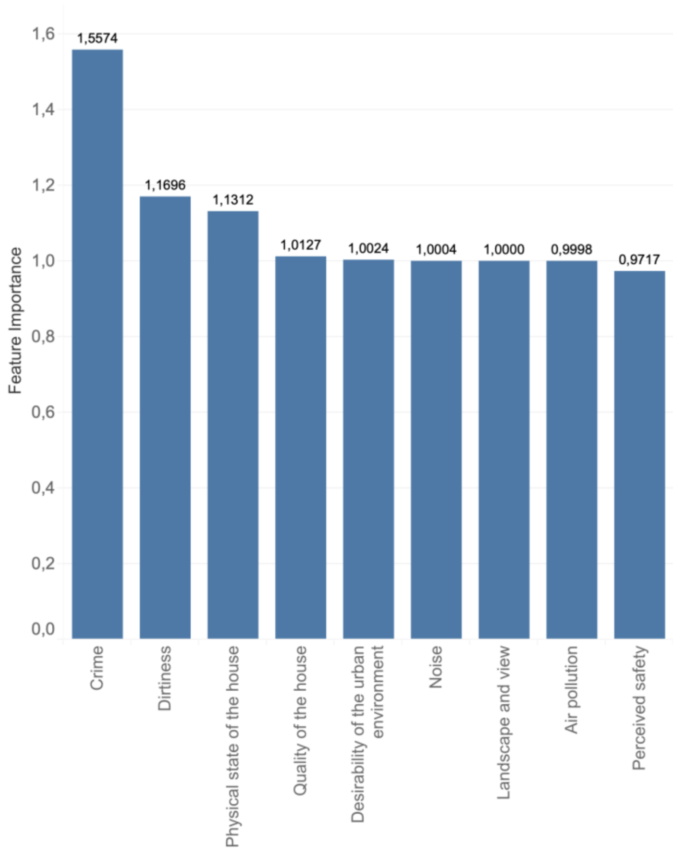


Fig. 7 Group feature importance SooS Catboost Experience constructs.

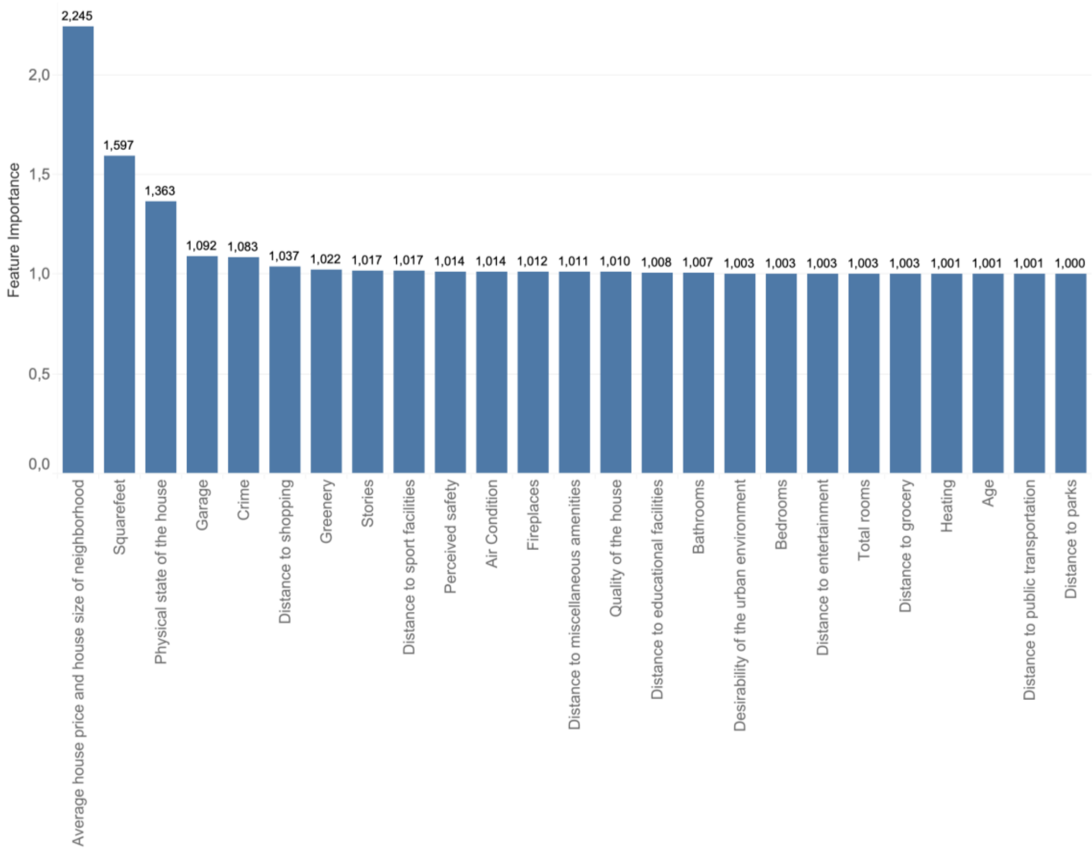


Fig. 8 Group feature importance SooS Catboost Search and Evaluation constructs.

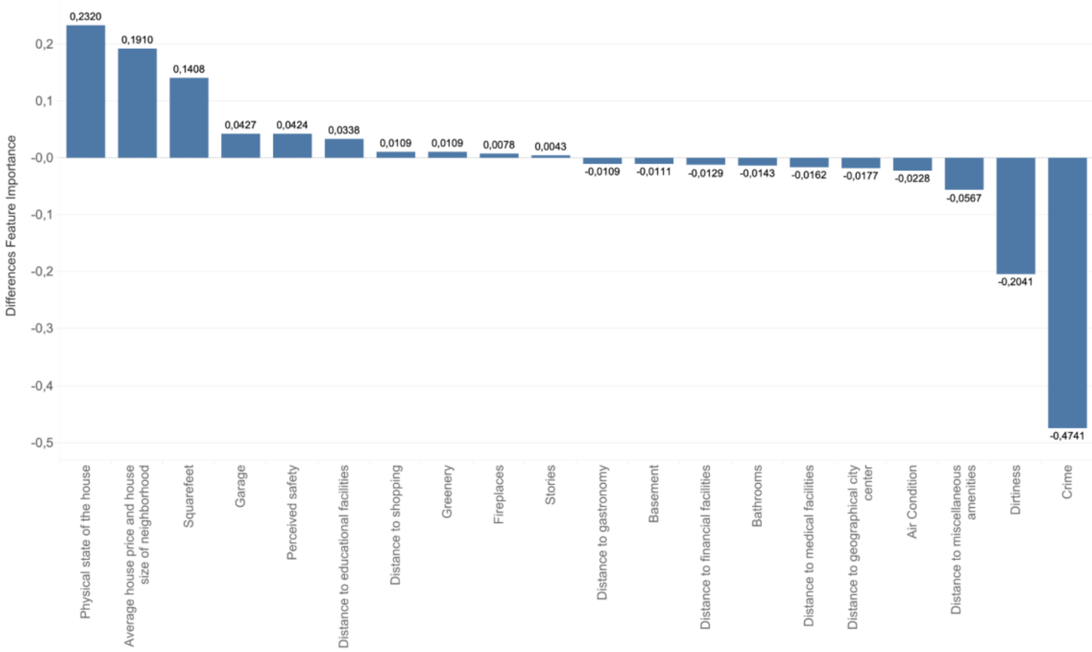


Fig. 9 Differences in Feature Importance between search (S) or experience (E) variables in a single model or combined. Delta = importance$_{combined}$ - importance$_{single}$ Highest and lowest ten variables selected. Values smaller than 0 indicate a decrease in import.

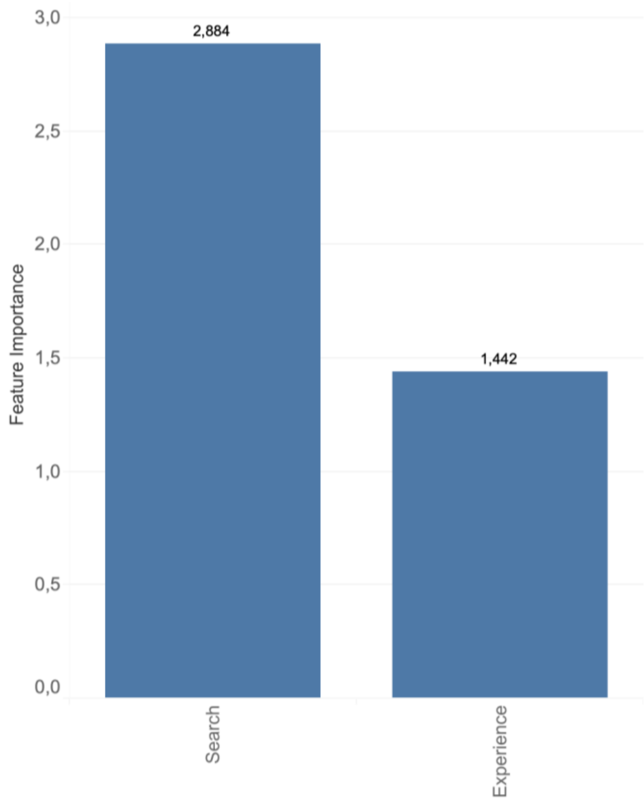


Fig. 10 Group Feature Importance for SEC Theory. Search qualities are two times more important in the overall best model than Experience qualities. Nonetheless, as Experience qualities have a Feature Importance larger than 1, they also contribute to the model performance, matching the Out-of-Sample and SooS performance evaluations.

5. Discussion

Our goal was to investigate the predictive performance of search and experience qualities based on data extracted from GIS and used in 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 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, the 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 these results 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, when combined with search qualities, should be used for real estate appraisal because it can improve predictive accuracy. Up to now, a model using only experience qualities cannot outperform already existing search quality-based models. However, we acknowledge that the relative contribution of Search and Experience variables may vary depending on the model used. As shown in Table 3, different model types yield different patterns in feature importance, which should be interpreted as model-dependent associations rather than generalizable rankings. In particular, our models do not explicitly account for spatial autocorrelation, which may further influence the interpretation of spatial variables. We therefore rely on the model with the best predictive performance (CatBoost) to illustrate the empirical value of integrating expert-informed feature groups.

Based on the argumentation of Klein (1998), we use data to represent experience qualities, so that they can be elucidated and used in a quantitative analysis and demonstrated how expert classifications can be leveraged to integrate domain knowledge into ML models in a novel way. The extracted experience improved the predictive power of a hedonic real estate model, arguably, because reducing information asymmetries enhances price estimation accuracy. 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 qualities. 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. By incorporating expert classifications into our models, we enhance the interpretability of our findings and demonstrate that domain expertise can contribute to improving predictive accuracy. Nevertheless, it seems worthwhile the effort as the real estate appraisal performance can be improved by a considerable margin (15.4%).

From a theoretical perspective, our work extends the scientific discourse on the SEC framework by demonstrating that experience qualities—traditionally considered difficult to evaluate before purchase—can be quantitatively measured using GIS and ML. Prior research (Nelson 1970; Darby and Karni 1973) has emphasized that search qualities are easily accessible, whereas experience qualities require personal interaction, and credence qualities remain difficult to verify even after purchase. However, our study challenges this strict categorization by showing that modern technological advancements allow for experience qualities to be transformed into measurable attributes, reducing their dependence on direct interaction. This contributes to the theoretical foundation of information asymmetry and decision-making in digital markets by providing empirical evidence that IT-based transformation can shift traditional quality classifications. In contrast to automated decision-making systems often operating as black-boxes (Diakopoulos 2016), our approach white-boxes the appraisal process to understand how the price prediction is determined.

On a domain level, we found that location and image data can augment real estate appraisal with new aspects. Many of the extracted experience qualities—like noise level, number of shootings, aesthetics, or security score—could be mapped to location and image data. It appears that extending data analysis with secondary-use data can hold much potential for improving the predictive power of pricing decisions of complex goods.

Concerning knowledge generation, we used group feature importance and identified the physical state of the house, its 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 remained important for predictive performance. The 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 Iacobucci (1992) who claimed that real estate has search and experience qualities. Secondary-use data is a suitable mean to map experience variables that could not be integrated before, which might have led to underestimating their role. By aligning ML models with expert knowledge and classifications, we bridge a crucial gap between data-driven prediction and domain-specific interpretations, highlighting the role of experience qualities for increasing the predictive accuracy of pricing decisions.

From a managerial perspective, our approach can improve decision-making processes in the field. Improving, or at least maintaining livability is one important part of the job for city planners and governors (D'Acci 2019). While there are various approaches on 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 (D'Acci 2014). 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 (Shmueli and Koppius 2011), 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 (Adadi and Berrada 2018). 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 (Priefer 2023). 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 (D'Acci 2019). For example, gentrification and decreasing livability are two pressing issues in many cities. 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.

Our findings also align with the work of Resnick et al. (2000) and Dellarocas (2003), who studied early reputation systems in online markets. While these studies focused on user-generated ratings and trust systems, our approach provides a new perspective by integrating GIS and ML to extract Experience qualities from secondary-use data sources. This adds a layer of objectivity to real estate appraisal, reducing reliance on subjective user reviews and self-reported property characteristics.

6. Conclusion

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. Our paper is one of the first to inspect the role of search and experience qualities in predictive research by using location and image data on complex goods in pricing decisions. We encourage other researchers to investigate the role of other data—for instance interior images—for elucidating the search and experience qualities of complex goods, to reduce information asymmetries and foster pricing decisions. A particularly complex problem to address are the credence qualities of complex goods, which remained impossible to determine in our approach. Subsequent research also needs to identify if appraisal systems create self-perpetuating effects, since higher (lower) priced neighborhoods might be more (less) attractive to buyers, leading to higher (lower) prices, creating a vicious cycle.

Tables

<table>
<tr><th></th><th></th><th>Construct</th><th>Normalized</th><th>Quality</th></tr>
<tr><td rowspan="28">House</td><td rowspan="5">Size</td><td>Bedrooms</td><td>-1.375</td><td>Search</td></tr>
<tr><td>Bathrooms</td><td>-1.375</td><td>Search</td></tr>
<tr><td>Squarefeet</td><td>-1.500</td><td>Search</td></tr>
<tr><td>Total rooms</td><td>-1.625</td><td>Search</td></tr>
<tr><td>Lotsize</td><td>-1.375</td><td>Search</td></tr>
<tr><td rowspan="4">Interior Amenities</td><td>Basement</td><td>-1.000</td><td>Search</td></tr>
<tr><td>Fireplaces</td><td>-0.750</td><td>Search</td></tr>
<tr><td>Special Rooms</td><td>-0.688</td><td>Search</td></tr>
<tr><td>Luxury Features</td><td>-0.533</td><td>Search</td></tr>
<tr><td rowspan="2">Exterior Amenities</td><td>Garden</td><td>-0.125</td><td>Search</td></tr>
<tr><td>Garage or Parking (incl. parking prices)</td><td>-0.938</td><td>Search</td></tr>
<tr><td rowspan="4">Condition</td><td>Age</td><td>-1.313</td><td>Search</td></tr>
<tr><td>Restorations and repairs</td><td>0.250</td><td>Experience</td></tr>
<tr><td>Quality of the house</td><td>0.375</td><td>Experience</td></tr>
<tr><td>Physical state of the house</td><td>0.267</td><td>Experience</td></tr>
<tr><td rowspan="5">Aesthetic Appeal</td><td>Curb appeal</td><td>-0.500</td><td>Search</td></tr>
<tr><td>Greenery</td><td>-0.313</td><td>Search</td></tr>
<tr><td>Landscape and view</td><td>0.000</td><td>Both</td></tr>
<tr><td>Interior appeal</td><td>-0.063</td><td>Search</td></tr>
<tr><td>Building style</td><td>-0.750</td><td>Search</td></tr>
<tr><td rowspan="5">Structural Attributes</td><td>Stories (incl. attica)</td><td>-1.154</td><td>Search</td></tr>
<tr><td>Building material</td><td>-0.563</td><td>Search</td></tr>
<tr><td>Type of Property</td><td>-1.400</td><td>Search</td></tr>
<tr><td>Windows facing south</td><td>-0.875</td><td>Search</td></tr>
<tr><td>Foundation</td><td>-1.077</td><td>Search</td></tr>
<tr><td rowspan="2">Technical Equipment</td><td>Heating System</td><td>-0.563</td><td>Search</td></tr>
<tr><td>Air Condition</td><td>-0.625</td><td>Search</td></tr>
<tr><td rowspan="13">Location</td><td rowspan="4">Position</td><td>City</td><td>-1.438</td><td>Search</td></tr>
<tr><td>Zip code</td><td>-1.438</td><td>Search</td></tr>
<tr><td>Street and house number</td><td>-1.438</td><td>Search</td></tr>
<tr><td>Coordinates</td><td>-1.438</td><td>Search</td></tr>
<tr><td rowspan="9">Neighborhood Qualities</td><td>Distance to parks</td><td>-0.563</td><td>Search</td></tr>
<tr><td>Building density</td><td>-0.667</td><td>Search</td></tr>
<tr><td>Popularity in social media</td><td>-0.692</td><td>Search</td></tr>
<tr><td>Hydrographic conditions</td><td>-0.533</td><td>Search</td></tr>
<tr><td>Distance to gastronomy</td><td>-0.375</td><td>Search</td></tr>
<tr><td>Distance to shopping</td><td>-0.688</td><td>Search</td></tr>
<tr><td>Desirability of the urban environment</td><td>0.133</td><td>Experience</td></tr>
<tr><td>Distance to miscellaneous amenities</td><td>-0.563</td><td>Search</td></tr>
<tr><td>Distance to entertainment</td><td>-0.563</td><td>Search</td></tr>
</table>

		Distance to grocery	-0.875	Search
		Distance to sport facilities	-0.625	Search
		Distance to educational facilities	-1.000	Search
	Accessibility	Distance to geographical city center	-1.313	Search
		Distance to downtown	-1.313	Search
		Distance to financial facilities	-0.938	Search
		Distance to medical facilities	-0.875	Search
		Accessibility of employment and business	-0.250	Search
Livability	Mobility	Distance to Airport	-1.267	Search
		Distance to public transportation	-1.067	Search
		Mobility patterns	0.133	Experience
	Safety	Crime	0.400	Experience
		(Security) Fence	-0.067	Search
		Perceived safety	1.400	Experience
	Environmental Attributes	Noise	0.800	Experience
		Air pollution	0.286	Experience
		Dirtiness	0.733	Experience
		Solar radiation within rooms	0.929	Experience
	Educational Opportunities	School quality	0.333	Experience
Economy	Socioeconomic Attributes	Education level of neighborhood	0.875	Experience
		Mean income of neighborhood	0.571	Experience
		Employment (rates) of neighborhood	0.333	Experience
		Average house price and house size of neighborhood	-0.688	Search
		Population (density) of neighborhood	-0.875	Search
		Ethnic groups within neighborhood	0.250	Experience
	Financial Features	Property taxes	-1.533	Search
		Mortgage rates	-1.533	Search
		Ancillary expenses	-0.625	Search
		Financial ratios	-0.933	Search

Table 1: Results of the survey with normalized mean values. Negative values (<0): mostly Search. Positive values (≥0): mostly Experience.

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 2: Descriptive statistics of selected variables. A complete list is available in Online Resource E.

Algorithm	S Variables	E Variables	S & E Variables
LR	38,550± 6,801	41,278 ± 271	28,819 ± 787
LR*	46,315 ± 7,475	41,260 ± 248	63,959 ± 12,334
DT	43,003 ± 4,894	41,319 ± 2,823	40,921± 6,174
Catboost	**28,323** ± 24	**30,328** ± 704	**24,811** ± 787

Table 3: 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.

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

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