URBAN HOUSING IN THE DIGITAL AGE: THREE APPLICATIONS OF NATURAL LANGUAGE PROCESSING

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URBAN HOUSING IN THE DIGITAL AGE: THREE APPLICATIONS OF NATURAL LANGUAGE PROCESSING

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This dissertation investigates how online platforms such as Airbnb, Reddit, and Craigslist reflect and shape contemporary housing dynamics within American urban regions. It features three papers that each analyze user text data within these platforms through a combination of natural language-based machine learning modeling with qualitative reviews of user's written contributions. The first chapter examines how Airbnb hosts employ rhetoric to commodify their short-term rentals in reference to cultural narratives relevant to neighborhood gentrification and residential exclusion. The second study explores how Reddit users debate about regional housing by drawing on policy frames to justify their arguments and persuade other users. The third paper considers how landlords posting advertisements for rentals on Craigslist use the intentional delineation of move-in fee financial requirements to influence the behavior of prospective tenants. These three papers collectively delineate how behaviors regarding three distinct housing subjects- neighborhood cultural change, housing policy debates, and rental market searches- are now conducted within online platforms. Results across the three studies demonstrate how user interactions on these sites reinforce preexisting housing dynamics and inequalities regarding unit availability and affordability at both the individual household and metropolitan level. These findings emphasize how longstanding sociocultural understandings of housing are now reinforced within these emergent online communities. The dissertation additionally illustrates how a mixed-methodological framework combining computational tools with subjective interpretation of text data is an ideal approach for answering research questions relevant to the intersection of urban housing and digital platforms. All three chapters engage with policy implications relevant to their individual findings, and the dissertation concludes by considering its overarching applicability for future research, applied data science initiatives, and towards contemporary urban housing governance.

BIOGRAPHICAL SKETCH

Remy Stewart was born and raised in the San Francisco Bay Area. She received her Bachelor of Arts in Psychology from the University of California, Santa Cruz and her Master of Arts degree in Sociology from Cornell University. Her research interests during her doctorate career at Cornell focused on urban sociology, technology, computational social sciences, and social inequality. Her work has been published in journals including *Big Data and Society*, *Computer Supported Cooperative Work (CSCW),* and *Cityscape*, and has been funded by the National Science Foundation Graduate Research Fellowship Program. She has worked as a Data Science Fellow for the Cornell Center for Social Sciences and has interned with the US Bureau of Labor Statistics and National Opinion Research Center during her graduate career at Cornell. She will be joining the digital design firm Figma as a Data Scientist following the completion of her PhD.

DEDICATION

I dedicate this dissertation to my stepmother Josephine Minola and to my niece Evelyn Miller. Losing Josephine defined the start of my graduate career, while welcoming Evelyn marked the end. Jo, I promise to carry your legacy of empowered womanhood with the greatest honor throughout every step of my journey. Evelyn, I cannot wait for you to be a part of all of said grand adventure ahead.

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Onwards and upwards from here.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

INTRODUCTION

The universal human need for housing and shelter remains constant within a contemporary world otherwise characterized by rapidly changing social, economic, and governmental structures. Housing shapes daily behaviors, social opportunities, financial security, and a variety of individual and family outcomes across the life course (Pattillo 2013; Zavisca and Gerber 2016). Its status as a necessary good that is actively commodified within regional markets reproduces housing's position in the United States as an unequally allotted asset across racial, ethnic, class, and gender social divisions as regarding factors such as quality, cost, and accessibility. Public policy initiatives at the national, state, and regional level ongoingly attempt to navigate the range of inequities embedded within American housing (Joy and Vogel 2021).

Housing is a physical place-based commodity, but it is increasingly interacted with through online platforms as technology integrates itself into virtually all modern markets. Individuals and families coordinate their housing searches, discuss their housing experiences, and deliberate housing policies through these digital communities (Matthews 2015; Boeing 2021). Whether a technology platform has an explicit affiliation with housing such as Airbnb, Zillow, or Nextdoor, or alternatively hosts housing-related interactions between users within a broader suite of platform features such as on Craigslist or various social networking sites, both types of digital mediums now reflect or potentially influence housing dynamics across the U.S.

Despite the geographically distributed nature of digital platforms, a significant portion of online interactions relevant to housing are affiliated with localized regions given housing's inherent physicality (Sadowski 2020). Platforms that facilitate housing-relevant user interactions are often divided into regional sub-communities. It is predominately large urban metropolitan regions that obtain the critical mass of number of active users required to ongoingly sustain these localized digital spaces (Slyke et al. 2007). Furthermore, major urban regions are particularly relevant for exploring the intersection of technology and contemporary housing dynamics considering their recurringly competitive and stratified housing markets, commonly occurring policy deliberations around housing, and high levels of digital platform use among residents (Hodson et al. 2021).

Urban sociology's engagement with technology and online platforms' relationship to housing is nascent but steadily growing. The large number of different platforms, the range of housing policy topics of interest, and the diversity of metropolitan regions to consider causes said topic to be challengingly broad in scope yet simultaneously supports an abundant range of relevant research questions. A closely related subject within urban studies is regarding platform urbanism, referring to the expanding influence digital communities and the technology companies that create them hold towards shaping urban life and regional policy dynamics (Lee et al. 2020; Barns 2020). While this scholarship does not focus exclusively on housing, the theorization within platform urbanism research that "urban space can no longer be treated as merely spatial: the social practices associated to digital media... blur, if not erase, the line between the spatial and the digital" is highly applicable to interpreting said platform's relationship with urban housing dynamics (Törnberg 2022:5).

Two overarching directions within scholarship considering housing and digital communities are studies that engage in-depth with one or a few case study regions often as regarding a specific online platform, or alternatively research that explores national trends by aggregating data collected from multiple regional subcommunities (Stors and Baltes 2018; Lê et al. 2020; Besbris, Schachter, and Kuk 2021; Kennedy et al. 2021). The digital trace data generated by user behavior and created content on online platforms serves as the primary data sets underlying these studies (Golder and Macy 2014; Salganik 2018). Users directly communicate and transact with each other within public peer-to-peer exchanges through said communities, often through written posts that advertise, debate, and/or comment on content relevant to housing. This online trace data is therefore highly applicable for research that explores the dynamic housing policy landscape between individual platform users, technology companies, and regional political stakeholders and social institutions (Boeing et al. 2021).

Digital data relevant to housing is often expressed as text data, leading to natural language processing (NLP) to be an ideal subdiscipline among computational methods to analyze and interpret said data sources (Cai 2021). Text data is well-suited to explore research questions relevant to social dynamics within housing as individual language has long been of interest within the social sciences to understand nuanced concepts such as personal beliefs, cultural meaning-making, and the reproduction of social inequality (Evans and Aceves 2016; Hovy and Yang 2021). Research on these topics has been historically driven by qualitative methods that excel at navigating the subjectivity inherent within human language, such as when analyzing classic text data sources including transcribed interviews or archival documents (Macanovic 2022). NLP methods offer an alternative quantitative approach to analyze text data with its distinctive advantage of being able to process significantly larger sample sizes than manual qualitative reviews. These analyses often identify overarching patterns within a text corpus that a researcher may have otherwise remained unaware of through qualitative analysis alone. Advancements within NLP- particularly within machine learning-based language modeling- are also increasingly capable of identifying more context-specific expressions of language, further strengthening these methods' ability to account for complex language trends often of interest to computational social scientists (Nguyen et al. 2020; Hovy 2021).

Social scientists who employ NLP methods within their work have increasingly established that the combination of both computational and qualitative frameworks complementarily enables the robust analyses of text data via the respective strengths of each approach (Törnberg and Uitermark 2021; Carlsen and Ralund 2022). The aggregate linguistic relationships across documents that NLP models highlight informs researchers' qualitative reviews of text data to further interpret and contextualize core findings (Li, Dohan, and Abramson 2021). The concept that NLP methods do not replace qualitative analyses but rather that both approaches are necessary to answer social science research questions relevant to text data falls under a suite of emergent designations that include "computational grounded theory", "agnostic text analysis", and "computational mixed methods" (Nelson 2020; Grimmer, Roberts, and Stewart 2022).

The following three dissertation chapters investigating urban housing and digital communities via text data are directly grounded within this methodological paradigm that champions the pairing of computational tools and subjective interpretation of user language. While each article employs machine learning models because of how substantially these methods have pushed forward natural language processing's ability to handle complex language patterns, each work additionally highlights how qualitative reviews of the written contributions of platform users provides insights to answer each chapter's guiding research questions beyond the findings of NLP models alone.

Chapter 1, "Authenticity for Rent? Airbnb and Neighborhood Commodification" investigates how Airbnb hosts advertising their short-term rentals draw from cultural rhetoric associated with the housing dynamics of either gentrification- the replacement of low-income residents with higher-income residents in a neighborhood- or exclusion as the restriction of a neighborhood to only high-income residents due to the lack of affordable housing options. This work considers how hosts commercialize Airbnb listings through constructing their neighborhoods as desirable tourist experiences in conversation with longstanding city residents, amenities, and ingrained urban cultural narratives. Its findings highlight how rhetoric commonly associated with gentrifying neighborhoods are used by Airbnb hosts across different neighborhoods primarily to advertise historical residential subpopulations and how language around "family-friendliness" and "safety" characterizes residentially stable neighborhoods. Said work therefore offers insights regarding the role of cultural desirability and neighborhood commodification towards Airbnb's growth and subsequent impacts on urban rental markets as relevant to long-term unit availability and rent prices.

Chapter 2, "Local Residents as Digital Publics: Policy Framing within r/sanfrancisco Housing Discourse" is grounded within the emergence of regional city discussion forums on Reddit as prominent spaces for hosting online housing policy debates and explores how users within said communities present and justify their policy opinions. This study draws from a universal policy frame schema established within the computational social sciences to explore how users employ frames relevant to topics such as morality, legality, and/or culture when discussing housing policies, how framed arguments interact with expressed user sentiment, and how broader subreddit communities react to different frames within posts. Key findings from this chapter include the prevalence of economic frames within housing discussions on Reddit, how framed arguments are commonly presented with negative emotional sentiment, and the popularity of posts framed in context of local political outcomes with other Reddit users. This study aims to delineate an applied data science analytical approach that policy stakeholders within cities can adapt themselves to better measure and understand regionally tied online conversations around current policy issues within their cities.

Chapter 3, "Move-In Fees as a Residential Sorting Mechanism Within Craigslist Rental Markets" builds from the established interest within the sociology of housing regarding landlords' ability to shape and influence renters' housing search outcomes to examine equivalent behavior within popular online rental markets such as Craigslist. This study focuses on the specific mechanism of when and how landlords specify move-in fee requirements in their written Craigslist advertisements, referring to additional costs such as security deposits, application fees, and advanced rent payments required to secure a lease beyond a standard monthly rent payment. The chapter's analyses underscore how move-in fees are mentioned at lower rate than their estimated prevalence within rental markets, implying intentionality behind when landlords choose to delineate said fees. Additional results include the importance of both immediate and proximate poverty levels towards landlord's specification behaviors around move-in fees and how said fee presentations differ between baseline requirements of these lump sum charges contrasted to fees advertised in the context of rental market deals and discounted offers. This work's findings therefore lend support to ongoing policy initiatives within American cities to both limit requestable move-in fee amounts or assist low-income renters with affording fee payments, as well as towards promoting greater transparency around move-in fee amounts within Craigslist and similar online rental marketplaces.

These three featured studies each explore a different housing policy relevant issue as connected to three online platforms that have and will continue to mirror and/or shape residential cultures and housing markets. The first and third chapters' use of text data from Airbnb and Craigslist respectively highlights two online communities with strong affiliations to urban housing markets. The social networking site Reddit featured within the second chapter has experienced an organic emergence of regionally tied subreddits where housing is a common conversation topic among users. All three works investigate user intentionality and goal-seeking behavior relevant to housing captured through their written posts.

The first two papers consider research questions that call for a regional case study data collection approach and therefore feature Airbnb and Reddit data connected to San Francisco, California. I chose San Francisco as my focal American city to explore the relationship between housing and online platforms given its characteristics of having a costly and political contentious housing market and its city residents being highly technologically engaged (Walker 2018). The final paper considers written Craigslist advertisements across the largest 100 U.S. metropolitan regions and therefore features findings with a broad national perspective in contrast to an individual case region.

This dissertation's use of written user data sourced from digital platforms raises specific ethical considerations around user privacy and consent (Olteanu et al. 2019). The dissertation itself received an exempt status for the Cornell Institutional Review Board given its use of observational data from publicly available online platforms without any direct interaction with users themselves. However, I follow Salganik's establishment of "the IRB is a floor and not a ceiling" when ensuring ethical practices with online user behavioral data by implementing additional procedures within each of the chapters to protect user identities and minimize concerns regarding the secondary use of online user data within academic research (2018: 322). There is no provided information regarding user's names, addresses, or other personal identifiers within any of the chapters. Featured text quotations throughout qualitative analyses within the studies are paraphrased to minimize reattribution risk for specific users as well.

This dissertation offers three novel contributions within its interdisciplinary grounding of urban sociology and information and data sciences. First, the dissertation's studies further an emergent research agenda aiming to understand, measure, and interpret how modern online communities mirror and potentially impact housing dynamics within American cities, given the rapidly growing popularity of these platforms within urban regions. Its three chapters offers timely insights regarding how new technologies and novel online platforms are a now closely connected to how metropolitan housing markets transact, how urban neighborhoods are being residentially and culturally reshaped, and how housing is contested and addressed within public policy making.

Second, the three studies highlight multiple novel methodological approaches that combine recent advances within NLP-based machine learning, classic regression modeling techniques, and qualitative analyses of written user contributions. These works therefore delineate a mixed-methodological framework that emphasizes using methods that effectively engage with each of the proposed research question and demonstrate how the combination of diverse methods facilitates a holistic overview of the complex social dynamics captured within written user data from online platforms.

Third, its engagement with timely research questions with publicly available user data and emergent data science methods is designed to inspire aligned projects from both academic and applied researchers that can build from the approaches featured within each study. The dissertation focuses on the narrow topic regarding the relationship between housing dynamics and regional online communities, but many of the broader substantive questions it considers and methods it employs are readily translatable for a wider range of future research initiatives beyond the particular focus on housing.

This dissertation therefore advances an interdisciplinary investigation as relevant to both its substantive questions and methodological approaches regarding how housing markets, city neighborhoods, and policy implementation are conducted within and can be shaped by online platforms. Its use of NLP analyses along with the interpretive role of classic qualitative review of written text data demonstrates the importance of combining diverse empirical methods to best answer individual research questions towards a holistic understanding of these novel urban social dynamics. The dissertation's findings highlights how digital platforms are able to reproduce both longstanding inequities relevant to housing policy issues, as well as how said mediums introduce new opportunities to understand and address said challenges throughout American cities.

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CHAPTER 1

AUTHENTICITY FOR RENT? AIRBNB AND NEIGHBORHOOD COMMODIFICATION [1]

Abstract

Airbnb as an online short-term rental marketplace has had significant impact on the housing dynamics of major metropolitan regions. This work examines Airbnb's relationship with urban housing through the dual phenomena of neighborhood gentrification as the loss of low-income households along with neighborhood exclusion as the preservation of elite enclaves without affordable housing. I feature approximately 19 thousand unique San Francisco Airbnb listings spanning from 2016 to 2021 to investigate how Airbnb hosts draw from culturally linked rhetoric to advertise their units' neighborhoods. I combine natural language processing with qualitative content analysis to examine how hosts differ in their representations of their listing's neighborhoods with different housing dynamic backgrounds. My findings highlight how hosts within gentrifying, exclusionary, and residentially stable neighborhoods differ in their use of cultural rhetoric linked to gentrification and exclusion primarily through how they reference longstanding residential identity groups and local amenities. Language affiliated with gentrification is found to be widely used across both gentrifying and exclusionary neighborhoods, while rhetoric originally hypothesized as defining exclusionary neighborhoods is most strongly associated with neighborhoods not experiencing residential changes. These results underscore the reinforcing dynamics between Airbnb and how the cultural commodification of neighborhoods impacts urban housing markets, with subsequent implications towards ongoing challenges associated with maintaining historical residential communities within contemporary cities.

Introduction

The rise of the digitally mediated sharing economy has reshaped the relationship between technology and traditional market sectors across major metropolitan regions. Airbnb is a popular online platform linked to contemporary housing markets as a growing number of city residents rent out their housing as short-term lodging through Airbnb (Hoffman and Heisler 2020). Political controversy has subsequently grown around the platform regarding its potential contributions towards increasing housing prices and residential displacement (Guttentag 2013; Nieuwland and van Melik 2018). Said concerns centers on the shift of previously long-term rental units into short-term rentals with a resulting loss of available housing for city residents. Building on ideas of the "touristification" of urban neighborhoods, Airbnb's impact on housing markets consequentially links the platform to a given metropolitan area's dynamics of neighborhood change (Gravari-Barbas and Guinard 2017; Sequera and Nofre 2018).

Residential displacement as a housing policy issue is often considered in dual reference to gentrification, which in its original definition by sociologist Ruth Glass refers to the dislocation of low-income residents with the concurrent entry of higher-income households within a neighborhood (Glass 1964). A robust gentrification literature has solidified the phenomena's relationship to racial and ethnic stratification and urban inequality (Zukin 1987; Brown-Saracino 2017). An additional line of urban studies scholarship has explored neighborhood exclusion- referring to market dynamics and housing policies that ongoingly preserve high-income, predominantly White neighborhood enclaves with limited affordable housing- as a concurrent dynamic shaping urban residential segregation (Payton Scally and

[1] This chapter builds from prior research featured in Stewart, Remy. (2022). "Authenticity for Rent? Airbnb Hosts and the Commodification of Urban Displacement." *Proceedings of the ACM on Human-Computer Interaction, CSCW* 6(493): 1-28.

Tighe 2015; Goetz, Williams, and Damiano 2020). Neighborhood exclusion does not directly lead to the same degree of residential displacement in contrast to gentrification, given that low-income residents are not being as actively priced out of neighborhoods that they disproportionately do not live in to begin within. Gentrification and exclusion can instead be understood as dual forces shaping housing dynamics through different mechanisms but with outcomes that both disproportionally limit the availability of affordable housing.

Airbnb is increasingly prevalent within neighborhoods that are affiliated with either gentrification or exclusion (Cócola-Gant 2016; Grisdale 2021). This aligns with transitions within the tourism industry regarding travelers' growing interest in lodging located within residential neighborhoods instead of traditional hotels within central business districts (Paulauskaite et al. 2016; Tussyadiah and Zach 2017). Listing popularity within Airbnb is closely tied to specific neighborhoods, which are often the same locations where controversy around housing for long-term city residents are eminent issues within local politics (González-Pérez 2020; Cócola-Gant and Gago 2021). Neighborhood identities are a powerful force driving Airbnb bookings as clients search for lodging within neighborhoods that are considered culturally desirable often in reference to their residential composition, amenities, and social environments. The relationship between Airbnb's impact on housing markets and cultural understandings of neighborhoods is therefore a dynamic and potentially self-reinforcing system within cities that are popular Airbnb destinations.

This study explores the intersection of Airbnb, neighborhood cultural narratives, and urban housing dynamics by investigating how neighborhood descriptions written by Airbnb hosts draw from rhetoric used to constructed neighborhood identities. I examine how hosts describe their rental listing's surrounding neighborhoods within the case study city of San

Francisco through a mixed-methods design combining the exploratory machine learning method of topic modeling, generalized linear regression models, and qualitative content analysis. My results illustrate how hosts capitalize on rhetoric linked to gentrification and exclusion to advertise neighborhoods as products to potential clients in reference to longstanding residential groups and amenities that cultivate "authentic" travel experiences. I demonstrate how said neighborhood presentations reinforces the commercialization of neighborhoods through Airbnb as desirable commodities. I conclude by considering subsequent policy implications relevant to my findings given Airbnb's known impacts on unit availability within expensive and competitive urban housing markets.

Background

Airbnb as a novel online platform's influence on urban residential dynamics has become a growing topic of interest among housing scholarship. Previous studies have highlighted Airbnb's role on tightening already competitive housing markets and increasing rent costs (Lee 2016; Gurran and Phibbs 2017; Garcia-López et al. 2020; Barron, Kung, and Proserpio 2021). An additional line of research has explored user behavior on Airbnb regarding why hosts choose to list their housing and why guests decide to book lodging on Airbnb instead of through hotels (Ikkala and Lampinen 2015; Holikatti, Jhaver, and Kumar 2019; Quattrone et al. 2020). These concurrent literatures demonstrate that Airbnb guests book units in culturally attractive neighborhood destinations, leading to influxes of tourists that reduce unit availability and reshape neighborhood environments often against the preferences of longstanding residents (Cócola-Gant and Gago 2021).

This work expands from this prior scholarship by investigating how user behavior may serve as a key mechanism reinforcing Airbnb's popularity within urban residential neighborhoods through the commodification of neighborhoods as culturally desirable rental experiences. This is most closely aligned with Stors and Baltes' previous research on Airbnb hosts' intentional construction of neighborhood identities through a mixed-methods study of hosts' written descriptions of their neighborhoods (2018). I build from this previous research to further consider how Airbnb hosts' representations of urban neighborhoods is tied to whether a neighborhood is experiencing gentrification, exclusion, or neither housing dynamic.

There are distinct incentives for property owners to prioritize marketing their housing as short-term Airbnb rentals instead of as long-term leasable units. The entry of Airbnb as a viable business model is in part due to the abrupt increase of the prospective profit margin for a given housing unit that the digital marketplace facilitates. This builds from Neil Smith's urban rent gap theory, which refers to the difference between the current income stream generated by a property versus its potential profitability (Smith 1979). This untapped value is linked to the desirability of a unit's location often based on its proximity to the city center or popular amenities, contrasted with it currently being characterized as a predominantly low-income neighborhood. Investment in unit renovations can facilitate significant growth in profits for landowners by attracting new higher-income residents. The establishment of Airbnb introduces a comparatively unprecedented form of rent gap within urban regions (Wachsmuth and Weisler 2018). Instead of the multi-year timeline of unit redevelopment featured in traditional rent gap theory, owners can quickly increase their net property income by repeatedly listing their units on Airbnb over securing a long-term tenant. This transition from long-term to short-term rentals implies a similar consequence towards displacing previous residents in favor of tourists as aligned with traditional rent gap theory.

While rent gap theory regarding the profit opportunity of short-term over long-term rentals remains applicable for units within exclusionary neighborhoods, the resulting implications towards displacement are not as directly translatable as within gentrifying neighborhoods. Airbnb units within exclusionary neighborhoods were often already high-cost units within the standard rental market. However, the transition of these units into Airbnb listings contributes to total rental unit loss within metropolitan regions that subsequently raises aggregate prices across rental markets (Barron, Kung, and Proserpio 2021). This is additionally exacerbated by the growth of commercial Airbnb listings, referring to housing units dedicated to short-term renting and managed by professional real estate firms rather than the occasional listing of housing otherwise occupied by long-term residents (Wachsmuth et al. 2017; Törnberg 2022a). Research regarding the increasing professionalism of Airbnb landlords has led to the demarcation of "'buy-to-let' gentrification" referring to previously long-term rental housing now being purchased for use as permanent Airbnb rentals (Katsinas 2021).

Urban sociologists have ongoingly investigated cultural explanations for why individuals decide to move into a given neighborhood within a city. Certain urban neighborhoods possess meaningful cultural capital associated with their geographic location, residents, and amenities that are perceived as desirable commodities worth paying higher housing costs for (Judd and Fainstein 1999; Bridge 2006). Ideas around authenticity, hipness, and modern urban lifestyles are all factors identified within qualitative research as reasons behind why individuals choose to move into an "up-and-coming" neighborhood and consequentially facilitate gentrification (Brown-Saracino 2009; Hwang 2016; Hyra 2017). Interest in cultural diversity that contrasts longtime residents to new neighbors and businesses is a prominent theme within this line of research, as both a reason promoting movement into gentrifying neighborhoods and a source of tension between old and new residents (Törnberg and Chiappini 2020). Narratives regarding safety, family-friendliness, and cues towards wealth are all cultural identifiers associated with exclusionary higher-income neighborhoods (Karsten 2007; Campbell et al. 2009; Loughran 2014). Said themes are found throughout sociological investigations of urban class-based stratification, such as with the establishment of elite residential enclaves via supergentrification, Not-in-my-Backyard (NIMBY) politics, and anxiety around urban crime rates (Caldeira 1996; Scally 2012; Halasz 2021). These forms of rhetoric towards gentrification and exclusion respectively have been shown to influence a household's decision to move into a particular neighborhood within a city and may also therefore shape Airbnb booking decisions.

Neighborhood cultural desirability is also influenced by local amenities and entertainment opportunities (Clark 2011; Reitsamer, Brunner-Sperdin, and Stokburger-Sauer 2016). Gentrification is embodied by its new "hipster" businesses and venues such as coffee shops, dog parks, and trendy restaurants as it is with change of individual residential demographics (Deener 2012; Grier and Perry 2018). Similar amenities are coveted within exclusionary neighborhoods, catering to a clientele with a high discretionary income and solidifying the elite status of said neighborhoods (Savage 2017). Given the importance of these establishments for constructing desirability for potential new residents, Airbnb hosts likely capitalize on local amenities to further advertise their unit's neighborhoods.

Previous research has demonstrated that Airbnb guests use the platform in part because of their interest towards obtaining an "authentic" neighborhood experience by staying in Airbnb accommodations within culturally valuable locations (Ashworth and Page 2011; Paulauskaite et al. 2016; Guttentag et al. 2017). Hosts can draw on these cultural narratives to commercialize their listing and successfully convince a potential guest to book their Airbnb unit (Törnberg 2022b). This reinforces the desirability of said neighborhood identities and may commemorate the consequences of either gentrification or exclusion as an appealing feature associated with a listing's location.

Scholarship on both neighborhood gentrification and exclusion within American cities additionally highlights the multi-year transitional stages of both processes in contrast to a binary simplification of a neighborhood qualifying as broadly gentrified or exclusionary (Brown-Saracino 2017). These dynamics are more accurately represented as stages of residential change at different magnitudes of transitions between old and new residents and amenities. Examples include the differences between early stages of gentrification where longstanding low-income residents still reside within the neighborhood versus well-established "advanced" gentrification associated with significant turnover in residential composition, or a comparable pattern regarding early exclusion within socioeconomically mixed locations versus established exclusion for high-income enclaves (Murray 2017; Ocejo 2019). Current exclusionary neighborhoods themselves have different histories with residential change as well, either as historical elite enclaves or as neighborhoods experiencing early gentrification within initial transitions occurring in the 1970s and 1980s (Schuerman 2019). Differences in cultural identity construction relevant to these finer-grained delineations of housing dynamics is an underexplored subject within research on cultural narratives and neighborhood change. I therefore consider how distinct stages of gentrification or exclusion may contribute to differences in language use by Airbnb hosts as supported by accessible data for a broader range of neighborhoods.

Furthermore, a focus on neighborhoods with established gentrification or residential exclusion raises the inherent counterfactual comparison regarding how hosts advertise neighborhoods that are stably associated with either a lower-income or mixed-income population without a history with either residential dynamic. Given the popularity and diffusion of rhetoric affiliated with either gentrification or exclusion regarding topics such as authentic urban experiences or safe neighborhoods, the potential use of similar language to commodify listings within less culturally commodified residential areas is a relevant yet underexplored subject.

Present Study

The present study combines scholarship on housing markets, Airbnb, and urban cultural consumption by investigating the language used by Airbnb hosts within written descriptions of their listing's neighborhoods. I focus on how hosts employ rhetoric previously highlighted within research examining the creation of neighborhood cultural identities to construct their listings as desirable commodities within the short-term rental market. I therefore follow Stors and Baltes' research precedent in investigating "hosts' potential to contribute to the discursive and performative reframing of residential neighborhoods into urban tourism areas" (2018: 166).

I feature Airbnb neighborhood descriptions for units located in San Francisco, California within this study. I chose San Francisco as my focal region for three distinct reasons. First, the city has a strikingly unit-limited and costly housing market that has navigated contentious politics around neighborhood change for decades (Opillard 2015). Second, San Francisco has both gentrifying and exclusionary neighborhoods with well-established cultural narratives that hosts can draw upon within their neighborhood descriptions. Examples of these neighborhoods include the Mission District and Chinatown that contend with ongoing gentrification, along with

Nob Hill and Pacific Heights as known exclusionary enclaves. Finally, the city itself is the founding location and current headquarters of Airbnb which has produced a large local marketplace for the platform.

Following my selection of San Francisco as my case study region, I identified three primary research questions to guide this study:

1. What are the primary topics and keywords San Francisco Airbnb hosts use to describe their listings' surroundings across all neighborhoods?
2. Do terms I hypothesize aligned with either gentrification or exclusion possess statistically significant relationships with either housing dynamic as linked to the spatial locations of San Francisco Airbnb units?
3. How do hosts represent their neighborhoods and its associated residents, businesses, and amenities as linked to different neighborhood housing experiences?

I address my first research question through the unsupervised natural language processing method of topic modeling, which inductively discovers principal themes regarding what Airbnb hosts decide to emphasize across the collected neighborhood descriptions. I then employ generalized linear models to identify associations between neighborhood housing experiences and discovered topics affiliated with candidate keywords linked to gentrification and exclusion to answer my second research question. I conclude by conducting a qualitative review of hosts' neighborhood descriptions to understand how the written presentations of neighborhoods differ by experiences with gentrification, exclusion, or no residential change. This design therefore combines the respective strengths of computational, statistical, and qualitative approaches to produce a comprehensive understanding regarding Airbnb host language and the production of neighborhoods as consumable experiences.

Data

I sourced San Francisco Airbnb listings spanning from December 2015 to October 2021 from the Inside Airbnb open-access data initiative compiled by Murray Cox (2021). This repository provides monthly web scrapes of all listings within San Francisco. Neighborhood location, listing latitude and longitude, time of posting, how long each host has been active on Airbnb, and hosts' written neighborhood descriptions are included for each listing record. I merged all San Francisco listings over the 62 months into one data set and preserved only the most recently observed record for a given unit if it is advertised over multiple months. I removed instances of hosts renting out multiple units that reuse the same neighborhood descriptions.

To label each listing based on its neighborhood's experience with either gentrification, exclusion, or a stable residential composition, I draw from the Urban Displacement Project (UDP) at the University of California, Berkeley's working methodology for classifying residential dynamics across US metropolitan regions (Chapple and Thomas 2020; Thomas et al. 2020). UDP's seminal research on neighborhood change categorizes urban neighborhoods through the concurrent forces of gentrification and exclusion. The Project's methodology uses a variety of neighborhood economic measures derived from multiple data sources including the US Census, American Community Survey (ACS), and Zillow's housing and rental prices index. Classification across different housing dynamics within the schema focuses predominantly on changes in neighborhood income levels, housing and rental prices, and residential racial, ethnic, and educational obtainment characteristics. UDP's working methodology additionally accounts

Table 1.1 Neighborhood categorization schema adapted from the Urban Displacement Project

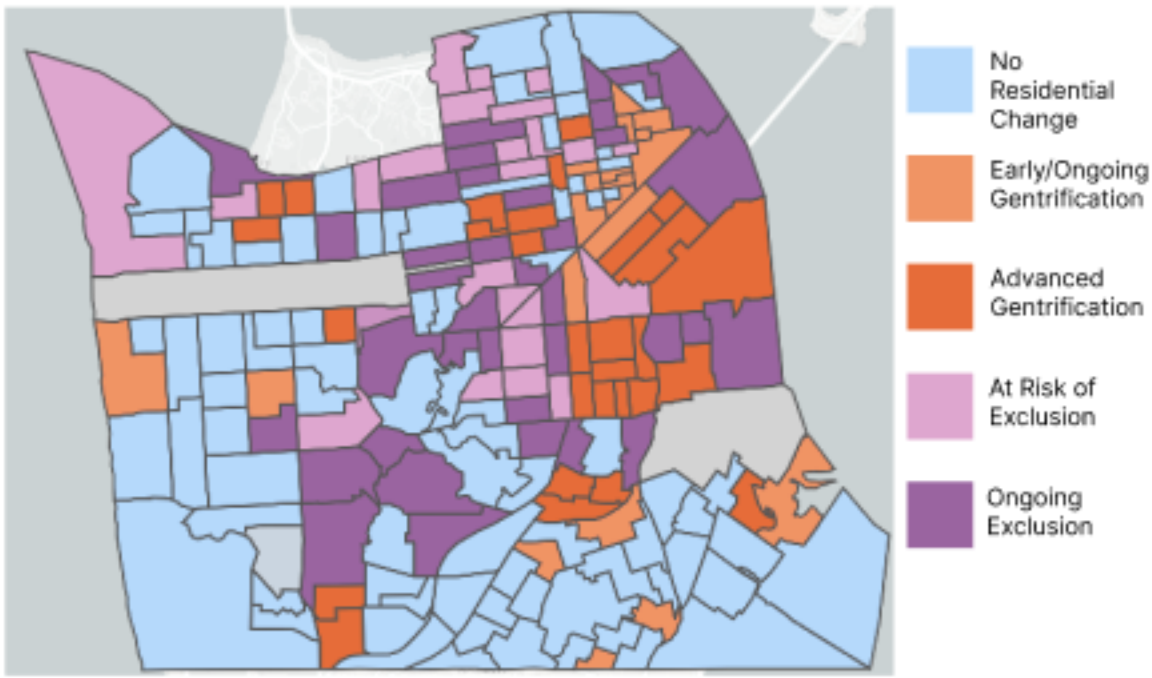
Classification	Criteria	Sample Size
Stable Low or Moderate Income (No Change)	- Either a low-income tract in 2018 or moderate-income tract in 2018 - No observed loss of low-income households or increased housing costs from 2000-2018	5,812 (29.5%)
Early or Ongoing Gentrification	- Low-income tract in 2018 with affordable housing - Increases in housing costs between 2012-2018 - Local increase in rent greater than regional median - Gentrified in 1990-2000 or 2000-2018	1,427 (7.2%)
Advanced Gentrification	- Moderate or high-income tract in 2018 - Increases in housing costs - Gentrified in 1990-2000 or 2000-2018	4,121 (20.9%)
At Risk of Exclusion	- Moderate or high-income tract in 2018 - Increases in housing costs	3,294 (16.7%)
Ongoing Exclusion	- Moderate or high-income tract in 2018 - Increases in housing costs - Loss of low-income households, 2000-2018 - Declining low-income in-migration, 2012-2018 - Median income higher in 2018 than in 2000	5,062 (25.7%)

for different stages of residential change, such as regarding the magnitude and length of ongoing residential turnover between neighborhoods that are experiencing the first indicators of gentrification compared to well-established gentrified neighborhoods with a significant reduction in low-income residents.

Table 1.1 delineates the five-category schema adapted from the Urban Displacement Project that I employ within this study to categorize Airbnb listings with their associated neighborhood housing market dynamics. The schema features both an aggregate three-class differentiation between neighborhoods experiencing gentrification, exclusion, or no change outside of a stable low-or-moderate income residential composition, as well as relevant subdivisions regarding the current stage of gentrification or exclusion. Please refer to Appendix 1.A for additional information regarding how UDP operationalizes average tract income level, housing cost increases, and indicators of gentrification based on applied thresholds of change for the underlying Census, ACS, and Zillow data sets. This classification schema effectively balances relevant differences such as between early stages of gentrification compared to neighborhoods that have experienced substantial gentrification with a level of categorical coarseness that ensures large enough sample sizes to produce methodologically robust findings. It also accounts for neighborhoods that have not experienced any considerable residential change during the past two decades, which serves as a reference group regarding Airbnb hosts' use of cultural narrative terms between gentrifying, exclusionary, and residentially stable neighborhoods.

Figure 1.1 visually represents the distribution of UDP neighborhood categories across the San Francisco census tracts. I merged the approximate latitude and longitude coordinates of the Inside Airbnb listing records with their equivalent Census FIPS codes to match each listing with its respective category. Neighborhoods that are predominantly non-residential such as the Golden Gate Park recreational area are not classified under the five-category schema and are shaded in grey in Figure 1.1. I therefore removed records that are in these census tracts that do not include a UDP classification group. This produces a final corpus of 19,717 listings with unique neighborhood descriptions across the entire city. Listings are approximately uniformly

Figure 1.1 Urban Displacement Project's neighborhood change categorization spatial distribution across San Francisco census tracts.



distributed throughout the data collection period with small modes in listing counts in the summers of 2017 and 2020, while the last scraped month of October 2021 has a significantly higher count given that I preserved the most recent record of listings posted over repeated months. Listings are concentrated around the northeast downtown area of San Francisco, with units in nearby neighborhoods such as Hayes Valley and Mission District having the highest listing counts in contrast to neighborhoods on the western and southern borders of the city such as the Outer Sunset and Sunnyside. The average host membership with Airbnb is 4.6 years with a 2.7 year standard deviation, with a given host ID having an average of 1.7 unique listings.

Methods

After merging the Inside Airbnb data set with the UDP neighborhood change classification schema and finalizing the corpus of Airbnb neighborhood descriptions, I performed standard text preprocessing on the description text. I deleted meaningless text characters such as leftover HTML tags or nonstandard alphanumeric characters, as well as the neighborhood names themselves given their inherent multicollinearity with specific neighborhoods. I additionally remove stop words from the descriptions, referring to common words such as “the” and “it” that offer minimal substantive content towards understanding how Airbnb hosts depict their listing's neighborhoods. The mean description length for all listings following preprocessing is 63 words with a standard deviation of 45 words with a right skew caused by a minority of longer descriptions.

I then applied parts of speech tags to the tokenized words within each description to identify the most occurring nouns, adjectives, and adverbs. I use the Universal Dependencies (UD) English treebank morpho-syntactic annotation framework to generate part of speech lists (de Marneffe et al. 2021). I read through each part of speech word collection and identified candidate words relevant to prior urban cultural consumption scholarship that occurred in at least 10 unique neighborhood descriptions (Davis 2006; Zukin 2010; Hyra 2017; Lees & Phillips 2018). I refined this candidate list by having it externally reviewed by two additional scholars with substantive expertise in urban sociology and housing policy scholarship. My subsequent initial working term list is featured in Table 1.2.

Hypothesizing terms conceptualized to measure abstract phenomena such as cultural representations of gentrification and exclusion is an inherently subjective process. The division

Table 1.2 Candidate term lists and occurrence counts across neighborhood descriptions.

Gentrification Candidate Terms				Exclusionary Candidate Terms			
Term	Count	Term	Count	Term	Count	Term	Count
hip	1,315	chic	238	safe	3,377	picturesque	122
urban	771	up and coming	238	quiet	3,480	calm	94
unique	769	hottest	220	friendly	1,340	serene	94
trendy	684	diversity	156	family	970	tranquil	70
diverse	670	gritty	100	families	527	secure	56
culture	669	gentrification	99	upscale	360	secluded	38
cool	428	stylish	64	quaint	352	idyllic	25
eclectic	358	fashionable	55	peaceful	317	sophisticated	21
authentic	265	gentrifying	26	cozy	200	sophistication	15
hipster	262			rich	193	classy	14
				secret	149		

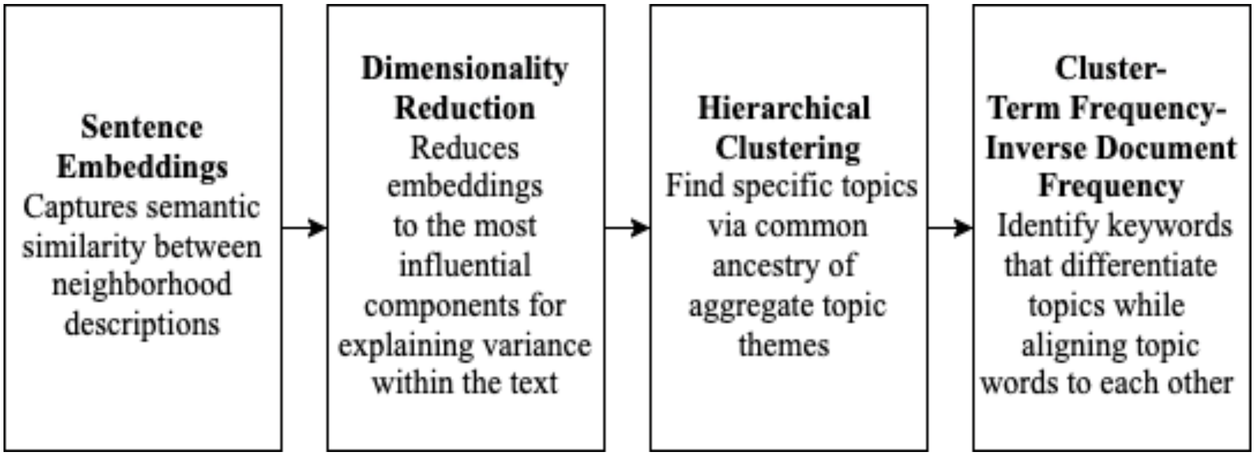
featured in Table 1.2 between words I theorize as having a greater prior probability of association with either gentrification or exclusion is inherently contestable and is open to disproval by the following analyses. I therefore identified these words to be empirically tested, particularly as regarding my second research question relevant to the statistical association between these candidate keywords and the actual language use trends of Airbnb hosts advertising gentrifying, exclusionary, and residentially stable neighborhoods.

My NLP model of choice to answer both my first and second research questions is BERTopic, a neural network-based subtype of the broader unsupervised machine learning algorithm family known as topic models. Topic models map document-topic and topic-word co-occurrence probability distributions for a given text corpus to discover relevant vocabulary groupings and associations. Topic models are methodologically well-suited for exploratory research on cultural themes and have therefore become an NLP method of choice within computational social science research (DiMaggio et al. 2013; Fu et al. 2021). While topic model variations such as Latent Dirichlet Allocation (LDA) and Structural Topic Models (STM) are the most common topic models algorithms featured in previous research, these established methods often encounter challenges regarding the interpretability of found topics and the ability to handle semantic nuances within entire documents regarding different contextualized meanings of words within topics (Chang et al. 2009; Roberts et al. 2014).

Neural topic models are recent innovations within the topic model methodological research community that are designed to effectively incorporate contextual variation between how the same word can be used with different underlying meanings across documents. These methods employ recent NLP methodological advances in transformer neural network architectures that model the similarity of complete text documents through sentence-based text embeddings (Reimers and Gurevych 2019). An example of a context-specific difference in word use within San Francisco Airbnb neighborhood descriptions that neural topic models successfully account for would be “great views of the bay” referring to the close visibility of the Pacific Ocean while “keeping the chaos at bay” as a neighborhood’s separation from more population dense neighborhoods within the city. Neural topic models additionally improve the coherence of found topics, referring to how similar words assigned to a given topic are to each other (Bianchi, Terragni, and Hovy 2021).

I employ BERTopic as my neural topic model architecture given its growing use in recent topic modeling research within the computational social sciences (Grootendorst 2022; Kellert and Zaman 2022; Lasser et al. 2022). There are four underlying methodologies behind the complete BERTopic model as delineated within Figure 1.2. First, BERTopic uses sentence embeddings from transformer neural network models pre-trained on large text corpuses to create

Figure 1.2 BERTopic algorithm four-part methodological workflow.



base vector representations of a given corpus' documents. These embeddings are intended for semantic similarity classification tasks to identify how similar entire documents are to each other rather than mapping individual words such as in "Bag-of-Words" vectorization commonly used within classic topic models.

Sentence transformer embeddings represent each document across 384 embedded dimensions, which captures a greater degree of information than what is likely needed to discover the primary topics within the neighborhood descriptions. The second stage of the BERTopic model therefore performs dimensionality reduction via the Uniform Manifold Approximation and Production (UMAP) algorithm (McInnes, Healy, and Melville 2020). UMAP advances common dimensionality reduction techniques such as Principal Component Analysis (PCA) by balancing both the global representation of text that best explains the overall variance of similar sentences within the neighborhood descriptions along with local representations specific to the corpus such as mentions of distinct San Francisco amenities. BERTopic then performs clustering on the reduced embeddings to identify the number of inductively discovered topics via the HDBSCAN (Hierarchical Density-Based Spatial Clustering of Applications with

Noise) algorithm (McInnes and Healy 2017). HDBSCAN creates a hierarchical cluster structure that continues the goal of balancing aggregate topic themes with sub-topics that identify specific examples of global topic trends. Said method provides results such as separate topics that highlight "cafe, breakfast, coffee" and "restaurant, pizza, bistro" as under the common ancestry of a food establishment topic within the neighborhood descriptions. BERTopics' reported topic keywords are identified through the final modeling stage of fitting cluster-specific term-frequency inverse-document frequency (c-TF-IDF) scores for words associated with found topics. c-TF-IDF places greatest weight towards assigning unique keywords to topics that are concurrently not semantically similar to other topics' keywords. This improves the distinctness of the individual topics.

BERTopic effectively features both topics on expected common subjects within Airbnb neighborhood description such as mentioned popular tourist destinations that are not immediately relevant to my research questions, as well as topics that directly reference the candidate key words I hypothesized to be affiliated with different experiences with gentrification or exclusion. This provides both a holistic overview of all the topics that hosts are addressing within their neighborhood descriptions as well as the specific neighborhood identity language relevant to my research interests.

Choosing the number of topics within fitted topic models to best represent the relevant themes throughout a given corpus is a contested subject within the topic modeling methodological community (Fu et al. 2021). BERTopic inductively identified 108 topics within the Airbnb neighborhood descriptions when ran without any provided guidance towards the number of topics it should discover within the corpus. I reviewed these initial topics and noted multiple topics that either conceptually overlapped with each other in their keywords or alternatively did not provide much substantive insight towards discovered themes within the text. This indicated that the model could likely be further refined by reducing the number of identified topics. I therefore draw from a thematic saturation methodological approach originating from case number selection within qualitative research that prioritizes optimal case counts based on when no more novel information is obtained to guide my selection of the number of topics (Small 2009). I experimented with 10-topic size reductions starting from 100 topics by refitting the BERTopic model on the San Francisco Airbnb corpus and compared the found topics between the models. I additionally employ topic coherence scores as a measure of topic fit regarding keyword co-occurrences across the documents (Röder, Both, and Hinneberg 2015). The generated coherence scores expressed minimal variation across the fitted models. Through this procedure, I identified 70 topics as the ideal number for my model that balanced size with subject variety throughout the Airbnb neighborhood descriptions.

BERTopic calculates the probabilities of a document's affiliation with each topic which serves as a measure of topic prevalence, referring to the likelihood of a document being assigned to a topic given its expressed text (Grimmer, Roberts, and Stewart 2022). Topic prevalence is commonly regressed on independent covariates to explore how document categories are associated with identified topics. I therefore model the relationship between the Urban Displacement Project's neighborhood categorization affiliated with each Airbnb listing towards the dependent outcome of topic probability for topics that feature a keyword within my candidate term list. I follow previous work regarding modeling topic prevalence by employing the gamma probability distribution as a general linear model family function with a logit link. The gamma distribution is an ideal choice for continuous positive numbers with a disproportionally higher number of small values with minimal variance and a minority of higher outcomes with greater variability (Johnson 2014). This characterizes topic probability distributions where most of the Airbnb neighborhood descriptions will not have a high probability of topic membership while a select few documents will be strongly affiliated with a topic. The logit link transformation successfully fits the nonlinear estimates of topic membership probability within the GLM that I then additionally convert into odds ratios. All reported covariate results and their affiliated statistical significance for the topic prevalence models are adjusted for multiple comparisons via the Holm-Bonferroni correction method (Holm 1979).

I then proceeded to qualitatively review the neighborhood descriptions themselves with close reading guided by the emergent themes highlighted by the BERTopic model (Pääkkönen and Ylikoski 2021). I began by sampling neighborhood descriptions that include at least one of the candidate keywords and coded descriptions regarding how hosts described the neighborhood and its affiliated residents, amenities, and businesses. I performed stratified sampling to obtain a minimum of 10 descriptions for each of the five neighborhood category types for both the initially hypothesized gentrification rhetoric and exclusionary rhetoric. Listings often featured keywords from both candidate term lists simultaneously, and I therefore drew additional neighborhood description samples until meeting thematic saturation towards identifying aggregate keyword use trends (Saunders et al. 2018). After reading 164 neighborhood descriptions, I then reviewed my applied codes to identify overall trends within the neighborhood descriptions both by respective neighborhood classification types within the Urban Displacement Project schema and across all listings undifferentiated by neighborhood housing dynamics. The key findings from this collective review in conversation with the quantitative results are featured as follows.

Results

To answer my research questions following the methodological workflow delineated above, I first consider the quantitative results of the BERTopic model to then guide my qualitative analysis of the neighborhood descriptions.

BERTopic Model & Topic Prevalence

My first research question focuses on identifying the most common topics and their associated keywords that hosts use to describe their unit's neighborhoods, both as regarding common subjects relevant to San Francisco tourism as well as towards the use of keywords identified within my candidate term list. BERTopics' underlying hierarchical clustering framework provides a natural structure to report overarching themes present within the 70 topics, as many of the individual topics capture specific subgroups relevant to broader concepts. I reviewed the top 10 keywords assigned to each of the 70 topics and applied codes to each topic regarding my interpretation of the collective subject each group of keywords referenced to. This analysis inductively highlighted recurring themes among the 70 topics.

Table 1.3 synopsizes the aggregate neighborhood description topical themes within the BERTopic model, while the full list of 70 topics and their most associated keywords are available in Appendix 1.B. The prevalence of topics defined by keywords that emphasize subjects such as popular tourist destinations and regional transportation systems validates that the BERTopic model successfully discovered topics that intuitively align with content Airbnb hosts are likely to include within their neighborhood descriptions. It additionally verifies that the BERTopic model correctly identified how local vocabulary such as San Francisco's Bay Area Rapid Transit (BART) and Muni bus system relates to global concepts around transportation or

Table 1.3 Primary topic themes within BERTopic results.

Theme Title	Example Words	Topics Within Themes
Food & Amenities	café, bar, restaurant, shops, stores	14, 21, 32, 34, 48, 69
Location	distance, location, central, walking	19, 28, 29, 31, 47, 67
Transportation	parking, bart, station, muni, uber	13, 22, 27, 50, 57, 59
Entertainment	beach, ocean, stadium, park, moscone center, fillmore,	5, 11, 23, 26, 35, 38, 42, 49, 58
Rental Unit	apartment, guide, room, guest	37, 51, 62
Tourist Attractions	golden gate, fisherman's wharf, painted ladies, union square	1, 4, 7, 40, 60
Neighborhood Culture	hip, diverse, latino, lgbt, african	24, 25, 36, 46, 61, 63, 64
Neighborhood Environment	safe, quiet, peaceful, clean, upscale	6, 9, 43, 44, 70

that the "painted ladies" architecture attraction and the "union square" public plaza are regional destinations beyond a non-contextual interpretation of the words themselves.

While examining the top keywords across all 70 topics within the model, I began to identify two broad trends regarding topics that include one of my identified candidate terms among their most associated keywords. First was the use of terms I originally theorized as being more associated with the phenomena of gentrification within topics that concurrently referred to identity groups such as Latino, African American, or LGBT residents. I denote this topic cluster as indicating an emergent 'Neighborhood Culture' theme within Table 2. Additionally, I also discovered a concurrent pattern of terms I hypothesized to be more closely related to residential exclusion as often co-occurring with additional keywords regarding environmental factors such as cleanliness and noise. I therefore labeled this theme as encompassing topics that appear to represent Airbnb hosts using these candidate terms to describe the "Neighborhood Environment". I use these two discovered topic superclusters relevant to my candidate terms of interest to inform my approach towards addressing my second research question regarding if topics that include these terms demonstrate statistical associations with a neighborhood experiencing either no change in housing dynamics, early or advanced gentrification, or is at risk of or experiencing ongoing neighborhood exclusion. I identified 15 out of the 70 topics as relevant towards this research question and therefore model each separately as the topic prevalence outcome variable across individual GLM regression models.

Table 1.4 illustrates logistic regression model results of the association between a higher probability of a topic being present within a neighborhood description as covarying with neighborhood experiences with different stages of gentrification or exclusion. Neighborhoods that remain either predominantly low-income or moderate-income in median residential income levels serves as the reference group across all models. I distinguished two primary findings as most relevant to my research interests following my review of these model results.

First, rhetoric I originally hypothesized to be likely more affiliated with gentrifying neighborhoods are closely matched with specific residential groups and the neighborhoods where said populations have historically lived within the city. For example, topic 36 characterized by the keywords of "latino, culture, grittiness, hotspot, hipster" is associated with a higher use likelihood by Airbnb hosts describing all four modeled types of neighborhood change in contrast to the nonchanging San Francisco neighborhood reference group. Neighborhoods experiencing advanced gentrification have the highest odds of language captured within topic 36 appearing

Table 1.4 Generalized logit model results on topic prevalence scores.

Topic	**Early Gen**	**Advanced Gen**	**At Risk Exclusion**	**Ongoing Exclusion**
6- city, fog, neighborhoods, friendly, family	0.885 (0.071)	0.975 (0.054)	1.050 (0.062)	1.135 (0.060)
9- safe, quiet, clean, neighbors, noise	0.652 (0.177)	0.552 ** (0.104)	0.679 (0.136)	0.688 (0.122)
24- culture, hippie, vintage, love, counterculture	0.930 (0.147)	0.971 (0.106)	1.251 (0.146)	1.555 *** (0.160)
25- diversity, african, cultural, mix, up and coming	0.909 (0.102)	1.146 (0.081)	0.850 (0.081)	0.781* (0.066)
30- quiet, noise, safe, residential, located	0.665* (0.108)	0.736* (0.083)	0.659** (0.080)	0.808* (0.086)
36- latino, culture, grittiness, hotspot, hipster	1.450 *** (0.123)	2.784 *** (0.164)	1.381 *** (0.087)	1.178 *** (0.066)
39- family, friendly, professionals, community, people	0.315 *** (0.094)	0.541** (0.112)	0.530 ** (0.117)	0.700 (0.137)
43- beautiful, peaceful, quiet, friendly, quaint	0.599 (0.130)	0.765 (0.114)	0.807 (0.129)	0.850 (0.120)
44- safe, security, safety, cameras, surveillance	1.424 (0.295)	1.017 (0.145)	1.190 (0.182)	1.305 (0.176)
46- gay, lgbt, historical, vibrant, community	0.934 (0.162)	1.028 (0.123)	2.291 *** (0.296)	1.901 *** (0.215)
61- faves, vibes, bustling, hottest, dope	1.033 (0.281)	1.435 (0.270)	1.041 (0.209)	0.972 (0.172)
63- hottest, redfin, market, affords, voted	0.614 (0.130)	0.903 (0.132)	0.676 * (0.105)	1.051 (0.145)
64- working, class, real, revitalizing, modernization	0.648 * (0.114)	0.687 ** (0.083)	0.614 *** (0.080)	0.708 ** (0.081)

69- michilin, amazing, shops, eclectic, wonderful	0.950 (0.160)	1.141 (0.132)	1.058 (0.131)	1.150 (0.125)
70- upscale, height, affluent, richness, thriving	1.033 (0.261)	0.714 (0.124)	0.719 (0.135)	1.030 (0.169)

within the Airbnb neighborhood descriptions. Additional groups such as the LGBT+ community and members of progressive countercultural political movements are referenced in topics 46 and 24 respectively along with words I hypothesized to be more affiliated with gentrification. Said topics hold strong associations with exclusionary neighborhoods rather than gentrifying neighborhoods. Popular San Francisco neighborhoods that are distinctly associated with these social groups such as the Castro District for the LGBT+ community and Haight-Ashbury for countercultural movement members are classified under the Urban Displacement Project as neighborhoods at risk of exclusion and experiencing ongoing exclusion respectively. These findings imply that my rhetoric I originally theorized as associated with gentrification is tightly coupled with neighborhoods being advertised by Airbnb hosts in reference to historical residents, whether or not the neighborhood itself is experiencing either gentrification or exclusion.

Furthermore, the significant coefficients for topic 39 with "family, friendly, professionals, community, people" reporting log odds below the value of one for early gentrification, advanced gentrification, and at risk of exclusion indicates that said rhetoric aligns with my expectation towards not being associated with gentrifying neighborhoods while simultaneously not characterizing exclusionary neighborhoods as I originally hypothesized. The observed non-significant difference between ongoingly exclusionary neighborhoods and neighborhoods not experiencing either gentrification or exclusion as the categorical reference group suggests that both neighborhood types have listings that employ said language around family-friendliness. Topic 30 regarding "quiet, noise, safe, residential, located" significant coefficients for a reduced log odds comparing the four types of neighborhood change to neighborhoods not experiencing either gentrification or exclusion implies that these stable residential locations are the neighborhood typology most characterized by my originally hypothesized rhetoric associated with exclusionary neighborhoods. An additional emergent finding is regarding the robust association of neighborhoods not experiencing residential change with topic 64 regarding both "working class" residents while simultaneously highlighting "revitalization" and "modernization" within the neighborhood. Said results highlight a distinct language trend by Airbnb hosts to characterize said neighborhoods separate from gentrification or exclusionary processes.

In summary, these model results indicate that my proposed keywords for advertising gentrifying or exclusionary neighborhoods are not restricted in their use to particular neighborhood housing experiences. Language I originally proposed to be more affiliated with gentrification is heavily defined by affiliation with longstanding resident identity groups for both neighborhoods experiencing different stages of either gentrification or exclusion. Furthermore, rhetoric I theorized to be affiliated with exclusionary neighborhoods did not demonstrate a statistically significant relationship with qualifying San Francisco neighborhoods among the Airbnb descriptions. The results of the generalized linear models instead suggests that nonchanging residential locations are more affiliated with the proposed exclusionary keywords.

Qualitative Neighborhood Description Review

Following my quantitative analysis of the common neighborhood description topics and rhetoric trends within the neighborhood descriptions, I conducted close reads of the descriptions to explore how hosts incorporate said language into complete narratives regarding their unit's neighborhoods. Descriptions across the San Francisco neighborhoods often highlighted recurring features that align with hosts' dual incentives to advertise both San Francisco as a travel destination as well as their individual unit's suitability as a short-term residence. Common subjects across listings align with the discovered aggregate topics by the BERTopic model such as the unit's proximity to tourist destinations, accessibility to public transportation, and the location of amenities such as proximate restaurants and shops.

A primary finding from my quantitative analysis is regarding how rhetoric I originally hypothesized to be associated with gentrification is instead driven by neighborhoods' affiliation with historical residential groups across both gentrifying and exclusionary neighborhoods. I found throughout my close readings of the neighborhood descriptions that Airbnb hosts demonstrate an ongoing awareness of the contrast between old and new residents and businesses within their neighborhoods. Many descriptions distinguish between neighborhood amenities associated with long-term residents from new establishments. This is exemplified by a host's description of the historically Latino Mission District as follows, which is classified as a neighborhood experiencing advanced gentrification under the UDP classification schema:

> "The neighborhood offers a delightful mix of culture, foods, and trendy people. Fresh produce is right outside of local Latino markets while craft roasted coffee is brewed from top-tier cafes along our eclectic main streets. Whether you're in the

> mood for fine dining, the greatest taquerias, lowbrow bars, or the best street food, the Mission has it."

Said contrast between longstanding neighborhood establishments such as taquerias and "lowbrow" bars compared to new coffee roasters and expensive restaurants is presented as desirable for the variety of choices they offer to guests. This exemplifies the two axes of how hosts advertise the Mission District neighborhood within Airbnb as both originally a Latino community enclave as well as fashionably novel with the introduction of new establishments and higher-income residents through gentrification. This duality is characterized as allowing guests to explore more "authentic" neighborhood experiences while also including options that cater to more elite, upper-class, and White lifestyle interests. As noted by Törnberg and Chiappini, Airbnb hosts successfully "package local culture into consumable experiences for an outsider group, as the neighborhood is framed as a playground for touristic urban fantasies" (2020: 563).

Similar language is used by Airbnb hosts to describe neighborhoods experiencing residential exclusion in reference to affiliated identity groups. This was exemplified by hosts' descriptions of Haight-Ashbury classified as an ongoingly exclusionary neighborhood as concurrently presented in its historical affiliation with countercultural political movements through language I originally predicted to be associated with gentrification:

> "This artistic neighborhood is known for its vintage boutiques, unique architecture, and eclectic food options. People come from all over to experience its free-spirited culture. This also draws in some countercultural folks, so it's probably not your cup of yerba mate if you're not okay with panhandling."

The host's use of language such as "unique" and "eclectic" situates Haight Ashbury within a similar presentation of novelty and authenticity as the Mission District but in reference to different residential histories. Said rhetoric was employed across exclusionary neighborhoods that are either longstanding elite enclaves or experienced early gentrification within the 20th century, which further demonstrates the popularity of this neighborhood presentation style across listings. However, the above description alludes to an emergent finding within my qualitative review regarding how hosts advertising either gentrifying or exclusionary neighborhoods differ in their presented relationships with historical neighborhood residents. The “not your cup of yerba mate” reference at the end of this description comment alludes to a popular tea within San Francisco, making this sentence a direct reference towards a class-based aversion of panhandlers by potential guests. I discovered a greater tendency by hosts advertising neighborhoods experiencing either initial or advanced gentrification to positively frame historical residents within their neighborhoods, while hosts advertising exclusionary neighborhoods were more likely to adopt either a neutral or hostile stance towards city residents, particularly those who are homeless. Consider the contrast in the presentation of residential diversity by a host advertising the Bayview neighborhood that is currently experiencing early gentrification:

> “This is a diverse residential neighborhood with residents who’ve lived here for decades. All ethnicities are represented here unlike other places in the city. Previous guests have given us lower ratings for thinking it’s a ‘gritty and unsafe neighborhood’, which we don’t agree with at all. If you’re not tolerant of diverse backgrounds, then this probably isn’t the location you’re looking for.”

This host makes an explicit defense of the neighborhood's diversity to the point of dissuading potential customers from booking their Airbnb if they are not equivalently supportive of the neighborhood's residents. This alludes to the emergent trend within the descriptions of hosts within gentrifying neighborhoods often expressing a more positive framing of longstanding residents than hosts advertising neighborhoods experiencing exclusion.

It is relevant to note that the observed trend of neighborhood descriptions that take a more protective stance towards diverse longstanding residents is closely linked with San Francisco neighborhoods where a disproportionate number of Black residents reside within the city. Said descriptions were also more likely to report a high probability of affiliation with Topic 25 as the only topic explicitly referencing "African" as one of its top keywords along with "diversity" and "cultural. Given previous findings within neighborhood change scholarship regarding a lesser likelihood of experiencing gentrification for neighborhoods with more Black residents (Hwang and Sampson 2014; Timberlake and Johns-Wolfe 2017), the occurrence of language defending residential diversity among San Francisco neighborhoods with a higher proportion of Black residents implies that Airbnb hosts renting units within these neighborhoods approach advertising their listings with a degree of awareness of the stigmatized status of said locations. Hosts' commodification strategies therefore stage diversity as desirable while simultaneously adopting a uniquely defensive stance regarding the desirability of neighborhoods with more Black residents.

The quantitative results of this study additionally indicated that my originally hypothesized exclusionary rhetoric instead demonstrates no distinct affiliation with exclusionary neighborhoods, instead being characterized as robustly not affiliated with gentrifying neighborhoods and linked to San Francisco neighborhoods that have not experience any residential change. My qualitative review provided context to this finding by corroborating the use of this language within neighborhoods experiencing either ongoing residential exclusion or no distinct housing dynamic. A host's advertisement for Noe Valley as a neighborhood experiencing ongoing residential exclusion exemplifies this as follows:

> "This neighborhood has a calm atmosphere where you can find fresh vegetables at the weekly farmer's market or enjoy a bottle of wine at one of the bistros. The clean central street has great boutiques and cafes, which makes it a prime location for family strolls, couples on dates, and dog walkers."

This host portrays Noe Valley as an amiable location with agreeable neighborhood residents and a relaxing environment. The amenities that this quote highlights such as farmer's markets and wine bars both are associated with expensive high-class lifestyles. There are recurring references towards pleasant walks throughout the neighborhood, clean and tidy streets, and amenities that cater to expensive consumption habits throughout Airbnb descriptions advertising exclusionary neighborhoods. Similar language is used to describe the stably mixed-income Mission Terrace neighborhood, although with differences alluding to the more residential status of this neighborhood with a lesser importance placed on advertising expensive amenities:

> "This is a modernizing area in San Francisco that has both the quiet and peace of a nice residential neighborhood with close access to other busier and livelier locations (shops, groceries, bars, dance clubs) on the southern side of the Mission."

While San Francisco neighborhoods that are stably low or mixed income are commonly described by Airbnb hosts with rhetoric regarding being quiet, safe, and family-friendly residential locations more so than exclusionary neighborhoods, my qualitative review highlighted how Airbnb hosts present these neighborhoods differently regarding how commodifiable the neighborhoods are themselves as tourist experiences. Exclusionary neighborhoods are often portrayed as desirable destinations with their affiliated elite amenities while retaining a presentation of calmness and security equivalent to stably residential locations. Said rhetoric was notably absent from descriptions of neighborhoods experiencing gentrification, which instead were often framed as exciting opportunities for adventurous experiences in reference to their residential diversity.

Discussion

Airbnb as a growing online short-term rental marketplace has now become an influential force impacting local housing and travel economies throughout major metropolitan regions undergoing residential change. This work expands on previous scholarship exploring how the cultural identities of urban neighborhoods are commodified on Airbnb through considering how neighborhoods' histories with gentrification, exclusion, or stable residential compositions influences how Airbnb hosts construct the desirability of their unit's location. My mixed-methods findings demonstrate how San Francisco Airbnb hosts employ rhetoric often associated with gentrification regarding authenticity, hipness, and diversity in conversation with historical residential groups to present neighborhoods as exciting travel experiences, whether or not the neighborhood itself is actually experiencing gentrification. I additionally found that rhetoric regarding family-friendliness and safety is used by Airbnb hosts primarily to describe stably low-income or mixed-income neighborhoods in contrast to my original predictions towards said language's greater affiliation with exclusionary neighborhoods.

The commercialization of neighborhoods through these language trends testifies to their ongoing influence in driving travel and lodging decisions for tourists such as Airbnb guests. By intentionally drawing from rhetoric regarding diversity or family-friendliness, Airbnb hosts are reinforcing these neighborhood identities as purchasable experiences via the short-term marketplace. Said neighborhoods are characterized and consumed through their relationship with historical residential groups in the case of language I originally hypothesized as affiliated with gentrifying neighborhoods, or alternatively through the implied absence of certain city residents within the "quiet" neighborhoods experiencing no residential change.

Given the observed influence Airbnb has to further restrict competitive housing markets and increase rental prices, these findings highlight a cultural mechanism through which Airbnb retains its popularity and subsequently continues to influence residential dynamics within urban neighborhoods (Garcia-López et al. 2020; Barron, Kung, and Proserpio 2021). While urban displacement within cities is a complex phenomenon influenced by a convoluted network of social, economic, cultural, and political factors beyond Airbnb alone, the marketplace's growth and transition of long-term housing to short-term units disproportionally impacts marginalized residential populations within cities that can often no longer afford to live within neighborhoods characterized by limited long-term housing availability and high rents. Airbnb hosts' reinforcement of neighborhood cultural narratives implicates the online marketplace within this process given how said language may promote a higher booking rate and solidify the economic incentives to prioritize short-term over long-term rentals.

This empirical investigation contributes to prior urban sociology scholarship by attesting to the ongoing relevance of rhetoric previously linked to cultural narratives regarding neighborhood change. Examples include the importance placed on "authenticity" and "diversity" when constructing neighborhood desirability as well as emphasizing "family-friendly" and "safe" residential areas within a city (Brown-Saracino 2009; Zukin 2010; Goodsell 2013; Hyra 2017). This study demonstrates how said language already noted by scholars is reproduced within emergent digital platforms such as Airbnb. It therefore contributes to urban sociology research regarding the intersection of city neighborhoods and culture by identifying how previous findings within the discipline are replicated within new online mediums.

This study's findings indicate multiple policy implications. Major cities across various countries are currently navigating how to best approach local Airbnb market regulation in context of the platform's relationship with collective rental housing availability and prices. Previous studies that examine Airbnb's effects on housing markets have emphasized industry regulation and initiatives that support retaining long-term city residents to mitigate the loss of available housing units within their policy recommendations (Gurran and Phibbs 2017; Wachsmuth and Weisler 2018). Implemented policies intended to curb Airbnb's impacts on housing and displacement have included restricting the amount of properties advertised per host, unit occupancy rate limitations, licensing and registration requirements, and tax obligations specific to the short-term rental market (von Briel and Dolnicar 2021). However, there are ongoing challenges towards actively enforcing compliance with these established regulations towards local Airbnb markets across cities.

These results call attention to the more conceptually abstract consequences that the advertising behavior of Airbnb hosts and associated booking interests of guests has on city neighborhoods and local communities. There are a range of related policy initiatives across cities with the goal of promoting diverse neighborhoods and retaining long-term residents that may otherwise be displaced from popular metropolitan regions within increasingly expensive and unit-limited housing markets. These include affordable and mixed-income housing development and investment in longstanding small business and community initiatives (Ghaffari, Klein, and Baudi 2017; Klein et al. 2019). Research has demonstrated that policies that focus on physically retaining marginalized households within changing neighborhoods do not prevent other forms of cultural and political displacement from also occurring within the community, testifying to the complexity of these dynamics and the ongoing challenges towards how to best address their consequences (Grier and Perry 2018; Addie and Fraser 2019).

Airbnb as a private company is now an additional factor among many regarding the relationship between tourism and residential change within major metropolitan regions, which additionally raises questions towards the effectiveness of traditional policy initiatives to mitigate residential displacement within housing markets increasingly influenced by online platforms owned by private companies (van Doorn 2019). Prospective attempts to address the inequities of urban displacement in light of the growing short-term rental sharing economy will therefore need to successfully navigate the respective and potentially conflicting interests of Airbnb itself, platform users, city residents, and other political stakeholders.

One limitation of this study is its restricted scope to San Francisco and subsequently the city’s unique cultural history and relationship with residential change. I cannot assume my findings are robust to the circumstances of other major metropolitan regions both within the United States and in other countries. This is a common limitation throughout research on cultural representations of urban neighborhoods given the close relationship between neighborhood identities and unique residential histories. A future direction stemming from this initial work would therefore be replicating this same mixed-methods approach with Airbnb neighborhood descriptions from other major urban regions. This would test the validity of my results regarding San Francisco as applied to other cities and explore how differences in regional contexts may lead to additional, complementary, or divergent findings.

Another limitation of this study's design is that I am using a secondary data source of web scraped Airbnb listings rather than featuring primary data such as interviews with Airbnb users and city residents. These collected listings have the advantage of being representative of hosts' genuine portrayals of their listing's neighborhoods. This mitigates potential response biases if hosts were directly asked to describe their neighborhoods to an outside researcher. However, this produces a trade-off in my interpretation of the subjective meanings behind neighborhood descriptions with the assumptions I must subsequently make as a third-party researcher analyzing the listings without being able to ask hosts directly about the intentions behind their descriptions. This is furthermore connected to these listings as being representative of only the perspectives of Airbnb hosts without comparative insight from other relevant parties such as Airbnb guests, long-term neighborhood residents, and beyond. A future research direction stemming from this work would therefore be qualitative fieldwork conducted directly with various stakeholders connected to Airbnb within San Francisco.

As cities contend with Airbnb's impact on rental markets, this work demonstrates how San Francisco Airbnb hosts commodify cultural neighborhood narratives. Residential displacement is a complex urban phenomenon brought about by a wide range of social and economic forces beyond exclusively Airbnb. However, the online marketplace's advertisement of short-term housing for tourists allows these listings to serve as mirrors regarding how language and cultural presentations of neighborhoods contributes to wider residential dynamics. As Airbnb marketplaces continue to expand and hosts further strengthen the association between their short-term rentals and travel experiences defined by neighborhood identities, this study emphasizes the need to consider how Airbnb user behavior may have a long-term influence on rental housing markets across diverse urban contexts.

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Appendix

Appendix 1.A Urban Displacement Project (UDP) classification metrics operationalization protocol.

Tract Income Level Definition: Income calculations are sourced from 1990 to 2010 US Census and American Community Survey (ACS) 5-Year estimates from 2008-2012 and 2013-2017. Low-income tracts are those with household median incomes 80% or less of regional area median incomes, moderate-income tracts are within the 80-120% income range, while high-income tracts are greater than 120% of the regional median. UDP classifies tracts with 55% or more of the population belonging to a given income group as predominantly low, moderate, or high-income.

Housing Cost Increase Definition: Housing cost estimates are also sourced from the Census and ACS, along with the Zillow Home Value and Rent Indices for 2000, 2012, and 2017. Housing cost increases are defined as whether rental or home values experienced either a relative price increase higher than the regional median cost or a greater than 5% relative increase of the tract median cost over the 2000 to 2017 year range for home prices or from 2012 to 2017 for rental prices.

Gentrification Definition:

First, tracts are defined as vulnerable to gentrification within the base year of either 1990 or 2000 if they within this year:

1. Have below regional median housing values or rents.

2. Meet two or more of the following criteria:

    A. Are above the regional median percentage (RMP) of the tract population that is low-income.

    B. Above RMP of the tract population that is non-white.

    C. Above RMP of the tract population that are renters.

    D. Below RMP of the tract population that is college educated.

Following the identification of an initial vulnerability to gentrification within the starting year of the comparison time frame, neighborhoods are classified as having experienced gentrification based on meeting the following conditions:

3. Tract experienced an increase higher than the RMP of its college educated population.

4. Tract experienced an increase higher than the RMP of median residential income.

5. Tract experienced an increase higher than the RMP in housing and/or rental prices.

Appendix 1.B 70-topic BERTopic model results and top five keywords.

1	wharf, fisheman, lombard, square, coit	25	diversity, african, cultural, mix, up and coming	49	beach, blocks, ocean, beachside, dunes
2	valencia, corridor, street, blocks, districts	26	beach, ocean, golden, close, distance	50	balboa, subway, bart, station, mins
3	fillmore, pacific, japantown, alta, plaza	27	muni, walk, bus, station, minute	51	apartment, room, floor, bedroom, private
4	golden, gate, park, bridge, irving	28	blocks, block, away, restaurants, market	52	precita, harvest, cafe, park, hillside
5	bay, views, city, stadium, area	29	score, paradise, walker, walkability, transit	53	tech, airbnb, companies, headquarters, pinterest
6	city, fog, neighborhoods, friendly, family	30	quiet, noise, safe, residential, located	54	merced, lake, stonestown, galleria, golf
7	alamo, ladies, painted, square, famous	31	location, central, everything, downtown, easy	55	murals, oldest, founded, walls, adorn
8	moscone, center, union, convention, buena	32	thai, sushi, vietnamese, burma, japanese	56	prevalent, homelessness, homeless, borders, convenient
9	safe, quiet, clean, neighbors, noise	33	south, tech, market, industrial, entrepreneurs	57	lyft, uber, transit, stops, access
10	uion, square, building, gritty, nitty	34	yoga, studio, pilates, gym, fitness	58	zoo, parkside, pine, west, lake
11	garden, academy, museum, japanese, sciences	35	opera, hall, symphony, center, ballet	59	sfo, airport, minutes, cal, station

12	duboce, triangle, lower, park, tree	36	latino, culture, grittiness, hotspot, hipster	60	davidson, mount, midtown, sutro, terrace
13	bart, station, muni, close, bus	37	locations, guide, check, listing, guidebook	61	faves, vibes, bustling, hottest, dope
14	cafe, bar, breakfast, coffee, tartine	38	south, beach, embarcadero, bay, waterfront	62	nearby, guest, floor, working, quiet
15	district, life, galleries, colorful, art	39	family, friendly, professionals, community, people	63	hottest, redfin, market, affords, voted
16	mclaren, portola, john, bruno, largest	40	victorian, homes, edwardian, visitors, houses	64	working, class, real, revitalizing, modernization
17	nopa, panhandle, alamo, ladies, mill	41	polk, street, union, gulch, hyde	65	turtle, line, lurline, irving, directly
18	cortland, avenue, views, alemany, shops	42	beach, ocean, lands, surfers, outerlands	66	software, south, internet, moscone, headquarters
19	distance, walking, restaurants, bars, within	43	beautiful, peaceful, quiet, friendly, quaint	67	everything, distance, walking, need, everywhere
20	canyon, village, gialina, corneta, store	44	safe, security, safety, cameras, surveillance	68	judah, blocks, outerlands, helpful, beach
21	shops, stores, bars, coffee, groceries	45	ucsf, hospitals, campus, kaiser, medical	69	michilin, amazing, shops, eclectic, wonderful
22	parking, cleaning, street, free, car	46	gay, lgbt, historical, vibrant, community	70	upscale, height, affluent, richness, thriving
23	legion, honor, beach, ocean, museum	47	heart, financial, district, location, central		

24	culture, hippie, vintage, love, counterculture	48	westwood, fitness, avenue, target, racetrack		

CHAPTER 2

LOCAL RESIDENTS AS DIGITAL PUBLICS: POLICY FRAMING WITHIN R/SANFRANCISCO HOUSING DISCOURSE

Abstract

American city residents are increasingly debating social policies within online public platforms such as social media sites. Individuals' expressed policy opinions are commonly defined by the *framing* used to present one's beliefs, referring to the intentional emphasis of policy characteristics tied to prevailing considerations within governance and social systems that influences the persuasiveness of a policy argument. This study explores the use of policy frames within online public discussions via a localized case study regarding San Francisco housing policy on the social media platform Reddit. I combine natural language processing via supervised machine learning, regression modeling and qualitative analysis to illustrate how the members of an online community with a robust policy discourse culture employ and respond to policy frames. My findings highlight relevant trends regarding differences in the popularity of diverse policy frames, how frames are concurrently presented with expressed emotional sentiment, and how other community members react to framed policy opinions. This work therefore offers an exploratory analysis of policy framing within one digital community that delineates a methodological framework that can be reproduced for different online platforms and policy topics.

Introduction

The general public impacted by social policies are debating and shaping their policy beliefs increasingly within online committees while concurrently transitioning away from traditional physical mediums (Bennett and Segerberg 2013; Sunstein 2017; Forestal 2021a). Discussions occurring within social media sites such as Facebook, Twitter, and Reddit have been found to influence American political outcomes within both national and regional contexts (Santos, Bernardini, and Paes 2021; Forestal 2021b). These trends have promoted research to understand how individuals learn about policies and attempt to persuade others to support their policy beliefs throughout online communities (González-Bailón, Kaltenbrunner, and Banchs 2010; Boulianne 2015; Jungherr, Rivero, and Gayo-Avello 2020). As modern governments navigate policy design in a political context now characterized by the intersection of in-person and online lives, empirical approaches that can effectively analyze and describe these online conversations have become a pressing interest of political stakeholders.

A longstanding subtopic within policy studies is policy framing, referring to the intentional presentation of a policy opinion by referencing culturally widespread concerns within social policy design that are applicable to a range of political issues (Rein and Schön 1977; van Hulst and Yanow 2014). The repeated use of many policy frames has facilitated an interest within the computational social sciences to explore and develop natural language processing techniques to identify frames within digitized text data via machine learning (Card et al. 2016; Johnson, Lee, and Goldwasser 2017; Hofmann, Pierrehumbert, and Shütze 2021). While this past research has focused on the intersection of social media and political engagement at national levels, a large segment of policy initiatives that directly impact constituents are regionally tied to local city governments. This work therefore considers policy framing within a regional online community linked to a specific city to explore how framed discussions are liable to shape local policy outcomes.

To investigate policy framing within regional online discussions, this work considers the case study of frame use within housing policy debates in the r/sanfrancisco Reddit community. My research explores how users within this discussion forum employ different frames to present their housing policy opinions, how frame use interacts with the emotional expressions of users, and how post popularity within the larger community differs by frames. I developed a supervised machine learning language model to automate the identification of policy frames within 46 thousand r/sanfrancisco user comments. I then addressed my research questions by employing both close reading of over 1,500 comments to identify policy framing themes, as well as fit multinomial logistic and negative binomial regression models to statistically characterize framing trends. Highlights from my findings include the prevalence of economic frames, the relationship between sentiment and frames regarding morality, quality of life, and culture, and the popularity of political frames within the larger r/sanfrancisco community. This work therefore advances an innovative approach to public opinion measurement and policy discourse analysis that can be reproduce by researchers and stakeholders across political contexts with varied policy interests.

Background

Digital Publics & Reddit

Proposing, contesting, and deciding on policies within democratic governments has been historically tied to designated public physical spaces and media artifacts such as town squares, discussion forums, and distributed print text (Habermas [1989] 1991). Scholars have noted the essential role public spaces play towards promoting deliberative democracies, in which impacted citizens can debate with each other and subsequently shape political outcomes (Chambers 2003; Dahlberg 2011). Political opinions within modern governance are now commonly broadcasted via the Internet in a transition away from physical public spaces and objects (Gimmler 2001; Bennett and Pfetsch 2018). Forestal highlights the emergence of *digital publics* as online platforms such as social media sites that now provide a similar environment as historical public spaces to debate political topics and "give individuals the grounding necessary to meaningfully discuss issues of the day in an increasingly fast-paced and frantic globalized world" (2021a: 312). Political engagement within social media communities that serve as digital publics has been subsequently linked to higher levels of offline political action among platform users (Lane et al. 2017; Kim and Ellison 2021).

Online political discussion research has become a robust subfield within the computational social sciences (González-Bailón et al. 2010; Rho et al. 2018; Tachaiya et al. 2021). However, said explorations has emphasized federal policy issues with national participants over regional political arenas such as city governments. Public opinion at the metropolitan level as debated through media outlets can powerfully impact regional policy implementation (McLeod, Scheufele, and Moy 1999; Trounstine 2009). The intersection between digital policy communication and local politics is a relevant topic to further explore, given that residents have a greater ability to shape policy outcomes within regional politics compared to national initiatives (Haro-de-Rosario, Sáez-Martin, and Caba-Pérez 2016; Kwon, Shao, and Nah 2021; Nah et al. 2021).

Reddit is a popular site among American social media users that is characterized by active discussions towards both original user posts and in response to external media content

(Roozenbeek and Palau 2017). Among the multiple social media sites where digital publics are created and maintained, Reddit's platform design and emergent community norms are well-suited for supporting ongoing conversations centering politics and policy (Forestal 2021a). The site's structure centers around subreddits that engage with an expansive range of conversation subjects. Users create posts and comments relevant to the topic of a given subreddit, leading to communities focused entirely on political discussions such as "r/politics".

Reddit minimizes requirements to publicize personally identifiable information, such as by encouraging the use of chosen usernames over actual names. This promotes user semi-anonymity and mitigates the impact of social desirability bias on user's expressed opinions towards politically contentious topics (Kruse, Norris, and Flinchum 2017; Jones-Carmack 2019). The site also includes a score feature where other users can indicate their support or disapproval by "upvoting" or "downvoting" a comment. This measures the collective reaction towards a comment within a given subreddit community. These design features are factors behind why Reddit has become a popular platform to research online political discussions (Guimarães, Terolli, and Weikum 2019; Rajadesingan, Budak, and Resnick 2021).

Reddit hosts subreddits dedicated to individual cities such as "r/nyc" and "r/LosAngeles". While policy discussions are not the explicit focus of these subreddits, they are a common topic of interest among participating users. This makes local subreddits an opportune environment to explore digital public deliberation of regional policies because of the organically emerging investment in these conversations by users. Subreddits are not representative of the total voting population on regional policies given the site's user demographic skew towards White, male, and college educated individuals on the platform (Hargittai 2020). However, traditional political participation outlets such as community forums or media publications also commonly do not represent a diverse range of voter perspectives (McCabe 2016; Einstein, Palmer, and Glick 2018). Online mediums such as regional subreddits are therefore one discourse space out of many for a particular locality that each have their associated representation biases. Given the platform's design advantages and popularity for hosting conversations linked to specific cities, subreddits are overall an appropriate environment to investigate how local policymaking is impacted by online policy discourse.

Policy Framing & Local Housing

Stakeholders often argue for their political opinions by referring to a variety of policy frames that are both nationally widespread and closely connected to longstanding American cultural narratives and priorities (van Hulst and Yanow 2014). *Policy framing* refers to the highlighting of select features of an issue and downplaying of other characteristics to delineate a specific argument or belief around a policy topic (Rein and Schön 1977; Entman 2007). Frames are commonly employed by government officials, mass media outlets, and the general citizenry to justify policy preferences, oftentimes with the additional objective of attempting to persuade others and influence policy outcomes (Björnehed and Erikson 2018). Intentionality is a core component behind policy framing with stakeholders cultivating policy portrayals based on their chosen frames and parallel absence of alternative perspectives. While there are no specific strategies within framing that ensures widespread support of a policy argument, research has demonstrated that frames that appeal to widespread cultural norms and values are recurringly dominant within policy deliberations and can influence whether recipients of a framed opinion decide to support or oppose an expressed policy belief (Braun 2015). This additionally intersects with the tactical use of emotional sentiment and affective appeals within framing to promote audience buy-in and motivate political action (Gross 2008; Klein and Amis 2021).

Frames are often applicable to diverse policy topics due to their cultural ubiquity towards formulating and defending various policy opinions. These universal frames draw from embedded understandings of politics, culture, and social processes within the U.S. (Chong and Druckman 2007; Kangas, Niemelä and Varjonen 2014). For example, an interest towards the moral implications of a proposed policy can be applied to divergent subjects such as regulations to combat climate change contrasted to justifying foreign military campaigns. The same frames can also be differentially employed to support or oppose the same policy proposal. The economics of rent control policies can be framed to support the policy- such as by emphasizing landlords' financial interests towards consistently increasing already expensive rents- or to oppose it by focusing on the potential consequences of attempting to regulate the housing market.

Amber Bodystun and colleagues built from the academic precedent of researching policy framing within text media documents such as newspapers by highlighting the subject's suitability to be analyzed through contemporary computational methodologies. The authors note that while policy discussions are often context specific**, "**issue framing [itself] exhibits many empirical regularities across policy debates" (2014: 4). These regularities as distinguished by recurring keywords and sentence structures within framed policy discussions that are ideal features for building robust supervised machine learning models to automate frame classification. Bodystun and colleagues identified fifteen candidate policy frames established within the framing literature, which then a subset of these original authors spearhead a data annotation initiative to label frame use within 26 thousand news articles covering multiple policy topics such as gun control, abortion, and same-sex marriage (Card et al. 2015). This produced the publicly available

Media Frames Corpus, which provides the large collection of annotated text required to build machine learning classification models that can then identify frames within other collections of text data.

The release of the Media Frames Corpus has led to the widespread adoption of Boydstun and colleague's frame schema within computational analyses across policy topics, online platforms, and in different languages. A subset of studies that employ the Media Frames Corpus investigate frames on newspaper articles similar to the corpus' original data source (Field et al. 2018; Morstatter et al. 2018; Kwak, An, and Ahn 2020; Roy and Goldwasser 2020). There is additionally high transferability between the Media Frames corpus data and social media policy debates given the observed prevalence of common policy frames within digital media outlets (Entman 1989; Chong and Druckman 2007). Scholarship researching framing and expressed sentiment on social media has commonly investigated politician's use of frames designed to inspire emotional reactions on Twitter (Johnson, Jin, and Goldwasser 2017; Johnson et al. 2017; Shurafa, Darwish, and Zaghouani 2020). Mendelsohn, Budak, and Jurgens were the first to consider wider public opinion over political leaders when investigating policy frames within Twitter discourse on immigration (2021).

My work advances this literature by exploring the specific case study of frame use within online discussions in the r/sanfrancisco subreddit community as regarding housing policy. While framing within regional policymaking has been an ongoing research interest among urban studies scholars, said scholarship has focused primarily on government officials, media outlets, and local organizations over public conversation on social media (Richardson and Jensen 2003; Metzger and Wiberg 2018; McArthur and Robin 2019). Housing is an ideal topic to explore when investigating regional policy framing because it is inherently localized and is therefore a subject directly tied to regional residents. Research has demonstrated that housing is a prominent discussion subject within American city subreddits that host recurring debates of policy proposals regarding topics such as affordable housing and homelessness (Straub-Cook 2018; Lê et al. 2020). I chose San Francisco as my case city subreddit because of the region's high levels of citizen investment towards housing policy initiatives and discussions, given the city's notoriously unaffordable and supply-limited housing market (Rosen and Sullivan 2014). The r/sanfrancisco subreddit is an active community with over 270 thousand members that commonly features conversations around housing policies. I therefore consider the specific case study of online discussions regarding housing policy within San Francisco via the r/sanfrancisco subreddit as the focus of this study.

Present Study

This study investigates the use of policy frames within the r/sanfrancisco subreddit to understand how platform users debate and react to framed arguments regarding local housing policies. The work deviates from previous framing scholarship that has focused on federal-level policies or on known "opinion leaders" such as major media outlets or politicians by instead considering how the general public that are members of online regional platforms debate local policy topics. By focusing on the case example of San Francisco regional housing, I delineate a workflow for discourse analysis within digital publics that may be replicated for both academic research across policy topics as well as within applied data science in civic technology sectors.

This study is guided by four research questions that each explore a respective component of policy framing within the r/sanfrancisco community:

1. What are the most and least common policy frames used within r/sanfrancisco comments regarding housing policies?

2. What are the commonly discussed topics within comments that employ a given policy frame?

3. How does frame usage differ by the expressed emotional sentiment of the commenter?

4. How do comment scores as a measure of community reaction to a comment vary by employed frames? Additionally, are there significant associations between comment sentiment and each framed comment's score?

The first and second research question focus on the descriptive exploration of policy frame usage within r/sanfrancisco housing discourse. The third inquiry investigates how framing as closely tied to opinions and persuasion can be additionally understood through its relationship with emotional expressions. The final question considers how the wider r/sanfrancisco community engages with framed arguments via comment scores as a measure of popularity. These four research questions are designed to enhance understanding towards policy discourse processes and intentional framing at both the individual comment level as well as across collective discussion within the digital public debate space of the r/sanfrancisco subreddit.

Data

I retrieved a sample of r/sanfrancisco comments via the Pushshift Python library developed by Baumgartner and colleagues that directly queries the Reddit Application Programming Interface (API) (2020). The sample features comments over direct user posts since comments are the primary medium within subreddits where users actively frame arguments regarding policy topics in conversation with each other. I first collected the submission IDs of all posts spanning from January 2015 to December 2021 that mention the keyword “housing” and then gathered all comments from these qualifying posts. I chose the broad term of “housing” over more focused alternatives such as “rent control” or “homelessness” to capture the widest range of conversations regarding SF housing instead of vetted discussions surrounding pre-selected policy topics. Each record includes the raw comment text, the poster’s username, date and time of posting, an identifier of which post ID the comment responded to, and the comment’s score. After dropping duplicated comments such as spam posts and those less than five words long due to their limited substantive relevance, the final data set features 44,680 comments.

I preprocessed each comment to only include alphanumeric characters, standard punctuation, and emoticons and emojis. I created multiple variables to include within my following regression model analyses. I generated categorical variables to control for temporal and seasonality effects of the year, month, day of week, and hour of day of when the comment was posted. I truncated all comment text to 300 words to address outlier comments with longer lengths, and then generated a word count for each comment following its preprocessing and truncation. The mean comment length is 51 words while the standard deviation is 52 words, alluding to the sizable right skew caused by a minority of particularly long comments. Please refer to Appendix 2.A for visualizations of each control variable’s distributions. I additionally produced a binary indicator regarding whether a comment was responding to an original post or to another user’s comment. This accounts for differences in policy framing behavior when users are in direct conversations with other commenters rather than replying to the post itself.

Table 2.1 Brief descriptions of final policy frames adapted from the Media Frames Corpus

Policy Frame	Description
Economics	Financial circumstances, resources & capacities, economic markets
Equality	Equality between groups, ethics & social responsibility, fair outcomes
Law & crime	Legal systems, law enforcement & criminal justice, state regulations
Health & safety	Well-being, personal safety, illness & sanitation, mental health
Quality of life	Living standards, community & environments, ease of daily life
Culture	Personal identities, subgroup membership, norms & values
Politics	Government figures, public opinion, political ideologies, voting

I obtained access to the Media Frames Corpus after corresponding with and receiving direct approval from the corpus' primary investigator Dallas Card. The corpus features fifteen frames that range in their relevance to San Francisco housing policy discourse. I remove frames that have lesser degree of applicability towards regional housing policy such as regarding national security, as well as combine frames that engage with similar topics such as legality and crime. Reducing the number of frames is additionally beneficial towards developing a supervised machine learning model by reducing the amount of language variation the model would be required to learn to differentiate between frames. I therefore focus my analysis on seven primary frames as featured in Table 2.1 that have an associated 26,704 annotated records from the Media Frames Corpus. Please review Appendix 2.B for more comprehensive explanations of each frame sourced from Bodystun et al. (2014) and the Media Frames Corpus documentation, and to Appendix 2.C for the annotated record counts of the final seven frames.

Policy frame identification via supervised learning is best supported by data previously labeled for frames within the same text-based domain. Contextually relevant data allows the classifier to learn the unique language trends of an online community as relevant to policy framing. This is particularly critical for regionally specific discourse that often mentions local politicians, neighborhoods, and policy initiatives the model would not have prior familiarity with through learning on the Media Frames Corpus alone. I therefore created an additional data set of 1,400 annotated r/sanfrancisco housing policy comments sampled from my original comment data retrieved from the Reddit API. I labeled each comment for their primary policy frame with a resulting 200 unique records for each frame. I then removed these annotated records from the full data set of collected r/sanfrancisco comments to prevent data leakage for the policy frame predictions on the non-labeled records (Kaufman et al. 2012).

As an individual from the San Francisco metropolitan region and a previous professional within regional housing policy services, I am qualified to annotate these records for their policy frame use given the challenge of understanding the nuances of the niche topical domain of San Francisco housing politics for an unfamiliar reviewer. However, this raises concerns towards the influence of my personal biases regarding how I perceived and labeled frame references as a process inevitably impacted by my own subjective interpretations. I therefore recruited an external reviewer- one of my previous coworkers within my housing services career who has similar expertise in San Francisco housing politics- to annotate 325 of these records across the seven frames without prior knowledge regarding my own generated frame labels. I computed the Krippendorff's alpha inter-annotator metric between the two sets of annotations and found a score of 0.725 on the metric's -1 to 1 axis. This level of inter-annotator agreement is comparable to aligned scholarship that also generated original datasets for computational analyses of policy framing (Card et al. 2015; Mendelsohn et al. 2021).

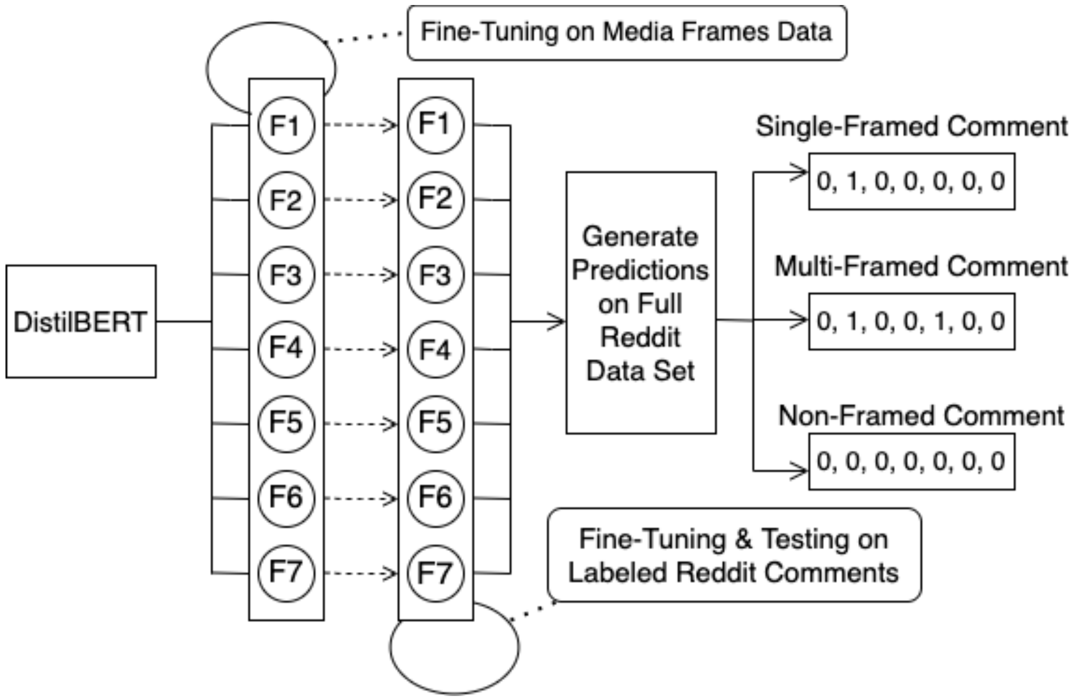
Methods

Fine-Tuning a Supervised Classifier Model

My first methodological step to investigate my guiding research questions is to identify policy frames used within housing discourse on the r/sanfrancisco subreddit through supervised machine learning classification. Policy framing is a linguistically complex process which makes accurately classifying when framing occurs a challenging modeling task. Recent advancements within NLP modeling that accounts for factors such as the sequence of words within sentences have made robust policy frame identification significantly more feasible. The innovation that has greatly improved the performance of supervised language classifiers is the widespread adoption of attention-based transformer model architectures. *Attention* refers to these models' design feature of being able to weight the importance of surrounding words within text towards understanding the relevance of a target word when producing final classifications (Vaswani et al. 2017). This technique provides these models with the capability to incorporate context-informed language use patterns.

The Bidirectional Encoder Representations from Transformers (BERT) model has facilitated the sharp popularity growth of transformer models (Devlin et al. 2019). BERT and subsequent models that build from its architecture are trained on large text corpora and are made publicly available to researchers via initiatives such as the Hugging Face's transformers Python library (Wolf et al. 2020). The widespread accessibility of these models promotes the use of a method known as transfer learning, referring to when a pretrained transformer model serves as a

Figure 2.1 DistilBERT three-stage one-versus-all frame classification pipeline.



base model to then fine-tune with additional data for a domain-specific classification task (Gururangan et al. 2020). This combines the model's awareness of English language trends from its initial development with additional learning of the unique features of a particular text corpus.

BERT's language classification capabilities are associated with high computational demand. DistilBERT is a smaller version of BERT that obtains 97% comparable accuracy to BERT on standard benchmark datasets within NLP model development while using less compute and obtaining faster run times (Sanh et al. 2019). This adapted model was created through the method known as knowledge distillation, where a compressed "student" model makes classification predictions based on the informed output of a larger "teacher" model (Hinton, Vinyals, and Dean 2015). I therefore use DistilBERT as my transformer architecture of choice given its combined resourcefulness and strong classification performance.[2]

Figure 2.1 delineates my workflow for training fine-tuned DistilBERT classifiers to predict policy frames. I employ a "one-versus-all" model framework in which I train seven separate classifiers for each policy frame tasked with predicting whether each respective frame is present within a comment. This design guides each model towards learning the unique linguistic features of individual frames. DistilBERT's general syntax and contextual word use knowledge serves as the models' baselines. I initially fine-tune DistilBERT on the Media Frames Corpus records to introduce the model to the policy frame classification task. I then employ these specialized policy frame classifiers to further train on the annotated r/sanfrancisco comment set. The separation of policy frame learning into two stages allows for the classifiers to first learn general trends regarding language and employed frames to subsequently promote the effective learning of domain-specific policy framing present within r/sanfrancisco housing policy discourse. This model structure is therefore intended to optimize predictive performance on frame identification.

I apply all seven models to the full data set, allowing for comments to be classified as having one or more frames. The one-versus-all framework additionally identifies comments that do not draw from any of the policy frames and therefore serve as a reference group to contrast with framed comments. I qualitatively reviewed these non-framed comments and found that they were commonly off-topic from housing policies and featured everyday conversational language that does not involve policy framing such as "I like your point" or "Thanks for supporting me".

While this model design effectively addresses the presence of multi-framed and non-framed comments within the data set, a one-versus-all architecture additionally introduces challenges surrounding class imbalance. There are consistently more records that do not use one

[2] DistilBERT is the original transformer language model I used for my supervised machine learning method for this study, which was later advanced by the DistilRoBERTa architecture as featured in Chapter 3 of the dissertation. I replicated this workflow with DistilRoBERTa embeddings instead of DistilBERT and found equivalent performance on the seven policy framing classification tasks.

of the policy frames than comments that do employ the frame that each respective model is trained on. Model performance can therefore report an inaccurate level of robustness via its strong predictive ability on the majority "all" class with concurrent weak performance towards the minority "one" class. To address this limitation, I calculate class weights for each model that are proportionally inverse to the individual frame frequency contrasted to all other data records. I additionally use the F1 score metric as my primary indicator of model performance. The F1 score represents the harmonic mean between the two sub-metrics of precision and recall:

Equation 2.1 Precision Score Metric

$$\frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$$

Equation 2.2 Recall Score Metric

$$\frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

Precision is a metric design to prioritize a lower false positive rate within classification predictions. In contrast, recall focuses on identifying all the members of a class and therefore emphasizes a lower false negative rate. The F1-score balances the goals of both high precision and high recall as follows:

Equation 2.3 F1 Score Metric

$$\frac{2(\text{Precision} * \text{Recall})}{\text{Precision} + \text{Recall}}$$

The F1 score incorporates the number of incorrect predictions through both false positives and false negatives rather than referring exclusively to predictive accuracy that is easily inflated by class imbalance. It is therefore a robust metric to gauge model performance within my one-versus-all classification structure.

I divide the Media Frames Corpus into a 70% training, 10% validation, and 20% testing data set split, while concurrently dividing the r/sanfrancisco annotated data with the same training, validation, and test proportional partitions. The validation set serves the purpose of supporting hyperparameter tuning within my classification model development. Hyperparameters refer to multiple configuration choices required to instantiate a supervised classifier that are externally set by the researcher rather than optimized by the model within training. The validation set serves as a designated portion of the data to experiment how different hyperparameter settings impacts model performance. This design safeguards the testing set as an unseen data sample preserved to establish the model's finalized predictive abilities after training and hyperparameter tuning.

I experiment with four of DistilBERT's hyperparameters via the validation data sets within both the initial training on the Media Frames Corpus and while fine-tuning on the annotated r/sanfrancisco records. The *number of epochs* designates how many times the classifier will completely pass over all records of each data set. The *learning rate* dictates how much the model updates its internal weight structure regarding the importance placed on individual words towards predicting a given policy frame. The *batch size* specifies how many data set records are processed by the model at a time before performing a weight update. Finally, *weight decay regularization* decides whether to introduce a penalty term within the model's computation that assists with preventing the model from overfitting to the training data and subsequentially demonstrating poor performance with unseen records. I search through multiple specifications of each of these hyperparameters by comparing the F1 scores on the validation set. All models obtained higher accuracy with the smallest tested batch size of 8 records and with a 0.01 weight decay parameter. I identified variation regarding the ideal number of epochs and learning rate across the models which can be reviewed within the table featured in Appendix 2.D. I use the highest-scoring hyperparameter specification to generate performance estimates on the test data partition for each of the seven models. I then produced final predictions on the 44,680 r/sanfrancisco housing policy records after the optimal hyperparameters have been identified for each model.

After generating classification predictions on the complete comment data set that provides me the ability to address my first research question, I then further considered the emergent trends I identified regarding the housing topics r/sanfrancisco users were employing policy frames to present within the comments. I returned to the 1,400 comments I annotated to prepare the classification training data set and reviewed each of the seven policy frame categories to distinguish the primary housing discussion points that recurringly occurred for each respective frame. Comments affiliated with a given policy frame were consistently driven by a select few discussion points among the r/sanfrancisco posts. I recorded the most commonly occurring discourse themes by frame category and identified the top two emergent conversational themes for each frame. [3] I therefore delineate these discourse patterns to highlight the primary conversational topics within r/sanfrancisco comments about housing and how said comments are differentially presented across the seven policy frame groups.

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[3] These patterns were corroborated by the additional 160 records I reviewed that were classified by the DistilBERT model rather than by my manual annotation as delineated in the following results section, providing additional support towards the validity of these identified qualitative themes across the r/sanfrancisco comments.

Modeling Emotional Sentiment and Community Response

Following the policy frame identification of the complete r/sanfrancisco housing comments data set and qualitative review of the use of policy frames among user comments, I then created an additional variable to capture expressed sentiment within comments. Sentiment analysis within NLP is commonly operationalized as detecting the differences within text that possess either a positive, negative, or neutral emotional expression. Sentiment identification via transformer models is a recent methodological approach that has achieved high performance on sentiment classification tasks (Myagmar, Li, and Kimura 2019). A popular choice for sentiment analysis with data sourced from social media sites such as r/sanfrancisco is BERTweet, a transformer language model trained on approximately 850 million Twitter records (Nguyen et al. 2020; Pérez, Guidici, and Luque 2021). The additional fine-tuning of the base BERTweet model on tweets labeled for positive, negative, or neutral emotional sentiment produced a sentiment analysis-specific variation of the model towards the goal of learning the distinct features of sentiment communication on social media, such as slang, idiosyncratic punctation and capitalization, and the implied sentiment of emoticons and emojis. While BERTweet is trained on Twitter data rather than Reddit posts as the featured social media platform in this study, there are no publicly available sentiment analysis models fine-tuned on Reddit data, while tweets are subjectively closer to Reddit comments in their linguistic trends than alternative data sets commonly used for sentiment modeling such as e-commerce product reviews or movie ratings. BERTweet is therefore a sound choice for sentiment analysis on the r/sanfrancisco comments given its combination of both the strong classification performance of transformer NLP model architectures with an added specialization towards handling the unique linguistic trends of sentiment expressions on social media platforms.

After classifying the emotional sentiment of each comment, I ran a series of multinomial logistic regression models to model the probability of a comment expressing either a negative or positive over neutral sentiment given that the comment employs a specific policy frame. Each model incorporates controls for the comment's year, month, day of the week, and time of day of posting, the word length of the comment, and whether the comment is responding to the original post submission or towards another user's comment. I used the Holm-Bonferroni correction method to adjust for the use of multiple hypothesis tests across all generated p-values (Holm 1979).

My third research question explores how policy framing within housing discourse is associated with the broader r/sanfrancisco community's reaction towards expressed frames. I used Reddit's comment score feature to operationalize community response, where the system of upvoting or downvoting comments produces an average score that can gauge the comment's popularity within the subreddit. While most comments receive a small number of upvotes, a select minority receive significantly higher scores as an indicator of their widespread support by other users. I employ negative binomial regression for predicting comment scores given the over-dispersion of score variance that violates standard Poisson count model assumptions (Hilbe 2011). Since my guiding research question is focused on the popularity of expressed frames, I exclude comments that receive a negative downvote score. This additionally structures the partitioned data set to be closer to an underlying negative binomial probability distribution. I first consider the baseline association between expressed frames and comment scores, and then move to fitting interactions between frames and sentiment towards score predictions. Both models incorporate the same control variables and multiple testing corrections as the multinomial regression models for expressed sentiment.

Results

Classifying Policy Frames & Sentiment

To establish a baseline comparison for model performance of the DistilBERT language models fine-tuned for each policy frame, I first fit a simple logistic regression classifier with a L2 regularization term with term frequency-inverse document frequency (TF-IDF) vector transformations of the combined data sets. Said model does not incorporate contextual knowledge of proximate words and is not pre-trained on a large text corpus in contrast to transformers such as DistilBERT. The logistic regressions therefore serve as minimum threshold of predictive performance on each policy frame classification task that gauges the subsequent improvements achieved by each stage of the DistilBERT model's training.

Table 2.2 provides the F1 score, precision, and recall results on the test data set for the DistilBERT training on the Media Frames Corpus, r/sanfrancisco annotated comments, and for the logistic classifier baseline. Both reported stages of DistilBERT performance follow from the identified optimized hyperparameters for each one-versus-all classifier on the validation set.

These results present two key trends. First, the fine-tuned DistilBERT models report significant improvements over the baseline logistic classifier in model performance across all policy frames. The mean gain in F1 score performance comparing the baseline logistic classifier to the final DistilBERT r/sanfrancisco test set is 0.57 with a standard deviation of 0.08. Second, DistilBERT's performance across both fine-tuning stages closely mirrors each other, in that policy frames that report a higher F1 score for the Media Frames Corpus such as economics and politics frames have equivalently greater classification performance within the r/sanfrancisco test set, and concurrently lesser performance for both tuning stages for the quality of life and culture

Table 2.2 F1, precision, and recall scores for one-vs-all policy frame classification.

Policy Frame	Logistic Regression			DistilBERT Media Frames			DistilBERT r/sanfrancisco		
	F1	Precision	Recall	F1	Precision	Recall	F1	Precision	Recall
Economics	0.259	0.228	0.294	0.826	0.835	0.817	0.825	0.842	0.808
Equality	0.126	0.033	0.263	0.640	0.604	0.682	0.730	0.686	0.779
Law & Crime	0.432	0.448	0.419	0.854	0.871	0.838	0.923	0.941	0.906
Health & Safety	0.144	0.119	0.180	0.778	0.792	0.765	0.795	0.812	0.778
Quality of Life	0.077	0.101	0.060	0.693	0.686	0.701	0.629	0.583	0.682
Culture	0.175	0.141	0.231	0.722	0.707	0.740	0.628	0.591	0.670
Politics	0.226	0.254	0.198	0.895	0.899	0.891	0.894	0.899	0.888

frames. These trends align with frames that have a greater or lesser number of labeled records respectively within the Media Frames Corpus as referrable in Appendix 2C. This alludes to the importance of a high number of training records to optimize model learning. These results overall correspond with the outcomes of previous research regarding the average distribution of model performance across policy frames as measured by F1, precision, and recall scores (Roy and Goldwasser 2020; Tourni et al. 2021; Mendelsohn et al. 2021).

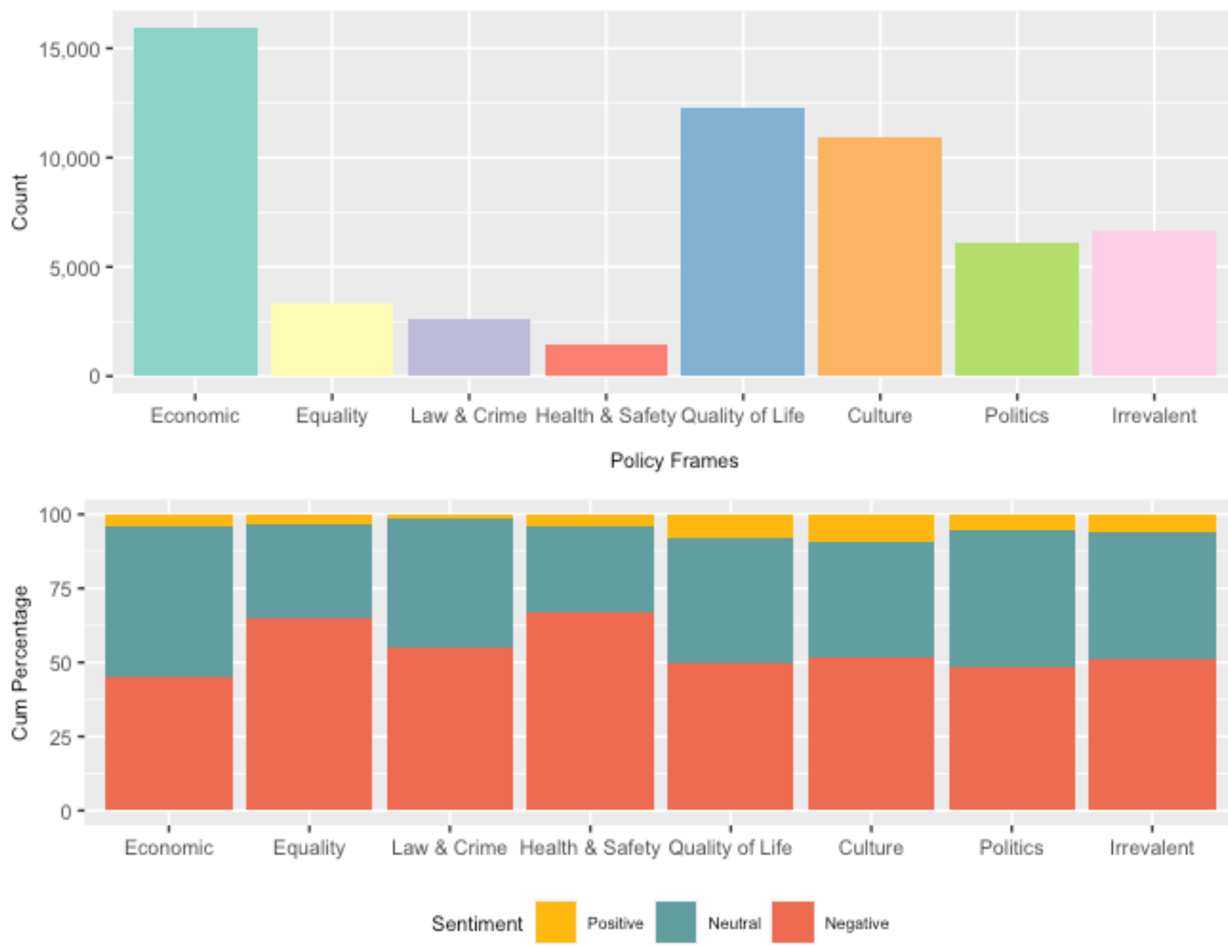
Figure 2.2 visualizes the prevalence of frames following the classification of the complete r/sanfrancisco data set as relevant to addressing my first research question regarding the total distribution of frames within the sample. These results suggest that r/sanfrancisco users most commonly draw upon the economics frame when discussing housing policies, while community members use the health and safety frame the least often. 30% of r/sanfrancisco comments are classified as expressing multiple frames, with the most frequent combinations of frames closely matching the most predominantly occurring frames overall as delineated within Appendix 2.E.

The overall confidence in these frame results is directly tied to each frame's classification performance as indicated by the F1, precision, and recall scores. The economics frame obtaining the greatest frame prevalence is a particularly robust finding given that the DistilBERT model fine-tuned for the economics frame reports high F1, precision, and recall scores for both the Media Frames Corpus and r/sanfrancisco training stages. This logic concurrently applies for identifying the comparably sparse prevalence of the Law & Crime frame within the final predictions data set, given that this classifier model similarly reported robust performance across the three scores. In contrast, the high rate of the Quality of Life and Culture frames within Figure 2.2 must be interpreted with a degree of caution, given that these two frames' models demonstrated the lowest classification performance rates. Both models report an overall level of performance via its F1 scores in the 0.6 range from the metric's 0 to 1 scale. The low precision score results indicate the higher potential of false positive classification, implying that the quality of life and culture frames' 2nd and 3rd frequency ranking respectively among all frames is likely impacted by an inflated classification likelihood. This is therefore a limitation towards robustly confirming these frames' prevalence rate within r/sanfrancisco comments.

Figure 2.2 additionally illustrates the results of the BERTweet sentiment classification. This descriptive distribution indicates potentially significant differences regarding the association between different policy frames and expressed sentiment. r/sanfrancisco comments that express a negative sentiment are the majority with a 50% occurrence rate across the data set, while emotionally neutral comments represent 44% of the records.

Strikingly, an overall positive sentiment is found within only 6% of comments. I suspect

Figure 2.2 Count and cumulative percentage of classified policy frames and expressed emotional sentiment by frame.



that there are three potential influences behind this finding. First, public discourse of controversial topics such as housing policy is often fundamentally argumentative and therefore often possesses a negative sentiment. Politically opposed users on Reddit recurringly demonstrate hostile behavior towards each other as corroborated by prior research, which additionally reflects the general ongoing prevalence of antisocial political interactions across social media platforms (Rajadesingan et al. 2021). Second, housing policy attempts to confront social problems innately tied to negative experiences such as homelessness and evictions. Even comments who may be expressing a positive sentiment towards a policy may be challenging to classify if they are concurrently referencing the wide range of negatively toned factors within social issues. Finally, I observed within my qualitative review that comments that are less inflammatory present their arguments often via analytically delineated claims that are emotionally neutral rather than positively connotated. I therefore predict that these three factors promote the low prevalence of positively expressed commentary within r/sanfrancisco.

I additionally conducted a robustness check of the policy frame and sentiment classifiers' performance by comparing the model's predictions to my own interpretations through a subset of hand-classified records. I randomly sampled 20 comments classified for each policy frame that additionally included the non-framed reference group from the generated r/sanfrancisco frame prediction data set. I labeled these 160 records for both the primary expressed policy frame of the comment as well as the comment sentiment as either positive, negative, or neutral. I then computed the Krippendorff's alpha between the models' and my own generated labels for each comment. I operationalized inter-rater agreement for policy frame classification based on if the primary policy frame I established is present within any of the potentially multiple frames identified by the DistilBERT models.

The final frame Krippendorf's alpha value is 0.77, while the sentiment classification's equivalent metric is 0.56 in context of the term's -1 to 1 scale. Both results validate a baseline moderately high level of agreement between the models' performance and my own identification of policy frames and expressed sentiment within the r/sanfrancisco comments. It is reasonable for the policy frame alpha value to be higher compared to sentiment classification given that the DistilBERT models were fine-tuned for frame classification on multiple training data sets as well as supported by their classification framework that allows for multiple frames rather than exclusively one identified expressed sentiment.

I additionally reviewed the selection of comments that received conflicting classification results between myself and the BERTweet sentiment model. The sentiment classifier consistently struggles with the use of sarcasm and irony commonly found throughout r/sanfrancisco comments, often leading to a neutral sentiment classification that I am able to identify as innately negative in tone. Additionally, select comments contained both positive and negative components that promoted classification uncertainty, such as those structured in the format of “I love this policy, but I hate this politician”. I also struggled with how to best interpret the overarching sentiment of these comments, so classification inaccuracy towards equivalent comments within the model is to be expected. This testifies to the unavoidable presence of interpretation subjectivity towards opinion expressions that are challenging to categorize within predictive language modeling.

Rhetoric of r/sanfrancisco Policy Framing

With the complete data set of r/sanfrancisco comments classified for policy frames, I then investigated my second research question regarding what the most discussed topics and themes across each frame are. Labeling the 1,400 annotated records drawn from the collected r/sanfrancisco data along with the additional 160 records for the classifier validation check facilitated my close reading of the comments. I identified and iterated on recurring topics found throughout the comments and subsequently highlight prominent subjects that are associated with each policy frame in Table 2.3. Both the comments I read before building the classifier and those identified by the classifier model feature the same recurring topics as connected to each policy

Table 2.3 Classified r/sanfrancisco comment examples by policy frame.

Policy Frame	**Identified Housing Policy Discourse Themes**
Economics	- Economic principles references such as supply & demand
	- Tension around how to allocate financial resources
Equality	- Moral obligation to protect vulnerable groups within housing
	- Fairness of applied laws for affected parties
Law & Crime	- Navigating complex laws and regulation within housing
	- Fear of crime associated with housing developments
Health & Safety	- Homelessness discourse centering drug use and mental health
	- Public health implications of housing policy during COVID
Quality of Life	- High costs of living facilitating displacement & community change
	- Neighborhood dynamics with proximate homeless encampments
Culture	- Navigating unique San Francisco political identities
	- Cultural tensions between old and new city residents
Politics	- Referencing local politicians and their housing policy agendas
	- Impact of voter preferences on predicted policy outcomes

frame. I consider how user comments allude to these themes for each policy frame in turn.

r/sanfrancisco community members who presented arguments with an economics frame commonly referred to core economic theories as relevant to housing. This was often used to attempt to explain the root causes behind housing unaffordability and scarcity within San Francisco, as well as for debating the potential impact of policies that would place regulations on the regional housing market. An example comment from a user defending landlords' right to raise annual rents is: "It's just basic Economics 101- demand is outpacing supply, and you'd be stupid to not try to make a profit from it." This user justifies their support of landlords' rent increases by presenting the behavior as aligned with a longstanding economic theory. An additional theme within economically framed comments is regarding dilemmas on how to best spend finite resources towards addressing problems within regional housing. Said comments primarily focused on the ongoing scarcity of available funding or labor.

Comments that drew upon morality frames often alluded to a perceived ethical obligation to prioritize initiatives that assist vulnerable groups within housing policy. The most common subjects of said frames were homeless individuals or lower-income renters. A user employed the morality frame in their response to a comment regarding the challenges associated with sheltering homeless individuals who have a history of destructive behavior within temporary housing: "Stop crying about it and own up to your collective duty. You can't not have housing. Be a decent person." Said comment frames its support for transitional housing on the human need for shelter and subsequent moral obligation for social systems to provide this necessity. Fairness framing was also found throughout comments that discussed equal treatment across groups within policy implementation that drew from ideology regarding fundamental political rights. This was exemplified in discourse around housing construction requirements, with discussants often drawing on the need for equal opportunity to obtain housing across social groups versus property owner's right to decide how their land should be used.

Users who employed frames around law and crime commonly discussed the legal complexity of housing policy implementation and enforcement, often in reference to potential incongruities between ideal policy design versus implementation in practice. This is exemplified by one user's comment regarding how a landlord would be unable to evict a tenant within a rent-controlled unit due to having inconclusive evidence towards their behavioral misconduct: "You know the lawyers would try to come up with something, but legally [the owners] have nothing to work with." This remark demonstrates how commenters framed their opinions towards policies in context of the legal systems they function in. Additionally, I observed users framing their policy opinions by their implications towards promoting or mitigating San Francisco's high rates of property crime. Said commentary repeatedly portrayed affordable housing construction or homelessness service facilities as subsequentially leading to increased crime within surrounding neighborhoods.

Health and safety frames were closely linked to discourse towards individuals experiencing homelessness, with rhetoric frequently mentioning substance use, mental health, and dangerous conduct. Said framing was used both in support and opposition of policy designed to aid homeless individuals, such as with sympathetic views towards challenging mental illnesses contrasted by critical commentary of the safety risk of behaviors such as leaving used needles on sidewalks. A concurrent theme around health and safety was framing housing policy decisions in context of the COVID-19 pandemic. This was seen within discussions of California's eviction moratorium and the multiple points of uncertainty about whether the ban would be extended and the potential risk of a mass eviction event if it was discontinued. One user implied a subsequent spike in COVID-19 cases caused by this potential mass displacement as follows: "Wait for the eviction wave and see what they'll say then about overburdened hospitals." Said commentary exemplifies how housing policy opinion framing became closely tied to health implications within the context of the pandemic.

r/sanfrancisco comments classified as using the quality-of-life frame frequently discussed how housing unaffordability and gentrification was promoting reduced living standards for longstanding residents which induces displacement to other regions and subsequently reshapes local communities. This is succinctly characterized by the following comment as regarding the gentrifying Mission District, “Most of them can’t even afford housing anymore unless they move all the way out to Stockton, and before you know it the whole area becomes a soulless hipster hellhole.” Stockton is a region over an hour away from San Francisco with a significantly lower cost of living, demonstrating how this user frames housing unaffordability as facilitating an unfavorable outcome for both previous residents and in the resulting quality of the neighborhood. Declining quality of life standards was also recurringly mentioned as regarding homelessness. Said framing commonly referenced both unhoused residents themselves who were perceived as not receiving adequate assistance within regional policy initiatives as well as housed residents who argued that the high rate of homelessness within the city degraded overall neighborhood living standards.

Cultural framing was presented throughout user discussions in reference to either San Francisco’s progressive political culture or as regarding cultural conflict between longstanding city residents versus “techie” newcomers. The first theme is illustrated by the following comment regarding ongoing resistance towards building affordable housing within the city: “It seems like they’re just classic San Francisco progressives- all on their elitist high horses around social justice until they’re potentially inconvenienced by it.” This user references the collective understanding of a political culture within the city that was criticized for acting incongruently between their claimed leftist ideologies compared to actual housing policy decisions. The second theme captures frame use that contrasted the cultural differences between affluent technology workers that have been moving into San Francisco from more diverse current residents. Said commentary approached housing issues relevant to these residential transitions as having subsequent implications towards the inclusion of cultural groups throughout the city.

Finally, users drew from political frames within the predictable circumstance of discussing local political figures and agencies. These comments frame their explanations for why politicians decided on specific actions within housing policy issues as demonstrated by the following example: "But the city and supervisors want to keep making money on the homeless 'non-profit' complex they designed." This comment exemplifies how this user presented their opposition to a policy intended to increase funding to homeless service centers based on their perception of corrupt underlying political interests. I additionally observed how r/sanfrancisco community members often framed their policy positions based on their perceptions of expected majority voter interests. Said references grounded their arguments on their expectations towards what policy initiatives would likely to receive enough votes to be politically viable.

While reviewing this range of framing themes across r/sanfrancisco comments, I corroborated the recurring applicability of multiple frames within a given comment as incorporated within the supervised classification model design. Multiple of the above examples can be viably argued to touch on numerous frames, such as with the comment identified as expressing a quality-of-life frame also seemingly commenting on the cultural transitions within the Mission District. I predominantly agreed with instances where the model identified a comment as expressing multiple frames within my qualitative review. This testifies to the importance of the multiple frames classification methodology for accurately representing frame usage within r/sanfrancisco.

Employed Frames, Expressed Sentiment, and Community Reaction

Within my qualitative review of the r/sanfrancisco comments, I observed the ongoing prevalence of sentiment expression variation across the range of topics that users employed

Table 2.4 Multinomial logistic regression results of association between policy frames and expressed sentiment

Policy Frame	Negative Sentiment	Positive Sentiment
Economics	0.703*** (0.016)	0.581*** (0.030)
Equality	1.834*** (0.072)	0.809† (0.079)
Law & Crime	1.098* (0.046)	0.275*** (0.045)
Health & Safety	1.793*** (0.109)	0.814 (0.119)
Quality of Life	1.063* (0.025)	1.488*** (0.067)
Culture	1.087** (0.028)	1.555*** (0.074)
Politics	0.885*** (0.027)	0.790** (0.053)
AIC	76,950	76,950
Observations	44,680	44,680

† $p < 0.10$ * $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$

policy frames towards. Furthermore, the descriptive distribution of the BERTweet sentiment classification results indicates potential associations between users' frame use and the sentiment they present their housing policy opinions with. I therefore further investigate these trends as follows through multinomial regression modeling. Each policy frame serves as a categorical predictor towards the association of a given framed comment having a negative or positive sentiment as follows.

Table 2.4 delineates the model results as expressed in odds ratios. The model includes controls for comment posting hour, day of week, month, year, word length, and whether the comment is responding to either the initial post or to another user's comments. All reported significance levels are adjusted for multiple comparisons via Holm's Bonferroni correction. The reference group for policy frames is non-framed comments, while the reference for emotional sentiment is the neutral expression group.

The reported value of 0.703 for the economics policy frame as regarding negative sentiment can be interpreted as a 29.7% reduction in the odds of being expressed in a negative instead of neutral sentiment for economically framed comments compared to non-framed comments. The subsequent odds ratio of 1.834 for the equality frame coefficient implies an 83.4% increase in the odds of an expressed negative sentiment for equality-framed comments. The negative sentiment model results therefore suggests that the equality and health & safety frames demonstrate the strongest association towards being presented via a negative sentiment, while economics and politics report the lowest affiliation. I found within my qualitative comment review that equality and morality frames were often raised by users to condemn behaviors as unethical when arguing against other users' expressed policies opinions. Concurrently, comments framed as relevant to health and safety recurringly discussed subjects with embedded negative connotations such as homelessness, drug use, mental health challenges, and the public health consequences of COVID-19. I therefore align these model findings directly with the observed frame use patterns of the comments themselves.

For the overall rare occurrence of comments that convey a positive sentiment, the multinomial logistic models indicate that positive expressions are most associated with the culture and quality of life frames while economics and politics once again report the lowest odds of positive sentiment use. I reviewed to the comment data set to reflect on this finding and noted that users who drew from the quality of life frame often spoke fondly of San Francisco residency overall, problematizing gentrification in part because of forcing individuals to move to lower-cost regions despite wishing to remain in the city. The same cultural diversity that creates housing policy tensions is itself a significant reason expressed by residents as to why they enjoy living in San Francisco. While both frames address contentious policy issues, they appear to often draw from a place of affection towards the positive attributes of the city that likely promotes the higher odds of being classified as expressing a positive sentiment.

The recurrence of economics and politics as significant terms with values below a 1.00 odds ratio provides strong evidence of these frames being characterized by neutral sentiment expressions as the underlying reference group within the model. Upon further reflection, economically framed comments frequently referred to core concepts within market theory to attempt to rationally validate policy opinions via the insights of a well-established scientific discipline. I was initially surprised by the neutral sentiment association of comments that employ political frames given my observation of many users' critiquing political figures. Revisiting these comments with a closer review for common argument structure provided additional insight towards these model findings. Politically framed comments often closely inspected politicians' and governmental organizations' behaviors, with many of the comments I read contrasting what they approved and disapproved of as regarding these political agents' actions around housing policy. I therefore theorize that said tendency to compare both points of agreement and disagreement with political figures' policy agendas may be a potential factor behind politically framed comments' association with neutral sentiment expression.

Correctly identifying the sentiment of opinions that express both positive and negative valences as "mixed polarity" expressions is an ongoing challenge within text data methodological research (Kenyon-Dean et al. 2018; Barnes, Øvrelid, and Velldal 2019). I explored the impact of neutrally classified comments that express a mixed polarity sentiment versus a firmly neutral sentiment through an alternative model specification. I operationalized mixed polarity within r/sanfrancisco neutrally classified comments based on if the BERTweet model estimated that a comment had a 15% probability of being a negative comment and a 5%

probability of a positive comment, given the high and low negative and positive sentiment assignment probabilities respectively within the data set overall. All other neutral comments were labeled as "true neutrals".

I employed the same multinomial regression models as featured in Table 2.4 with the three sentiment categories of positive, negative, or mixed polarity neutral being compared to the true neutral comments as the reference group. I found that comments expressing the economics and equality frames were significantly more likely to be associated with mixed polarity neutral expressions, while culture frames were less associated with the mixed polarity neutral sentiment. Said findings run counter to my initial interpretations of economics framed comments being linked to true neutral sentiments while political frames would be associated with mixed sentiment polarities. These findings instead suggest that economic framed comments have a higher odds of being expressed through both positive and negative comparisons, while there is no significant relationship for neutral political comments as being more likely to be expressed as "true" versus "mixed" sentiments within my results.

My final primary research question investigates the wider r/sanfrancisco community reaction to framed comments both across all frames and as intersected with expressed sentiment. I am explicitly interested in comment popularity as indicated by positive comments scores. I employ two negative binomial regression models, with the first considering the baseline relationship between frames and comment score and the second incorporating interaction terms between frames and sentiment as shown in Table 2.5.

These results indicate that comments that employ either the politics or quality of life frames have robustly greater odds towards obtaining a higher comment score compared to non-framed comments. This implies that the common themes featured within r/sanfrancisco comments that that draw from these frames- such as expressing opinions on specific political

Table 2.5 Negative binomial regression results of comment score by policy frame & sentiment

Policy Frame	Baseline	Interacted
Economics	0.959** (0.013)	0.929** (0.018)
Economics x Neg Sent	-	1.071 (0.028)
Economics x Pos Sent	-	1.094 (0.064)
Equality	0.975 (0.021)	0.958 (0.036)
Equality x Neg Sent	-	0.989 (0.046)
Equality x Pos Sent	-	1.309 (0.146)
Law & Crime	0.982 (0.024)	0.982 (0.036)
Law x Neg Sent	-	0.995 (0.048)
Law x Pos Sent	-	0.721 (0.145)
Health & Safety	1.037 (0.034)	0.987 (0.059)
Health x Neg Sent	-	1.066 (0.076)
Health x Pos Sent	-	0.765 (0.133)
Quality of Life	1.111*** (0.014)	1.096*** (0.022)
Quality x Neg Sent	-	1.030 (0.028)
Quality x Pos Sent	-	0.935 (0.048)
Culture	0.952** (0.014)	0.983 (0.022)
Culture x Neg Sent	-	0.952 (0.029)
Culture x Pos Sent	-	0.992 (0.055)
Politics	1.292*** (0.022)	1.261*** (0.031)
Politics x Neg Sent	-	1.041 (0.036)
Politics x Pos Sent	-	1.050 (0.080)
Negative Sentiment	-	1.071† (0.025)
Positive Sentiment	-	0.971 (0.045)
AIC	214,906	214,287
Observations	40,908	40,908

† $p < 0.10$ * $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$

figures or touching on changing living standards and community within the city as linked to housing unaffordability- are more popular with other users within the subreddit. Said association for both frames remain after each comment's sentiment is additionally controlled for.

Economics and culture demonstrate a lower odds of obtaining a high comment score within the model results, although cultural frames are no longer significant after incorporating the sentiment interaction term. Even if economically grounded explanations are common throughout r/sanfrancisco, these results imply that said frequency does not necessarily translate to a high level of popularity with other users. I conjecture that this trend may indicate a saturation effect driven by the high prevalence of comments that express the economic frame throughout the data set. The pervasiveness of said framing strategy may lead to comments that employ the economics frame to be perceived as less persuasive by other r/sanfrancisco users. This finding indicates an emergent direction for future research regarding frame frequency and audience response within policy discussions in digital public platforms.

The final key result from the negative binomial models is regarding how none of the framed comments report a difference in odds ratio towards obtaining a higher comment score as dependent on their expressed sentiment. This finding is counterintuitive to my initial prediction of sentiment impacting the popularity of policy frames as demonstrated within prior research. This suggests that expressed sentiment is not a significant factor in the community reaction towards a comment beyond the frame it employs within r/sanfrancisco housing policy discourse. Building from my previous alternative specification of mixed polarity neutral expressions, I additionally explored the results of a four-category sentiment interaction model with neutral sentiment split between mixed polarity r/sanfrancisco comments compared to true neutral comments. The model results delineated that equality and morality framed comments that expressed a mixed neutral stance report a significantly greater odds ($p < 0.05$) of a higher comment score count than true neutral comments. All other terms reported the same results regarding the lack of influence of sentiment interacted with frames on comment scores. This implies that along with politics and quality of life frames, equality and morality framed comments that specifically express both positive and negative sentiments within their delineation of a policy opinion are popular within the r/sanfrancisco community as measured through comment scores.

Discussion

This work explores how culturally ubiquitous policy frames are used within online discussions on r/sanfrancisco to present policy opinions and persuade other platform users. It highlights a framework for investigating localized digital public policy debates as relevant to contemporary online political engagement via a mixed-methods approach that classifies frames through NLP-based supervised machine learning, statistically models their association with relevant factors such as emotional sentiment and community reaction, and qualitatively explores common discussion topics linked to each unique policy frame. While this work features the case study of housing policy discourse within the r/sanfrancisco subreddit, its design and guiding questions are adaptable for a variety of topics and domain applications.

My methodological approach combining three distinct methodologies successfully addressed each of my four guiding research questions. Economics frames focusing on markets and resources were found to be the most commonly occurring frame, while health and safety is the least occurring frame. Discourse linked to specific policy frames covers a range of subjects such as housing unaffordability, homelessness, urban displacement, neighborhood culture, and beyond. Most framed discourse expressed a negative sentiment while emotionally neutral comments are also abundant. Comments that employ morality and equality frames are associated with negative sentiments while culturally framed comments have the greatest likelihood to employ a positive sentiment. Politically framed comments are the most likely to obtain a positive community response as measured by comment score along with equality and molarity frames that express a mixed polarity sentiment, while the economics frame is the least likely to gain notable popularity. Sentiment was found to have a minimal effect towards the popularity of framed comments overall.

The primary methodological limitation of this study is classification inaccuracy. Supervised machine learning models are fundamentally predictive and therefore inevitability produce a select number of incorrect classification decisions. This is particularly true within the intersection of machine learning and natural language processing given the challenges of accurately categorizing complex human language patterns. Model performance often has a higher degree of inaccuracy when attempting to achieve subjectively complex tasks such as identifying policy frames. My DistilBERT models' performance varied across the identified frames within r/sanfranscio housing policy discourse. False positives and negatives therefore impact the overall validity of the observed policy framing trends and are a conditioning factor towards the study's findings.

This study is intentionally limited in the scope of its findings in exclusively considering the niche topic of housing policy within San Francisco. Future work would therefore explore the robustness of this study's proposed design for different regions, policy issues, and online discussion platforms beyond r/sanfrancisco housing policy discourse. A broader goal underlying this research is to delineate an empirical approach that has the potential to become more widely applicable for exploring policy framing across different regions and topics. I envision my presented methodological workflow as potentially adoptable by local stakeholders within regional policymaking to measure public discourse by highlighting key metrics such as frame prevalence, emotional sentiment, and community reactions to policy discussions.

Said intention behind my research design has sizable policy implications. Understanding voter preferences and ideological reasoning within regionally tied social media outlets is increasingly important within local governance given that framed discourse can have a significant impact on constituent's policy opinions and subsequent voting decisions. As more residents participate in the digital publics of social media platforms, computational analysis of public discourse similar to this study offers a promising approach to understand contemporary policymaking and to gauge stakeholder opinions towards individual policy initiatives. This is additionally relevant given ongoing challenges towards accurate policy opinion measurement in traditional public opinion research via surveys as related to issues around sample representativeness, response rates, and cost (Couper 2017; Prosser and Mellon 2018).

This study introduces a novel framework to understand digital public discourse within regional social media communities. It is aligned with applied initiatives to further consider the essential influence online platforms have towards modern policymaking as local governments increase their institutionalization of civic technology and explore the potential of data science to better serve their constituents. This preliminary exploration therefore offers a promising direction at the intersection of innovative machine learning methods with applied use towards supporting robust democratic policy making that can be further expanded on and refined across a range of regions and relevant policy topics.

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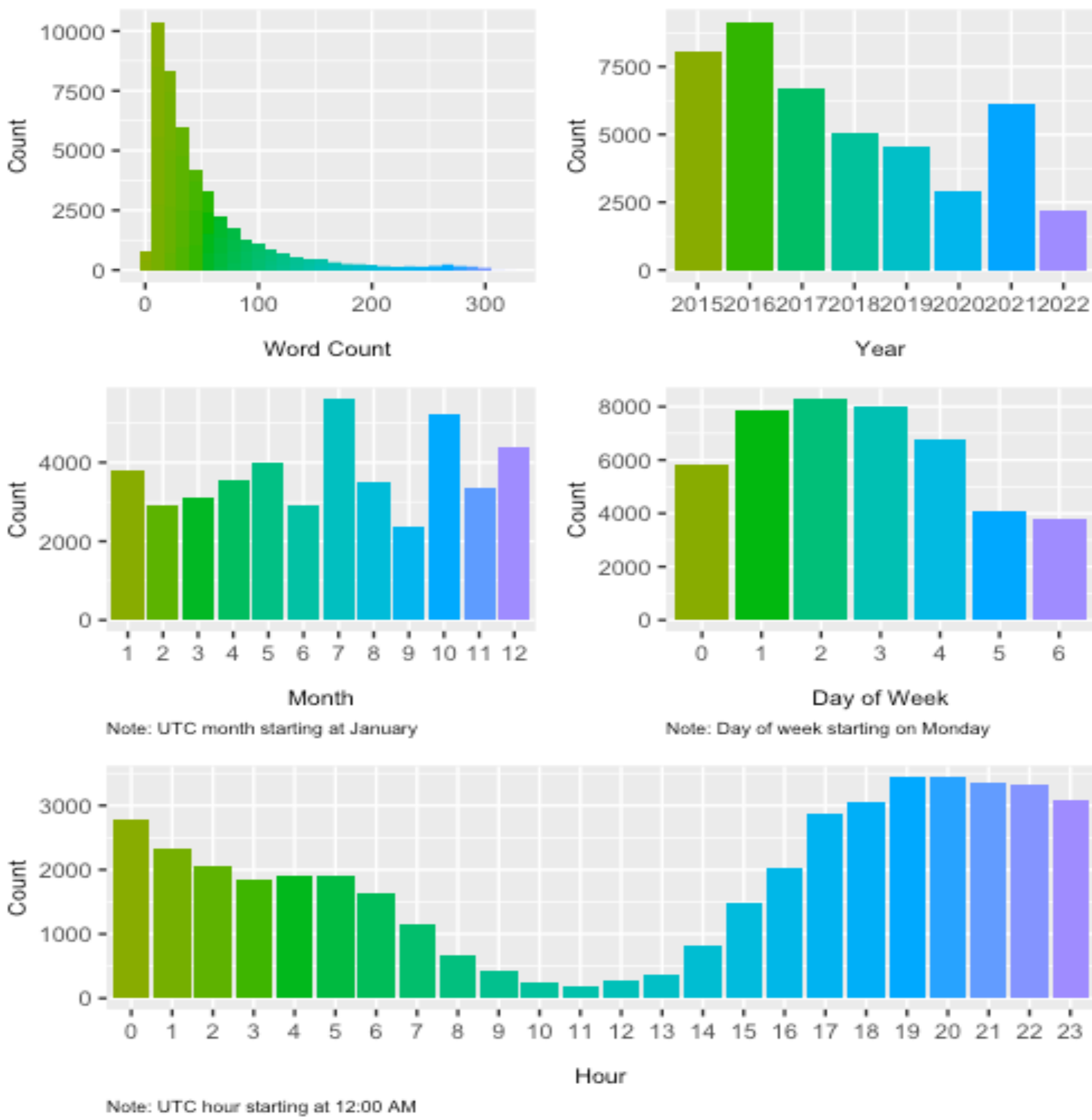
Appendix

Appendix 2.A Control variable count distributions.



Appendix 2.B Policy frame classification schema definitions adapted from Boydstun et al. 2014

1. Economic & Resources frames: The costs, benefits, or monetary/financial implications of the issue to an individual, family, community or to the economy. The lack of or availability of physical, geographical, spatial, human, and financial resources, or the capacity of existing systems and resources to implement or carry out policy goals.
2. Equality, fairness, and morality frames: Any perspective, policy objective, or action that is compelled by duty, honor, righteousness or any other sense of ethics or social responsibility. Consideration of the equality or inequality with which laws, punishment, rewards, and resources are applied or distributed among individuals or groups.
3. Legality, Crime, and Punishment frames: Specific policies in practice and their enforcement, incentives, and implications. Includes understandings of the enforcement and interpretation of laws by individuals and state actors, breaking laws and crime, and potential punishments.
4. Health and safety frames: Discourse regarding illness, disease, sanitation, physical health, mental health, prevention of or perpetuation of harm, personal & infrastructure safety.
5. Quality of life frames: The effects of a policy on individuals' wealth, mobility, access to resources, happiness, social structures, ease of daily routines, community life, etc.
6. Cultural identity frames: The social norms, trends, values, and customs constituting cultures and subgroups broadly defined, as they relate to a specific policy issue.
7. Political & public opinion frames: Any political considerations surrounding an issue. Explicit statements that a policy issue is good or bad for a particular political party or figure. Additionally considers public political opinion and voter preferences.

Appendix 2.C Count of records by frame within the Media Frames Corpus.

Economics	Equality	Law & Crime	Health & Safety	Quality of Life	Culture	Politics
3, 555	1, 913	7, 763	1, 669	1, 318	2, 096	8, 377

Appendix 2.D Finalized hyperparameters for Media Frames Corpus and r/sanfrancisco one-versus-all DistilBERT policy frame classifiers.

	Media Frames		**r/sanfrancisco**	
Policy Frame	# of Epochs	Learning Rate	# of Epochs	Learning Rate
Economics	3	5e-5	3	5e-5
Equality	3	5e-5	2	5e-5
Law & Crime	2	5e-5	2	4e-5
Health & Safety	3	5e-5	2	4e-5
Quality of Life	2	4e-5	3	4e-5
Culture	3	4e-5	3	5e-5
Politics	3	5e-5	3	5e-5

Appendix 2.E Counts of policy frame co-occurrences across r/sanfrancisco comments.

	Economics	Equality	Law & Crime	Health & Safety	Quality of Life	Culture	Politics
Economics	0	825	807	89	4902	652	1116
Equality	825	0	132	73	713	903	259
Law & Crime	807	132	0	147	252	130	148
Health & Safety	89	73	147	0	415	160	16
Quality of Life	4902	713	252	415	0	2570	250
Culture	652	903	130	160	2570	0	1221
Politics	1116	259	148	16	250	1221	0

CHAPTER 3

MOVE-IN FEES AS A RESIDENTIAL SORTING MECHANISM WITHIN CRAIGSLIST RENTAL MARKETS [4]

Abstract

As rental transactions within American urban metropolitan regions are increasingly being conducted through online marketplaces such as Craigslist, longstanding research interest towards how housing agents such as landlords shape residential sorting outcomes are now being investigated within these digital platforms. Posted rental advertisements on Craigslist represent the start of rental transactions where landlords can attempt to shape which prospective tenants apply to a unit based on what information they do or do not specify within their advertisements. This article considers the potential sorting mechanism of move-in fees, referring to additional up-front costs required to secure a lease beyond monthly rent that can make a rental unit financially untenable for many low-income households. This study investigates mention rates of different types of move-in fees within Craigslist rental advertisements, how landlords' specification of fees differs by neighborhood racial and socioeconomic characteristics, and how fees can be employed with different market sorting intentions. My results highlight that move-in fees are mentioned within Craigslist advertisements at a lower rate than their estimated prevalence within housing markets, with high-poverty neighborhoods being both more likely to encounter a specified fee while simultaneously less likely to encounter move-in fees presented as a market deal or discount. Said findings emphasize how move-in fees are differentially employed by landlords within online rental markets, lending support towards policy initiatives that aim to increase

move-in fee transparency within platforms or financially assist households towards affording move-in fees.

Introduction

Housing searches conducted within American cities have experienced two notable transitions within the last few decades. The first is the increasing prevalence of renting over homeownership within urban regions, while the second is the rise of households using online platforms to search for and secure housing (Boeing and Waddell 2017; Joint Center for Housing Studies 2022). Sites such as Craigslist, Zillow, and Apartments.com are now one of the primary mediums where renters find their current residences compared to traditional sources such as through newspapers or word of mouth (US Census Bureau, 2019). These online marketplaces offer city-specific forums to advertise available units and facilitate communication between landlords and prospective tenants.

There is an established interest within the sociology of housing exploring how actors such as landlords, real estate agents, mortgage lenders, and beyond shape housing search outcomes with broader implications towards residential sorting and neighborhood segregation (Krysan and Crowder 2017; Hwang and McDaniel 2022). Recent studies have investigated equivalent behavior on online housing search sites given the prominent role these platforms now play in promoting interactions between housing actors and prospective residents (Boeing et al. 2020; Goodchild and Ferrari 2021). This study builds from previous scholarship that use NLP methods to examine how written advertisements on these sites potentially shape housing

[4] This chapter builds from prior research featured in Stewart, Remy, Chris Hess, Ian Kennedy, and Kyle Crowder. (2023). "Move-In Fees As A Residential Sorting Mechanism Within Craigslist Rental Markets." Forthcoming in *Cityscape*: 1-14.

searches (Delmelle and Nilsson 2021; Besbris et al. 2021; Kennedy et al. 2021). Said work theorizes housing agents as intentionally choosing both what to include and not mention when writing and posting their advertisements, as well as how they may frame their chosen language towards specific goals within rental transactions such as obtaining tenants with desired characteristics and dissuading applications from other renters.

I build from this recent scholarship investigating how online rental advertisements shape housing outcomes via NLP methods by considering the underexplored subject of when landlords specify move-in fees in Craigslist rental advertisements. *Move-in fees* refer to the range of additional costs associated with securing a rental outside of a baseline monthly rent payment such as security deposits, application fees, and advanced request for the first and/or last months' rent. These fees shape tenants' prospective rental choice sets due to raising the up-front cost required to secure a lease, which within urban rental markets where renters are increasingly struggling to afford rising costs can make an otherwise ideal rental financially untenable (Rohe 2017; Rosenblatt and Cossyleon 2018).

This study's findings highlight how landlords on Craigslist specify move-in fee requirements at a substantially lower rate than their estimated prevalence within rental markets, indicating a potential intentionality behind when landlords choose to delineate said fees. I find that landlords are most likely to specify fees when their advertised unit is located within or proximate to neighborhoods with high poverty levels, while concurrently being less likely to present said fees in context of a market deal such as a discounted security deposit amount or waived application charge when near high-poverty neighborhoods. These results suggest that landlords use move-in fees to shape rental market behavior particularly for lower-income residents and neighborhoods.

Background

With a growing proportion of residents living within large U.S. metropolitan regions being now renters over homeowners, online marketplaces such as Craigslist have become a leading medium for both fostering landlord and tenant rental transactions and towards shaping collective residential sorting patterns within cities (Costa et al. 2021). Landlords post advertisements on city-specific forums within Craigslist that commonly delineate unit features such as monthly rent amount, the unit's surrounding neighborhood, unit and neighborhood amenities, and rental lease terms.

The growing influence of these marketplaces towards rental searches and aggregate residential sorting within urban metropolitan regions has encouraged research that explores these written advertisements through text analysis methods (Besbris et al. 2021, 2022; Kennedy et al. 2021; Adu and Delmelle 2022). These studies have found that landlords vary in their language and topics specified within these advertisements, implying intentionality behind what landlords decide to delineate within their listing advertisements and how they frame rentals and their surrounding neighborhoods as ideal housing options for specific applicants. Said research demonstrates that landlords tailor provided unit and leasing information based on surrounding neighborhood demographics including racial, ethnic, and socioeconomic composition. Examples of found behaviors include highlighting neighborhood amenities within Whiter and more affluent neighborhoods while concurrently emphasizing exclusionary restrictions towards applicants in lower-income and more racially diverse locations such as regarding credit score limits and criminal background checks. This variability in whether or what type of information is provided within the advertisement and what landlords require from potential renters who respond to the listing often reinforces preexisting residential stratification patterns by shaping how prospective tenants understand their eligibility for each advertised unit.

Landlords' incentives to tailor the information they provide within their rental advertisements is grounded in the unique characteristics of urban rental markets versus home purchases. Individual landlords are often the sole agents vetting prospective tenants within rental markets compared to the multiple actors involved with home ownership transactions such as real estate agents and loan brokers (Korver-Glenn 2018; Besbris 2020). There are consistent shortages in rental unit supply compared to demand in populous urban regions particularly for affordable units, leading to posted advertisements often receiving hundreds of inquiries or tenant applications. Landlords are therefore motivated to quickly narrow the applicant pool through various vetting criteria from the initial posting of their online advertisement.

Said circumstances of attempting to expeditiously reduce large applicant pools additionally intersects with the common landlord behavior of screening prospective tenants through discretionary criteria that has been shown to promote discrimination against protected subgroups under the Fair Housing Act (FHA). Interviewed landlords within qualitative research emphasize the importance they place on leasing to households that will practice desired behaviors such as consistently paying rent on time and being unlikely to damage the property, with landlords often depending on in-person meetings to appraise and screen potential tenants (Rosen 2014; Desmond 2016). While posted Craigslist advertisements represent a preceding stage within rental transactions before an in-person walkthrough of a unit, landlords are likely aiming to maximize the chances of prospective renters aligning with their subjective criteria of "good" tenants from this initial stage of rental searches.

This process is impacted by known discrimination from landlords towards lower-income applicants, Black and Latino households, and/or households receiving government rental assistance such as through the Section 8 Housing Choice Voucher (HCV) program (Flage 2018; Ferreri and Sanyal 2022). These groups are recurringly stereotyped as less reliable and more disruptive tenants, leading to a range of exclusionary practices to either avoid renting to these groups or to steer these households into particular rental units and neighborhoods. While legislation such as the FHA aims to protect against explicit discrimination towards protected classes, legal grounds for disqualification such as credit scores, eviction histories, criminal records, and beyond disproportionally vet the same marginalized rental households (So 2022).

Scholarship has highlighted how landlords coordinate rental market sorting through implementing exclusionary criteria regarding renter's prior backgrounds on factors such as credit scores and past eviction records (Bhatia 2020; Rosen et al. 2021). A comparatively underexplored yet powerful additional sorting mechanism is regarding move-in fees. Common examples of these fees include security deposits, rental application charges, credit report or background check payments, advanced rent payments such as for the first month and last month of the lease, and other miscellaneous expenses required by the landlord. These added costs can sizably increase the financial burden a household must incur to obtain rental housing and often transitions an otherwise within-budget unit via monthly rent alone to an unaffordable price due to the large lump sum of money necessary to pay all mandated move-in fees.

Move-in fees appear as a secondary topic throughout research highlighting challenges faced by tenants from marginalized groups towards obtaining rentals (Duke-Lucio, Peck, and

Segal 2010; Orians 2016; Rosenblatt and Cossyleon 2018; Messing et al. 2021). Said fees impose often insurmountable financial burdens and therefore can substantially shape a household's choice set of prospective rentals. They have been found within commercial housing market surveys to be commonly requested by landlords, but their ability to shape aggregate rental market outcomes remains underexplored within housing scholarship (Garcia and Berchick 2021). Landlords' intentional delineation – or lack thereof – of move-in fees within online rental advertisements is therefore a relevant topic to further consider as an influential market sorting mechanism.

Move-in fees can be theorized as grounded in exclusionary vetting of lower-income applicants who cannot afford to pay the requested up-front costs. However, an alternative scenario where a landlord may choose to specify a move-in fee in a rental advertisement is in context of a market deal, such as for a discounted security deposit amount or a waived application fee. This behavior may be linked to a landlord's underlying goal to secure a tenant for a less desirable rental unit due to an unfavorable location or unit disrepair, or alternatively for luxury units that cater to a small portion of the rental market and yet consist of a sizable amount of recent rental unit construction within U.S. cities (Graham 2015; Lauermann 2021). Both examples represent cases where move-in fees serve as an incentive to apply to a unit rather than as a restrictive criterion. These contrasting circumstances testifies to the importance of considering varying contexts regarding how landlords employ written advertisements to shape aggregate rental market outcomes. While diverging in their presentation of the same underlying requirement of additional expenses beyond a monthly rent payment to secure a lease, both examples demonstrate how move-in fees are liable to structure the rental search outcomes for renters whether through financial exclusion or incentivizing applications through market discounts.

Move-in fees' influence on rental market dynamics has promoted recent policy initiatives within states such as New York, Washington, and Utah to either limit requestable move-in fee amounts or requiring landlords to state all expected charges from the initial advertisement of a rental unit (Stewart-Cousins 2019; Judkins 2020). This indicates that said fees are increasingly recognized as important factors shaping rental markets that have remained largely underexplored and unregulated despite their widespread prevalence. Understanding how said fees are leveraged by landlords within online rental advertisements therefore supports said policy initiatives by highlighting how fees are encountered by tenants their housing searches.

Previous literature examining Craigslist rental advertisements has emphasized how the information provided within listings varies based on the racial, ethnic, and socioeconomic characteristics of a unit's immediate neighborhood. However, landlords have been shown to consider the broader metropolitan residential characteristics when deciding how to market a listing, such as regarding adjacent neighborhoods where prospective tenants often currently live (Logan and Zhang 2010; Desmond 2016; Krysan and Crowder 2017). This work therefore expands its scope to consider how both immediate and proximate neighborhood residential demographics may impact a landlords' tendency to specify move-in fees. Said approach accounts for landlord's behaviors within online platforms being impacted by the wider rental market characteristics within a metropolitan region given landlord's likely awareness towards a unit's marketability within the context of both the unit's immediate and proximate neighborhoods.

Present Study

This study investigates how rental searches conducted through Craigslist online marketplaces are shaped by the sorting mechanism of move-in fees. I am particularly interested towards how landlords may tailor their written specification of fee requirements within Craigslist advertisements to influence the behavior of prospective applicants across different metropolitan neighborhoods. I examine how this potential intentionality behind when move-in fees are specified by landlords may differ by racial, ethnic, and socioeconomic neighborhood characteristics. I additionally consider how move-in fees can vary in their shaping of rental market behavior as either a means of exclusion or to incentivize applications through advertised market deals. Said investigation is guided by the following four research questions:

1. What are the baseline mention rates of different types of move-in fees among Craigslist rental advertisements?
2. How are move-in fee market deals commonly presented within advertisements?
3. How do move-in fee mention rates vary by both immediate and proximate racial, ethnic, and socioeconomic neighborhood demographics?
4. How does fee specification differ across these neighborhood characteristics when mentioned in context of a market deal?

The first research question aims to measure the prevalence of move-in fees throughout Craigslist rental advertisements overall, while the second question focuses on the qualitative characteristics of move-in fee market deals featured within the advertisements. The third question builds from the identification of different specified fees to examine how landlords differ in their mention likelihoods across different neighborhood residential characteristics. Following previous findings regarding which tenant subgroups landlords most actively vet within rental transactions, I predict that landlords will be more likely to specify move-in fees for units located within neighborhoods with either higher neighborhood poverty levels or higher proportions of Black or Latino residents. My final question incorporates divergent intentions underlying move-in fee mentions and how fees presented in the context of special market offers may target specific neighborhoods. These four research questions collectively investigate how move-in fees within Craigslist advertisements potentially impact residential sorting outcomes across diverse metropolitan neighborhoods.

Data

The data featured in this study is a collection of web scraped Craigslist rental advertisements across the 100 largest United States metropolitan regions as measured by residential population size spanning from July through August 2019. The data was collected through a combination of the Helena web automation and Python programming languages with daily collection of newly posted advertisements (Hess and Chasins 2022). Landlords often post their advertisements multiple times, and unique listings were therefore identified by dropping records with duplicate text descriptions. This produced a final sample of 1.3 million advertisements spanning 41,620 Census tracts across the two-month data collection period.

Rental unit information compiled from the scraped listings includes all of the specified advertisement text, the asked rent price, the unit's square footage, and the unit's approximate latitude and longitude. These records were merged with the 2015-2019 American Community Survey 5-year census tract estimates to link each rental advertisement with its respective neighborhood characteristics. Census tract housing measures paired to each advertisement includes median tract rent, proportion of housing units occupied by renters, share of single-family housing units, share of housing in buildings with 20 or more individual units, and share of residents who live in the same unit as the prior year. Racial/ethnic composition is measured through a categorical variable regarding if the majority residential group within a unit's census tract is Predominantly White, Black, Latino, Asian/Pacific Islander, or Multiethnic for tracts with no majority group. Tract socioeconomic status is measured by a high poverty indicator variable for poverty prevalence at 20% of the tract population.[5] To measure the impact of surrounding neighborhood characteristics on landlord's move-in fee specification behavior, I additionally created spatially lagged variables measuring adjacent tract racial/ethnic group composition and high poverty levels. Adjacency to high poverty is coded as a 1 if any tracts that an advertisement's census tract shares a tract border with is a high-poverty neighborhood. Adjacent racial and ethnic composition is represented as the proportion of tracts with shared borders categorized under one of the five categorical groups.

I then created an annotated data set from 800 records of the collected Craigslist rental advertisements identified within my following methodology as specifying a move-in fee requirement to develop a supervised classifier model from to answer my third research question. I individually reviewed and labeled randomly sampled records from the move-in fee advertisement subsample for whether the fee is presented as a market deal, such as at a reduced price, a limited-time special offer, or a waived fee requirement. I operationalize a "deal" based on the advertisement's presentation of the specified deposit amount as equivalent to a discount or

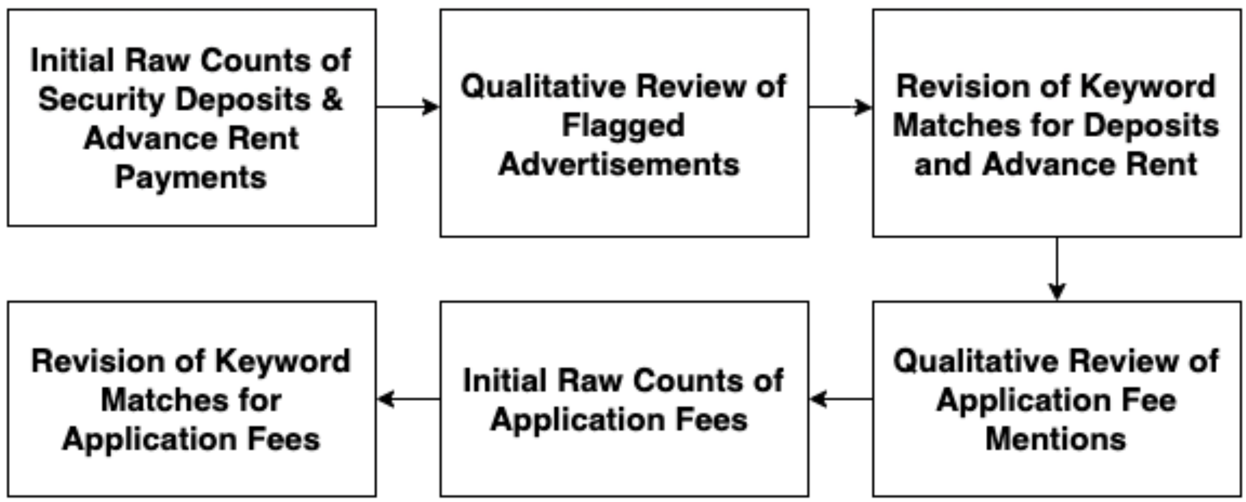
[5] An alternative specification of census tract being classified as high-poverty based on a 30% tract poverty level was additionally tested with no found difference in the following substantive conclusions.

desirable offering, and not exclusively based on the offered amount being lower than the rent alone in the case of security deposits or advanced rent payments. I sampled records until obtaining 400 examples of move-in fee deals and 400 cases of specified fees without a publicized deal. 100 of these records (50 deals and 50 non-deals) were equivalently labeled by one of my co-authors from the original collaborative research project this chapter builds from. The Krippendorff's alpha inter-annotator score between the two sets of annotations was 0.87 from the metric's -1 to 1 scale, indicating a high level of agreement between my own and my colleague's identification of move-in fee deals. This annotated data set was therefore used as an original training, validation, and testing data set for my supervised text classification methodology to identify move-in fee market deals within all of the Craigslist rental advertisements flagged as specifying a move-in fee requirement.

Methods

To answer my first research questions regarding landlords' specification rates of move-in fees, I established a text analysis workflow to robust identify when said fees are included within a Craigslist rental advertisement. I employed an iterative computational grounded theory approach that combines string matching with close reading of advertisements initially flagged as delineating move-in fees to identify points of revision within the text matching workflow (Nelson 2020). This procedure incorporates qualitative review to properly respond to unexpected language use patterns identified within the advertisements and revise the move-in fee matching parameters to best fit the data. Said approach emphasizes the importance of learning and incorporating the unique language trends and varying contexts for move-in fee mentions within

Figure 3.1 Text matching workflow for identifying move-in fee mentions within Craigslist rental advertisements.



the text matching procedure by combining the respective strengths of both computational and qualitative insights (Grimmer et al. 2022).

Figure 3.1 illustrates the text analysis workflow used to identify different move-in fee requirements within the Craigslist advertisements via the stringr text manipulation package within the R programming language. I first performed standard text preprocessing by removing non-alphanumeric characters within the advertisement text and then created the first versions of indicator variables for records that included "deposits", "first month", or "last month" within their text. I qualitatively reviewed these initially matched records and discovered two unexpected trends within the advertisements. First was the prevalence of pet deposit requirements for prospective applicants with pets, which produced false positives regarding matching with security deposit mentions. Second was the variety of written formats expressing the same fee requirements, such as "1st month" contrasted to "first mo." for first month's rent payments. I therefore revised my text matching script to account for these emergent findings such as by removing all "pet deposit" mentions within the advertisements and by using regular expressions to account for language variations for the same fee type specification category.

I then followed a similar iterative match and review approach for "application", "screening", "processing", "verification", and "credit check" fee mentions. My qualitative review of the advertisements indicated two additional points of revision. I removed "broker fee" from the match parameters as this fee is almost exclusively affiliated with the New York-New Jersey-Newark metropolitan region and therefore is not representative of national move-in fee specification trends. I also exclusively flagged advertisements that explicitly indicate a "fee" or "charge" in contrast to a generic "application" being required, as there is missing information within these advertisements whether said application is associated with a charge.

After distinguishing records that delineate move-in fees, I proceeded to annotate the 800-record advertisement sample regarding whether the move-in fee is presented in context of a market deal to develop a supervised machine learning classifier from. This facilitated my qualitative review of the advertisements that lead me to identify emergent trends regarding how move-in fee deals were commonly presented as relevant to my second research question. After creating the annotated move-in fee data set, I reviewed the 400 records labeled as specifying a move-in fee and coded the advertisements for notable trends regarding how fee special offers were presented. The following presented results highlight the most recurring patterns within this sample regarding how landlords framed move-in fee market deals within their advertisements.

After creating these indicator variables for advertisements that specify each move-in fee type, I then proceeded to model the likelihood of either a security deposit, application fee, or advanced rent payment being mentioned within an advertisement as associated with both neighborhood and rental unit characteristics. I employed logistic regression models with fixed effect terms for metropolitan regions based on core-based statistical area (CBSA), month, and week of posting to account for between-group variation across these variable clusters. All models are controlled for the variables sourced from both the web scraped advertisements along with the matched ACS measures as delineated within the previous Data section. I additionally used clustered standard errors by region to account for error dependence for listings posted the same metropolitan area. Reported coefficients are adjusted for multiple comparisons via the Holm Bonferroni correction and are reported as odds ratios for simplified interpretation compared to log odds terms (Holm 1979).

Following the text matching and logistic regression modeling to address my first three research questions, I then moved towards developing a supervised machine learning model to classify whether a mention of a move-in fee within a listing was presented as a market deal. I experimented with three different model architectures. I first fitted a supervised logistic regression model with L2 regularization and term frequency-inverse document frequency (TF-IDF) text vectorization as a baseline measure of move-in fee deal classification performance. I then proceeded to fit both a gradient boosted decision tree (GBDT) model with TF-IDF text vectors via the Scikit-learn library as well as a fine-tuned DistilRoBERTa transformer language model through the Hugging Face library both within Python. The GBDT model attempts to differentiate move-in fees presented as a market deal from general mentions by creating an ensemble of classification trees where tree node splits are based upon keywords that best distinguish the two classes (Friedman 2001). The use of a gradient descent optimization algorithm within GBDT guides each sequentially fitted tree within the ensemble model to improve on the misclassified records of previous trees. The fine-tuned DistiRoBERTa model uses pre-trained language embeddings that account for contextualized word meanings across the full advertisements through the mechanism of attention as delineated within Chapter 2 of the dissertation (Vaswani et al. 2017; Sanh et al. 2019; Liu et al. 2019).

I conducted hyperparameter searches for both the GBDT and DistilRoBERTa models based on F1 score performance. For the GBDT model, I optimized the number of fitted trees within the model, the learning rate regarding how much each tree contributes to the final advertisement record classification decision, and the maximum node depth of each tree. Hyperparameters tuned for the DistilRoBERTa model include the number of epochs designating the number of times the model is fitted on the complete annotated set of advertisements, the batch size of the number of advertisement records passed into the model at a time, and the learning rate. I trained each model on 70% of the annotated advertisements and used 10% of the annotated data as the validation set for hyperparameter optimization. I then generated final performance metrics from the best-performing GBDT and DisilRoBERTa models on a 20% testing data set from the annotated records.

Following my identification of the highest performing model based on F1-score performance, I then employed the developed supervised classifier to generate predictions on the 295,396 advertisements flagged as specifying a move-in fee regarding whether said mention is presented in the context of a market deal. I removed advertisements used within the annotated supervised classification model development data set to prevent data leakage within the generated predictions (Kaufman et al. 2012). I then fitted logistic regression models with the market deal predictions as the dependent variable and the same suite of unit and neighborhood-level covariates and fixed effect terms featured within the initial regression models. I consider both the baseline association of the covariates towards whether a deal is specified as well as when controlling for which type of fees among security deposits, application fees, and/or advanced rent payments are delineated through subsequent model comparisons. These results are reported via odds ratios following Holm-Bonferroni corrections as well.

Results

The following findings address my four proposed research questions by first considering the results of the text matching workflow towards identifying move-in fee specification rates as well as qualitative insights gained from reviewing the sample of advertisements delineating move-in fee market deals. I then investigate both the likelihood of advertisements mentioning different types of move-in fees as well as move-in fee market deals identified via supervised classification as affiliated with neighborhood characteristics via logistic regression models.

Text Matching & Qualitative Review

The previously delineated workflow for detecting move-in fees within Craigslist advertisements identified that move-in fees are mentioned within the advertisements at a sizably lower frequency then their estimated prevalence throughout metropolitan housing markets. Table 3.1 details the proportion of advertisements that specify each fee type along with examples of how said mentions are commonly represented throughout the advertisements. The specification rate of 21% of advertisements for security deposits is markedly lower than the estimated prevalence within approximately 88% of national U.S. rental market transactions (Garcia and Berchick, 2021). The single-digit proportions of advertisements mentioning application fees and advanced rent payments imply a lower specification rate for these move-in fees compared to their actual prevalence within urban rental markets as well, although said conclusions are impeded by missing data since the national occurrence rate of these fees have not been

Table 3.1 Move-in Fee Prevalence and Text Representation Examples

Move-in Fee	Proportion	Text Examples
Security Deposits	21%	- "Security deposit requested upon signing." - "$100 off deposit this week only!"
Application Fee	6%	- "Pay application fee online (non-refundable)." - "Verification fee charged with credit check."
Advanced Rent Payments	3%	- "1st & last month rent required to secure unit." - "First mo rent + deposit will be paid via check."

previously measured in contrast to security deposits. Given the discovered low mention rates of move-in fees overall, these results imply that landlords are intentionally deciding to specify said fees when they choose to include these requirements in their advertisements in contrast to a baseline propensity to not mention said fees whatsoever.

After successfully highlighting all records that specify move-in fees and creating the annotated move-in fee data set to use for supervised classification, I returned to the 400 records I labeled as promoting a market deal when mentioning a move-in fee and coded these advertisements regarding how said fee deals were presented within landlords' written advertisements. I discovered three recurring themes throughout this subset of rental advertisements relevant to understanding move-in fee market deal dynamics as expressed within Craigslist rental markets.

First, move-in fee deals often came from advertisements that appeared to be affiliated with commercial landlords and property management companies rather than individual landlords. I identified these advertisements through their common delineation of the company name and/or website link used for applications, although many advertisements remained ambiguous regarding whether they were created by commercial firms or smaller-scale individual landlords. Renter management firms own a growing portion of the national rental market within the United States and have been found to commonly require move-in fees from renters (Hochstenbach, Wind, and Arundel 2021; Fields 2022). In contrast, the 400 records I reviewed featuring general mentions of move-in fees without a stated market deal often did not specify a property management company. While I am limited in my ability to directly verify whether commercial firms or individual landlords created these advertisements based on the advertisement text alone, the difference in property management firm references implies that move-in fee market deals are particularly popular among commercial landlords posting on Craigslist.

Second, move-in fee deals were often framed as time-limited and contingent on quickly signing a rental lease. This created a sense of urgency around the special move-in fee offer, such as the following example from an advertisement within the Phoenix, Arizona metropolitan region of: "limited special $100 off the administrative fee if you apply within 48 hours of touring [the unit]." Said conditions likely promotes hasty decisions to sign a lease and may be used as a tactic to limit applicants' availability to identify unfavorable features of advertised units or to attempt to negotiate leasing terms.

Third, move-in fee deals were more likely to co-occur with statements regarding openness towards prospective applicants that were often explicitly told not to apply to a rental within advertisements that did not specify a move-in fee, such as Section 8 Housing Choice Voucher recipients, applicants with eviction histories, and/or renters with poor credit scores. Landlords within this move-in fee deal advertisement sample appear to target renter subgroups that are otherwise often discriminated against within the rental market as an ideal demographic with these listings, using move-in fee deals paired with time limits to incentivize quick lease signing. These three trends within the move-in fee deal sample overall indicate intentionality behind landlords' use of special offers with move-in fees to shape the behavior of prospective tenants, particularly by commercial landlords advertising on Craigslist.

Move-In Fee Logistic Regression Models

Following the text matching identification of move-in fee mentions within the Craigslist rental advertisements, I then employ logistic regression models to investigate how racial, ethnic, and socioeconomic neighborhood characteristics at both the immediate and adjacent tract level impact the likelihood of a move-in fee being specified within a listing. Table 3.2 illustrates the model results for mentions of security deposits, application fees, and advanced rent payments for first and/or last month's rent respectively.

The first aggregate trend indicated by the models featured in Table 3.2 is the influence of unit-level characteristics such as the monthly rent price and square footage as well as tract attributes relevant to the rental market such as the median tract rent and share of housing units occupied as rentals across all three models. Higher asked rents for both individual units as well as across the census tract and as a greater proportion of renters within a tract are associated with reduced move-in fee specification rates, while more square footage within a listing is affiliated with a lower odds of mentioned move-in fees. While these covariates serve primarily as control terms to focus instead on neighborhood residential characteristics as relevant to my third research question, their consistent significance throughout the models indicate the importance of unit-level and neighborhood rental market attributes towards conditioning these models' key

Table 3.2 Logistic Regression Models of Move-in Fee Mentions Within Craigslist Ads

	Security Deposits	**Application Fee**	**Advanced Rent Payments**
Rent Asked (100s)	0.971 (0.005) ***	0.977 (0.005) ***	0.966 (0.007) ***
Square Footage (100s)	1.042 (0.006) ***	1.036 (0.008) ***	1.056 (0.008) ***
Median Gross Rent (100s)	0.972 (0.006) ***	0.954 (0.010) ***	0.965 (0.009) *
Share Renter Occupied	0.996 (0.001) *	0.995 (0.001) **	0.992 (0.002) *
Multiethnic	0.924 (0.057)	0.961 (0.091)	0.874 (0.085)
Predom Black	0.883 (0.151)	0.944 (0.159)	0.974 (0.217)
Predom Latino	0.879 (0.120)	0.882 (0.120)	0.976 (0.161)
Predom Asian/PI	1.203 (0.242)	1.260 (0.429)	0.770 (0.238)
Adjacent to Predom Black	1.343 (0.303)	1.612 (0.383)	1.687 (0.529)
Adjacent to Predom Latino	0.900 (0.137)	0.891 (0.157)	0.724 (0.162)
Adjacent to Predom Asian/PI	0.764 (0.252)	0.541 (0.392)	1.059 (0.388)
Adjacent to Multiethnic	0.884 (0.102)	0.820 (0.111)	0.822 (0.165)
Adjacent to High Poverty	1.144 (0.056) *	1.180 (0.061) *	1.220 (0.088) *
High Poverty	1.082 (0.080)	1.318 (0.116) *	1.391 (0.124) **
Log Likelihood	-618,32	-268,605	-163,114
Num. obs.	1,285,094	1,285,094	1,285,094

Note: Standard errors clustered by metropolitan area *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$

results as regarding racial, ethnic, and socioeconomic characteristics at both the immediate and proximate tract level.

All three logistic regression models demonstrate that the presence of either immediate or proximate tract-level poverty is associated with a higher odds of each type of move-in fee mention. Security deposits are more likely to be specified when an adjacent tract has high poverty levels, while application fees and advanced rent payments are requested more often for tracts experiencing either immediate or proximate poverty. These results suggest that landlords advertising on Craigslist are particularly influenced by the socioeconomic position of a unit's own and bordering neighborhood when deciding to specify move-in fee requirements. This is aligned with my initial predictions regarding the impact of socioeconomic status towards landlords' tendency to specify move-in fees, lending evidence to the use of said fees to shape the rental search outcomes of lower-income households proximate to a unit. The stable association of adjacent poverty levels towards a higher move-in fee mention rate for all three types of fees emphasizes the importance of broader market characteristics beyond the immediate census tract an advertisement is located within towards landlord's delineation of move-in fees.

The primary takeaway presented by the model results featured within Table 3.2 is that there is no association between landlords delineating a move-in fee requirement and the racial and ethnic residential composition of both the immediate and adjacent tracts across the three models. This finding contradicts my initial prediction of landlords being more likely to request move-in fees when advertising units located in or proximate to neighborhoods with a Black or Latino residential majority. These results run counter to my original expectations regarding the influence of racial and ethnic residential composition on landlords' specification rates of move-in fees. However, said findings cannot be interpreted separately from the concurrent influence of high poverty on each type of move-in fee having a higher odds of being mentioned given the close relationship of race and socioeconomic status within U.S. metropolitan regions (Quillian 2012; Hwang and Sampson 2022). While a unit being located within or proximate to a predominantly Black or Latino neighborhood may not be associated with a greater likelihood of a move-in fee being specified, the fact that majority Black and Latino metropolitan neighborhoods often simultaneously experience higher poverty levels within U.S. metropolitan regions implies that the results regarding neighborhood socioeconomic status may indirectly have disproportionate impacts on Black and Latino tenants as well. The identified influence of neighborhood poverty levels on move-in fee mention rates therefore simultaneously implicates that Black and Latino renters may encounter said specified fees more often within their online housing searches, even if the racial composition of the unit's own and nearby neighborhoods is not the primary factor influencing landlords' observed move-in fee mention rates.

Given these unexpected findings regarding racial and ethnic neighborhood composition on move-in fee delineation rates within these initial regression models, I additionally tested alternative model specifications to further explore these results' internal validity. These include removing the immediate and proximate poverty variables from the models to explore racial and ethnic composition's exclusive effects without concerns regarding variable multicollinearity, as well as different operationalizations of race and ethnic neighborhood composition such as the percentage of Black residents or alternatively the percentage of White occupants while controlling for poverty level. When specifying the models with either a categorical delineation or percentage Black or White residents without controlling for poverty, advanced rent payments are the only move-in fee that demonstrates a moderate effect ($p<0.05$) with being more likely to be specified for listings proximate to predominantly Black neighborhoods. This expands to application fees along with advanced rent payments as regarding proximity to predominantly Black neighborhoods when the immediate percentage of White residents is the racial/ethnic specification for the model, while the immediate percentage of Black residents reports no significance across the move-in fee types. Immediate and proximate poverty remained significant for all three move-in fee types across these models as well.

My interpretation of the results is that while they provide important insights regarding the findings' robustness towards alternative model specifications, the overall conclusions regarding the heightened importance of poverty over racial/ethnic composition towards landlord's specification of move-in fees within Craigslist rental advertisements remains the same. The close relationship between neighborhood racial and ethnic composition and poverty levels within American urban neighborhoods is a critical sociohistorical context that implies that marginalized racial and ethnic groups are more likely to encounter move-in fees within Craigslist rental advertisements given the regression models' indication towards the significance of poverty levels. However, my examination of alternative model structures reinforces that immediate and proximate poverty levels are the factors with the most robust relationship with higher move-in fee specification rates overall within the Craigslist advertisements data.

Classifying & Modeling Move-In Fee Deals

After fitting the logistic regression models measuring how neighborhood characteristics are associated with the specification rates of different types of move-in fees, I then build from these results to consider how the same racial, ethnic, and socioeconomic attributes are affiliated with the presentation of move-in fees as market deals contrasted to general fee requests within Craigslist rental advertisements. I employ supervised machine learning classification to identify when fees are broadcasted at a discount, as a special offer, or other representation of market deals among the 295,396 written advertisements identified through my text matching workflow as delineating a move-in fee requirement. I compared the performance of three different

Table 3.3 F1, precision, recall, and accuracy scores by supervised classifier

Policy Frame	Logistic Regression	Gradient Boosted Decision Tree	DistilRoBERTa
F1	0.737	0.721	0.847
Precision	0.777	0.791	0.827
Recall	0.700	0.663	0.869
Accuracy	0.750	0.744	0.845

supervised classification model architectures- a baseline regularized logistic regression classifier, a hyperparameter-tuned gradient boosted decision tree (GBDT), and an equivalently tuned DistilRoBERTa transformer model- on training, validation, and testing divisions of the annotated move-in fee advertisements data set.

Table 3.3 delineates the model performance results of the three supervised classification architectures, while the identified best-performing hyperparameters for the GBDT and DistilRoBERTa models are specified within Appendix 3.A. The DistilRoBERTa model fine-tuned to predict move-in fee market deals was identified as the best performing model across all four tested metrics among the three architectures. The GBDT model's poorer performance in comparison to the baseline logistic regression classifier on metrics including the F1 score and overall prediction accuracy implies that the GBDT's more complex tree-based gradient descent optimization framework does not substantively improve the text classification task of identifying move-in fee market deals. The GBDT's distinctively low recall score indicates that this model is recurringly missing moving-in fee deals within the text which produces a high false negative rate. This implies that the GBDT model is likely overfitting to the training data with subsequent reduced performance on the test data set. DistilRoBERTa's sizable improvements on the F1 score and accuracy metrics indicates that the transformer architecture's pre-trained ability to consider words within differing contexts as featured within the Craigslist advertisement text is key to improving the classifier's performance. I therefore used the fine-tuned DistilRoBERTa model as my final supervised classifier architecture of choice to generate market deal predictions on all identified move-in fee specifying Craigslist advertisements.

With the complete data subset of advertisements requesting a move-in fee payment successfully classified by the DistilRoBERTa model, I then proceeded to fit logistic regression models on the generated predictions towards move-in fee market deals as the outcome variable. 43% of the advertisements specifying a move-in fee were classified as presenting said fee in context of a market deal based on the DistilRoBERTa model predictions. Table 3.4 delineates the logistic regression results with a move-in fee market deal specification as the outcome variable when considering both exclusively unit and neighborhood level covariates and while additionally controlling for the type of requested move-in fee(s) within the listing.

These results overall corroborate the findings from the previous logistic regression models that considered the specification rates of different types of move in-fees while adding additional insights regarding how move-in fee market deals contribute to the core conclusions. Poverty levels are found to influence move-in fee market deal delineation while racial and ethnic neighborhood composition within both the immediate and proximate census tracts do not report an equivalent influence, which is closely aligned with the previous model findings. The model results within Table 3.4 demonstrate that is it exclusively adjacent poverty levels that decrease landlords' log odds of offering a move-in fee market deal rather than immediate tract-level poverty. Alternative model specifications with no poverty covariates report that proximity to predominantly Black neighborhoods is associated with a higher likelihood of a presented market

Table 3.4 Logistic regression models of move-in fee market deals within Craigslist advertisements.

	Baseline Model	Fee Type Model
Rent Asked (100s)	0.985 (0.004)**	0.987 (0.005) †
Square Footage (100s)	0.970 (0.005) ***	0.968 (0.005) ***
Median Gross Rent (100s)	1.024 (0.009) †	1.023 (0.009) †
Share Renter Occupied	1.000 (0.001)	1.000 (0.001)
Multiethnic	1.112 (0.084)	1.130 (0.081)
Predom Black	1.369 (0.214)	1.316 (0.190)
Predom Latino	1.104 (0.177)	1.113 (0.176)
Predom Asian/PI	1.143 (0.202)	1.159 (0.210)
Adjacent to Predom Black	0.884 (0.180)	0.897 (0.168)
Adjacent to Predom Latino	1.097 (0.215)	1.123 (0.217)
Adjacent to Predom Asian/PI	1.042 (0.215)	1.055 (0.216)
Adjacent to Multiethnic	1.148 (0.140)	1.174 (0.140)
Adjacent to High Poverty	0.894 (0.041) *	0.876 (0.039) *
High Poverty	1.110 (0.071)	1.086 (0.064)
Security Deposit	-	0.336 (0.034) ***
Application Fee	-	0.898 (0.055)
Advance Rent	-	1.486 (0.124) ***
Log Likelihood	-196,035	-191,400
Num. obs.	295,396	295,396

† $p < 0.10$ * $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$

deal, while operationalizing racial neighborhood composition by percentage of White residents is affiliated with a lower odds ratio of a specified move-in fee with more White neighborhood occupants.

Said findings combined with the previous logistic regression model results suggest that landlords are more likely to specify a move-in fee requirement when advertising a unit proximate to lower-income neighborhoods, but that said move-in fees are less likely to be promoted with a market deal or discount. This implies that move-in fees may be used by landlords to vet lower-income applicants from proximate neighborhoods, while units within surrounding neighborhoods that are affiliated with wealthier residents are more likely to be advertised to via a move-in fee market deal. However, the alternative model specifications suggest that proximity to Black residents leads to a greater market deal mention rate while neighborhoods with more White occupants have a lesser likelihood of encountering a market deal. This implies that landlord's use of move-in fee market deals within Craigslist advertisements is influenced in more distinct directions by race and ethnic composition and poverty levels as separate sociodemographic factors than as regarding move-in fee mention rates overall as demonstrated within the initial model results. The significance of adjacent poverty level remains when the type of specified move-in fee is controlled for as well, with security deposits found to be associated with a significantly lower odd ratio while advanced rent payments are linked to a higher odd ratio of being mentioned with an associated move-in fee market deal.

I interpret these quantitative results in reference to the emergent qualitative themes I identified through reviewing the written language of advertisements broadcasting move-in fee market deals to identify two separate trends around when market deals are specified within Craigslist advertisements that align with the triangulated findings. Two of my core findings from my qualitative review of these listings is regarding the presence of commercial rental companies towards delineating market deals and the use of time limits to encourage quick leasing decisions. I theorize that market deals are commonly applied to two distinct types of rentals within Craigslist, the first being expensive rental units such as those constructed in the growing submarket of luxury rental developments and the second being affordable rental options often built simultaneously with higher-priced units for commercial rental firms to capitalize on funding opportunities such as the Low-Income Housing Tax Credit (LIHTC) (McClure 2019).

Both types of rentals may be advertised with move-in fee market deals by landlords towards an end outcome that produces the observed finding in the logistic regression models regarding higher adjacent poverty levels leading to less deals being specified. For luxury rentals, said units are targeted to the market subgroup of higher-income renters to begin with. For affordable housing options, higher adjacent poverty rates implies a larger prospective applicant pool that may lead to a lesser need to employ a move-in fee market deal to incentivize interest towards a given unit. Additionally, proximity to predominantly Black neighborhoods leading to higher market deal specification rates may be potentially connected to contemporary mixed-income development initiatives with policy aims to address residential segregation between residents from predominantly Black or White neighborhoods (Chaskin and Joseph 2015). My interpretation of the combined results across the qualitative advertisement review and the logistic regression model results therefore proposes multiple market circumstances that may promote Craigslist landlords to offer deals on move-in fees as a finding from my analyses well-suited for further exploration beyond these initial results.

Discussion

As more renters within U.S. metropolitan regions conduct their housing searches via online platforms such as Craigslist, this work highlights how move-in fees serve as a mechanism for landlords to shape residential sorting outcomes for renters across income levels. My findings indicate that move-in fees are mentioned within Craigslist rental advertisements at a lower rate than their estimated prevalence within rental markets, with the most influential factor towards a landlord specifying a move-in fee being immediate and/or proximate neighborhood poverty levels. Additionally, move-in fee market deals that broadcast reduced or waived prices through time-limited offers primarily spearheaded by commercial landlords are found to be less likely for units near higher poverty levels. These results imply that move-in fees may be used by landlords to steer the housing market behaviors of lower and higher-income renters in contrasting ways- one of unit exclusion due to high up-front costs for lower-income renters outside of specific market deal offerings, and one of presented discounts for higher-income tenants that otherwise do not experience move-in fees as significant financial barriers shaping their prospective rental choice sets.

This study's findings illustrate how landlords can employ move-in fees to shape rental market options particularly for low-income renters that already face challenges around obtaining affordable housing in costly and unit-limited urban rental markets. It therefore lends support to policy initiatives that aim to either restrict landlords' use of move-in fees or alternatively support low-income renters towards affording encountered fees within their rental searches. The first category of policies have begun to be adopted by select states and metropolitan regions in recognition of the sizable influence move-in fees can have towards rental market outcomes, particularly as regarding limits on requestable security deposits (Stewart 2022). This work highlights that security deposits are just one among multiple types of move-in fees required by landlords within rental transactions. The up-front cost of a security deposit along with an application charge, credit score verification, and a potential advance rent payment can add to a cumulative lump sum payment considerably higher than a security deposit alone. This work therefore simultaneously supports policies that restrict the askable amount of move-in fees for regions that have not adopted any legislation relevant to this financial burden, as well as broaden the scope of previously implemented policies to address the wide variety of move-in fees found within rental advertisements. However, said policies are of limited use if they are not actively enforced via timely repercussions for violations. Said policy administration can begin at the initial stages of rental market transactions by screening advertisements posted on online rental marketplaces such as Craigslist that exceed regional move-in fee limit amounts with imposed legal and financial repercussions for repeated infractions.

The second policy direction this study's results supports is regarding public assistance provided to renters to afford move-in fee payments. This policy approach acknowledges that while landlords reserve the right to require move-in fee payments, the up-front costs of even a comparatively low-priced collection of fees will effectively remove a prospective rental from low-income renters' housing choice sets. This is an emergent policy direction featured within recent guidance published by the U.S. Department of Housing and Urban Development that encourages public housing authorities to use discretionary funds to assist Section 8 voucher recipients with move-in fee payments that are not otherwise accounted for in standard voucher program implementation (HUD PIH 2022). However, Section 8 voucher holders represent a small portion of low-income renters within the U.S. overall (Rosen 2020). Financial assistance towards affording move-in fees would therefore be best served by implementation at multiple levels of governance and public programs beyond federal HUD initiatives alone for maximum impact towards securing rentals for low-income households.

These large-scale policy agendas have been gaining momentum across federal, state, and local governments, but they are recent initiatives without broad implementation. An intermediate action that this study’s results lend support towards can instead occur directly from Craigslist’s own policies, namely requiring that all move-in fees affiliated with a given rental unit be clearly stated within posted rental advertisements. One of this work's findings is regarding the sizably lower mention rates of move-in fees compared to their estimated overall prevalence within rental markets, indicating that the chosen specification of fees may itself serve as a means for landlords to shape rental market searches. Implementing a requirement to explicitly list requested fees would address how the practice of selective information provision is one means that housing agents continue to influence rental market outcomes. While said change in listing requirements within Craigslist would not remove challenges around move-in fee affordability, it would at a minimum mitigate how fees can vet applicants based on whether these common requirements are even explicitly stated.

A limitation of this study is that its featured data is restricted to a two-month collection window of Craigslist advertisements posted during 2019. It is therefore comprehensive in its collection of two months' worth of posted listings across the 100 largest U.S. metropolitan areas, but it is limited in its temporal scope. This is in part caused by the high computational and data storage resources required to coordinate a more extended Craigslist web scraping procedure. The findings featured in this work are therefore contingent on the short time window of collected data, and future work expanding from this study would attempt to replicate its findings with a longer time frame of gathered advertisements. This would verify that the results are not conditional to a seasonal trend for the July and August 2019 months' worth of data. A longer data collection period would additionally empower future research employing causal analyses to investigate how newly adopted regional policies regulating move-in fees impact landlord's specification rates between pre-and-post regulation implementation.

Another limitation of this work is that it spotlights only advertisements sourced from Craigslist which is one online rental marketplace among multiple others including

Apartments.com, StreetEasy, and regional Facebook housing forms. These alternative platforms may feature entirely different dynamics around landlord's use of move-in fees than what was highlighted within this study regarding Craigslist advertisements. While future work would therefore expand from this study to investigate move-in fee specification trends within other online rental marketplaces, this also presents challenges regarding building and maintaining web scrapers to collect advertisements from a wider range of websites. Said initiative would therefore likely be combined with a broader data aggregation computational project linked to the previous limitation regarding this work's short time window that orchestrates multiple simultaneous advertisement compilations from each site over time.

Craigslist rental markets offer unprecedent access to housing opportunities for tenants across U.S. metropolitan regions while also simultaneously facilitating new means for housing agents such as landlords to shape residential sorting outcomes starting from the written advertisement of available rental units. This work emphasizes how the underexplored subject of move-in fees is a residential sorting mechanism landlords can draw from to influence prospective tenant behavior, as regarding when fees are or are not specified within rental advertisements as well as the use of fees in context of market deals. The recent interest in housing policies designed to either regulate the amount of askable fees or alternatively assist tenants with affording these fees enforces the timeliness of research around this specific component of rental transactions, particularly as relevant to online marketplaces where more tenants are increasingly searching for and obtaining rental housing from.

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Appendix

Appendix 3.A Final optimized hyperparameters for GBDT and DistilRoBERTa supervised classifiers

Supervised Classifier	**Hyperparameters**
Gradient Boosted Decision Tree (GBDT)	- Learning Rate: 1e-2 - Number of Trees: 600 - Max Node Depth: 5
DistilRoBERTa	- Learning Rate: 2.5e-4 - Batch Size: 8 - Number of Epochs: 5

CONCLUSION

The relationship between offline housing dynamics and online communities within American cities grows progressively stronger as housing is increasingly discussed and transacted on digital platforms as highlighted throughout this dissertation. Housing is already a commodity characterized by eminent challenges around affordability, availability, and effective policy design. Online platforms are now closely linked to urban markets, culture, and governance, and their potential influence is much broader than user interactions isolated to the platforms themselves. This dissertation illustrates the contemporary intersection of urban housing processes and digital platforms via three examples each featuring different online platforms, different policy topics, and different methodological approaches by combining machine learning based NLP methods along with qualitative reviews of platform user's written contributions. While each chapter considered policy recommendations and opportunities for future research following their respective findings, the dissertation in its entirety offers additional insights regarding its aggregate implications relevant to contemporary American urban housing.

First, the dissertation's highlighting of the growing intersection between physical housing outcomes and digital user interactions within online platforms emphasizes how contemporary housing topics are now best engaged with in reference to these online communities. Housing topics featured within this dissertation such as gentrification, rent control, or rental market sorting outcomes can no longer be clearly separated from Airbnb, Reddit, or Craigslist as relevant to policy deliberation and implementation. These platforms now intersect with physical housing dynamics whether directly through user behavior within each online community or indirectly though discussions hosted by the platforms.

The platforms themselves differ to the degree in which they either actively shape urban housing in novel ways- such as Airbnb's transition of previously long-term housing to short term rentals- or rather serve as new spaces where housing dynamics defined previously by in-person interactions are now replicated online, such as housing policy debates within Reddit or rental searches through Craigslist. Both types of platform dynamics are relevant to contemporary housing policy even with their different levels of direct impact towards modern city housing. For platforms such as Airbnb that explicitly alter housing availability by converting long-term rentals to short-term listings, there is an ongoing need to advance strong policy agendas across urban regions to govern the relationship between these platform and local housing markets. For platforms that host interactions regarding housing that previously occurred through alternative channels such as physical print media or in-person communication, these platforms now provide opportunities to better understand and address longstanding challenges within contemporary housing through their greater visibility within publicly available digital data. Whether for framed housing policy discussions as featured in Chapter 2 or rental unit searches highlighted in Chapter 3, topics of established interest to housing stakeholders are now occurring within digital mediums that provide more streamlined access to measure and interpret these processes to inform public policy.

This dissertation emphasizes how technology literacy among policy stakeholders is growingly essential to effectively reason through housing topics that are now connected to online platforms. While stakeholders do not need to be active users and experts of the platforms themselves, this work reinforces how at least some degree of familiarity is necessary to accurately identify how said platforms either shape or reflect urban housing. This dissertation therefore supports initiatives through training and cross-institutional collaborations to advance the digital literacy and technological engagement of city governments, urban planning and social service agencies, and the variety of other historically non-technologically focused stakeholders involved with urban housing in their daily work (Pittaway and Montazemi 2020; Velle-Cruz et al. 2020).

Second, this dissertation demonstrates the potential impacts that stem from leveraging data science methods for civic initiatives through the ability to gain insights from digital data sets to benefit regional communities and inform policy outcomes. A sizable portion of user interactions within online platforms is preserved as written text data as highlighted within the three chapters. This is a data type that offers both the unique opportunity to understand city resident's perspectives on housing policy topics, as well as the challenge of effectively processing and modeling this more complex form of data in contrast to more structured formats such as survey responses (Grimmer et al. 2022). Data science techniques such as natural language processing methods have great potential to deliver insights from text data relevant to urban policy stakeholders. However, said methods have had limited adoption within civic technological spaces given their computational and methodological complexity.

This dissertation offers three examples that demonstrates how NLP can be used effectively within policy-orientated research. By combining NLP machine learning modeling with qualitatively reviewing key themes within the text itself, each article aims to delineate how said approaches can be adopted for aligned research initiatives by civic organizations. This is intended towards the goal of moving applied data science away from predominantly high-tech corporate use and instead towards wider adoption within government and nonprofit sectors. While current research on data science methods within the public sector has focused on concerns regarding algorithmic bias within implemented machine learning models, said approaches are at their core methodological tools that can also be used in initiatives that deliver impacts explicitly grounded in social beneficence and public service (Eubanks 2017; Engin and Treleaven 2019). This work directly aligns itself with this paradigm as relevant to the growing implementation of data science within public institutions as an opportunity to better understand, measure, and address complex social challenges relevant to modern urban governance.

Third, this dissertation's findings supports ongoing policy initiatives that aim to hold the companies that create and manage online platforms accountable for their product's implications on both housing in particular and towards a broader liability for platforms' social impacts overall. This has been an ongoing challenge throughout international cities given the exponential growth of many platforms, difficulties associated with individual regional governments attempting to regulate multi-national corporations, and the sheer complexity of attempting to reasonably address how said platforms can exacerbate preexisting social problems within cities (Nieuwland and van Melik 2018; Gorwa 2019; Barns 2020). Companies differ in their openness to collaboration with and overall sense of accountability towards local governments, and enforcing attempted regulations and policies aimed at spatially tied online platforms often encounters active opposition from these powerful firms (Flew 2022). Said circumstances therefore imply that broadly institutionalizing standards of corporate responsibility regarding their platform's influence on urban processes will be at its most effective when actively enforced by multiple levels of federal, state, and municipal governance.

While technologies, online platforms, and specific policy issues have experienced rapid changes as relevant to housing within American cities, the universal need for housing and its associated governance complexities remains constant. This dissertation offers three examples regarding the connections between housing and neighborhood dynamics and online user behavior in diverse but consistently regionally-linked digital platforms. It therefore scratches the surface of the broader empirical need to better understand the novel challenges that have emerged with the linking of these offline and online realities that can be extended through future research considering different housing topics and platforms. Said work is highly relevant to produce timely policy recommendations to better serve the housing needs of diverse residents within American cities throughout our contemporary digital age.

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