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Leveraging Data Analytics To Enhance Affordable Housing Initiatives And Community Development

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As the nation struggles with a rapidly increasing need to address homelessness and other critical affordable housing and related community needs, access to quality data and its appropriate analysis and use to drive initiatives and programs takes on ever increasing importance. This paper discusses the expanding trend toward a greater reliance on data analytics to drive crisis and program responses at the federal, state, and local levels. We explore the data sets currently in use to define special populations, highlight gaps, and recommend desired attributes and enhancements to further improve their contribution to accurate housing demand modeling. We also present and discuss important issues related to the extraction and use of data from other disciplines and areas of public policy and the merits and risks of key econometric modeling approaches that are currently in use.

The implications of adequate modeling and its incorporation into local economies, residents, and asset bases are significant for all levels of government as well as to the banking community and other stakeholders such as philanthropic foundations. Getting this analysis and modeling correct is especially vital now as we confront an explosive surge in housing insecurity amongst many populations throughout the country as a result of COVID-19 and other broader economic and related inflationary pressures and uncertainties. The probability of a chaotic and inaccurate distribution of rescue package funds for housing-related initiatives and programs is particularly high given the high volatility of responses to crisis situations both in terms of demand and the behavioral aspects associated with them. The implications and unintended consequences could be severe if not debilitating for many recipients and the communities in which they are located without the benefit of effective behavioral modeling techniques incorporated into analysis.

Keywords: Affordable Housing, Homelessness, Data Analytics, Housing Demand Modeling, Special Populations, Data Gaps, Econometric Modeling, Crisis Response, COVID-19 Impact, Housing Insecurity, Behavioral Modeling, Public Policy Data, Local Economies, Government Programs, Philanthropic Foundations, Rescue Funds Allocation, Inflation Pressures, Community Needs, Housing Programs, Stakeholder Analysis.

1. Introduction

Historically, the greatest origins of social strife in the United States have come down to two common denominators: we all need a decent house to live in, and a job that pays a living wage. No matter how brilliant the fabric of a society, when parts are neglected, it is but a question of

time before they begin to wear, fray, and rot. Residents of impoverished neighborhoods and communities in the United States have long endured unacceptable conditions of insufficient or overcrowded housing, deteriorating services, and lack of opportunities or access to jobs that pay sufficient wages to support their families. More than 37 million Americans now live in poverty, and many in poverty pay rents that are too high in proportion to their incomes: rents that consume a large portion of their earnings, leaving little for necessities such as food, clothing, and adequate health care. Local, state, and federal agencies are confronted with the challenge of alleviating the occurrence of communities afflicted with poverty, structural deficits, violence, and crime. One approach to reversing this trend has been the investment in affordable housing initiatives through public-private partnerships in which the private housing sector collaborates with the government to provide housing and stimulate demand. However, many of these initiatives have met with little success due to mismanaged resources and poor planning where not all community demographics have duly been considered.

In partnership with the law, local housing authorities and community development agencies have the rights — but not the obligations — to bring local resources of money and labor into the affordable housing equation. With today's economy, there is a heavy reliance on data to make important community-related decisions. Data are used to determine everything from what makes up an economically disadvantaged community to what resources are available to help a community recover from economic hardships to whether or not they are relevant or used. Because of the growing wealth of information available, the Public and Private sectors can become diligent stewards of recent technological advancements and ensure that the needs and desires of all members of a given community are taken into account during the planning stages of any affordable housing project, thereby circumventing future neighborhood disarray, discrepancies in data, and wasting resources.

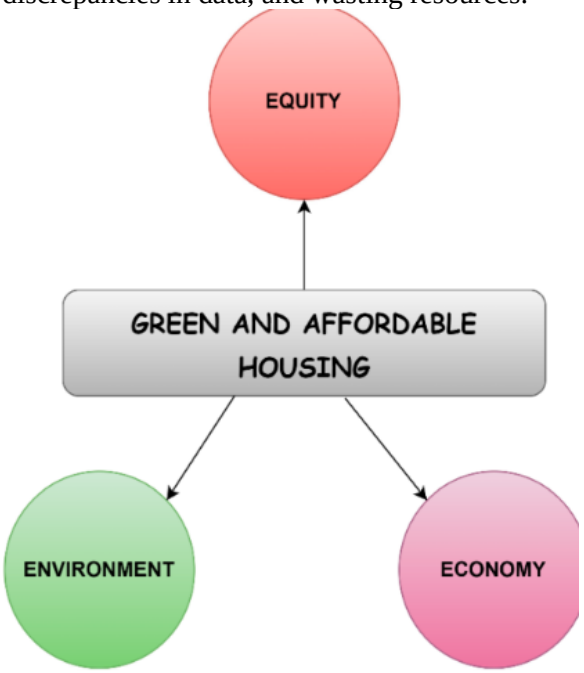

Fig 1 : Financing Options for Green and Affordable Housing

1.1. Overview of the Study

Affordable housing is a dynamic in which there is a substantial imbalance between low wages, the primary basis for determining subsistence income, and housing costs of all types, whether they are rental, new construction, or home purchase. Housing has cost too large a proportion of disposable income for a too large segment of the low income distribution. Housing is better than money because it solves a problem not easily solved by a cash grant. Available data are used to estimate the demand for housing assistance. Features to which commodity and advertising and subsidies are directed include rent, gross housing costs for tenants, net housing costs for the low income, and particular aspects of housing subsidies.

Housing specialists have often pointed out that supply conditions of sellers of housing differ from those of other market products. Such differences can be important in determining how equilibrium prices adjust to perturbations in demand. Even real estate agents have observed that selling a house is not like selling a can of beer. Housing is a pretty lumpy group of commodities; it is not easily transacted on the fly at current market prices. Households generally plan housing consumption for long periods of time and do not revise plans at short intervals to catch predicted changes in the relative price of housing. There are various possible causes of inadequacies in available accommodations. One convenient classification scheme is based on who bears costs associated with inadequacy. Government at probably all levels can cause housing shortages or surpluses, but local governments appear to hold the trump cards. In the view of many housing economists, the United States has only a very modest housing subsidy in the form of income tax exemptions on net imputed rent in excess of mortgage and property tax payments. Almost all industrialized countries provide their citizens with much larger subsidies.

2. Understanding Affordable Housing

It is important that we first ground ourselves on the definition of what affordable housing is to present the key aspects around the subject matter of this theme. One of the most adopted definitions states that housing costs – the mortgage or rent payment plus utilities – should consume no more than 30 percent of a household's gross income and at least 29 million renters have housing costs that exceed 30 percent. That definition serves as a threshold, but other housing-related factors do have important implications in its definition, such as safety or quality.

Since the 1969 Commission on Interstate and Defense Highways showed that the United States already had 37 million persons living in poverty, affordable housing has been a crossroad for political issues like poverty or tax breaks/residential home equity. More than 50 years later, it could even show that affordability is the most common problem facing tenants in most countries because housing affordability matters for our overall well-being. With more and more people worldwide living in cities, we are facing critical problems in our urban centers: the lack of affordable housing; and with it poverty and social inequalities have long been an obstacle to community development and cohesion in cities. Embedding the right of every citizen to have access to affordable, safe, decent and adequate housing is not only a commitment made by their governments but one that can only be safeguarded through community development strategies.

2.1. Definition and Importance

Affordable housing is a term generally used to describe housing which is affordable for most people. The simple definition of affordable housing can also be defined as housing that is considered affordable by the community rather than the individual. Affordable housing enables participants to converge on their concentration in economic production. However, these easy definitions hide the fundamental contradictions within the idea the poor naturally have housing needs which, if met, create conditions which promote the general improvement of the economy. Housing is an input necessary for the work of those who provide labor services. The dynamics at work are predictable when rates of pay fall to a level at which housing costs consume a large part of income. Workers tend to migrate to other communities where the relationship of housing cost to income is more favorable.

Housing is a basic human need, along with food, water, clothing and basic health care, and it is important for all levels of society. While country-based systems are different, the principle is the same everywhere – they are there to meet local needs and help people. Affordable housing plays a crucial role in promoting sustainable communities. Affordable housing not only provides shelter but also reduces risks associated with substandard living conditions. The lack of affordable housing for very low-income households can lead to negative consequences, such as increases in homelessness or substandard housing conditions with many undesirable characteristics such as overcrowding. Studies have indicated a clear relationship between housing costs and poor health. A prior-year survey found that people without health insurance are more likely to report housing cost as a major problem than those with health insurance. The same study revealed that almost one in five rural uninsured adults had problems paying their housing costs compared with one in ten insured adults and that insured rural adults are less likely to change the location of their household.

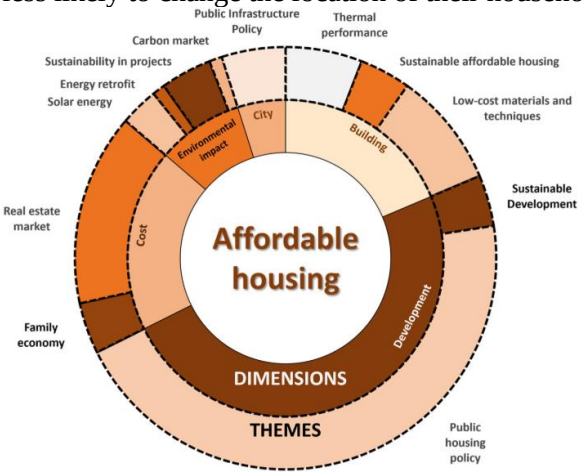

Fig 2 : Sustainable Affordable Housing

2.2. Current Challenges

High costs are a common challenge faced worldwide, particularly in urban centers where demand outpaces supply. Development costs of affordable housing have risen dramatically in recent years, outpacing inflation and wage growth. Upon review of the costs of affordable housing, given limited public sector resources, the situation is grim. Unmet housing need is

frequently cited as a major failure in current housing programs. This unmet need is not the sole responsibility of the affordable housing program; many forces work to create demand for assistance from these programs, including poverty, inadequate wages, and financial constraint. It is these unmet needs, in addition to factors related to the qualities of traditional affordable housing such as poor design, bad management, lack of adequate amenities, and concentration, that have led to the failure of many government affordable housing initiatives.

Governments around the world have increasingly turned to partnerships with the nonprofit sector and the private market as a way to ameliorate both the demand and their lack of resources. Creativity, pragmatism, and experimentation characterize proposed new innovative affordable housing initiatives. These new policies are designed to leverage private investment in the construction and management of units targeted to lower-end markets by offering financing options, technical and regulatory assistance, tax incentives, decreasing the time between site identification and project completion, and direct market intervention in the form of adjustments to market rents using direct subsidy programs such as personal tax credits or rebates, rent allowances, special accommodation programs, and housing vouchers. Employers and unions can also be brought into these partnerships in a concrete and direct fashion.

Equation 1 : Housing Affordability Index (Data-Driven):

$$H_a = \frac{M_i}{H_c}$$

where:

- H_a = Housing affordability index
- M_i = Median household income (community-level)
- H_c = Median housing cost (rent or mortgage)

2.3. Role in Community Development

There is a consensus that affordable housing with an appropriate degree of independence can improve physical and mental health. Affordable housing may also act as a regional and policy lever by generating ripple effects. One of the most promising regional and policy-oriented effects is education emanating from the link between affordable housing, education, and economic prosperity. Specifically, affordable housing may allow low-income families to move closer to better schools, helping to level the playing field for disadvantaged children and thus demonstrating potential to enhance inter-generational equity. This may lead to the larger objective of poverty alleviation that in turn may generate increases in regional economic development. Local government leaders are faced with a dilemma - how to get more people to utilize the services of their city without taxing residents who already provide the needed tax base. The answer appears to be to attract corporations. One way to attract corporations is to create an environment that is attractive to the employees of those corporations and to make it easy for employees to work there.

Every evening, state and local housing officials witness the migration to suburban jurisdictions by families who are seeking affordable housing. In many states, this internal migration contributes to the imbalance in economic and population growth among certain jurisdictions. The cities that are experiencing growth in population and industry find themselves being continually inundated by needy families seeking rental assistance, while the suburbs are as

unfeeling towards these same families as they are to their own working poor. External factors are impotent against this flight to affordable housing, but local affordable housing policy can help to mitigate the adverse consequences of internal housing migration.

3. Data Analytics Overview

1. Definition of Data Analytics

Data analytics refers to an ecosystem of solutions and techniques that can collect and evaluate data from diverse sources. This process takes the form of finding patterns in data or computing descriptive statistics, or procedures that enhance the understanding of data that previously lacked content, context, and structure. Today, data analytics consists of distinct analytics approaches including techniques that appropriately value data, ensure data quality, apply exploratory techniques, evaluate knowledge structure and knowledge discovery, that deal with pattern recognition, predictive analytics, and diagnostics, and manipulative and prescriptive techniques. Descriptive and predictive analytics can be considered core functions for information and knowledge discovery, pattern recognition, and prediction.

2. Types of Data Analytics

Descriptive data analytics support retrospective business investigations to answer questions regarding what happened in the past. For a business, the goal of utilizing descriptive analytics is to discover and summarize patterns from its business data over some time to answer questions about past business events. Diagnostic data analytics support discovery and exploration of relationships and impact of business variables to analyze past business activities. Diagnostic analytics is focused on understanding cause-and-effect relationships for a business.

Predictive data analytics generate knowledge that is useful for predicting future behavior. Organizations use predictive analytics to guide business planning, discover trends and patterns in their business data, introduce new products to the marketplace, design better products, anticipate customer purchasing habits, and tailor a marketing message. Prescriptive data analytics help organizations make better decisions for the future. These capabilities leverage data from multiple sources and deal with dilemmas regarding mobility, risk management, legal issues, and other critical aspects flinging open the doors for new innovations and ideas.

3.1. Definition of Data Analytics

In the present day, a tremendous amount of data is being generated with rapid advancement of technology. However, it is important to know how to handle this data in order to get useful information for decision making. Data Analytics provides a set of methods to reveal hidden patterns in data that can give organizations deep insights into the real world. Specifically, Data Analytics is the science of analyzing data sets in order to draw conclusions about the information they contain, increasingly with the aid of specialized systems and software. In general, Data Analytics is the analysis and interpretation of data, which then delivers an informed perspective on that data, enabling organizations to make actionable conclusions. Data that undergoes analysis can consist of many disparate formats that come from multiple locations. Furthermore, analytics uses data visualization to present the trends and the facts in a concise format that gives stakeholders an overall summary of the progress of important business functions. As the definition states, Data Analytics employs a set of techniques aided by specialized systems to analyze data and reveal patterns that aim to help organizations in

their decision making process. These system approaches are necessary since the data consists of structured and unstructured data originating from many disparate sources. Furthermore, the data is usually vast, and its scale is rapidly growing which overwhelms manual processes to get meaningful insights. In addition, the field is composed of several disciplines including statistics, mathematics, and artificial intelligence, which translates into a breakthrough of new ideas for successful data modeling, analysis, and visualization.

3.2. Types of Data Analytics

Organizations can use many different forms of data analytics to help them achieve their business objectives, employing relative to the diversity, volume, and velocity of the collected data as well as the assigned goal. The following subsection briefly describes the main types of data analytics. These types are descriptive, diagnostic, predictive, prescriptive analytics, each one progressively taking input from more aspects of the challenges at hand than the previous; and they usually rely on more sophisticated computing capabilities as they become more refined.

Descriptive analytics, the simplest type, describes what has happened to organizational data over specific time periods through basic statistical functions such as mean or median, with intensity being more crucial at operational levels. They allow users to pull out traditional reports and identify patterns that may help design the next steps.

Diagnostic analytics is an extension of descriptive analytics, helping organizations to discover the cause of a particular event or phenomenon. It often includes simple data visualizations, such as pie charts, histograms, and scatter plots. Diagnosis may also resort to correlation, regression, and other techniques, many of which are developed in statistics. Data preparation is intensive for diagnostic analytics, which may include a lot of outlier removal and imputation of missing values.

Predictive analytics guide organizations on what the probable outcomes of a given situation might be. They use modeling techniques – both predictive and the simpler classification ones, as well as forecasting techniques that excel at showing trends or predictable outcomes. Predictive analytics have gained popularity among organizations at tactical and operational levels because of their ability to forecast volumes of inventories, consumer demands, or customer arrivals, and the relationships among evident data variables. Customers' propensity to buy can also be predicted at strategic levels using simple logistic regression.

3.3. Tools and Technologies

The challenges of data analytics are to organize useful information and translate it into meaningful interrelated news in a structured manner using the appropriate tools and technologies. The large volume of data collected from various sources leads to challenges of de-normalization, finding patterns, trends, filtering out noise, etc. to predict future events. Various tools and technologies are available to facilitate analysis, deep learning, pattern finding, model prediction, visualization, etc. These can be broadly categorized into hardware for data storage at different levels, Data Handling/Analytics tools, Data Visualization Tools, Learning/Pattern Finding Tools, and Data Model Prediction tools.

With the advent of modern computing technologies, such as Cloud computing, virtual machine/servers, high assert systems, and GPU, large volumes of data can be handled easily.

A number of new avenues have come up for data storage and handling like database management and big data test storage with tools. Several analytics tools are available which provide opportunities for data wrangling, analysis, workflows, transformations, and reporting dashboards. For advanced machine Learning, Deep Learning, and visualization at a higher level, have been widely used. Open-source implementations of ML algorithms are also available in these tools. However, the choice of the appropriate technology would depend on a number of factors including availability, complexity of models and types of data, prediction/learning accuracies, and resource management.

4. The Intersection of Data Analytics and Housing

Housing policy and planning have the potential to impact people's well-being and quality of life in fundamental ways. Amongst other challenges, affordable housing and housing affordability are a pressing concern for many areas in the U.S., and housing supply is arguably one of the most important contributors to solving the fact that a significant number of renters are cost burdened, and have to allocate over half of their incomes to housing alone. Access to affordable housing may help improve residents' health and economic outcomes; it may help keep people out of poverty and alleviate homelessness; and it can lead to other benefits, such as improving educational attainment and access to resources. Policy and planning have a crucial say in making sure urban areas have sufficient and adequate housing supply, and that the costs associated with housing do not come to impact populations at the lowest rungs of the income ladder. Data analytics addresses this question from a different perspective: it aims at identifying and surrounding geographic areas where housing is needed, and the type and quantity of housing development required.

Data-driven decision making has entered the political lexicon like few concepts before. Governments have ramped up their ability to collect and analyze data, on everything from traffic patterns and energy use, to population migration and housing characteristics; and are hoping to use said information to help policymakers make better decisions and for the public sector to perform better. The housing sector is not immune to the use of data analytics: both in the U.S. and abroad, researchers, nonprofits, and governmental bodies alike are delving into data to produce information on how pollution concentrations impact housing values; on how gentrification affects born and local migrators; on how using data services may alleviate housing discrimination; and predicting neighborhood change; amongst other questions.

Fig 3 : The Impact of Data Analytics

4.1. Data-Driven Decision Making

Data innovation and analytics dominate the discourse of effective and impactful policy implementation. Decision makers at various levels recognize that data harnessed effectively can lead to an amplified impact of policies. The rigor around evidence-based policy decision making has increased, so have the resources allocated in curating and cleaning data and using analytics for policy decision making. At the heart of this evidence-based policy decision making processes lay questions posed by decision makers and the actions taken based on the answers provided by analysts. Recognizing the gap between policy questions and the knowledge distilling methods utilized to answer them can help bridge the gulf between data-driven decision making and analytics.

Data Insights for Policy Questions: Helping analysts uncover poignant and precise policy questions can enable them delve into analytics rigorously asking and exploring the relevant data features. The analysis of the broader housing market performance have helped deal with questions around affordable and subsidized housing. Housing affordability and segregation remain pressing social issues in urban America. The decision making continues to be complex, but becoming adept at answering the hard questions can lead to better policy decisions about the health and mapping affordable housing distribution and subsidy strategies, housing design, job access and creation, de-concentration of poverty, and source place mobility. Housing policy questions today encompass areas beyond traditional focus on so-called housing issues to consider linkages with economic, workforce, and local services access. By bypassing the traditional fragmented, insular focus on housing issues and not recognizing linkages with move and stay investors nor with locational choices for their employers – the place of interaction capability, local services access, incentives that drive are not equal across location – can play a significant role in affording relief to community problems.

4.2. Predictive Analytics in Housing

At all levels of government, budgets are austere, and there is a widespread demand for government efficiency. In housing and neighborhood development, funds must be competed for across what are seen as many worthy but disparate activities, among them, homeless services, housing repair and rehabilitation, racial desegregation, immigrant assimilation, affordable rental housing, public and assisted housing, housing for people with disabilities, sustainable suburban and urban development, poverty alleviation, cooperative housing, rural economic development, disaster recovery, and family self-sufficiency. Now more than ever, there is recognition that housing, too, is a social determinant of health, and must have a central role in improving population health and reducing the burden of diseases with high health care costs.

Allocation of resources to housing and associated services is limited, as is the capacity of these sectors to deliver on health objectives. The case must be made that spending cuts in essential services can be offset by financial returns in other sectors. But decision-makers need hard data to support those arguments. Predictive analytics is the means to propel the conversation from rhetoric to hard data support. Predictive analytics can speed decision-making processes. Big data can trigger a fast political response. Predictive analytics and communication of data relies on data visualization and can have a powerful effect on helping stakeholders visualize change. A platform that employs rich simulation models, and which predicts the likely future behaviors

of key economic and social indicators, can have a positive effect on community dialogue, engagement, and social license because it also employs rich data sets that are locally relevant. The capacity to simulate and visualize model outcomes can help communities reconcile differing worldviews, such as disagreement about the effects of development on property values, as well as uncertainty about future trajectories. The ability to simulate virtual "what if" questions using local models that employ regionally relevant data can improve buy-in to the selected options infrastructure funding decisions. Predictive models can simplify complex issues and communicate data to lay audiences by reducing multivariate information into local stories and vignettes that can be manipulated to get a feel for how underlying factors operate and interact.

4.3. Geospatial Analysis for Community Planning

The integration of spatial analysis into community planning has been present since the mid-20th century with the use of Geographic Information Systems (GIS). Spatial analysis and GIS consolidate decision-making in the development process. Planning challenges have long called for the integration of spatial data to support equitable development efforts. Over five decades, many planning applications have come to rely on geospatial data ranging from risk analysis to site selection, service estimation, and access modeling. Yet, despite the sheer volume of real-estate and city data, decision-making remains tacit and challenged by epistemic uncertainty. This makes the informed use of geospatial data in housing plans critical to achieving equity. When the potential benefits of geospatial data in practice are effectively communicated — especially to the developers and stakeholders who might use these digital datasets — decision-making is likely to be improved. If these stakeholders internally offer perspectives and critical significance to the data, it can be compellingly valenced to validate its use.

The rising push for massive open online organization is yet another factor emboldened by data analytics and housing equity. The lack of luck to consult a place-based expert who integrates and analyzes the available data acts more as an impediment to equitable decision-making than the mere availability of data. Thus, population-level housing and neighborhood change analysis that informs day-to-day decision-making is radically being re-done as new, affordable tools are developed, filled with curated visualizations, and provided to non-experts and technical decision-makers alike. With this increased implementation of easy-to-use data tools and further innovation toward machine learning, the intervention of decision-making is completed with algorithms that inform planners and policy-makers at all stages — from plan development to implementation and monitoring.

$$R_e = \frac{\sum_{i=1}^{n} D_i \cdot I_i}{B_t}$$

Equation 2 : Resource Allocation Efficiency:

where:

- R_e = Efficiency of data-informed resource allocation
- D_i = Data-prioritized need index for zone i
- I_i = Investment directed to zone i
- B_t = Total available budget
- n = Number of target zones or communities

5. Challenges in Implementing Data Analytics

While there is considerable potential in the value that data-driven practices can offer to the housing and community development sector, it is not without its challenges. The effort to stage a data revolution in this area must contend with a variety of practical concerns: growing fear over the use of individual-level private data, especially as it relates to the incredible granularity of census data resulting through increased budgets for the census; the relative absence of datasets that integrate information across domains in a fashion accessible to those outside the state and local statistical agencies; a lack of support for enhancing data skills and literacy among staff in workforces that have often turned over or grown more senior; and weaknesses in the incentives for the housing field – at both the local level and within the federal system overseen by the Consumer Financial Protection Bureau – to provide high-quality reporting at the levels of detail needed by researchers and policy analysts alike.

Beyond these practical concerns, the architecture of the sector poses significant additional challenges. Because affordable housing is a production that is most often managed locally through place-based efforts at the level of cities, counties, and housing authorities, there are nested institutional evolutions that shape response. The local management of the place-based affordable housing production system and community development sector can create additional barriers to implementing more data-driven approaches to both economic development and housing. It is frequently the case that the benefits of a successful place-based policy will be dispersed throughout the region, while costs accrue to the local government administering the investment program. The political dynamics of regionalism do not at all favor leadership by the center, either in carving out funding or project authority for municipalities or subregions or in building coalitions to address issues that have effects beyond the borders of local jurisdiction.

Fig 4 : Challenges in Establishing a Data Analytics Capability

5.1. Data Privacy Concerns

With great power comes great responsibility. Sensible access and usage of data is often overlooked by data analysts concerned mostly with the output from their analytics. In recent years, corporate surveillance through data-gathering technologies has proliferated, making them way more powerful. Personal data is now also gained without social consent or exchange of value, usually through mobile devices that track our every move or social networks, which gather all our connections, preferences, fears, and opinions to pursue addictive business models based on insatiable user engagement, often distorting their users' preferences or worldview. So, when people think about affordable housing and community development initiatives being mixed with powerful big data analytics, they may quickly start feeling paranoid about the data analytics industry without any governance. It is what happens, for instance, with the co-governance model, often advocated in the literature or its submodel, the data collaborative. It proposes combining public data, private data, and community-generated information to create better urban data and analytics to support public policy decisions. Is the creation of public-private partnerships based on data collaboration models the future of local governance? Surely community engagement is key in this process.

However, in a world driven by mass surveillance, the concept of privacy has been reshaped. People expect less and less privacy from brands; many even actively endorse share-and-care sharing through the creation of niche social networks based on trust. But, researching these data-sharing motivations, it soon becomes clear that the desires for social recognition or connection trumps privacy protection wants. So, what is the impact of this shift on creating awareness concerning privacy risks? Moreover, the question persists: Will it be enough to create mediated spaces for co-collection and borrowing resources? How can we ensure that the personal motivation for sharing rides both the specific private goal and the overall good of the city?

5.2. Access to Quality Data

Data on affordable housing is often limited in geographic scope and time periods available. The federal government is the primary collector of housing data—most notably through the American Community Survey, as well as through the Development Assessment Projects used to evaluate housing programs and the Census of Population and Housing. Yet despite the expansive nature of the Census, state and local governments collect much of the data on affordable housing properties. Many data systems used at the local level are more comprehensive than those at the federal level. However, inconsistent definitions, hold-over effects from the Great Recession, and questions about data quality plague the data available. The low-income housing tax credit is a key mechanism for providing affordable housing units. An online data system operates that displays information on low-income housing tax credit projects. However, questions remain about how to best leverage this information at scale.

One of the goals of data analytics projects is to minimize the amount of manual data collection that we are doing, and instead build systems for continual monitoring of a problem that business leaders within philanthropy or government need to address. In order to get there—where we have effective, systematic ways of measuring housing conditions—there needs to be a commitment from funding agencies to focus on housing problems, to be willing to take risks in tackling difficult data problems, and to resource a collaboration between data scientists

and housing analysts. This is seen in work on health problems like health disparities, and work on the employment side. These investments pay off into better understanding of problems, leading to better-designed policies, which further leads towards less "drift" on the parts of government or philanthropy that are involved in funding programs. Housing—we believe—deserves that level of commitment!

5.3. Skill Gaps in Workforce

The shortage of personnel trained in the analytics skills needed to leverage Data Analytics technology is perhaps the most significant barrier faced by community development practitioners. There has long been a skills gap in housing agencies, development companies, and Neighborhood Development Organizations when it comes to building sophisticated data analytics pipelines, from project design to data collection to generating actionable insights. This challenge has become more urgent with the next gen of Data Analytics technology that enable new analytical applications. Were these organizations already behind the technology curve in the decade leading up to COVID-19, the pandemic has undoubtedly accelerated that backward slide.

In addition, there is a growing need in the nonprofit sector for agencies with experience at the intersection of policy and technology to help these organizations synthesize the massive amounts of complex housing data being generated in today's gig economy. In this respect, providing guidance to Neighborhood Development Organizations in interpreting reports from their internal systems or external digital consultancies will be paramount, as will addressing workforce issues to ameliorate staff fatigue associated with the increased expectations related to managing the technological side of nonprofit work. Nonprofit leaders welcome the use of digital Data Analytics technology to make analytic insights available to staff at every level in the organization, but it remains important to leverage the insights from the backend experts about how to best utilize the programs being sold by various tech providers – especially in these times when the nonprofit sector is scrambling to fill the gap left by layoffs in the digital gig economy.

6. Strategies for Effective Implementation

The findings and recommendations from the previous sections make the business case for the increased use of data analytics tools and techniques in affordable housing initiatives and in the development of local communities; however, the realization of this potential will require strategies for effective implementation. More specifically, building partnerships with data analytics tech companies, training and capacity building for local agencies, and engaging community stakeholders are three essential strategies to leverage partnerships for broad and deep implementation of data analytic tools and techniques. In this section, we will describe these strategies in more detail and provide examples of activities and initiatives that illustrate these strategies.

A community is exploring collaborative data-driven partnerships to expand the application and use of data analytics tools and techniques. Local organizations have set up a Data Partners group to explore new methods to collect, share, and utilize data in the region. Organizing local organizations to utilize a shared data infrastructure is a critical first component in this process. A critical step in the initial phases was the establishment of an inventory, listing the data

resources that are currently being gathered by local partners. The group then prioritized selected resources and prepared a data plan to facilitate improved access to shared data. The purpose of the Data Partners group is to encourage collective use of specific datasets to enhance programs and services as well as to promote the regional perspective as discussions regarding the collection and sharing of data resources continue. The Data Partners Group is also considering other initiatives to promote the use of data. These might include hosting technical training sessions regarding the utilization of specific data sets and reviewing case studies from other regions.

6.1. Building Partnerships with Tech Firms

Here we propose three vital strategies to implement the recommendations made in the previous section effectively. The first is partnerships with tech firms. The essence of our recommendations is leveraging tech - specifically, tech firm capabilities to improve functions of housing and community development agencies. Yet, this dependence on tech is fraught with dangers as tech firms are driven by profit motives, with little concern for the public good. To ameliorate these issues, while enhancing the quality of services provided to the public, we propose partnerships between tech firms and social or non-profit housing firms. The sense of social responsibility embodied in the profit-sharing and not-for-profit models of these social firms, which provide housing and social welfare services, can help ameliorate some of the problems associated with the for-profit model of tech firms. In addition, where applicable, the knowledge and experience that these social firms possess in housing, urban and community systems can further enhance the efficacy of tech-enabled solutions.

The rationale for engaging tech is that traditional public sector functions such as data collection, analysis and dissemination have suffered from stagnation, inefficiency, and ineffectiveness, primarily due to a combination of increasing workloads, bureaucratic inertia, and lack of adequate resources. In addition, the cultural differences between the public and private, for-profit sector - including the focus on not cutting corners in delivering a public good; politeness, professionalism, and punctuality in dealing with the public; obeying rules even if it costs more; a willingness to put in long hours to get the job done; the drive to innovate; etc., can hinder the transition to private, tech-enabled solutions. These kinds of concerns are not unique to the public sector.

6.2. Training and Capacity Building

To unveil the practical challenges that come along with affordable housing data analytics, we first have to build the necessary training and capacity in the practitioners' community. Although the availability and accessibility of tools and technologies in affordable housing analytics have improved, the awareness of practitioners on how to effectively integrate such tools into the everyday practice still lacks behind. Initiatives that allow many practitioners to gain exposure to and to develop skills around data analytics are vital. If successful, such initiatives could democratize access to the benefits of data-driven decision-making.

Accessible training programs, typically delivered over a short timeframe and designed for working professionals, can ensure broad exposure at mass scale. These programs should cover why, when, and how to use data analytics, in particular, tools currently available as well as new tools as they are developed. They should also explore and help resolve the practitioners' established intuitive approaches to current business processes that prevent them from taking

advantage of analytics. For some, more intensive training will be required to enable judges, lawyers, and low-income housing tax credit housing managers to build their own housing data analytics systems, of their choosing, for their low-cost needs. Additional training is needed for housing stakeholders and for community groups that currently lack the tools and skillsets to effectively employ data analytics to support their overall missions. Such programs should also offer opportunities for participants to collaborate around the continent on valuable housing and community problems, share lessons learned and insights gained, and undertake tangible affordable housing and community development-related projects.

6.3. Engaging Community Stakeholders

Stakeholder engagement in housing planning, policy making and program implementation is a critical component of successfully developing and sustaining affordable housing initiatives. Residents and policymakers stated that collaborations among communities, developers, and municipalities are key to successful development. A challenge in stakeholder engagement is including all citizens, which can be difficult in gentrifying neighborhoods with new residents and investor-landlords. Housing analysts have suggested that competition among residents for neighborhood resources may lead to strained community relationships. It is critical to consider how demographic shifts and unequal resource distribution affect power dynamics among various stakeholders. Programs that increase the capacity of community members to identify issues and limitations within their neighborhoods and advocate for effective actions contribute to the social capital of low-income neighborhoods. Neighborhood residents may have limited time and capacity to engage in the public planning process, while some affordable housing developers may lack a comprehensive understanding of neighborhood needs and resident priorities. As such, residential and developer priorities may conflict. Start-up grants to low-income neighborhoods along with technical support could help community members gain experience in the planning process, determine the issues they find most important. Connections to external stakeholders can provide community residents with information that helps them advocate for their priorities in the planning process. Responsive communication by planners, developers, and managers can also bolster productive relationships with community members.

7. Future Trends in Data Analytics and Housing

The rapid developments in computing, data collection, and organization will soon find their way into housing analysis. Long gone are the days when analysis consisted of tedious collection and compilation of spreadsheets using data that was a year or two old at best, supplemented by on-the-ground visits and reviews of claims. In just a few years, advances in data analytics will make planning effortless, allowing quick responses to current needs and problems, easy assessments of the impact of past initiatives, and the expedited creation of better-housed, healthier communities. This chapter outlines three areas where innovations promise to radically improve housing policy development and results.

Artificial intelligence and machine learning have taken center stage in developments across sectors, from product recommendations to medical diagnostics. The big three technologies in this area are natural language processing, computer vision, and extended reality. Natural language processing allows researchers to summarize large text documents, generate reports and memos in natural human language, and translate from one language to another. In the

housing sector, it can facilitate quick parsing of all the financial data received from property owners, as well as reports from and interactions with those who live or lived in the properties. This function can now be run using various document editing tools. Computer vision makes it possible for companies or government agencies to analyze thousands of images without having to examine each, identify damage, and give it a dollar value. In housing, this means that potential funders can prioritize properties that urgently need assistance. It allows the identification of potentially blighted properties.

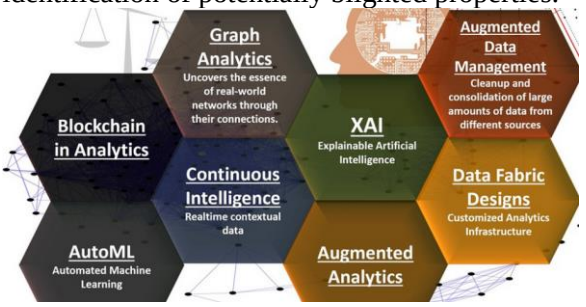

Fig 5 : Future Trends in Data Analytics

7.1. Artificial Intelligence and Machine Learning

Artificial Intelligence (AI) and Machine Learning (ML) are among the many technological advances that have gained traction over the last two decades, offering new capabilities that were previously inconceivable. While magical "black boxes" that offer solutions to all problems remain at the limit of science fiction, recent advances in AI and ML have shown incredible successes in very narrow and specific areas, making them increasingly powerful tools. Moreover, these technologies are increasingly easier to use, with turnkey solutions available from many commercial vendors. The shifts toward more flexible data infrastructures have been driven by the need for speed, growing interest from the private sector in new data partnerships and development resources, and, in some cases, pressure for open-source code. These forces have accelerated collaboration with the private sector. Businesses are leading the way in developing powerful new analytic methods and have much to offer public agencies and nonprofits. New possibilities for cross-sector partnerships are evolving quickly and should drive additional innovation. These technologies work by examining combinations of input variables to predict various kinds of outcomes. For example, a predictive model could use a combination of region, family structure, rent levels, household income, unemployment, and other accessible geographic, economic, and demographic information to predict homelessness for each family or person residing in a particular area or community. It could then be used to identify new clusters of individuals or households at risk of homelessness on an annual or more frequent basis. AI and ML can also be used to assess risk in the production of new rental developments. For these kinds of specific applications, new models developed by the private sector or nonprofits could help to improve on more conventional methods like regression analysis.

7.2. Real-Time Data Utilization

There is a growing trend in the increasing use of real-time data, as contrasted to historical data, for decision-making purposes. Smart sensors, mobile phone GPS, social media connections,

and other devices are enhancing the amount, quality, and frequency of real-time data at much lower costs. Enhanced data from these devices are being integrated into analytics dashboards and decision support systems to allow public housing officials to visualize traffic patterns on highways, the extent of house vacancy in new neighborhoods, and the volume of pedestrian traffic on sidewalks near retail businesses. Data incorporating street parking information is being used by parking officials to monitor traffic congestion in certain districts and develop real-time responses, including updating parking meter fees, deploying additional personnel, and improving the timing of traffic signals. A local housing authority has partnered with a local research center to develop an innovative security system combining real-time video feeds, gunshot-detection sensors, and environmental sensors. These types of partnerships among public agencies and local researchers will likely expand in the future, as the availability of multi-source, real-time data grows and the tools to utilize it become cheaper and more available. It will require careful design to ensure that such systems are used legitimately and do not violate privacy considerations. The increasing sophistication of argumentation and analytics software will allow non-experts to pose complex questions to public data and receive insightful and useful answers.

7.3. Smart Cities and Infrastructure

The Smart Cities and Infrastructure research team asks the question, if cities can get smart? From a concept that was born in the information technology realm where people experienced productivity gains from interconnected systems for functions such as logistics, it was just a matter of time before cities were approached in the somewhat similar model. “Creating smart cities or smart urbanization based on the IT revolution to aid urban development does appear the clever answer to today’s global urbanization crisis.” The term ‘smart city’ refers to a city that uses digital technology to enhance performance. For example, in a smart city involves its citizens, progressive businesses, and the entire city government. Using rich data from residents and businesses and doing it in a transparent manner, the city becomes receptive to citizen needs and developing programs. Thus, while positive about the concept of smart cities, we should also add caution, as urban experts warn about other negatives of cities gone smart. They worry about reducing the vital importance of the public realm in the city.

The virtualization of the city through wireless communications and the collection and use of social data has implications for the economic and social structure of cities. Have urban economies and societies become so flexible that economy can be decentralized into ‘urbanized countryside’ or even ‘depleted former termite cities’? At the other end of the social spectrum, the use of pervasive cameras, sensors, and software programs raise concerns about loss of privacy. One country seems to be taking a striking plunge into this with its vast urban surveillance programs.

8. Policy Recommendations

While local housing agencies are generally aware of the potential for data-informed decision-making, the discussion of incorporating data efforts to improve affordable housing work often remains rhetorical. Regionally, local housing agencies recognize that they lack the funding and capacity to implement and share comprehensive data efforts. This realization has led to a greater willingness to discuss new collaborative technical assistance and data funding

approaches. Yet currently, collective action on this scale remains distant. Further, as local data initiatives are pursued, there is limited guidance on how they will be funded, sustained, or governed to maximize the utility of available local data. To have collective impact, we need to build a learning network, support initial experiments, and work on the funding, governance, and technical assistance questions as we go. Other policy levers, such as a requirement that housing agencies using government funds to adopt data or improvement resources can be deployed to bring it to the front. Local data partnerships hold the promise of closing feedback loops across housing investments, monitoring and oversight. Data-informed action around an initial data sharing.

Integrating Data Analytics into Housing Policies

If demand for joint learning demonstrates the potential for actionable learning, then the next step is the integration of that knowledge about partnership practice into housing policy. We are both deepening our existing city and state-level collaborations focused on operational data use to drive impact in communities, in excited ways, with data-informed state and local policy, working at the intersections between disparate local data initiatives, and helping build local partnerships to enable more coordination with peers neighborhood, so-called Learning Community Accelerator. As we do these essential tasks, we are also increasingly being asked to connect the work to state and federal policies and programs.

8.1. Integrating Data Analytics into Housing Policies

The use of data analytics to support housing policy is still in its infancy. Policymakers should increase funding for jurisdictions and agencies willing to build out data analytics capabilities for housing policy. The promise of engaging private sector partners in these efforts is enticing, but care must be taken to insulate the data infrastructure from unseen conflicts of interest and from the whims of the private sector. The results of publicly funded data analytics projects should be open to the public. The ethical and scientific practices developed by the Open Science movement should guide the research and development work that informs housing policy and its implementation.

Policymakers should craft requests for proposals from private partners that make clear how private sector profit motives must be identified and managed. When private partners are selected for the work, it should take the form of a collaboration—rather than a top-down vendor-client relationship—so that the work is being informed and guided by publicly commissioned expertise. Doing this maximizes the knowledge transfer from the private partner to the public employees designated to continue the work after the private partner leaves, which typically may be as short a period as two or three months. It is often said that opening the hood on a black box provided by a private vendor is not possible, but that obstacle can be managed through proper contract language that emphasizes on-the-job training for the public employees once the product has been delivered. Otherwise, the agency will remain mired in ignorance of the technical aspects of development to which they almost certainly do not have access.

8.2. Funding for Data Initiatives

To fund data analytics initiatives and enable data sharing and open data, we're calling on government agencies at all levels to include new data analytics efforts in their budgets. At the federal level, new initiatives might focus on training state and local agency staff in data

analytics, evaluating state and local strategies to collect advanced data, monitoring practices across these jurisdictions, and funding initiatives for census-supported data collection. Agencies should augment their budgets and priorities that drive a focus on equitable housing solutions with allocations for data resources. We recommend dedicating specific funding to encourage states and local governments to dedicate resources for data sharing collaborations and capacity building initiatives. With additional capacity across jurisdictions and the right collaborative arrangements, state and local agencies could be better positioned to lead joint new data efforts.

Several federal, state and local level data efforts could spur agencies to rethink their data use. The information technology budgets could lead to decreases in data costs over time. Specific calls for plans could build on recommendations for the American Community Survey. Collaborations between various organizations could lead to innovative new policies at the state level. Specific funding for collaborative activities could link to economic development funding or housing assistance funding. Finally, state or local opportunity grants that are tied to new data collaborations could be included in mayoral transitions or state improvement plans.

8.3. Creating a Data Sharing Framework

As the volume and variety of housing data increase, it is important to create partnerships that support data linkage, protocols to help share curated data, and new methods and tools to facilitate the creation of data products. Some agencies may want to curate data that specializes in housing quality for internal purposes only, while others may be interested in data that emphasize neighborhood restoration and improvement for online public-facing data products. A data sharing framework should take into account the user group and their specific needs. Some groups may have less capacity or less access internally and need curated and cleaned data regularly for their internal purposes. Others may be producing data products for external users and will need more flexible products with specialized data selected for specific audiences. Some may have the resources to consolidate and create a one-stop-shop of housing data, while others look for pathways to data support for producing new data products.

A data sharing framework should support the specialized products that address the specific policy needs of diverse internal and external users. A user-centric flexible data product linked to national standards and featuring local conditions would benefit local integrated data efforts for community engagement with policy, program, and development initiatives. Local governments could leverage the public-facing product to apologize for residents' and organizations' pain about the data used in policies. As we have seen with policy actions that have disproportionate negative effects, residents who are not at a particular political table can also be the most informed about their communities and neighborhoods. The data sharing framework could build confidence and trust around data linkage and consider the ethical implications of the creation and availability of curated data products that are used internally. Support can also be given to close the digital divide with local governments through specialized products that build human capacity to engage marginalized and disadvantaged populations in the development and implementation of responsive housing policies.

$$C_d = \frac{O_s - B_s}{T_i}$$

Equation 3 : Community Development Impact Score:

where:

- C_d = Development impact score
- O_s = Outcome score after analytics-guided intervention
- B_s = Baseline score before intervention
- T_i = Time interval of project execution

9. Conclusion

Although housing affordability is a large concern for residents, policies to create affordable housing often have tradeoffs, and policymakers face many competing demands. Traditional qualitative evaluations of housing initiatives do not provide the data necessary to determine the effects associated with affordable housing and may expose policymakers to significant risk. Data analytics examines housing affordability trends to understand the dynamics and relationships among critical underlying factors. But housing affordability is obviously a complex issue influenced by many related factors, and available datasets are often made using different methodologies and for different purposes. Predicting policy effects is also inherently highly uncertain. For these reasons, data analytics in the field of affordable housing cannot be seen as a replacement for policy expertise or qualitative investigation, and it is critical to itemize what data analytics might help accomplish in evaluating affordable housing initiatives. Towards bridging the gaps in housing affordability due to dynamic socioeconomic landscapes and cycles, data analytics can highlight the main determinants affecting housing affordability, provide national- and metropolitan-level estimates, and forecast housing affordability to provide stakeholders the tools to formulate, monitor, and evaluate policies addressing the challenge of affordable housing. Additionally, stakeholders also need to commit to developing and continually validating effective data analytics models to support policies addressing affordable housing. Policy stakeholders and researchers may facilitate this development by focusing collaborative efforts on energy and economic policy, the analysis of standard measure income and affordability gaps for millennial and elderly housing demand sectors, and efforts to integrate disparate long-term data series covering regional, economic, and housing unit characteristics.

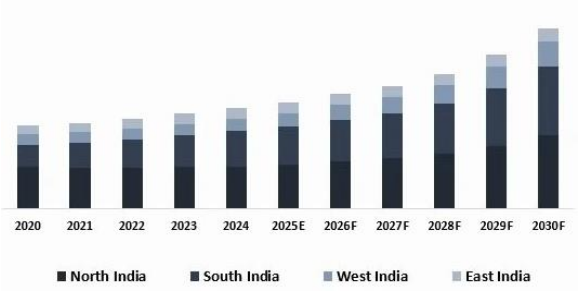

Fig 6 : Affordable Housing Market Size

9.1. Final Thoughts and Future Directions

The objective of this work was to explore how data analytics can be leveraged to enhance affordable housing and community development. Seven different approaches and methods used across different domains and communities have been documented. The findings indicate a positive disruption in the field due to the advent of new tools and methods, as well as increasing access to data and computing power. Most of the reviewed initiatives had an impact in terms of enhancing community participation, democratizing access to information, and improving decision making. Actual tools available for practitioners, affordable housing developers, and local governments, however, continue to be scarce. The challenges for the future are then threefold.

On the one hand, new algorithms and methods need to be developed that can further improve the analytics and policy development process. Most of the methods and approaches that were discussed, with a few notable exceptions related to new participatory design environments, have not moved beyond the prototypical stage. Decision making, however, is more often than not a multi-stakeholder, multi-objective process, which seldom can be effectively addressed with existing methods. Space limitations preclude us from describing multi-objective optimization frameworks here, save to inform the reader that they exist.

On the other hand, focus needs to be placed on identifying research problems worth addressing. The cross-fertilization of disciplines has done much in broadening the scope of what we can and should address as researchers and practitioners, but it has also made approaching problems in a meaningful way that is not one-off extremely hard. Meaningful, reflective work is better handled by teams that understand these problems and use analytics as a support tool, making interdisciplinary teams preferable.

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