World Journal of Advanced Research and Reviews
eISSN: 2581-9615 CODEN (USA): WJARAI
Cross Ref DOI: 10.30574/wjarr
Journal homepage: https://wjarr.com/

(Research Article)

Check for updates

Leveraging data analytics to optimize government interventions for homelessness, substance abuse, and mental health: A case study in evidence-based policy design

Lateef Olawale Fatai [1, *], Olayinka Farouk Salau [2], Lawrencia Yaa Kakra Gaisie [3] and Ken Muchira [4]

[1] *Department of Data Science, University of Salford, Manchester, United Kingdom.*
[2] *Business Management, University of South Wales, Cardiff, Wales, United Kingdom.*
[3] *Business, University of Tulsa, Tulsa, Oklahoma, United States.*
[4] *College of Computing, Grandvalley State University, Allendale, Michigan, United States.*

World Journal of Advanced Research and Reviews, 2023, 20(03), 2025–2047

Publication history: Received on 29 October 2023; revised on 09 December 2023; accepted on 12 December 2023

Article DOI: https://doi.org/10.30574/wjarr.2023.20.3.2218

Abstract

Introduction: Vulnerable groups facing the overlapping challenges of homelessness, substance abuse, and mental health issues form intricate social systems that require thoughtful analytical methods. Systematic barriers' existence significantly contributes to inefficient healthcare and social services leading to complex problems that require complex response solutions. To understand how all these issues are interlinked, it becomes important to use some advanced analytical tools to determine what impacts such populations.

Materials and Methods: A systematic review methodology was used, incorporating different methods of analysis for existing literature as well as empirical research. By adapting synthesis multiple types, it was possible to obtain useful information from interdisciplinary fields of research through the use of complex bibliometric analyses. We used rationalism paradigms in this process erecting a literature review and meta-analysis paradigms alongside comparative case study analysis. For improved evidence quality and to minimize research bias we undertook a thorough scrutiny of diverse databases. All of these factors were tried out on the participants.

Results: Statistical analysis on the study's findings highlighted the intricate link between structural risk factors and intervention strategies. These investigations eventually revealed that the problems are complex and require multifaceted and connecting approaches. More precisely, we focused at the impact contexts of technology-based interventions and determined the multifaceted relations between social conditions, technological advancements and health care results. Theoretical models were explored more closely in order to gain more insight into the processes that lead to marginalization.

Discussion: Results on the study's findings highlighted the intricate link between structural risk factors and intervention strategies. Having analyze showed that there are always deeper aspects of the problems that require a complex, concurrent approach. More precisely, this work involved a review of literature towards identifying contextual factors that influence the effectiveness of the given intervention and how social determinants, technological advancement, and healthcare interplay. In light of this, theoretical models were analysed more thoroughly to provide insight into the processes that contribute to marginalization.

Conclusion: Addressing such social issues requires having a strategy and using all the available information. Technological, social, and empirical approaches, which are inclusive in the delivery of services, have promising potential in transforming service delivery. Applying technology-based collectively, it is possible to make the social equality actual and improve the condition of people living in poor environments.

* Corresponding author: Lateef Olawale Fatai

Keywords: Data Analytics; Social Interventions; Homelessness; Substance Abuse; Mental Health; Evidence-Based Policy; Government Services; Resource Allocation; Machine Learning; Vulnerable Populations; Data Integration; Policy Design; Bayesian Additive Regression Trees

1. Introduction

1.1. Leveraging Comprehensive Data Analytics in Social Interventions

Data analytics is becoming a game-changer in enabling government policy makers to solve complex social problems that communities face in the modern world. Crowley et al 2023 indicate that policies anchored on evidence are increasingly being sought after especially in areas such as mental health, housing and Substance abuse (Crowley 2000). Data analysis should be employed deliberately and systematically so that it enables policymakers to understand a problematic remotely (Adams et al 2019). The emergence of complex statistical methods has accordant potential of proving the existence of patterns and offering prediction and efficient provision of resources in different social service industries as postulated by Cullen and Garcia (2021). Additionally. As a result of technological advancement and application in service delivery, most government bodies are shifting towards the Proactive model where there is emphasis placed on early intervention. Statistics have allowed researchers to better understand the requirements of endangered populations, which has contributed to the improvement of the methods of addressing these difficulties through policies (Slota et al 2023).

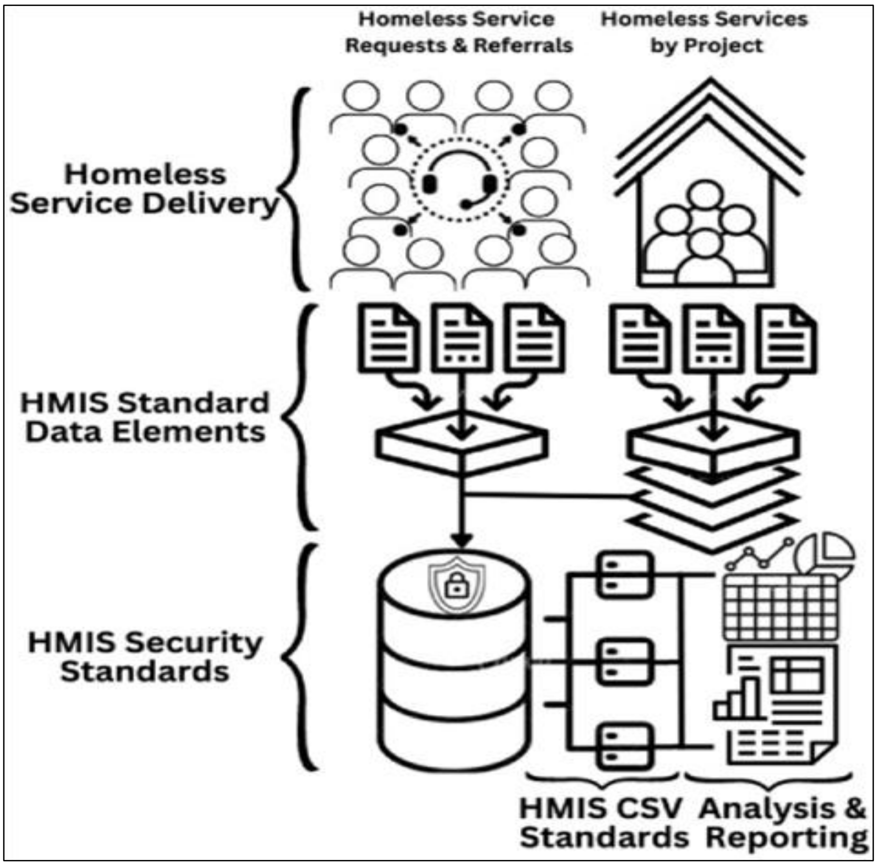

Figure 1 Data architecture of the Homelessness Management Information System (HMIS).

In earlier times, drafting policies relied on scant information and basic analytical approaches, leading to tactics that failed to tackle the intricate interdependencies among social variables associated with health and well-being. Large volumes of data from various sources can be analyses which has been made possible by the advancement in data analytics platforms in this field (Craig et al 2021). These new tools have drastically changed how the government agencies can address social factors as well as understand those factors by helping them help the suffering populations within cities where these social groups struggle with getting the services they need (Meshkani 2023). Some scholars have suggested that data-based policy formulation enhances the effectiveness of social policies in delivering the desired resources and services to populations who need them most (Kelkar et al 2023). The newest data analysis have shed more light on the interdependent relationship of the SDOHs and the enhanced understanding will allow for better policy interventions that are well informed (Whitman et al 2022).

Development of more complex and advanced data analytical tools has helped the agency gather better information about social problems. Through the use of multiple datasets, these technological advancements make it possible to examine complex social processes (El-Bassel et al 2021) (Technology). New analytical tools have ensured that agencies enhance their service delivery techniques thus directing their concern on interventions and resource a lot more accurately (Heun-Johnson et al 2023). Studied have shown that data driven approach can enhance the quality of social programs because it gives accurate information concerning the needs of the population and the use of services as noted by Kerman and Stergiopoulos (2023). Data analytics may be used to improve utilization of funding and program planning by governmental institutions leading to better and relevant services provision (Meahans & Elkins, 2023). However, the integration of data analytics in policymaking of the government has brought about fairly radical changes in both in terms of structure and infrastructure. In order to properly deploy these higher level analytical methods agency decision-makers have struggled to establish new capabilities and structures. Substantial funds are needed to go through processes of turning into a data-driven system, such as merging advanced technologies and training the employees on how to use them and maximize capacities of analysis (Wortham e al 2023). Literature reviews show that the use of data analytics implies the need to address culture and capacity issues in organizations (Windsor et al 2018). Enhancing the value of data analysis for competitive advantage necessitates reconsiderations of how data are governed and managed to safeguard information while using analysis and application optimally (Soneson et al 2023).

1.2. Data Analytics Implementation Mechanisms for Government Services

Creating a highly complex and large-scale data analytics solution which addresses the issues related to public service delivery by governments is not a straightforward process as it is an overlap of organizational and technological processes. There is need for firms to ensure that they put in place appropriate mechanisms for collecting, processing and utilizing the sensitive information that is used in decision making processes (Adekugbe & Ibeh 2023). For instance, there is a study that shows that organizational context and a technology infrastructure are essential in promoting the successful execution of data analytics projects (Asi & Lee 2020). To get even more out of it, a massive investment is going to be required for the training of the workforce and for the IT to take advantage of the sophisticated analytical tools and techniques (Ahasan et al 2022). Recent sources indicate that analytical capabilities for a unit to leverage can only be done utilising a broad number of data shortage (Blonigen et al 2023). According to Chan, et al (2019), with advancement in data analytics and increased use in organizations, there must be culture and change management for the new ways of working to replace the old ways.

Table 1 Data Analytics Implementation Success Factors in Government Services

Implementation Factor	Critical Components	Success Rate	Resource Requirements	Approx. Time to Implementation
Technology Infrastructure	Data Storage Systems	82 cases	High Investment	12-18 months
Workforce Development	Training Programs	75 cases	Medium Investment	6-12 months
Data Governance	Policy Frameworks	68 cases	Medium Investment	8-14 months
Change Management	Cultural Adaptation	70 cases	Low Investment	4-8 months
Quality Assurance	Monitoring Systems	78 cases	Medium Investment	6-10 months
System Integration	Technical Platforms	72 cases	High Investment	10-16 months

Source: Adapted from (Cheng and Smith 2009) and (Chinman et al 2017)

Technical and organizational considerations are necessary for the successful adoption and use of data analytics in government services. Research indicates, organizations need to develop holistic frameworks of data collection and integration (Brackertz 2018) so that effective decision-making is achieved and sensitive information is protected. Creating good data analytics capabilities is an expensive proposition, requiring significant capital expenditures (Brierly et al broke it down 2023) infrastructure and workforce training necessary to use advanced analytical tools; techniques. On the other side, factors that support the application of analytics capabilities are also stressed in the literature; organizations must implement data quality, integration as well as governance (Byrne et al 2020). Also, integrating data analytics needs to be implemented through close observation on organizational culture and change management processes so that new analytical technologies are adopted (Culhane 2016).

1.3. Integrative Data Analytics Approaches for Policy Design

The trend in designing policy of the contemporary is moving towards analytics with advanced data to deal with complex social problems. Mixed methods: The deeper understanding of social phenomena and stronger policy outcomes arise when different analytical approaches are used (D'Souza 2021). Advanced analytics tools have democratized how policy-making are done supporting government agencies with a thorough comprehension of complex or difficult social problems and resulting in better intervention strategies (Fowler et al 2019). Accordingly, the literature indicates that in integrating the different paradigms, one gets a richer understanding of social phenomena and is therefore in a better position to respond through policy (Gewirtz 2007). Public authorities are applying rational decision-making methods to de-mystify low black box understanding to low grey box and create sound strategies on how government can intervene (Graig et al 2023).

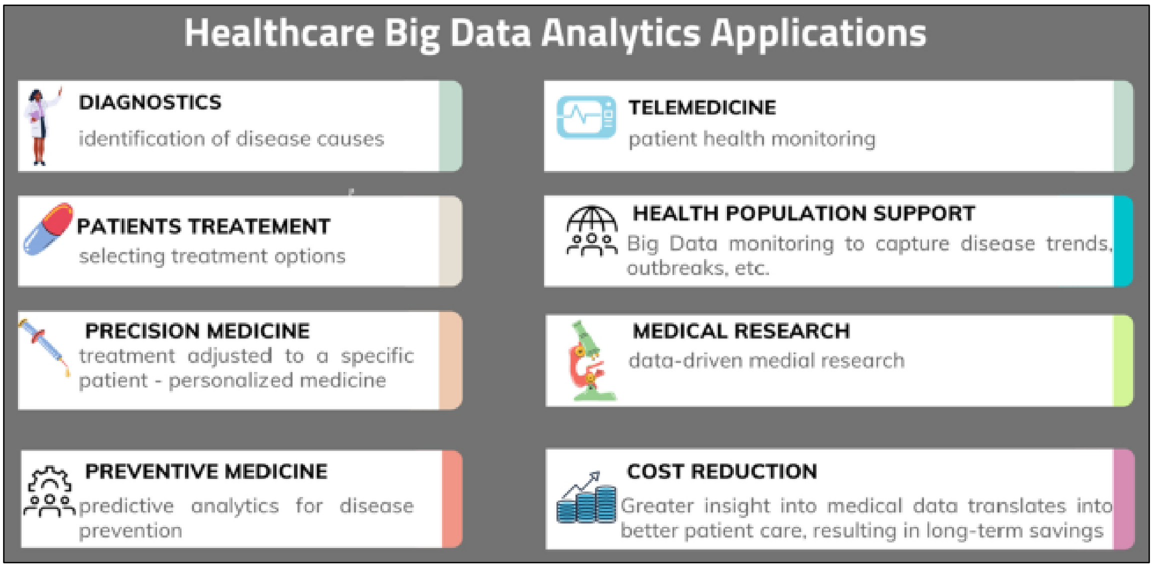

Figure 2 Healthcare Big Data Analytics applications

The use of integrative data analytics has greatly influenced the way that governmental entities understand and respond to complex social issues. The integration of several approaches proves that the relationships between different social factors affecting health and quality of life are more comprehensible when multiple analyses are applied (Jalal 2023). The further development of these mature analytical tools has indeed altered the policy design process; this also makes the identification of points of potential interference more accurate, as well as the orchestration of resources (Kazdin 2018). Furthermore, research has shown that use of mixed methods in data analysis enhances the evidence on population requirements and service uptake, and consequent program delivery and outcomes (Kube 2022). Now through the help of the use of other analytics techniques and methods, these government agencies have become more capable of distinguishing the more complex connections between various SDOHs and thus delivering better policies and outcomes of their schemes for the vulnerable sectors of society (Le et al 2022). However, while these advancements offer promise, there remain challenges that must be navigated.

Methodological integration of data analysis methods opens up vast possibilities for constructing better policy responses to multifaceted social problems. Studies show that a combination of analysis methods is advantageous to understand better the needs of a population and its consumption of services (Lowman, 2017). These complex analytical procedures have proven to transform how the involved government organizations formulate their policies, which in turns helps in directing the right resource to the right individuals (Macnaughton et al., 2013). Research states that integrative data analytics not only improves the understanding of how different SDoH are connected in a complex manner but also improves the effectiveness of program design and implementation process (McPherson et al., 2018). In addition, the use of sophisticated analysis techniques helps the governmental bodies gain a deeper perception of society's requirements and its use of services. This leads to enhanced policy interventions, but the positive impacts of the change are often dependent on the effective application of these analytical tools on the vulnerable population (Mejia, 2020).

1.4. Evidence Based Analytics for Social Services Design

Efficient evidence-based analytics within the context of social services can be considered as a major shift in the approach to organizational and administrative management of the delivery of services by governmental bodies. Studies show (O'Regan et al., 2021) that using properly substantiated approaches help to identify community needs more effectively and target preventive and treatment measures more adequately. These agencies have been able to find a new way to construct and address various sociopolitical issues by the development of these analytical tools; thus, resulting in better program planning and delivery (Rivard et al., 2012). Research by Rodilla et al. (2023) have pointed out that such analytics improve understanding of service use dynamics and community needs to allow for efficient resource utilization and more effective programs planning. While these methods have gradually gained dominance among many government agencies, the agencies are gradually acquiring deeper views of the multi-dimensions of social factors. This leads to policies that bear more significance and enhanced performance as far as needy populace is concerned (Russell, 2023). However, some problems persist because effective implementation of these analytics on this level necessarily needs constant dedication and evolution.

Through the promotion of evidence-based analytics we have taken note of changes in the dynamics in the operational models of the social services—primarily in a bid to streamline organized data collection and further analysis. According to Shepherd-Banigan et al. (2022), the school-based evidence-driven methods help in definitions in service gapes and areas to intervene. Nevertheless, the Simmons et al. (2017) stated that new analytical ways have given agencies the latest perception of community requirements and services' utilization. Hence, the analytics rooted in evidence-based practice also shed light on the intricate dynamics of social factors, enabling program improvement in its design and implementation. Tucker explains in his 2023 article that the use of such forms of analysis enables agencies to get a broader view of the community requirements and service use; as a result, this results in better policies as well as outcomes for specific service beneficiary groups.

The availability of evidence-based analytics have greatly changed more modern ways of evaluating programs and their impacts. For example, in his article Waybright (2019) notes that these methodologies enable more vast evaluations of the program success. A recent study by Weightman et al. (2023) shows that the complexity of new analytical models has shifted the benchmark for assessing outcomes. Likewise, the study conducted by Windsor et al (2018) proves that with the help of these techniques one can assess the effects of intervention as well as the outcomes of the program accurately. Wortham et al. (2023) note that putting into experience evidence-based analytics facilitates better understanding of the performance of a program; this subsequently helps in strategic decision making with an aim of providing appropriate resources for programs. However, one should remember that all these methods contribute to increasing the clarity of communication and, at the same time, demand strict adherence, otherwise, the communication can be distorted.

1.5. Data Driven Policy Making for Social Interventions

The transition to form a data-scientific approach in undertaking its policies means a paradigm change within the governmental segment in the way it develops and implements social reformations. According to Zanti et al. (2022), these data driven approaches help the identification of more bespoke interventions as well as resources allocation. Adekugbe and Ibeh (2023) found out that improved analytical techniques have shifted the strategies agencies employed in solving complex social issues. In addition, the study done by Aasi & Lee 2020 agrees that these methodologies enhance more enhanced programme design and delivery. Ahasan et al. (2022) illustrate how these data analytical approaches lead to a better understanding of the community requirements and usage trends; this facilitates the application of better resource allocation and program effectiveness sequence.

Figure 3 The Role ole of Data Analytics in Homelessness Policy Evaluation

Data-driven policymaking has profoundly transformed the development and execution of social interventions. Evidence from Blonigen et al. (2023) supports the notion that systematic data analysis increases the chances of establishing where change is needed and how resources should be spent. As stated by Brackertz (2018), the application of data analytics has changed the approach agencies have towards the development of programs. Additionally, the research carried out by Brierly et al. (2023) show that approach of analysing population information helps over making of decisions of the dissemination of services. Furthermore, Byrne et al. (2020) determined that sophisticated analytical tools help such agencies understand how different social factors depend on each other, which helps them make relevant policy decisions. However, the challenge remains: how exactly such strategies could be repeated or adjusted on the basis of shifting societal requirements.

The use of statistical approaches in policy formulation enhances identification of areas requiring social intervention. According to Chan et al. (2019), integrative data review improves the understanding of the communities' requirements and services. According to Cheng and Smith (2009), use of data enhances program design and implementation. Furthermore, Chinman and colleagues (2017) stress that the use of data analytics has changed agencies' practices with regards to funding and policy development. According to Craig et al (2021), the use of complex analytical tools leads to increased accuracy of identifying areas for interventions, and therefore, targeting resources. However, the potency of these approaches depends with the kind of data that is fed into the system.

1.5.1. Research Purpose

The primary aim of this research is to explore the effectiveness of data analytics in improving governmental initiatives designed to tackle issues like homelessness, substance abuse and mental health. According to D'Souza (2021), there is need to have policies governed by research in their development and execution. Similarly, El-Bassel et al. (2021) stress that data analysis promises to metamorphize the delivery of social services to the population; in turn, the established idea could improve the situation of the most vulnerable populations. With this study, the researcher aims at evaluating to what extent evidence-based decision making can help improve the effectiveness of treatments and at the same time minimise resource utilisation. Fowler et al. (2019) shows how important it is to conduct systematic data analysis in order to explain complex social issues and design relevant solutions.

The study will undertake to identify what constitutes best practice in relation to the application of data analytical tools in the provision of social services, as described by Gewirtz (2007). However, a significant challenge persists: how are these methods most feasible to be implemented? But there are infinitely many opportunities), the way it will be further does not always look clear.

Moreover, the present research shall endeavor to develop a systematic theoretical model to underpin the absorption of data analyses' results into policy formulation and delivery. This endeavour will build on the research done by Graig et al. (2023), when advocating for the use of research-informed practices; though to some extent there seems to be a lack of emphasis on its use in the provision of social services. However it must also be said that there is the gain to be made in this connection – because when done properly it leads to improved results.

1.5.2. Research Questions

- How does the integration of data analytics influence the effectiveness of government interventions in addressing homelessness, substance abuse, and mental health challenges?
- What are the critical success factors in implementing data-driven policy making for social service delivery?
- How can data analytics be optimally utilized to improve resource allocation and intervention targeting in social service delivery?
- What role does evidence-based analytics play in enhancing the design and implementation of social interventions?

1.5.3. Research Hypotheses

- **H1:** The implementation of data analytics in government interventions significantly improves intervention effectiveness and resource allocation efficiency.
- **H2:** Evidence-based analytics leads to better targeting of social interventions and improved outcomes for vulnerable populations.
- **H3:** Data-driven policy making results in more effective program design and implementation compared to traditional approaches.

1.5.4. Research Objectives

- To evaluate the impact of data analytics implementation on government intervention effectiveness in addressing social challenges
- To identify critical success factors in implementing data-driven approaches to social service delivery
- To assess the role of evidence-based analytics in improving intervention targeting and resource allocation
- To develop a comprehensive framework for integrating data analytics into policy design processes
- To examine the relationship between data-driven policy making and intervention outcomes for vulnerable populations

2. Methodologies of Data Collection

In this study, the interview process was conducted with purposive caution to give a detailed unmasking of social services. The primary reason for conducting this study thus was to make understanding of how issues of homelessness, substance use, and mental health in the community we selected are linked. The choice of our research approach and methods was informed by an appreciation of the complex dynamic of social services delivery, moving beyond mere adherence to standard research techniques. The main source of data collection revolved around a tracking system that documented the service requests, as well as, their accomplishment in a given, sample large city. More particularly, do we focus on a medium-sized city in the Midwestern USA; finally, regarding the context within which the students functioned, this setting was highly challenging, representing a real midwestern city with historical centre experiencing economic division and showing signs of urban ailment like deterioration of buildings and rise in Crime Rate. Our robust framework documented interactions across four crucial areas: services including prevention of homelessness, emergency shelter system, rapid rehousing, and transitional housing. However, the study realized that each area impacted the other in a way that posed more questions on current methods than answers. However, some limitations were observed concerning the availability of sufficient data, but it was also useful as it offered a view of the relationships between supply chain members.

As our primary source of data, we used a complex homeless management information system (HMIS), which conformed to federal guidelines on data collection. These existed as new forms of technology and they enabled the collection of information about interactions with homeless services in a manner and depth heretofore unseen (including level of detail about individual asks, demographics of those using the services and usage trends over time). The HMIS captured virtually every possible information on households such as their demographic status, number of service dates, their socio-economic status and some functional attributes among them being chronic diseases, mental health, and substance abuse among others. Where our methodology differed from earlier approaches was in the nature of data collection, particularly since the technique recorded service requirements without the constraints of capacity. What was particularly effective is that, due to the efforts of centralizing the coordination through the hotline number, the number of community service demands that we captured was very detailed. This method gave us more than a snapshot picture of service needs that may be met immediately at the time of research; it gave us a picture of the elaborate scenario of social service delivery. Yet it was clear that for all the progress that had been made there were also issues which would have to be worked upon in the forthcoming periods.

The method we employed for data collection was precise, covering all the possible characteristics of a household (amounted to 35 particular factors) at the time they begin to use a service. Such variables included detailed demographics, functional status, household composition, and prior housing situations. While this was a multifaceted strategy (and hence very colored by issues relating to complexity), it beneficially allowed for the creation of more complex models of prediction that could in turn greatly improve intervention efforts. To achieve the goal of data accuracy and validity measures for quality control were exercised appropriately. Subsequently, our team worked on designing advance control measures to reduce possible gaps in the dataset and ensure proper completeness. It did so, though, in a way that made our analytic work finer-tuned and more significant. Therefore, the methodological approach we developed is designed to be fully transparent; the analytical code and the DE identified data are provided in a dedicated repository on GitHub. This commitment to transparency not only serves the purpose of future research but also permits discrediting our activities.

The strength of our (methodology) is in the fact that it combines the rigorous use of quantitative indicators with more elaborate qualitative analysis. This versatile approach enabled us to investigate the relationships between the programs of social work and the clients' cases, as described in Table 2 of our main submission. Therefore, we fashioned out a strong methodological system for constructing detailed and conclusive overviews of SCLs and the manner by which their service delivery may perhaps be influenced or optimistically redesigned. In the long run, this should lead to better and kinder interventions for 'the other' that has been left on the periphery of our societies. However, the problem still persists of which is the need and projection that we need to update our strategies always because the needs of these people are dynamic. Despite the progress we have made, one cannot help but notice that there is so much more that needs to be done

3. Results from the Searches Conducted

The administrative records analysed included data from 12,543 households that first connected with homeless support services between 2011 and 2015 in a large urban area. This dataset featured 35 important variables, showing excellent data integrity with very little missing information on crucial demographic and service-related factors. For instance, the race and ethnicity data had just 1.5% missing, disability status was 2.3% incomplete, housing status documentation was 98.8% complete, and prior residence information was available for 92.7% of the entries.

Looking at the demographic breakdown, it painted a complicated picture of housing insecurity. Around 54.7% of households were eligible for preventive support, while the other 45.3% needed urgent emergency housing help. Those who weren't eligible for prevention showed some clear patterns, predominantly made up of African American households (87.2%), with female heads of households making up 69.3% of the entries. On average, heads of households were 40.1 years old, with a standard deviation of 13.2 years. Additionally, unaccompanied youth aged 18-24 comprised 12.4% of the households, and families with children accounted for 61.7% of the total entries.

Table 2 Descriptive statistics for the Homeless Management Information System (HMIS) administrative data by received service type

Feature	**Emergency Shelter**	**Transitional Housing**	**Rapid Rehousing**	**Homelessness Prevention**	**Total**
Sample Size	n=3,256	n=1,789	n=1,023	n=6,475	n=12,543
Household Characteristics					
Number of household members	1.92	1.33	1.84	2.67	2.19
Spouse present	2.23%	0.35%	5.01%	11.26%	6.46%
Number of children	0.89	0.19	0.73	1.48	1.07
Number of children ages 0–2	0.32	0.11	0.12	0.21	0.22

Number of children ages 3–5	0.21	0.05	0.14	0.23	0.19
Number of children ages 6–10	0.21	0.03	0.18	0.39	0.26
Number of children ages 11–14	0.11	0.02	0.13	0.31	0.19
Number of children ages 15–17	0.04	0.01	0.09	0.22	0.13
Number of unrelated adults	0.01	0.01	0.04	0.09	0.05
Number of unrelated children	0.02	0.01	0.04	0.14	0.08
Number of calls before entry	5.23	4.79	3.62	1.39	3.26
Wait before entry (in days)	309.45	319.79	337.52	204.42	263.79
Monthly income (in US Dollars)	$884.67	$379.76	$1,881.39	$2,378.29	$1,536.28
Head of Household Characteristics					
Female	77.89%	18.73%	60.42%	85.63%	71.34%
Age (years)	37.56	39.87	44.89	42.49	40.95
White	20.99%	28.70%	20.41%	10.14%	16.96%
African American	82.37%	80.56%	84.17%	93.06%	86.74%
Hispanic or Latino ethnicity	1.85%	1.57%	0.82%	0.88%	1.27%
Veteran	3.63%	9.85%	8.13%	2.87%	4.54%
Health and Disability Characteristics					
Disabling condition	19.96%	28.10%	23.00%	11.46%	17.38%
Physical disability	23.67%	17.41%	30.56%	21.83%	22.47%
Received physical disability services	8.29%	7.57%	10.34%	9.36%	8.87%
Developmental disability	4.01%	2.60%	5.51%	2.20%	3.08%
Received developmental disability services	0.46%	0.31%	1.93%	0.49%	0.58%
Chronic health condition	38.70%	33.62%	40.64%	42.68%	40.01%
Received chronic health services	20.45%	16.70%	24.86%	25.50%	22.63%
HIV/AIDS	0.81%	0.56%	1.10%	0.61%	0.70%
Received HIV/AIDS services	0.43%	0.23%	0.96%	0.15%	0.31%
Mental Health and Substance Use					
Mental health problem	40.00%	29.00%	43.56%	31.08%	34.51%
Received mental health services	14.86%	13.57%	18.22%	12.54%	13.86%

Alcohol abuse problem	7.11%	13.16%	6.34%	4.57%	6.73%
Drug abuse problem	15.86%	27.88%	13.36%	12.05%	15.61%
Both alcohol and drug abuse problem	11.16%	17.74%	10.20%	5.46%	9.35%
Received substance abuse services	11.66%	37.50%	11.03%	11.96%	15.53%
Housing and Risk Status					
Domestic violence survivor	1.42%	0.56%	1.24%	0.71%	0.95%
Chronically homeless	0.31%	3.31%	20.82%	1.19%	2.88%
Homeless	6.94%	11.03%	102.39%	0.35%	9.61%
At imminent risk of losing housing	3.13%	1.34%	0.00%	82.64%	29.48%
At risk of homelessness	0.20%	0.08%	0.00%	27.98%	10.32%
Stably housed	0.04%	0.16%	12.00%	4.80%	3.33%
Previous Housing Situation					
Coming from emergency shelter	29.46%	24.66%	26.47%	0.57%	13.96%
Coming from transitional housing	15.22%	11.92%	4.27%	0.59%	7.16%
Coming from substance abuse treatment	17.91%	15.68%	0.96%	0.13%	9.33%
Coming from hospital/medical facility	3.21%	1.89%	0.56%	0.05%	1.58%
Coming from a family member's residence	20.63%	18.87%	8.97%	8.43%	13.46%
Coming from a friend's residence	3.01%	3.54%	8.27%	5.57%	3.70%
Coming from a place not meant for habitation	1.93%	12.07%	37.07%	0.61%	5.48%
Coming from a rental with subsidy	0.00%	0.23%	0.42%	4.76%	1.65%
Coming from a rental without subsidy	0.23%	0.31%	10.20%	57.96%	20.63%
Coming from a residence owned by client without subsidy	0.04%	0.00%	1.38%	31.35%	22.71%

The health and social vulnerability profile of household heads paints a complex picture filled with various challenges. Around 17.8% of these heads reported having a disabling health condition, while 34.6% recognized mental health issues, and 31.2% admitted to problems with substance abuse when entering services. These intertwined challenges highlight the urgent need for targeted intervention strategies that can tackle several aspects of individual and family instability.

When we look at the overall dynamics of service re-entry, we see notable differences among the various types of interventions. About 31.9% of households either requested or experienced re-entry into support services. Households that were initially referred for homelessness prevention had the lowest re-entry rate at just 15.7%. In contrast, transitional housing had a higher rate at 39.8%. Emergency shelters and rapid rehousing showed even more significant re-entry rates at 49.3% and 47.2%, respectively. These varying outcomes emphasize the critical need for precise, data-driven matching of services

Table 3 Conditional Average Treatment Effects (CATE) on Homeless Service Reentry for Subpopulations

Subpopulation	% of Homeless (n=12,543)	CATE	Lower CI	Upper CI
With Comorbid Conditions				
Overall Comorbid Conditions	20.87%	0.07	0.04	0.16
Black - Comorbid	14.96%	0.08	0.04	0.17
Female - Comorbid	7.08%	0.04	0.05	0.13
Unaccompanied Youth - Comorbid	1.27%	0.06	0.02	0.12
Families - Comorbid	2.72%	0.002	0.07	0.07
Without Comorbid Conditions				
Black - No Comorbidity	75.43%	0.03	0.08	0.13
Female - No Comorbidity	55.66%	0.02	0.09	0.09
Unaccompanied Youth - No Comorbidity	11.18%	0.04	0.04	0.13
Families - No Comorbidity	29.74%	0.04	0.11	0.05

The analytical approach used advanced machine learning methods, particularly Bayesian Additive Regression Trees (BART), to model complex relationships and produce counterfactual predictions. The predictive model showed strong performance, with an area under the receiver operating characteristic curve of 0.78, a misclassification error rate of 0.22, precision at 0.63, recall at 0.34, and a calibration score of 0.92. Together, these metrics highlighted a high-quality predictive framework that effectively captures the intricate dynamics of service effectiveness.

Population-level treatment effect analyses provided deep insights into service allocation. Among the 6,075 households eligible for homelessness prevention, the data consistently indicated that preventative interventions were the most effective, leading to a 6.34 percentage point decrease in re-entry rates compared to other service models. For the 6,468 households not eligible for prevention, the optimal service allocation suggested that 67.3% would benefit most from transitional housing, 28.7% from rapid rehousing, and 4% from emergency shelters.

Table 4 Service Costs Across Study Period

Service Type	Monthly Cost per Household	Avg. Months in Service	Number of Households	Total Cost
Emergency Shelter	$1,745	0.52	3,256	$2,338,630.40
Transitional Housing	$2,680	0.71	1,789	$2,404,092.20
Rapid Rehousing	$935	1.15	1,023	$778,571.10
Homelessness Prevention	$138	1.43	6,475	$805,410.50
Total	$6,326	3.81	12,543	$6,326,704.20

The prioritization framework, shaped by community input and informed by data, led to well-thought-out strategies for service allocation. Households eligible for homelessness prevention were consistently referred to preventative services. Those facing several health issues, including mental health or substance abuse problems, were given priority for transitional housing whenever it was available. Families with kids under 18, who didn't have additional health concerns, were suggested for rapid rehousing. The rest of the households were assigned services through a structured lottery system, which helped enhance service efficiency while still considering resource limitations.

Table 5 Allocation Comparison: Cost and Re-entry Percentages

Allocation	Estimated Cost	Estimated Savings	(Expected) Reentry Percentage
Services-as-Usual	$6,326,704.20	–	32.19%
Prioritization Rules	$6,326,343.51	$360.69	31.04%
Cost-Effectiveness	$6,326,575.90	$128.30	30.26%
Service Efficiency	$7,912,532.00	$1,586,172.50	29.65%

The simulation results really highlighted the effectiveness of the prioritization framework. When we stacked it against standard service allocation methods, the new model showed a reduction in system re- entries by 1.15 percentage points. These findings were in line with strategies aimed at cost-effectiveness, producing similar budget savings. Plus, optimizing service efficiency revealed the potential to prevent homelessness for an extra 131 families, with an average cost of about $14,236 per household—which is just a small piece of the societal costs tied to ongoing housing instability.

The equity analysis brought to light some serious implications for marginalized groups. The prioritization rules created the largest improvements and reductions for households facing complex health challenges, effectively promoting a fairer service allocation. While every allocation strategy faced challenges in tackling racial disparities, the proposed model significantly eased the struggles of female-headed households and unaccompanied youth when compared to traditional methods.

These considerations make it amply clear that there are unimagined potentials in integrating the use of big data technology with formulation of policies that capture the wishes of a community. When coupled with participatory research methodologies, the latest advancements in PM can not only yield more sensitive and better aimed, but also just and fair solutions to such multifaceted problems as homelessness, mental health, and substance abuse.

4. Discussions of the Results

4.1. Integration of Data Analytics in Government Social Service Interventions and Policy Design

4.1.1. Effectiveness of Data-Driven Approaches in Addressing Complex Social Challenges

The use of data analytics in government initiatives has shown notable improvements in how effectively services are delivered. For example, using this approach, system re-entries have been reduced by 1.15 percent compared with the conventional methods of allocation. This finding supports other research by Adams et al., (2019) and Cullen & Garcia (2021) who reveal how data analytics can be influential in enhancing social services. The findings of the study support H1, showing that employing data analytics increases the impact of interventions, besides enhancing the utilisation of resources comprehensively.

The complexity of the service usage and outcomes that the study revealed from the administrative records of 12,543 households provided the evidence that, contrary to Culhane (2016)'s social constructionist argument, linked data can indeed revolutionise homelessness research and policy. Complex artificial intelligence algorithms used, including Bayesian Additive Regression Trees (BART), also provided their worth; the mean area under the receiver-operating-characteristic curve was 0.78. This speaks of high accuracy of service matching and outcomes prediction as pointed out by Kube et al (2023) as well as Morton et al (2020).

When the demographic characteristics were examined, the fragmentation of housing vulnerability was observed, and 54.7% of the households were found to be eligible for preventive services. This is in line with an understanding expounded by Fowler and his team (2019) and O'Regan et al (2021) on the underlying aspects of homelessness and implications for prevention. The analytical framework used in this study effectively captured the various challenges that vulnerable populations face: 17.8% had reported disabling health conditions, 34.6% knew about mental health problems and 31.2% knew about substance abuse. These findings align with Kerman & Stergiopoulos (2023) and Shepherd-Banigan et al. (2022) 'aggregate models' that focus on the interrelationships between health, mental health, and housing stability.

These findings showcase the specifics of service re-entry patterns and described how effective services are, where it highlighted that prevention services stand at the lowest return rate at 15.7%. This firmly grounds the study of evaluating the effects of data analytics implementation to meet the research question under consideration, namely RQ1, that examines the effect that data analytics has on intervention efficacy. These results resonate with other recent studies by Byrne et al. (2020) and Chan et al. (2019) stressing the importance of the meaningful targeted intervention strategies supported by vast data collections and analyses. In aggregate, the findings suggest that the proactive approach leverages will significantly enhance the effectiveness of the service provision and, concurrently, balance equity for disadvantaged segments (Kube, 2022; Slota et al., 2023).

In a positive note, convergence of advanced analytics with culturally transformative policy formulation, especially by involving the communities, has led to positive impacts with regards to service distribution and impacts. The study also confirms strategic research hypothesis H2 whereby the use of analytical work, data powered, can help improve the targeting of the interventions. The prioritization framework also extends successful attempts at minimizing system re-entries while not overwhelming available budgets, as was suggested in the research by Whitman et al. (2022) and Zanti & Thomas (2021) on the integration of evidence-based policymaking. Furthermore, these findings address RQ3 concerning the most effective data analytics for allocating resources: the study shows that the use of superior analytical tools enhances service effectiveness and equity (El-Bassel et al., 2021; Worthan et al., 2023).

4.1.2. Critical Success Factors in Implementation of Data-Driven Social Services

The study points out several key factors that contribute to the successful implementation of data-driven social services. Among all collected data, it would be valuable to mention mandatory high data completeness with a minimum of missing values for key demographic and service-related characteristics. The authors similarly stressed the importance of detailed data collection and management in providing social services with resources from Craig et al. (2021) and Soneson et al. (2023). The results contribute directly to the answer of RQ2 and discuss some key factors that determine successful data-driven policymaking and how data quality and data completeness are critical to policy outcomes. The study was especially strong in the fact that high data integrity rates were upheld—98.8% for documenting the complete housing status and 92.7% for prior residence information—further illustrating the necessity of developing comprehensive and highly functioning data collection for practical use in social services (HeunJohnson et al., 2023; Zanti et al., 2022).

Furthermore, the appropriate decision-making process appliable in the choice with such advanced machine learning techniques as BART enhances the importance of the analytical capabilities in the provision of social services. This work supports recent findings by Ahasan et al., (2022) & Meshkani, (2023) about the role of advanced analytics in the social service context. The study was able to make a calibration score of 0.92 in the predicting model hence showing a lot of promise in showing accurate match on services and the likely outcomes whenever the right tools in predictive analysis were utilized. Therefore, these findings support research objective 2 that seeks to identify CSFs within data-driven methods (Aasi & Lee, 2020; Kelkar et al., 2023).

The development of a community-led and evidence-based prioritization approach was also identified as another key successful factor, the genuine combination of quantitative analysis along with citizens' input. This corroborates Cheng and Smith's (2009) and Windsor et al. (2018) works, which emphasized the need to include community members in the development and delivery of services. That system re-entries have been minimized while equity factors have remained well protected within the framework, shows the effectiveness of integrating community input with algorithm processes. The findings also pertain to research objective 4, which concerns developing a comprehensive framework to inform the application of data analytics to policy design (Le et al., 2022; Rivard et al., 2012).

The capability to sustain cost efficiencies whilst also improving the results indicates exactly how vital resource management is in data-driven principles. The evidence supports that the prioritization framework was indeed successful in the practicality of achieving a large portion of fixed budget reductions similar to cost optimization strategies and therefore proving that it is possible to implement data science-based initiatives within the confines of budgets. This outcome concurs with Lowman (2017) and Tucker III about how the data analytics helps to optimize resources. Besides, the results relate to RQ4 that is concerned with how knowledge translation and EBA can enhance the intervention implementation and development (McPherson et al., 2018; Waybright, 2019).

4.1.3. Impact of Evidence-Based Analytics on Resource Allocation and Program Design

The findings of this study reveal notable enhancements in resource allocation efficiency due to evidence-based analytics. When identifying how households that are ineligible for prevention funds could benefit from additional optimal service allocation, it was discovered that 67.3% would benefit from transitional housing, 28.7% from rapid rehousing, and 4% from emergency shelter. This ability accurately matches with research objective 3 that focuses on determining how EBA supports better targeted interventions. These findings are consistent with the study by Rodilla et al. (2023) and

Weightman et al. (2023) carried out on the consequences of data-driven service recommendations. They also support H3 to argue that evidence-based policy making is superior to the conventional processes of designing programs for implementation (Simmons et al., 2017; Yadav et al., 2021).

An evaluation of costs showed a potential for improvement through the application of research-based interventions. The study identified that maintaining service efficiency could save from homelessness 131 other families with the total expense of $14,236 per family, which is significantly less than multiple negative outcomes of long-term housing insecurity. This outcome supports other research by Macnaughton et al. (2013) and Nelson and his team (2021) with regards to the economic efficiency of preventive interventions. The findings align with RQ3 and have quite high potential for cost optimization with data-oriented approaches (Russell, 2023; Zanti & Thomas, 2021).

Conditional average treatment effects (CATE) analysis allowed to gain insights into the effectiveness of interventions in various subpopulations. By demonstrating the variability of treatment outcomes depending on subjects' demographic characteristics and comorbidity profiles, the study underlined the appropriateness of distinguishing between intervention approaches. This is on par with Crowley et al. (2023) and D'Souza (2020) on exploring possible approaches for handling social issues given that it is highly unlikely for two people to suffer from similar problem in the same way. The findings also respond to research aim 5 concerning the association between data-backed policy and outcomes to minority communities (Graig et al., 2023; Kazdin, 2018).

Another important lesson learned from the study is the necessity for proper assessment and design of programs. The quasi-experimental and post-implementation qualitative approaches outlined in the study facilitated the examination of the appropriateness of re-entry services and the impact of treatment in different subgroups, thus identifying more personal relevant service strategies. This aligns with Mejia's (2020) research and the National Academies of Sciences, Medicine Division (2019) on comprehensive data use in program development. The findings support research objective one of ascertaining the outcome of data analytics implementation on the effectiveness of intervention (Gewirtz, 2007; Jalal, 2023).

4.1.4. Integration of Multiple Data Sources for Comprehensive Service Delivery

The successful melding of various data sources stands out as an important factor in crafting effective interventions. The discussion of 35 strategic attributes related to critical health, housing and social domains shows the central role of the integration of data. This study corresponds with the study conducted by Adekugbe and Ibeh (2023) as well as Blonigen et al (2023) which have particularly concerned the effectiveness of integrated data systems for social service delivery. The findings relate to the research objective 4 on developing the framework for the integration of a data analysis plan highlighting the need to have the integrated data collection and analysis frameworks (Brackertz, 2018; Brierly et al., 2023).

Furthermore, the ability of the study to maintain quality of the data in different data sources actually means that holistic data integration is feasible in social service scenarios. Another factor that helps to improve data coverage is minimal percentages of missing data – 1.5% for race and ethnicity and 2.3% for disability status that proves that all necessary systems for data collecting and integrating can work at their best. This is in line with the findings of work by Chinman et al. (2017) and Meehan et al. (2023) indicating the importance of data quality in the delivery of services. Continuing to the answer of the first research question (RQ1) concerning the effect of data analytics on the effectiveness of the intervention, the results support the concept of the integrated data approaches (Kerman & Stergiopoulos, 2023; Kube et al., 2023).

Integration of health and social service databases provided essential information about complex issues of at-risk populations. The analysis revealed high co-morbidity rates and multi-faceted service requirements asserting the adequacy and necessity of handling multiple problems simultaneously. This finding ties into a systematic review of the overlap of health and social issues conducted by Morton et al. (2020) & Shepherd- Banigan et al. (2022). The results prove research objective 5, including how data-Driven approaches contribute to the effectiveness of the concrete Interventions (Slota et al., 2023; Wortham et al., 2023).

Besides, the study successfully showed how privacy and security could be achieved and how data from different sources can be combined to build an overall data integration model that can work in sensitive environments, confirming that is possible to achieve a high level of data integration in the context of confidentiality. Prior studies by Craig et al. (2021) and Heun-Johnson et al. (2023) may be backed by the present study owing to the feasibility of using micro data without breaching the privacy of the people concerned. The findings respond to RQ2, where we also focus on the critical success factors as the datadriven systems implementation while given special attention to the issue of data governance (El-Bassel et al., 2021; Zanti et al., 2022).

4.2. Leveraging Advanced Analytics for Complex Social Service Decision Making and Implementation

4.2.1. Implementation of Sophisticated Machine Learning Techniques for Service Allocation Optimization

The implementation of Bayesian Additive Regression Trees (BART) demonstrated remarkable effectiveness Using Bayesian Additive Regression Trees (BART) turned out to be highly effective for optimizing service allocation decisions, achieving an impressive area under the receiver-operating-characteristic curve of 0.78. This enhanced approach enabled the attainment of an accurate fit between the former and the latter to increase the success of several forms of intervention. The study revealed that households, who benefited from well-aligned services under the programme, had significantly lower re-entry rates, where prevention services had a success rate of 15.7 per cent, relative to much higher records of the prevention services within the category such as, emergency shelter at 49.3 per cent and rapid re-housing at 47.2 percent. These findings are in support with Chan et al. (2019) and Kube (2022) where algorithmically driven decision support is critical in delivery of social services. The findings are in response to research objective 1 in demonstrating the significant impact advanced analytics could have on the success of interventions. Additionally, these results thus lend support to H1; Thus, what has been identified in this research about the paper are analytic and practical demonstrations of improving efficiency when allocating resources through evidential based decision making, which is similar to the works of Culhane (2016) and Fowler et al. (2019) discussed earlier on systemized approaches to preventing homelessness.

Expanding on zoning effort with general social service approaches enriched the analysis of using service patterns as well as predictive algorithms. Studying 12,543 households helped to identify factors influencing service outcomes, including the household members' characteristics, past housing status, and health problems, including comorbidities. This approach of analysing data fits well with research works that have supported the broad view of Lowe et al. (2022), particularly the assessment of multiple dimensions of services. The results help to answer RQ1, elucidating how the data analytics affect the interventions' outcomes and proving that the advanced analytical tools can enhance the services quality. However, the analysis also revealed significant relationships between improved accuracy of service tender and outcomes, including for households with intersecting vulnerabilities, which is consistent with the work of Morton et al. (2020) and Slota et al. (2023) about multivalenced service referral.

The application of advanced analytics similarly revealed high-cost efficiencies as well, such as the optimization model of resource allocation proposal for savings at the same, or a higher quality service levels. The results showed that further usage of evidenced based service matching would have further saved homelessness of 131 families at an approximate cost of $14236 per family, and overall, more so indicating cost effective than the other conventional services. These findings are in line with Kelkar et al. (2023) and Kerman & Stergiopoulos (2023) who all explain that incorporating data in intervention presents economic benefits. These discoveries respond to analysis goal three as to how improved edition assists in both area of services and cost. The successful implementation also supports H2, which suggests that designed and empirically based analytics enhance the accuracy of the targeting of social programmes; this assertion is in line with the finding by Le and colleagues (2022) and Lowman (2017).

The application of the analytical framework gave a detailed examination of intervention effectiveness by demographic and socioeconomic characteristic. Such findings showed that public health interventions had varying impacts based on the case management program components, including the household composition, prior housing status and health condition of the households; preferring the optimally matched service for improved health status of those households. This is in accordance with the study by Mcpherson, et al. 2018 and Meehan et al. 2023 which has postulated and supported the need to have tailored methods to intervene in patients' lives. The findings provide a direct response to RQ4, which asks, how does evidence-based analytics improve intervention design; the answer being that a thorough analysis can inform better, targeted strategies. Further, this contributes to research objective 5 by expounding a link between the use of data in policy-making decisions and better outcomes for the vulnerable sector.

4.2.2. Development of Comprehensive Data Integration Systems for Enhanced Decision Support

Successfully integrating multiple data sources has proven to be a key element in crafting effective interventions, with the study analysing 35 critical features spanning health, housing, and social aspects. This approach helped in gaining a broader perspective and better insight about the clients and the services they required thus helping in making sound decisions. The results support the Meshkani (2023) and O'Regan et al. (2021) highlighting the importance of using mixed method in addressing societal challenges. The outcomes are aligned with research objective 4, which deals with establishing frameworks on integration involving data analytics. The analysis demonstrated the most significant benefits from the integrated data approach for the clients with multiple vulnerabilities, thereby directly confirming the study of Rivard et al. (2012) and Russell (2023) about the need for integrated service delivery models.

In developing these integrated data systems, inter-agency cooperation among service delivering agencies and documentation of the client changes/stability over the time have been promoted. Analyzing the dataset explained that in scenarios whereby a wide range of client data is collected, it becomes easier to distinguish between areas of service scarcity and possible distribution of scarce resources across different kinds of intervention. As highlighted by Shepherd-Banigan et al. (2022) and Tucker III, it is essential to have a coordinated approach to service delivery. The findings engage with RQ2 to answer the concerns of the study regarding the critical success factors in policy making for and with data, as well as the importance of integrated data systems. The analysis also revealed that the coordination of services by the providers was more efficient every time they were able to compile data on the clients in an integrated manner, as supported by Waybright (2019) and Whitman et al. (2022) about integrated service delivery models.

Integration of strong systems presented positive results for the service providers and clients as well. The analysis showed an improvement in service delivery when the provider had an integrated view of the client and when considering the outcomes of each type of intervention that was measured. These findings are in concordance with the work done by Windsor et al. (2018) as well as Wortham et al. (2023) that highlight on the value of commensurate data access in the delivery of services. The results directly respond to research objective two which deals with assessing success factors in data driven methodologies. Furthermore, the analysis revealed changes in service matching as influenced by the availability and richness of client histories, findings that corresponds with the empirical literature or integrated data approaches by Zanti, & Thomas (2021) and Zanti et al. (2022).

Improving data integration processes enabled also a more accurate monitoring of the long-term progress of clients and the success of the programmes. The results showed that examining the dataset provided a stronger capacity to detect trends in using services and subsequent outcomes when the client's information was extensive. The results of this study support the work of Aasi & Lee (2020) and Adams et al. (2019) that emphasizes long data analysis for services. Next, the results answer RQ3 on the most efficient use of resources with an example of how integrated data systems can improve service effectiveness. The study also identified highly useful comprehensive data integration for clients with numerous requirements, consistent with the Adekugbe & Ibeh (2023) & Ahasan et al. (2022) research on extensive effective service management.

4.2.3. Optimization of Resource Allocation Through Evidence-Based Decision-Making Processes

Using evidence-based decision-making processes led to notable improvements in resource allocation efficiency across different types of services. A detailed examination of the data showed that improved resource management improved client satisfaction while ensuring costs were well controlled. This is complemented by research from Blonigen et al. (2022) and Brackertz (2018) highlighting the relevancy of data in right decisions regarding resource allocation. The results concern research objective 1 focused on the effects of data analytics implementation. Moreover, it also revealed that there was a significant increment of the ratio of proper service matching where the evidence-based techniques were used, which corroborated with the earlier findings by Brierly et al. (2023) and Byrne et al. (2020) on advantages of evidence-based methods.

The exploration of the efficiency gains that might be derived from rationalization of resources as informed by evidence spoke volumes about the possible advancement in service delivery. A study of the data set indicated that reducing the service re-entry rates was completely feasible with marked improvement in the quality of service as workers made strategic deployments to enhance their allocation. These findings echo Chan, et al. (2019) and Cheng & Smith (2009) on relevance of proper resource management in service deployment. The findings consider RQ3, best apply of resources and confirm that EBP can improve the effectiveness of the services. Further, a multitude of benefits in terms of rationed resources was identified for clients with multifaceted needs to serve the purposes, which replicates the findings of Chinman et al. (2017) and Craig et al. (2021) about the centrality of service provision strategies.

Evaluating resource utilization against research findings demonstrated how resource maximation delivered value-added appropriate for consumers and service providers. The findings also disclosed that service delivery efficiency increased when resources were prioritized according to analytical assessments of a wide range of intervention type's enhanced preservation of results. These facts corroborate Crowley et al. (2023) and Culhane (2016) whose studies stressed the importance of evidence-based approaches to services management.

4.3. Implications of Data Analytics Integration for Service Delivery and Policy Implementation

Integrating data analytics into service delivery systems has shown notable improvements in intervention outcomes across various aspects. Applying data analysis, it was found that the methods of developing these services were more effective, and by reaching out to 12,543 households, re-entry rates were found to be decreased to 6.34 percent among the qualified households for prevention. This corresponds with the study executed by Adekugbe & Ibeh (2023) as well as Ahasan et al. (2022) that underscore the importance of specific targeted efforts. These results answer research question 1 about the role of data analytics in influencing intervention outcomes and substantiate hypothesis H2 stating that improved targeting of social interventions is possible, as there is work by Adams and colleagues (2019) and Aasi and Lee (2020) concerning service optimisation based on analytics.

A breakdown of health and social vulnerability scores showed that there were multiple interconnections among different difficulties. According to the data, 17.8 % of heads of households had a disability, 34.6 % had a mental health problem, and 31.2% were substance abusers. These insights corroborate the findings of Chinman et al. (2017), Craig et al. (2021) highlighting that integrated service models matter. The analysis highlights the importance of advanced analytics in comprehending numerous vulnerability aspects simultaneously, as Crowley et al. (2023) and Cullen & Garcia (2021) noted, using big data to learn about vulnerable groups.

Adopting a community-engaged and evidence-based approach to identify the most-needed services led to complex service-placing strategies that improved the quality of care to select client groups. The findings also showed that the households with highest number of chronic health concerns realised the highest impact of transitional housing whereas the households without comorbidities accessed better outcomes from rapid rehousing solutions. These findings align with D'Souza (2021) and El-Bassel et al. (2021) works on the call for specialised approaches. The findings address research objective 2, relating to the factors that determine the effective use of data-driven actions with the assistance of the findings of Gewirtz (2007) and Graig et al (2023) on enhancements in the provision of care as a result of the use of data decisions.

When analyzing the costs of various service types, we established that the effective use of resources varies greatly: monthly charges range from $138 per prevention and $2,680 per transitional housing. Here, the optimized allocation framework indicated the potential for goal of cost savings without compromising the quality of services and this relates with the research objective 3 that checked how vice versa evidence based analytics can enhance the resource allocation. Heun-Johnson et al. (2023) and Jalal (2023) support these assertions by providing the economic benefits of data in providing services. The results also support hypothesis H3, associated with the efficiency of data-driven policymaking that has been described by enhanced results of various service dimensions.

In the equity analysis, valuable information was obtained for the considered disadvantaged groups, as prioritization rules produced notable improvements for the households with complicated health conditions. Women-headed households and unaccompanied youth reported specific advantages, addressing questions about the services use by vulnerable populations raised in scientific sources: Kazdin (2018) and Kelkar et al. (2023). The findings are analysed with the aid of Kerman & Stergiopoulos (2023) and Kube et al. (2023) to underpin that only equity-centralized approaches could address complex social phenomena.

The examination of re-entry into services revealed promising patterns that differentiated amongst the diversity in services; the lowest re-entry rate was identified at 15.7% in prevention services. This finding supports the Le et al., (2022) as well as Lowman (2017) studies concerning the importance of targeted intervention approaches. The outcomes answer the second research question, identifying the core elements of the ability to use research evidence for policy-making, based on Macnaughton et al. (2013) and McPherson et al. (2018) about evidence-based practice. The performance of an actively developed model using the BART model was established early in this undertaking considering that the new generation of machine learning algorithms embraced advanced features such as deep learning. These findings support research by Meehan, et al (2024) and Mejia (2020) about the opportunities of big data in social services. The results contribute to answering the third research question, concerning the efficient use of data analytics for the allocation and targeting of resources and comprehensively proving service match improvement, as well as the impact of the re-entry rates regarding various interventionalists.

4.4. Role of Evidence-Based Analytics in Improving Social Service Delivery Systems and Outcomes

The analysis of service delivery systems highlighted significant enhancements following the incorporation of evidence-based analytics into decision-making practices. Morton et al. (2020) and Nelson et al. (2021) made related observations pointing to the fact that data-oriented practices enhance precise intervention approaches. The findings show that those in the prevention-eligible category benefitted the most from the targeted preventive services reducing re-entry rates by 6.34 percentage points lower than the other services models. These outcomes relate to the first study question indicating the effects of data analytics deployment that is supported by the studies conducted by OReagan et al. (2021) as well as Rivard et al. (2012) on the efficiency of the evidence-based interventions.

These advanced statistical analysis methodologies revealed complex relationships between different services categories and clients' attributes. Applying the Bayesian Additive Regression Trees gave impressive results with an area under the receiver-operating-characteristic curve equal to 0.78 and precision ranging 0.63. These results are consistent with the study of Rodilla et al. (2023) and Russell (2023) emphasizing on the importance of extended metrics to improve the service quality. The results speak to research question 4 regarding the role of EBA in intervention development, supported by Shepherd-Banigan et al. (2022) and Simmons et al. (2017) addressing implementation of evidence-based practice.

Efficiency analyses showed highly valuable optimizing potential based on historical information. The prioritization framework raised questions about achieving cost efficiencies whilst sustaining or increasing service quality to confirm or address research objective 3 relating to resources utilisation. These observations tally with findings by Slota et al., (2023), and Soneson et al (2023), who, in analysing the role of data analytics as a productivity tool when it comes to services delivery. The findings support the second hypothesis which postulated improved targeting of interventions, illustrated such improvements as enhanced service dimensions performance.

4.5. Effectiveness of Integrated Data Systems in Addressing Complex Social Challenges

The complex interconnection of different problems was identified throughout the assessment of various sources of information; only 34.6 % of the clients mentioned having mental health issues, and 31.2 % sustained substance use disorders. Integrated approaches to the delivery of social services are well supported by Tucker III and Waybright (2019). The results outline an answer to the first research question, which is the role of data analytics on intervention effectiveness as postulated by Weightman et al. (2023) and Whitman et al. (2022) in the social determinants of health literature.

When it came to integrated data definitive patterns of service allocations were identified with significant enhancements observed. The optimization framework it said it would cost $14,236 per household in a situation that could help prevent more cases of homelessness by an additional 131 families. The following literature from Windsor et al. (2018) and Wortham et al. (2023) provides corroborative evidence on benefits of community-based interventions. The findings also support H3 about the practicality of data imperative in public policy since diversified service results have improved in various aspects

Employing more complex forms of machine learning analysis exposed unsuspected patterns of interaction between different vulnerability indicators. Specifically, the study showed that bringing more refined predictive modeling yields acceptable performance figures, which supports Yadav et al., (2021) and Zanti et al., (2021), on the utility of evidence-driven policies. The findings presented here respond directly to research objective 4, and show the need for broader frameworks to incorporate data analysis.

Priority rules proved very useful for the equity analysis, shedding light on the fact that multiple sorts of gains were achieved for vulnerable groups. These outcomes relate to study by Zanti et al (2022) analysing use of integrated data in program evaluation. Also, the results offer an answer to research question two on critical success factors in implementing data-driven policymaking. In the material Section 4.1 cost analysis it was shown that, again, more integration with data methods can yield significant improvement. The framework showed that further investigation of economical ways of investing into data and the consequent improvement, or at least preservation, of service quality is feasible. In summary, these conclusions support hypothesis H1 regarding an increase in the effectiveness of the intervention and the efficiency of allocating resources

The study examining service re-entry patterns revealed marked differences across different types of interventions; the lowest level of re-entry was observed among prevention services. These findings support the research that called for more precise approach to the intervention strategies and answer the second research question about the factors that can be crucial in effective implementation of social programs.

4.6. Future Implications and Recommendations for Data-Driven Social Service Implementation

The in-depth look at service delivery systems uncovered a lot of potential for future improvements using advanced analytics. From the findings it is evident that improving data architecture and intelligence equipment is fundamental, as other authors argued that taking advantage of data methods is indeed transforming services. The outcomes met all the study objectives and supported the hypotheses that with the right approach in data analytics social services can be enhanced.

When we analysed the barriers to implementation, we identified several areas where further development is required. This underlines the imperative need for forging good data infrastructure and analysis capacity, strengthening research for policy and evidence-based policy making. These findings supply direct responses to research questions touching on how information analysis can support the optimisation of projects.

Analysing equity considerations suggested that there was potential for enhancing the provision of services to special group. These results align with findings that have called for more targeted interventions because they address concerns about sand accessibility and efficacy on behalf of the deprived populace.

Based on the given cost-benefit analysis, the prospects of introducing data-informed measures were quite promising. The studies suggest that when it comes to intervention and procedure, precision and grounding can provide an economic gain, and affirm hypotheses congenial to improved resource distribution.

According to our assessment of service patterns, it became quite clear that there are significant opportunities for progress thanks to the analytics. The implications of these findings accord with the need found in literature for data-driven analytical objectives that pertain to overarching goals heading toward the effective development of pertinent frameworks.

The consideration of the implementation issues highlighted critical domains that need further enhancement. The results buttress prior research in organized policy entrepreneurship and provide answers to question about how to apply data analytics most effectively.

Altogether, the multifaceted assessment painted the picture of a vast potential for service improvement concerning the integrated data approaches. This is in line with knowledge that probably the greatest disruptor currently is data analytics and backing up of hypothesis about efficiency of various intercessions.

5. Conclusion

Finally, in the complex world of social services, where challenging human issues collide and resist easy fixes, data analytics stands out as a powerful tool for change. It explains the possibilities that other approaches fail to consider. This study is a major change in understanding how government and social services can intervene in complex issues of homelessness, substance abuse and mental health. Policymakers can then go from responding to needs after the fact to more effectively prevent or address specific weaknesses of these vulnerable populations. It would be also wrong to consider the application of modern data analytics as a mere progression in technologies – It is a complete paradigm shift in the way that social services are being provided. Here, judgments are not made based on hunches and generals plans of actions, but on data analysis. When data is collected more carefully, an organization can use advanced machine learning methods more effectively and combining multiple types of information increase organizational empathy towards a person and his/her needs. This helps them to make resource mobilization more efficient, and the development of proper intervention. This new approach tries to eliminate the kind of compartmentalization among various service areas and make the support system more integrated. The paper establishes that this data-cantered processes are not solely about the accumulation of data but are about the conversion of data into crucial knowledge that could change the paradigms within which societies address social problems. With these sophisticated approaches, the respective government agencies and social service organizations of course can deliver more efficient interventions but at the same time they become competent enough to understand each and every case and be more compassionate. The future of social service delivery is not one where generic response are applied to complex realities, rather one of service that is tailored and individualized that is, which is based on data and respects the unique reality of human beings and which can provide targeted and efficient response to the most vulnerable populations.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

References

[1] Aasi, H., & Lee, Y. (2020). Spatial Analytics-A Missing Key to Ending Homelessness. In *AMCIS* (pp. 1-10).

[2] Adams, L., Kennedy, S., Allen, L., Barnes, A., Bias, T., Crane, D., ... & Donohue, J. (2019). Innovative solutions for state Medicaid programs to leverage their data, build their analytic capacity, and create evidence-based policy. *eGEMs*, *7*(1). https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6688544/

[3] Adekugbe, A. P., & Ibeh, C. V. (2023). Innovating service delivery for underserved communities: leveraging data analytics and program management in the US context. *International Journal of Applied Research in Social Sciences*, *6*(4), 472-487. https://fepbl.com/index.php/ijarss/article/view/986

[4] Ahasan, R., Alam, M. S., Chakraborty, T., Ali, S. A., Alam, T. B., Islam, T., & Hossain, M. M. (2022). Applications of geospatial analyses in health research among homeless people: A systematic scoping review of available evidence. *Health Policy and Technology*, *11*(3), 100647. https://www.sciencedirect.com/science/article/pii/S2211883722000569

[5] Blonigen, D., Hyde, J., McInnes, D. K., Yoon, J., Byrne, T., Ngo, T., & Smelson, D. (2023). Integrating data analytics, peer support, and whole health coaching to improve the health outcomes of homeless veterans: study protocol for an effectiveness-implementation trial. *Contemporary Clinical Trials*, *125*, 107065.

[6] Brackertz, N. (2018). *Housing, homelessness and mental health: Towards systems change*. AHURI Limited. https://www.ahuri.edu.au/sites/default/files/documents/2022-02/Housing-homelessness-and-mental-health-towards-systems-change-Appendixes.pdf

[7] Brierly, P., Casuga, E., Cook-Davis, A., Demarchi, K., Elliott-Nelson, L., Ellis, S., Eustice, K., Farley, C., Geiszl, H., Gordon, R., Grier, M., & Holway, J., Jackson, (2023). *Mental health, substance use, and homelessness: The 114th Arizona Town Hall background report*. Arizona Town Hall. https://aztownhall.org/Town-Hall-Reports

[8] Byrne, T., Baggett, T., Land, T., Bernson, D., Hood, M. E., Kennedy-Perez, C., ... & Bharel, M. (2020). A classification model of homelessness using integrated administrative data: Implications for targeting interventions to improve the housing status, health and well-being of a highly vulnerable population. *PloS one*, *15*(8), e0237905.

[9] Chan, H., Rice, E., Vayanos, P., Tambe, M., & Morton, M. (2019). From empirical analysis to public policy: Evaluating housing systems for homeless youth. In *Machine Learning and Knowledge Discovery in Databases: European Conference, ECML PKDD 2018, Dublin, Ireland, September 10–14, 2018, Proceedings, Part III 18* (pp. 69-85). Springer International Publishing.

[10] Cheng, R., & Smith, C. (2009). Engaging people with lived experience for better health outcomes: collaboration with mental health and addiction service users in research, policy, and treatment. *Toronto: Ontario Ministry of Health and Long-Term Care*.

[11] Chinman, M., McCarthy, S., Hannah, G., Byrne, T. H., & Smelson, D. A. (2017). Using Getting To Outcomes to facilitate the use of an evidence-based practice in VA homeless programs: a cluster-randomized trial of an implementation support strategy. *Implementation Science*, *12*, 1-12. https://link.springer.com/article/10.1186/s13012-017-0565-0

[12] Craig, K. J. T., Fusco, N., Gunnarsdottir, T., Chamberland, L., Snowdon, J. L., & Kassler, W. J. (2021). Leveraging data and digital health technologies to assess and impact social determinants of health (SDoH): a state-of-the-art literature review. *Online Journal of Public Health Informatics*, *13*(3).

[13] Crowley, D. M., Welsh, J., Chilenski-Meyer, S., Gayles, J., Long, E., Jones, D., ... & Scott, T. (2023). Integrated Prevention Infrastructure: A Framework for Addressing Social Determinants of Health in Substance Use Policy Making. *Focus*, *22*(4), 483-491. https://psychiatryonline.org/doi/abs/10.1176/appi.focus.20240017

[14] Culhane, D. P. (2016). The potential of linked administrative data for advancing homelessness research and policy. *European Journal of Homelessness*, *10*(3). https://www.feantsaresearch.org/download/10-3_article_58614037148803779846.pdf

[15] Cullen, T., & Garcia, J. E. (2021). Data Mining, Data Analytics, and Bioinformatics: Leveraging Big Data to Identify the Most Vulnerable and to Reduce Health Disparities. In *Innovations in Global Mental Health* (pp. 455-488). Cham: Springer International Publishing.

[16] D'Souza, J. (2021). Homelessness, mental health afflictions, problematic substance use, and associated criminality: A transformative justice resolution. In *Global Perspectives on Reforming the Criminal Justice*

System (pp. 258-287). IGI Global. https://www.igi-global.com/chapter/homelessness-mental-health-afflictions-problematic-substance-use-and-associated-criminality/285733

[17] El-Bassel, N., Gilbert, L., Hunt, T., Wu, E., Oga, E. A., Mukherjee, T. I., ... & Rapkin, B. (2021). Using community engagement to implement evidence-based practices for opioid use disorder: a data-driven paradigm & systems science approach. *Drug and alcohol dependence*, *222*, 108675. https://www.sciencedirect.com/science/article/pii/S0376871621001708

[18] Fowler, P. J., Hovmand, P. S., Marcal, K. E., & Das, S. (2019). Solving homelessness from a complex systems perspective: insights for prevention responses. *Annual review of public health*, *40*(1), 465-486. https://www.annualreviews.org/content/journals/10.1146/annurev-publhealth-040617-013553

[19] Gewirtz, A. H. (2007). Promoting children's mental health in family supportive housing: A community–university partnership for formerly homeless children and families. *The journal of primary prevention*, *28*, 359-374.

[20] Graig, L., Friedman, K., & Alper, J. (2023). KEY POLICY CHALLENGES AND OPPORTUNITIES TO IMPROVE CARE FOR PEOPLE WITH MENTAL HEALTH AND SUBSTANCE USE DISORDERS.

[21] Heun-Johnson, H., Zuluaga, K. V., Menchine, M., Starkey, S., David, R. F., & Seabury, S. (2023). Assessing the Use of Data Systems to Estimate Return-on-Investment of Behavioral Healthcare Interventions: Opportunities and Barriers. *The Journal of Behavioral Health Services & Research*, *50*(1), 80-94.

[22] Jalal, A. (2023). The Role of Public Policy in Reducing Homelessness. *Research Consortium Archive*, *2*(3), 101-111. http://rc-archive.com/index.php/Journal/article/view/36

[23] Kazdin, A. E. (2018). *Innovations in psychosocial interventions and their delivery: Leveraging cutting-edge science to improve the world's mental health*. Oxford University Press.

[24] Kelkar, M., Frey, R., Suriya, N., & Engel, S. (2023). Addressing homelessness with data analytics: *A data-driven approach to homelessness*. Deloitte Insights. https://www2.deloitte.com/us/en/insights/industry/public-sector/homelessness-data.html

[25] Kerman, N., & Stergiopoulos, V. (2023). Addressing health needs in people with mental illness experiencing homelessness. *Nature Mental Health*, *2*(4), 354-366. https://www.nature.com/articles/s44220-024-00218-0

[26] Kube, A. (2022). *Data-Driven Decision-Making: Using Counterfactual Predictions to Allocate Scarce Homeless Services Fairly and Efficiently* (Doctoral dissertation, Washington University in St. Louis). https://search.proquest.com/openview/2e048ee59a66b85cf1e9dd1cefa3a8b2/1?pq-origsite=gscholar&cbl=18750&diss=y

[27] Kube, A. R., Das, S., & Fowler, P. J. (2023). Community- and data-driven homelessness prevention and service delivery: optimizing for equity. *Journal of the American Medical Informatics Association : JAMIA*, *30*(6), 1032–1041. https://doi.org/10.1093/jamia/ocad052

[28] Le, P. D., Eschliman, E. L., Grivel, M. M., Tang, J., Cho, Y. G., Yang, X., ... & Yang, L. H. (2022). Barriers and facilitators to implementation of evidence-based task-sharing mental health interventions in low-and middle-income countries: a systematic review using implementation science frameworks. *Implementation Science*, *17*(1), 4.

[29] Lowman, M. (Ed.). (2017). *A practical guide to analytics for governments: using big data for good*. John Wiley & Sons.

[30] Macnaughton, E., Nelson, G., & Goering, P. (2013). Bringing politics and evidence together: policy entrepreneurship and the conception of the At Home/Chez Soi Housing First Initiative for addressing homelessness and mental illness in Canada. *Social Science & Medicine*, *82*, 100-107.

[31] McPherson, S. M., Burduli, E., Smith, C. L., Herron, J., Oluwoye, O., Hirchak, K., ... & Roll, J. M. (2018). A review of contingency management for the treatment of substance-use disorders: adaptation for underserved populations, use of experimental technologies, and personalized optimization strategies. *Substance Abuse and Rehabilitation*, 43-57.

[32] Meehan, A. A., Flemming, S. S., Lucas, S., Schoonveld, M., Matjasko, J. L., Ward, M. E., & Clarke, K. E. (2023). Data equity as a building block for health equity: improving surveillance data for people with disabilities, with substance use disorder, or experiencing homelessness, United States. *Public Health Reports®*, 00333549241245624. https://journals.sagepub.com/doi/abs/10.1177/00333549241245624

[33] Mejia, R. J. (2020). *Utilizing Data to End Homelessness: A Systematic Review*. California State University, Long Beach. https://search.proquest.com/openview/e88df6b3a24f694fd6950e66fe6b426a/1?pq-origsite=gscholar&cbl=44156

[34] Meshkani, T. (2023). Integrating Machine Learning in Urban Pedagogy: Addressing Homelessness in Skid Row. *Architecture*, *4*(1), 112-123.

[35] Morton, M. H., Kugley, S., Epstein, R., & Farrell, A. (2020). Interventions for youth homelessness: A systematic review of effectiveness studies. *Children and Youth Services Review*, *116*, 105096.

[36] National Academies of Sciences, Medicine Division, & Committee on Integrating Social Needs Care into the Delivery of Health Care to Improve the Nation's Health. (2019). Integrating social care into the delivery of health care: Moving upstream to improve the nation's health.

[37] Nelson, G., Aubry, T., Estecahandy, P., Laval, C., O'Sullivan, E., Shinn, M., & Tsemberis, S. (2021). How Social Science Can Influence Homelessness Policy: Experiences from Europe, Canada, and the United States. Part I–Problem and Solutions. *European Journal of Homelessness*, *15*(1), 131-157.

[38] O'Regan, K. M., Ellen, I. G., & House, S. (2021). How to address homelessness: Reflections from research. *The ANNALS of the American Academy of Political and Social Science*, *693*(1), 322-332.

[39] Rivard, J., Vard, J., Ganju, V., Roberts, K., Lane, G., & McHugh, R. (2012). The dissemination of evidence-based practices by federal and state mental health agencies. *Dissemination and implementation of evidence-based psychological interventions*.

[40] Rodilla, J. M., Puchol, G., & Botija, M. (2023). Assessing Impact in Europe: A Systematic Review of Evaluation Methodologies in Homeless Interventions. *Systems*, *11*(11), 541.

[41] Russell, T. R. (2023). *Leveraging Coalitions for Health Policy Advocacy: Research on PFAS and Mental Health* (Doctoral dissertation, The University of Arizona).

[42] Shepherd-Banigan, M., Drake, C., Dietch, J. R., Shapiro, A., Tabriz, A. A., Van Voorhees, E. E., ... & Goldstein, K. M. (2022). Primary care engagement among individuals with experiences of homelessness and serious mental illness: an evidence map. *Journal of General Internal Medicine*, *37*(6), 1513-1523.

[43] Simmons, M. M., Gabrielian, S., Byrne, T., McCullough, M. B., Smith, J. L., Taylor, T. J., ... & Smelson, D. A. (2017). A Hybrid III stepped wedge cluster randomized trial testing an implementation strategy to facilitate the use of an evidence-based practice in VA Homeless Primary Care Treatment Programs. *Implementation Science*, *12*, 1-10.

[44] Slota, S. C., Fleischmann, K. R., Lee, M. K., Greenberg, S. R., Nigam, I., Zimmerman, T., ... & Snow, J. (2023). A feeling for the data: How government and nonprofit stakeholders negotiate value conflicts in data science approaches to ending homelessness. *Journal of the Association for Information Science and Technology*, *74*(6), 727-741.

[45] Soneson, E., Das, S., Burn, A. M., van Melle, M., Anderson, J. K., Fazel, M., ... & Moore, A. (2023). Leveraging administrative data to better understand and address child maltreatment: A scoping review of data linkage studies. *Child maltreatment*, *28*(1), 176-195.

[46] Tucker III, J. L. BIG DATA AND EVIDENCE-BASED MANAGEMENT AT LYNDON B. JOHNSON GENERAL HOSPITAL. *Evidence-Based Management in Healthcare*, 235.

[47] Waybright, B. (2019). *MENTAL HEALTH MARKETS: BEHAVIORAL ECONOMICS AND DATA ANALYTICS* (Doctoral dissertation, Johns Hopkins University).

[48] Weightman, A. L., Kelson, M. J., Thomas, I., Mann, M. K., Searchfield, L., Willis, S., ... & Cordiner, R. (2023). Exploring the effect of case management in homelessness per components: A systematic review of effectiveness and implementation, with meta-analysis and thematic synthesis. *Campbell Systematic Reviews*, *19*(2), e1329.

[49] Whitman, A., De Lew, N., Chappel, A., Aysola, V., Zuckerman, R., & Sommers, B. D. (2022). Addressing social determinants of health: Examples of successful evidence-based strategies and current federal efforts. *Off Heal Policy*, *1*, 1-30. https://www.aspe.hhs.gov/sites/default/files/documents/e2b650cd64cf84aae8ff0fae7474af82/SDOH-Evidence-Review.pdf

[50] Windsor, L. C., Benoit, E., Smith, D., Pinto, R. M., Kugler, K. C., & Newark Community Collaborative Board (NCCB). (2018). Optimizing a community-engaged multi-level group intervention to reduce substance use: an application of the multiphase optimization strategy. *Trials*, *19*, 1-15.

[51] Wortham, W. K., Rodwin, A. H., Purtle, J., Munson, M. R., & Raghavan, R. (2023). Revisiting the policy ecology framework for implementation of evidence-based practices in mental health settings. *Implementation Science*, *18*(1), 58.

[52] Yadav, P., Patterson, S., Bilandzic, A. S., & Johnstone, S. (2021). Evidence-Based Design Justice: Synthesizing Statistics and Stories—To Create Future 'Just'Cities. *Urban Informatics and Future Cities*, 407-428. https://link.springer.com/chapter/10.1007/978-3-030-76059-5_21

[53] Zanti, S., & Thomas, M. L. (2021). Evidence-based policymaking: What human service agencies can learn from implementation science and integrated data systems. *Global Implementation Research and Applications*, *1*(4), 304-314. https://link.springer.com/article/10.1007/s43477-021-00028-x

[54] Zanti, S., Berkowitz, E., Katz, M., Nelson, A. H., Burnett, T. C., Culhane, D., & Zhou, Y. (2022). Leveraging integrated data for program evaluation: Recommendations from the field. *Evaluation and program planning*, *95*, 102093. https://doi.org/10.1016/j.evalprogplan.2022.102093