Using data for addressing social determinants of health: Local public health workforce skills and perceptions

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Abstract

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Constraints in local health departments (LHDs), including lack of accessible, data, workforce training capacity, and funding limitations, hinder LHDs in their efforts to address social determinants of health (SDOH). Improved workforce capacity, including training and skill development, are needed to support LHDs in their efforts to address SDOH and health disparities. This cross-sectional study sought to examine latent structures of public health skills, the relationships between public health skills and staff's support for affecting SDOH in their communities, and to develop a model for data-driven decision-making (DDDM). Three factors were identified in our factor analysis: 1) data and systems thinking, 2) planning and management, and 3) community collaboration. In our regression model, we found an interaction term between our two skills resulted in a negative association with between skills and staff's support for addressing SDOH. Our DDDM model identified organization-level factors and local health department staff modifiable factors. Potential outcomes included: improved resource allocation, policy implementation, and targeted interventions for populations in greatest need, ultimately reducing county-level health disparities. Training evaluation data further supported various aspects of our model. Findings from this study can inform future training and implementation of programs and policies aimed at SDOH.

Chapter 1: The complexity of data-driven decision-making in local health departments

Introduction

Local health departments (LHDs) are essential for coordinating disease prevention, developing health policy, and promoting population health. They are responsible for a wide variety of activities including, but not limited to: communicable disease control, environmental public health, maternal/child and family health, access to and linkage with clinical care, and chronic disease and injury prevention.[1] Local health departments also conduct research and disease surveillance, engage in community partnerships, help develop policy, and maintain organizational competencies.[2] Although historically the impact of preventative services has been difficult to measure,[3] robust measurement tools and improved statistical methods and policy evaluation have allowed for stronger empirical testing and measurement of associations between preventative services and health outcomes.[4–6] Despite that the positive impacts of public health services on health outcomes may be delayed or dispersed, and benefactors of public health are not always easily followed up or known,[3] it is now well established that prevention costs less than tertiary care or treatment and can significantly decrease mortality.[7–9]

Data Integration into LHD Activity

The CDC's recently revised model for the 10 Essential Public Health Services places health equity central and encourages LHDs to address systemic and structural barriers, such as poverty, racism, and gender discrimination,[2] which would suggest a greater emphasis on social determinants of health (SDOH) and upstream programmatic activity.[10–12] One of many strategies for ameliorating health disparities is creating upstream interventions and policies. In order to properly tailor these interventions to the correct geographical location and population, LHDs require data to inform this decision-making.[13,14] Although data-driven decision-making (DDDM)

in public health is not yet extensively described in the literature,[14–16] data are fundamental for public health workers to make programmatic and policy decisions often with limited training and infrastructure. Data are needed to monitor community health issues, plan for the future, and measure performance. However, data are often limited, of poor quality, or simply unavailable to LHD staff.[5,17] This issue intensifies in addressing health disparities and health equity, as data can be even more limited for marginalized communities most in need,[18] and in examining SDOH,[19] such as healthcare access, housing, socioeconomic status, and the built environment. Moreover, data use is only one of the many factors impacting LHDs in their promotion of population health improvement,[5,17,18] and the myriad of factors related to data use make understanding its role in public health decision-making complex.

Contextual and Environmental Factors of LHD Activity

Public health agencies and their leaders and staff are in particularly effective positions to address health disparities as community partners with a mission to improve population health; however, addressing SDOH and using data in the process also heavily rely on broader environmental and contextual factors in which LHDs reside. Contextual and environmental factors include mandated activities,[20] funding,[21] political climate,[22] boards of health,[28] and partnerships. First, LHDs have many competing priorities and certain mandated activities, such as investigating communicable diseases or assessing the health effects of hazard waste sites.[20] Local health department leaders have identified "mandated activities as their first priority in making programmatic decisions, and consider these activities a funding priority"[20(p2)] around which they are required to allocate resources. These mandated activities can easily shift resources away from more upstream activities and specific community needs.

Mandated Activities

Mandated activities are also directly related to the financial constraints of LHDs.[21] Funding is typically allotted only for specific programs and can only legally be used as such.[15] Thus, when budget cuts occur, implementing mandated activities are the top priority. More broadly, inadequate public health funding, exacerbated by the 2008 financial crisis, severely impacted the public health workforce, data capacity, and the ability to invest in preventative measures, such as those aimed at SDOH.[23] Budget cuts continued after 2008[24] and federal funding for public health preparedness and response programs decreased between the fiscal year 2019 and 2020, from $858 million to $850 million.[25] Thus, even if knowledge of SDOH and support for upstream activities is present among LHD staff, funding and mandated activities are among the most significant factors contributing to the implementation of preventative measures and addressing health disparities in our public health system.

Political Climate, Boards of Health, Accreditation

Public health staffs' autonomy in decision-making is also heavily dependent on the political climate,[22] boards of health,[26,27] and accreditation.[28] A multivariate analysis found economic elites and organized groups representing business interests had significant independent impacts on U.S. government policy, compared to average citizens and mass-based interest groups.[29] Boards of health allow a citizen forum for the development of public health policy, approval of budgets, and regulation of some public health activities such as drinking water and immunizations.[30] Boards of health can help drive LHD success through policy-making, oversight resource procuring,[31] and creating community linkages to hospitals, other health care providers, and other local government agencies.[27] These linkages have been significantly associated with board of health performance measures.[27] This organizational-level impact of boards of health could influence community partner involvement, local policy development, and funding

priorities surrounding SDOH, and data could shape some of the decisions made by boards of health. Although distal, the political climate and boards of health can influence local public heath funding, which does impact which programs and activities ultimately get carried out or implemented in a community.

Boards of health also have some influential role in directing, encouraging, or supporting LHD accreditation, and have been significantly associated with higher performance of governance functions.[26] Accreditation has important benefits to LHDs and can lead to evidence-based decision making, competitiveness for funding and workforce development by creating public health quality improvement standards within LHDs.[32] Accreditation also requires LHDs to develop and update community health assessments (CHAs) and community health improvement plans (CHIPs).[33] Data-driven decision-making could both inform how these CHAs and CHIPs are conducted and help update and maintain what topics and program areas, particularly regarding SDOH, communities have the greatest needs in. One study found accredited LHDs were more likely to report higher capacity for evidence-based decision-making, resource availability for evidence-based decision making, and evaluation capacity than LHDs that were not accredited.[28] This may suggest that accredited LHD staff could more effectively use data for decision-making, as accreditation requires LHDs to document that they "identify and use the best available evidence for making informed public health practice decisions." Accreditation and partnership could be of particular importance in small LHDs, which have more frequently listed a wide variety of partner types within their CHAs/CHIPs than large LHDs.[33] Despite this larger number of and types of partners, another study found rural LHDs had significantly lower odds of supporting "community efforts to change the causes of health disparities."[34] If relevant data on underserved populations were made more readily available and were combined with the Public

Health Accreditation Board's emphasis on engaging in cross-sector collaboration and with diverse partners, small LHDs could increase capacity for targeted interventions and other data-driven decisions.

Partnerships

Data-driven decision-making is further influenced by partnerships, both across LHDs and communities, and with academic institutions.[35–37] Local health department leaders participating in use of a Uniform Chart of Accounts (UCOA),[38] for example, have described access to shared financial data as valuable for better understanding resource allocation and service delivery measures. Academic partnerships, such as with the UCOA where capacity to support data management was made much larger through this partnership, can help support LHDs in their need for data and training surrounding data use. Such academic partnerships can also offer insight from researchers with key systems-thinking and data analytic skills and who are familiar with the evidence-based practice literature that LHDs, particularly rural LHDs, may be lacking. One study found the odds of providing one or more evidence-based chronic disease interventions were significantly higher in LHDs with *formal* academic health department partnerships, compared with LHDs with no academic partnerships.[39] This is also support by a scoping review of LHDs' role in obesity prevention that found 69% of studies noted existing partnerships or partnership development in LHD obesity prevention efforts.[40] The sharing of data through cross-jurisdictional resource-sharing[41] and mentorship between governmental agencies[42] could also help LHDs more comprehensively address health disparities and target upstream factors by combining specific areas of expertise. Thus, DDDM does not operate independently, but rather in the process of collaboration and partnership. This could be particularly important in the rural context, where workforce capacity to collect, analyze, and visualize data is even more limited.[43]

Partnerships are also closely tied to community need, availability, and capacity. One study assessed health priorities among health department staff and its community members and found notable differences between the 2 groups.[44] This underscores the importance of community input in addressing health disparities. Regardless of availability, data for decision-making can be rendered useless if it does not match community need.

Data-driven decision-making at the individual and organizational level, is currently not well understood in the literature. The process theoretically requires available, usable SDOH data, organizational readiness for change, trainings on using data and understanding health disparities, LHD staff with skills in using data, personal relevance or prioritization of SDOH among staff, staff motivation, and self-efficacy. These factors, theoretically, could ultimately lead to using data for decisions related to resource allocation, appropriate interventions for specific geographical areas and populations, and policy implementation. Thus, a theoretical gap remains regarding workforce skills, trainings, and staff perceptions of SDOH within the DDDM process.

Purpose

This study aimed to examine aspects of the DDDM process, and although the aforementioned environmental and contextual factors in public health are critical to LHD decision-making, they are too complex to examine as a whole given how limited current literature is for DDDDM. The purpose of this study was to better understand certain aspects of this complex process at the individual and organizational levels, including what skills relate to data use, whether these skills relate to staff's support for addressing SDOH in their jurisdictions, and the effect trainings have on staff's data use and understanding of health disparities. Findings from this study informed a model of DDDM in LHDs to address SDOH. Results from this study

have the potential to impact DDDM implementation in LHDs and better target future workforce trainings surrounding data and knowledge of SDOH and health disparities.

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Grouping public health skills to facilitate workforce development: A factor analysis of PH WINS

Abstract

Objectives This study examined whether distinct factors exist among public health skills, measured through the Public Health Workforce Interests and Needs Survey (PH WINS). Understanding how workforce training needs group is important for developing targeted and appropriate public health workforce trainings.

Design Exploratory factor analysis was used to examine public health skills among Tier One staff (non-managers) and a combined group of Tier Two and Three staff (managers and executives).

Setting Data for this study come from the 2017 PH WINS, which assessed public health workforce perceptions of training needs, workplace environment, job satisfaction, perceptions about national trends, and demographics. The analysis included 22 items.

Participants All public health staff in participating agencies were eligible to complete the survey. The national data set included participants from 47 state health agencies, 26 large local health departments (LHDs), and 71 midsize LHDs across all 10 Health and Human Services regions in the US (including LHDs from all states). The analytic sample was n=9,630 in Tier One, n=4,829 in Tier Two, and n=714 in Tier Three staff.

Main Outcome Measure Three factors were identified within the skills portion of PH WINS, using exploratory factor analysis. To interpret retained factors the following parameters were used: factor loadings greater than 0.4, factor cross-loadings less than 0.4 or higher than loadings on other factors, and communalities greater than 0.5.

Results Factors included 1) data and systems thinking, 2) planning and management, and 3) community collaboration; with slight variation in item loadings between Tier One and Tier Two and Three staff analyses.

Conclusion This study was the first known factor analysis of the training needs and workforce skills portion of PH WINS in the published literature. This study advances our conceptualization of public health workforce skills and has the potential to shape future critical workforce training development.

Keywords: data-driven decision-making, evidence-based public health, social determinants of health, health equity, workforce development

Introduction

Constraints in local health departments (LHDs), including lack of accessible, relevant data to guide practice, workforce training and competency capacity, and funding and infrastructure limitations, hinder LHDs in their efforts to address social determinants of health (SDOH).[1–5] Rural low-income and minoritized racial and ethnic groups experience higher rates of chronic health conditions such as cardiovascular disease, diabetes,[6] and cancer[7] with poorer health outcomes compared to urban populations. These disparities are predominantly rooted in differences in SDOH[8] and are the province of LHDs and their staff and leaders to address along with community partners and agencies.[9,10] Improved workforce capacity, including training and public health staffs' skill development,[11,12] are needed to support LHDs in their efforts to improve population health, given their limited resources and recent budget cuts.[3,13]

Several public health frameworks and emerging public health literature suggest that factors such as data-driven decision-making,[14–21] community collaboration and partnership,[21–23] cross-sector collaboration,[20,24,25] and cultural humility[26–28] are important in reducing health disparities and working towards health equity among LHDs. The Public Health 3.0 framework emphasizes a need for timely, reliable data, and cross-sector partnership across communities.[14] Other models, such as Center for Disease Control's (CDC) revised Ten Essential Public Health Services, include effective communication and improving public health through evaluation, research, and quality improvement.[29] Public health finance, also plays an important role in resource allocation that can support and promote health equity.[30] Literature suggests the public health workforce has varying skill levels surrounding finances for public health service and program delivery, public health agency funding, and public health business planning.[31] Similarly,

Boegart et al., found 1) budgeting and finance and 2) systems and strategic thinking to be the two areas of largest training needs in public health.

The public health skills proposed in the above frameworks[14,29] and targeted in public health interventions and observational studies[31,32] suggest distinct factors could exist within the public health workforce skill set to address local inequities. Understanding how these specific public health skills can be effectively grouped to facilitate learning, could help LHDs effectively plan training and workforce development activities by developing certain skills in combination with one another. Public health skill groupings are also important to understand as a means to facilitate training in response to the recent high turnover among public health staff and the subsequent, sudden upward mobility of staff in LHDs without necessarily having had significant leadership or management experience.[33] However, we found no formal exploratory factor analysis (EFA) regarding public health skills in the published literature.

Bogaert et al. found systems and strategic thinking to be a top training priority for PH staff, which included building cross-sector partnerships to address SDOH. However, the specific training areas described as within 'systems and strategic thinking' were only proposed to be correlated theoretically, based on frameworks from the literature.[11] Thus, a theoretical and empirical gap remains regarding how to develop public health skills that, addressed or grouped together, might facilitate more effective approaches to promoting health equity in public health.

The purpose of this study was to determine whether latent factors were present in public health workforce skills that represent distinguishable sets of skills. Understanding workforce training needs and varying skill levels are important for better targeting and developing public health workforce trainings, which would build capacity for interventions aimed at addressing SDOH and reducing community-level health disparities. In the face of public health funding and

infrastructure limitations, as well as a shrinking public health workforce,[34] it is imperative that workforce training remains relevant and practical, and that it addresses the day-to-day work of staff, particularly in combating complex health disparities.

Methods

Study Design and Study Sample

The secondary data for this study came from the 2017 Public Health Workforce Interests and Needs Survey (PH WINS), conducted by the De Beaumont Foundation. PH WINS is a nationally-fielded sample survey assessing public health workforce perceptions of training needs, work place environment, job satisfaction, perceptions about national trends, and demographics.[35] Public health staff from participating agencies were invited to participate and completed the survey via Qualtrics. Staff had to be at least 18 years of age and working for an LHD or state health agency at the time of survey completion. The PH WINS data set consisted of 47 state health agencies, 26 large LHDs, and 71 midsize LHDs across all 10 Health and Human Services regions in the US (including LHDs from all states).[36] Overall, 47,604 people responded to PH WINS in 2017 from within the participating agencies and across both frames (LHDs and state health departments). The PH WINS data consisted of three different staff groups: Tier One (non-supervisors), Tier Two (supervisors and managers), and Tier Three (executives). De Beaumont Foundation received an IRB Exemption for their study (PH WINS 2017, Protocol ID: 17-09-08). Our secondary analysis was considered exempt from Human Subjects review by the University of Washington, and data were managed in accordance with University of Washington's privacy and security standards.

Instrument

The original 2014 PH WINS was developed by incorporating previously validated workforce survey measures from the CDC's Technical Assistance and Service Improvement Initiative: Project Officer Survey; the 2009 Epidemiology Capacity Assessment; the Federal Employee Viewpoint Survey; the Public Health Foundation's Public Health Workers Survey; the Bowling Green State University Job in General Scale; and the University of Michigan Public Health Workforce Schema.[35] After components of each existing survey were combined into PH WINS, the measurement showed good internal reliability (Cronbach's alpha 0.76-0.88). Based on feedback from practice partners using 2014 PH WINS training needs results, the training needs were significantly revised and broadened to include more "specific, actionable skills"[36] in 2017. To guide the revised training needs in the 2017 PH WINS instrument, an environmental scan of existing instruments, processes, and frameworks was conducted.[11] Researchers identified 5 key frameworks, including eight priority training needs or skills areas, including: effective communication, use of data for decision-making, cultural humility, budgeting and financial management, change management, systems and strategic thinking, developing a vision for a healthy community, and cross-sector partnerships.[11]

Variables

Workforce skill questions were posed as skill levels on a 5-point Likert scale including, "not applicable, unable to perform, beginner, proficient, [and] expert." (Table 1). For our study responses were recoded as numerical data (e.g., 1,2,3,4,5) with 1 = "not applicable" and 5 = "expert." Responses of "not applicable" were removed to only examine correlations between skills being used by public health staff in their day-to-day work. We assumed that original categorical data, measured on a Likert scale, were consistent or proportional across response

categories. Despite the response "unable to perform" potentially being different from other categories (beginner, proficient, expert), it was reasonable to assume that moving from "unable to perform" to "beginner," and "beginner" to "proficient," were similar. After removal of "not applicable" responses, 9,630 observations remained in Tier One, 4,829 remained in Tier Two, and 714 remained in Tier Three staff.

Item wording varied slightly between Tier One and Tiers Two and Three. For example, for Tier One the item states, "what is your current skill level for participating in quality improvement processes for programs and services," and for Tiers Two and Three the item states, "what is your current skill level for applying quality improvement processes to improve agency programs and services." Tier One staff had a total of 21 skills items and Tiers Two and Three staff had 22 skills items, including an additional question on strategic planning that was only applicable to managers, supervisors, and executive staff. Table 1 provides a complete list of workforce skills items.

Analysis

An EFA was conducted first on Tier One and then on Tiers Two and Three staff data. Tiers Two and Three (managers and executive-level staff) have substantively different responsibilities and roles than Tier One staff, and may potentially have different training needs. Given no known previous EFA was conducted on any of these staff populations using PH WINS data, we did not conduct a confirmatory factor analysis. Separate analyses were conducted for Tiers One and Two and Three due to the different number of skills between Tiers and slight variations in item wording between Tier One and Tiers Two and Three (Table 1).

For this study, only the public health skills portion of the survey was used in the EFA. A five-step process was used for EFA including: setting up a correlation matrix, extracting factors,

factor structure rotation, defining the number of factors to retain in the rotation, using goodness of fit tests, and qualitatively labeling the factors.[37,38] First, principle components analysis was used to examine the potential number of factors to include and then scree plots were created to visually plot eigenvalues. An orthogonal, varimax rotation was used to interpret the factor structure and reduce the number of significant factor loadings.[39] Identified factors were not expected to be correlated with one another. To interpret retained factors the following parameters were used: factor loadings greater than 0.4, factor cross-loadings less than 0.4 or higher than loadings on other factors, and communalities greater than 0.5.[40] To assess goodness of fit, a chi square test statistic was used to test the proposed factor model structure against a null model.[38] Criteria for adequate model fit were: root mean square error of approximation below 0.05,[41] standardized root mean square residual below 0.08,[42] Tucker-Lewis index above 0.90.[43] All statistical analyses were performed using R, version 1.3.1093, and Psych packages.

Results

Based on scree plots and eigenvalues we proposed a 3-factor model for both EFAs (Table 2). Factor 1 included items related to: communication; identifying and using data to drive decision-making; and cultural humility in the workplace and in planning for programs and services. Factor 2 included items related to: financial planning and public health funding; change management; cross-sector collaboration; and quality improvement including community health assessments and improvement plans. Factor 3 included items related to: strategic planning and community collaboration and engagement. The additional item in Tiers Two and Three, 'integrate current and projected trends into strategic planning for programs and services' had a high loading on Factor 2. In Tier One, the item related to 'assessing external drivers in the environment that may influence your work' cross-loaded on all three factors, and was retained in

Factor 1 to align with loadings from Tiers 2 and 3. We labeled these three distinct factors as 1) *data and systems thinking, 2) planning and management,* and *3) community collaboration*.

Staff generally had similar skill level responses across Tiers for our three factors. The mean response for *data and systems thinking* was 4.00 in Tier One, 4.00 in Tier 2, and 4.14 in Tier Three (Table 2). The mean response for *planning and management* mean was 3.57 in Tier One, 3.86 in Tier Two, and 4.00 in Tier Three. The mean score of *community collaboration* was 4.00 in Tier One, 4.88 in Tier Two, and 4.00 in Tier Three staff.

Tiers Two and Three staff had a high percentage of staff with a Master's or Doctoral degree (51.2%, 76.5%, n= 5543), compared to Tier One staff (32.5%, n= 9695, x^2 = 706.61, p <.001). Tiers Two and Three also had a slightly higher percentage of staff with greater than five years of tenure working in public health (81.8%, 84.6%, 5543), compared to Tier One staff (60.7%, n= 9695, x^2 = 751.10, p <.001).

Item loadings varied slightly between Tier One and Tiers Two and Three staff. In Tiers Two and Three items related to 'using financial analysis methods,' 'implementing socially, culturally, and linguistically appropriate policies, programs, and services,' and 'identifying appropriate sources of data and information' had their highest loading on a different factor than in the Tier One EFA**.** Items related to 'persuasive communication,' and 'identifying funding mechanisms' cross-loaded on multiple factors in Tiers Two and Three staff, although their highest loading remained on the same factor as in Tier One. The item 'using financial analysis methods' also cross-loaded in Tier Two and Three.

Model fit statistics for both EFAs indicated acceptable fit of each of the items onto their corresponding factors. Tier One had a x^2 value of 5536.97 on 150 degrees of freedom (p<0), a root mean squared error of approximation of 0.02, a standardized root mean square residual of

0.03, and a Tucker-Lewis index value of 0.944. In Tiers Two and Three, the EFA model had a x^2 value of 2011.12 (p<.001), a root mean squared error of approximation of 0.03, a standardized root mean square residual of 0.03, and a Tucker-Lewis index value of 0.935.

Through EFA we also found that one item included in the PH WINS training needs/workforce skills portion was not associated with any of the three factors we identified—'assessing external drivers that could influence staff's work,' in Tier One.

Discussion

The three factors identified in the EFA for the Tiers examined here appear to represent distinct components of public health workforce skills: 1) *data and systems thinking, 2) planning and management,* and *3) community collaboration*. In qualitative interviews conducted in a separate study, LHD leaders expressed using data for program and service implementation and evaluation and communicating with partners and the public.[44] Our FA supports this, showing certain skills, including communication skills and data use skills loading onto the same factor. Given 'using and interpreting quantitative data' has been found to be a top informatics training need expressed by public health staff,[12] our FA results can be used in guiding what is included in future data use trainings.

We did not expect data use skills and cultural humility items to load onto the same factor (*data and systems thinking*). This could suggest that people with similar skill levels in data use also possess similar skill levels in cultural humility. This could also signify that the way staff develop or use these two separate skills may be similar. Or, staff with higher data use skills also had more education in other areas such as cultural humility. Although no associations or causal relationship can be drawn from this observation, the EFA suggests these two domains of skills,

data use and cultural humility, could be related to one another and could shape how future trainings on these topics are developed and delivered to public health staff. Combining both data use trainings and cultural humility trainings could be a more efficient path for local public health systems to address health disparities while integrating data into the process.[20,32,45,46] Combining trainings could also reduce the overall amount of training required of public health staff. Innovations such as dashboards and surveillance efforts that have increased data availability have recently offered opportunity to improve SDOH decision-making in LHDs.[15,32,47] Designing training that thoughtfully combines these skills could make implementation of data dashboards that have SDOH and health outcome data more effective.[15,48]

We did expect community collaboration to be an underlying latent structure of the data, and our findings supported this. This is also supported by the CDC's Office of Minority Health and Health Equity (OMHHE) framework that organizes public health practice into four domains, one of which is the development and maintenance of public health infrastructure including workforce skills, data systems—including "health equity variables"[(p423)] –and community and multisector partnerships.[46] This domain is also emphasized in the CDC's Public Health 3.0 framework,[14] as well as in semi-structured interviews with LHD leaders on facilitating factors that guide LHDs in transitioning from direct clinical service provisions to population-level interventions.[45] In these frameworks and studies, community collaboration is described as engaging organizations in intervention development and implementation, surveying community members on their satisfaction with programs, and maintaining relationships with policymakers or boards of health, for example. Understanding what comprises *community collaboration* as a public health skill could allow us to examine how this set of skills is related to staff's perception of SDOH in their jurisdiction. If community collaboration is indeed related to staff's desire to

address SDOH, it could be an important point of intervention in garnering support in LHDs to create upstream interventions aimed at structural inequities.

Differences in item loadings between Tiers One versus Two and Three EFAs suggest the workforce skills and training needs differ among public health staff. This is somewhat expected given that managers and executives have different roles and responsibilities in health agencies than non-manger staff. For example, managers, supervisors, and executives in Tiers Two and Three have greater budgeting and program oversight responsibilities,[49] which could explain why the 'modify programmatic practices in consideration of internal and external changes' item loaded high on factor two (*planning and management*) for Tiers Two and Three staff, but cross-loaded in Tier One staff. These different loadings support developing trainings for Tiers One and Two and Three separately, to target and cultivate the skills in their specific leadership roles. For example, managers and supervisors must focus on entire systems within public health and work across different sectors, rather than just one specific area or program, such as maternal-child health, for example. Furthermore, our findings show that backgrounds of people in Tiers Two and Three also differ from non-managers (Tier 1), with a higher percentage of advanced degrees and tenure working in public health. Given these different loadings between Tiers, future public health training content would likely benefit from being tailored by Tier, i.e. trainings for Tiers Two and Three may need to combine public health finance with data use trainings, as these items loaded onto the same factor, but not be included in training for Tier One staff.

Limitations

Due to the differing nature of non-manager, manger, and executive-level roles in public health, the wording of some items varied to match the level of responsibility of that staff Tier's role. This could have impacted how items loaded onto factors. We also recognize the limitations

and potential bias in factor loading estimates in converting ordinal data to numerical data.[38] However, in a review of factor analysis methodologies Robitzsch et al argues for a multitude of methods for factor analysis with ordinal data, including assuming multivariate normality and treating the data as continuous.[50] A "sketched" simulation design by Robitzsch et al, where ordinal variables were treated as continuous, resulted in unbiased loading estimates, suggesting the simulation studies examined could not necessarily be used to choose between the two (continuous versus ordinal) EFA methods.[50]

Conclusion

This study was the first known investigation to examine constructs present in the training needs and workforce skills portion of PH WINS. This study advances our conceptualization of public health workforce skills, and has the potential to shape future workforce training development. Further training supporting data use, systems thinking, and community collaboration skills could help LHDs better implement interventions aimed at SDOH.

Implications for Policy & Practice

- Three factors were identified in Exploratory Factor Analysis: 1) *data and systems thinking, 2) planning and management,* and *3) community collaboration*, that could shape and better target future public health workforce training development.
- Given that data use and cultural humility skills loaded onto the same factor, these skills could be developed and trained concurrently.
- Slightly different loadings between staff Tiers suggests that different staff (non-manager versus manager and executive staff) have unique training needs and could have tailored trainings based around their specific job responsibilities.

Table 1. PH WINS Public Health Skills Questions

Question: "What is your current skill level for?"
Responses: (Not applicable, Unable to perform, Beginner, Proficient, Expert)

Tier 1 Items	Tier 2 Items	Tier 3 Items	Analysis Code[1]
1) Communicate in a way that different audiences can understand	1) As Tier 1	1) As Tier 2	T2_target_comm
2) Communicate in a way that persuades others to act	2) As Tier 1	2) As Tier 2	T2_pursuade_comm
3) Identify appropriate sources of data and information to assess the health of a community	3) As Tier 1	3) As Tier 2	T2_identify_data
4) Use valid data to drive decision-making	4) As Tier 1	4) As Tier 2	T2_use_data_dm
5) Apply evidence-based approaches to address public health issues	5) As Tier 1	5) As Tier 2	T2_apply_ebis
6) Support development of a diverse public health workforce	6) As Tier 1	6) As Tier 2	T2_diverse_workforce
7) Incorporate health equity and social justice principles into planning for programs and services	7) As Tier 1	7) As Tier 2	T2_incorp_he_sj
8) Implement socially, culturally, and linguistically appropriate policies, programs, and services that reflect the diversity of individuals and populations in a community	8) As Tier 1	8) As Tier 2	T2_implement_cc
9) Use financial analysis methods in managing programs and services	9) As Tier 1	9) As Tier 2	T2_fin_analysis
10) Identify funding mechanisms and procedures to develop sustainable funding models for programs and services	10) As Tier 1	10) As Tier 2	T2_ph_funding
11) Implement a business plan for agency programs and services	11) As Tier 1	11) As Tier 2	T2_business_plan
12) Modify programmatic practices in consideration of internal and external changes	12) As Tier 1	12) As Tier 2	T2_inter_changes
13) Assess the drivers in your environment that may influence public health programs and services	13) As Tier 1	13) As Tier 2	T2_ext_drivers
	14) Integrate current and projected trends into strategic planning for programs and services	14) As Tier 2	T2_trends_stat_plan
14) Describe how SDOH impact health of individuals, families, and overall community	15) Build cross-sector partnerships to address social determinants of health	15) Influence policies external to the organization that address SDOH	T2_sdoh_cs_part
15) Participate in QI processes for programs and services	16) Apply QI processes to improve agency programs and services	16) As Tier 2	T2_qual_imp
16) Describe the value of community strategic planning that results in community health assessments and community health improvement plans	17) Apply findings from a community health assessment or community health improvement plan to agency programs and services	17) As Tier 2	T2_apply_cha
17) Describe your agencies strategic priorities, mission, and vision	18) Implement an organizational strategic plan	18) As Tier 2	T2_strat_mission
18) Describe the importance of engaging community members in the design and implementation of programs to improve health in a community	19) Engage community members in the design and implementation of programs to improve health in a community	19) As Tier 2	T2_engage_comm
19) Identify and engage assets and resources that can be used to improve health in a community	20) As Tier 1	20) As Tier 2	T2_comm_assets_res
20) Collaborate with PH personal across agency to improve health across the community	21) Engage in collaborations within the public health system, including traditional and non-traditional partners, to improve the health of a community	21) As Tier 2	T2_cs_collab
21) Describe your role in improving the health of the community	22) Assess how agency policies, programs, and services advance population health	22) Advocate for needed population health services and programs	T1_describe_role T2_assess_pols

[1]All questions in Tier 1 and 3 staff correspond to same analysis codes as Tier 2, unless otherwise noted.

Table 2. Descriptive Statistics

	Tier 1	Tier 2	Tier 3
Characteristic	**N = 9,695**[1]	**N = 4,829**[1]	**N = 714**[1]
Education			
Bachelors or less	6,462 (67%)	2,327 (48%)	165 (23%)
Masters/Doctoral	3,147 (33%)	2,471 (52%)	546 (77%)
Unknown	86	31	3
Public health tenure			
>5 years	5,883 (63%)	3,948 (83%)	604 (86%)
0-5 years	3,455 (37%)	795 (17%)	98 (14%)
Unknown	357	86	12
Data and systems-thinking	4.00 (3.75, 4.25)		
Planning and management	3.57 (3.14, 4.00)		
Community collaboration	4.00 (3.40, 4.00)		
Unknown	59		
Data and systems-thinking		4.00 (3.71, 4.14)	
Planning and management		3.86 (3.29, 4.00)	
Community collaboration		3.88 (3.38, 4.00)	
Data and systems-thinking			4.14 (3.86, 4.43)
Planning and management			4.00 (3.71, 4.29)
Community collaboration			4.00 (3.67, 4.33)

[1] n (%); Median (IQR)

Table 3. Tier 1, 2, and 3 Workforce Skill Exploratory Factor Analysis Results

Tier 1 Items (n=4,829)	*F1: Data and Systems Thinking*	*F2: Planning and Management*	*F3: Community Collaboration*
T1_target_comm	**0.68**	0.18	0.26
T1_pursuade_comm	**0.65**	0.25	0.25
T1_incorp_he_sj	**0.65**	0.18	0.28
T1_use_data_dm	**0.64**	0.23	0.26
T1_apply_ebis	**0.64**	0.19	0.24
T1_diverse_wf	**0.63**	0.25	0.14
T1_implement_cc	**0.63**	0.31	0.22
T1_identify_data	**0.61**	0.31	0.28
T1_ph_funding	0.21	**0.77**	0.20
T1_business_plan	0.21	**0.77**	0.15
T1_fin_analysis	0.22	**0.72**	0.30
T1_inter_changes	0.30	**0.70**	0.29
T1_cs_collab	0.32	**0.64**	0.39
T1_apply_cha	0.36	**0.60**	0.34
T1_qual_imp	0.33	**0.59**	0.32
T1_strat_mission	0.33	0.29	**0.71**
T1_sdoh_impact	0.37	0.20	**0.70**
T1_engage_comm	0.30	0.39	**0.69**
T1_comm_assets_res	0.29	0.38	**0.67**
T1_describe_role	0.33	0.33	**0.68**
T1_extern_drivers	0.41	0.44	**0.44**

*Pink shading: indicates cross-loadings >0.4

Tier 2 & 3 Items (n=714)	*F1: Data and Systems Thinking*	*F2: Planning and Management*	*F3: Community Collaboration*
T1_target_comm	**0.64**	0.33	0.23
T1_pursuade_comm	**0.51**	0.44	0.38
T1_incorp_he_sj	**0.61**	0.38	0.35
T1_use_data_dm	**0.58**	0.37	0.34
T1_apply_ebis	**0.74**	0.20	0.19
T1_diverse_wf	**0.71**	0.25	0.23
T1_fin_analysis	**0.49**	0.25	0.38
T1_qual_imp	0.33	**0.66**	0.31
T1_identify_data	0.35	**0.54**	0.36
T1_ph_funding	0.48	**0.54**	0.26
T1_business_plan	0.31	**0.71**	0.29
T1_inter_changes	0.32	**0.70**	0.27
T1_cs_collab	0.16	0.17	**0.61**
T1_apply_cha	0.24	0.31	**0.57**
T1_implement_cc	0.19	0.27	**0.62**
T1_strat_mission	0.20	0.19	**0.61**
T1_sdoh_cs_part	0.21	0.30	**0.57**
T1_engage_comm	0.21	0.17	**0.57**
T1_comm_assets_res	0.29	0.15	**0.59**
*T2_assess_pols	0.17	0.31	**0.61**
T1_extern_drivers	0.22	**0.75**	0.30
T2_trends_strat_plan	0.26	**0.74**	0.28

*Pink shading: indicates cross-loadings >0.4
*Blue shading: items that loaded on different factors in Tier 2&3 than in Tier 1
*T1_describe_role corresponds to items T2_assess_pols in Tier 2&3

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Public health skills and local health department staff's support for affecting social determinants of health

Abstract

Purpose. To describe relationships between data use skills and local health department staff's support for affecting health equity and the built environment.

Methods. We used national 2017 data from the Public Health Workforce Interests and Needs Survey (n = 4,829). Staff support for social determinants of health (SDOH) was operationalized by examining whether staff believed their agency should be involved in affecting health equity or the built environment. We used multivariate logistic regression to examine outcomes: support for addressing 1) health equity or 2) the built environment in their jurisdiction.

Results. Bivariate models showed positive associations between skills examined and support for affecting health equity and the built environment. An interaction between skills examined was significantly negatively associated with both outcomes. Graduate degrees among respondents increased the likelihood of support for health equity and built environment involvement.

Conclusion. Increased data use and community collaboration skills could bolster support for SDOH. However, the interaction between these skills should be further examined in combination to understand their impact on program and policy implementation aimed at SDOH.

Policy Implications. Training on data use and the linkage between SDOH and disparities could help staff better implement activities to achieve health equity.

Introduction

Despite 59% percent of local health department (LHD) leaders indicating in 2016 that their agencies use data to describe health disparities in their jurisdictions, less than 40% of surveyed LHDs indicate they prioritize resources for the reduction of health disparities. [1] Compared to urban populations, rural, low-income, and minoritized racial and ethnic groups experience higher rates of chronic health conditions such as diabetes and cancer [2,3] –diseases predominantly rooted in social determinants of health (SDOH). [4] Constraints among LHDs, including lack of accessible, relevant data to guide practice, [5,6] and limitations regarding workforce capacity, funding, and infrastructure hinder LHDs in their health improvement efforts.

Reliable, timely data are fundamental for public health workers (such as nurses, epidemiologists, program managers/supervisors) to make decisions and best use of limited resources and staffing. Data are also needed to monitor community health issues, plan activities, and measure performance; however, data can be limited at best, [7] and, at worst, unavailable. [8] Data regarding SDOH, [9] such as housing and the built environment are also limited, and even moreso for marginalized populations most in need.[5] Historically, data collection on social factors has not been a common LHD activity or spending priority.[10]

Literature broadly describes the built environment as places where people live, work, learn, and play. The Center for Disease Control's (CDC) Healthy People 2030 Built Environment objectives include goals surrounding housing, physical activity, environmental heath, and respiratory disease (CDC, 2020). Literature suggests the built environment plays a role in chronic disease outcomes and people's well-being.[12] LHDs play a role in developing policy and implementing programs aimed at the built environment to prevent related chronic disease (CDC, 2020). Built environment interventions include, for example, developing active

transportation, supporting community gardens, and creating physical activity interventions.[12] Implementing such interventions often requires cross-sector collaboration, data to understand local disparities, and an understanding of the linkage between SDOH and health outcomes. Impacting the built environment also requires support, buy-in, or intrinsic value placed on SDOH from LHD staff.[13] If staff believe their LHD should be involved in affecting SDOH,[13] they may be more likely to consider and implement upstream interventions.

Interventions to build capacity for data-driven decision-making (DDDM) and for affecting SDOH among LHDs have been developed. Dashboards such as CDC's Data, Trends, and Maps dashboard,[14] the City Health Dashboard,[15] and the SHARE-NW Dashboard[8] have been aimed at increasing data availability regarding SDOH. Research by Shah et al found that the number of information systems LHDs implemented significantly increased the odds of performing disparities activities in their jurisdiction (OR = 1.22, $p < .01$),[1] and that community partnes were eager to partner with LHDs to share data to address SDOH.[16] Such efforts to incorporate DDDM into public health practice is supported by CDC's Public Health 3.0 framework, which emphasizes data and cross-sector collaboration as key components to achieving health equity.

Studies also suggest the importance of community collaboration and partnership in affecting disparities.[17] Academic partnerships[18] and cross-sector work, including LHDs sharing data with other partners,[16] have all shown that community collaboration is more likely to generate implementation of upstream interventions aimed at structural change, rather than individual-level, behavioral change interventions.[14,15]

Literature also points to a persistent gap in knowledge and support for addressing or affecting SDOH among public health staff, and insufficient skills in data use. LHD leaders have

expressed a need for trainings on data use, data visualization, and health disparities for staff .[8] Studies have also found public health workers did not understand the "gradient" of disparities, defined by health outcomes worsening as people's socioeconomic status decreases.[19] However, it is not well understood whether skills related to data use are related to support or staff buy-in for affecting SDOH. Our conceptual model depicts the relationship between public health skills and support for SDOH (Figure 1). Understanding what relationships may exist between skills and staff perceptions, could help guide workforce development activities to more effectively help LHD staff address SDOH.

Interviews with LHD leaders have found a desire among staff for data and data visualizations on SDOH to facilitate understanding of factors contributing to health disparities.[20] This suggests a potential positive relationship between data use and systems-thinking skills and support for affecting SDOH. Understanding that system-level SDOH disproportionately and negatively impact health in certain under-resourced groups,[21] which creates downstream disparities, could motivate LHD staff to develop or implement interventions that are 1) aimed at supporting populations where SDOH more negatively impact health and 2) aimed at upstream factors such as housing, transportation, or economic stability.

Although increased data availability have facilitated some improved decision-making surrounding SDOH in LHDs,[1,14,22] and the CDC's Public Health 3.0 framework emphasizes data use and collaboration,[23] a theoretical gap remains whether public health skills in data and systems thinking or collaboration might influence staff support for affecting community-level SDOH. To address this gap, we used cross-sectional data to examine how public health staff skills in data use and community collaboration might affect their support for affecting health

equity or the build environment. Our study was designed to improve understanding of how staff skills and perceptions may ultimately impact LHD decision-making regarding SDOH.

Methods

Sample

The secondary data for this study were drawn from the 2017 PH WINS—a survey also also conducted in 2014 and intended to elucidate public health workforce strengths and gaps and to help inform national investments in workforce development.[24] The de Beaumont Foundation fields this national survey assessing public health workforce perceptions of training needs, work environments, job satisfaction, perceptions about national trends, and workforce demographics. [24] All state health departments were asked to have their staff participate and LHD staff were included from a national sample of medium and large metropolitan area LHDs. The 2017 data set consists of data from individuals across all US Health and Human Services regions (including LHDs from all states),[24] including state (n=47), large (n=26), and midsized (n=71) health departments. A total of 47,604 staff responded to PH WINS in 2017 from participating LHDs and state health departments, for an overall response rate of 48%. Details on survey sampling and design are discussed elsewhere.[24]

PH WINS data are organized by staff respondent tier—Tier One (non-supervisors), Tier Two (supervisors and managers), and Tier Three (executives). As we focused on those most likely to use data for local decision-making, we restricted our sample to only LHD Tier Two staff that responded to the entire training needs portion of the survey, including 22 skills questions and excluding 'not applicable' responses (n = 4,829). We excluded state agency staff, given our focus on skills and perceptions of LHD staff. Literature also suggests LHD leaders

may have a significant role in reducing disparities and greater decision-making power than state-level staff.[25] Our final sample size was 2,770 respondents.

Measures

Dependent Variables

We used two dependent variables to examine staff's perceptions of various SDOH—staff's support for addressing health equity or the built environment in their work. Support for SDOH was operationalized with two questions, "to what extent do you believe your agency should be involved in…" 1) Affecting health equity in your jurisdiction? and 2) Affecting the built environment in your jurisdiction? Both health equity and built environment outcome variables had ordinal 4-category Likert scales, which we recoded to binary as "not at all involved" and "not very involved" = 0, and "somewhat involved" and "very involved" = 1, for ease of interpretation. For a parsimonious model we included two of the seven PH WINS SDOH activities that were asked of participants as our outcomes. Other SDOH activities not included in this study were: K-12 education, economy, housing, transportation, and social support systems. We chose to focus on health equity, for its prominence in public health frameworks, and the built environment, as it includes a variety of structural factors including neighborhoods and places where people live, work, learn, and play.

Independent variables

Focal independent variables included *data and systems-thinking skill* (mean score= 3.93, 1-5), *community collaboration skill* (mean score= 3.70, 1-5). Participant scores ranging from 1-5 corresponded to response categories 'not applicable (1), unable to perform (2), beginner (3), proficient (4), [and] expert' (5).

Control variables included *education level* (Bachelor's degree or less, Masters/Doctoral) *tenure in public health practice* (0-5 years, >5 years), and *LHD size* (LHD serving populations <250,000, LHD serving populations >250,000). Respondents' geographical region, age, race, and ethnicity did not improve model fit and were not included as covariates.

The two skill-focused variables, *data and systems-thinking skill* and *community collaboration skill,* were established by an exploratory factor analysis determining underlying latent structures present in public health skills and to prevent issues with multicollinearity (Table 1).[26] Our factor analysis and subsequent model was motivated by our preliminary model examining a single specific data use skill, which was associated with a significant increase in odds for supporting affecting the built environment. Three factors were identified, including, *data and systems-thinking skills, community collaboration skills,* and *planning and management skills.* We then aggregated responses across all items within each identified factors to find mean scores. Items within each variable are denoted by 1, 2, or 3 suprascripts in Table 1.

Analytical Methods

Descriptive statistics were computed to assess baseline variations in staff's support for being involved in affecting SDOH in their jurisdiction. We conducted multivariate logistic regression to examine associations between staff's public health skills (*data and systems-thinking skill* and *community collaboration skill*) and their support for involvement in affecting health equity or the built environment. Given the theory-driven nature of our newly-created factors, *data and systems-thinking skill* and *community collaboration skill*, we used a forward stepwise approach to specify our model. We theorized that these skills are not independent, but interactive and tested an interaction between skills by introducing a product interaction term into the final multivariate model.

Results

Tier Two staff mean scores for *data and systems-thinking skills* was 3.93 and *community collaboration skill* was 3.70. Sixty-nine percent supported being "involved" in affecting the built environment, while 31% did not. Ninety-two percent supported being "involved" in affecting health equity and 6.28% did not. About half of managers and supervisors had a Bachelor's degree or less (56%), and less than half had a Master's or Doctoral degree (43%). Most staff had greater than five years tenure working in public health (81%), and 17% had five years or less tenure working in public health. Seventy-six percent of staff worked in LHDs serving populations >250,000, while 24% worked in LHDs serving populations <250,000.

In our initial bivariate model examining only the association of *data and systems-thinking skill* with support for SDOH, *data and systems-thinking skill* was significantly positively associated with support for affecting both health equity (AOR, 2.21; p <.001) and built environment (AOR, 1.29; p <.05) (Table 3). Similarly, a bivariate model of the effect of *community collaboration skill* was associated with a significant increase in odds of support for both health equity (AOR, 2.0; p <.001) and the built environment (AOR, 1.58; p <.001) (Table 3).

After adjusting for *community collaboration* skill and other covariates in a multivariate model, increased *data and systems-thinking* skill was no longer significantly associated with support for their agency's involvement in affecting health equity (AOR, 1.34; p .25), and was associated with lower odds of supporting affecting the built environment (AOR, 0.70; p <.01). *Community collaboration* skill remained significantly associated with an increased odds of staff supporting their agency's involvement in affecting health equity (AOR, 1.52; p <.05) and the built environment (AOR, 1.82; p <.001).

In our final model, with the addition of an interaction term between *data and systems-thinking* and *community collaboration* skills, the partial effect of *data and systems-thinking* on support for affecting health equity or the built environment depended on the level of *community collaboration* (Table 4). Increasing levels of *community collaboration* skill had an increasingly negative association between *data and systems-thinking* and support for affecting health equity. In our health equity model, when *community collaboration* skill level was 'unable to perform' (2), the effect of *data and systems-thinking* was still significantly positive, but at a 'proficient' level (4), the effect of *data and systems-thinking* became significantly negatively associated (a lower odds) with support for affecting health equity. At the mean value of *data and systems-thinking* (3.93) and *community collaboration* (3.70), where three corresponds to 'beginner' and four corresponds to 'proficient,' the interaction was associated with a lower odds of staff supporting affecting health equity (AOR, 0.45, *p value* <.001) in their jurisdiction.

Similarly with our built environment outcome, when *community collaboration* skill level was 'unable to perform' (2), the effect of *data and systems-thinking* was still significantly positive, but when the value was greater than 2.0, the effect of *data and systems-thinking* became significantly negatively associated (a lower odds) with support for affecting health equity. At the mean value of *data and systems-thinking* (3.93) and *community collaboration* (3.70), the interaction was associated with a lower odds of supporting affecting the built environment (AOR, 0.77, p <.05).

Having a Master's or Doctoral degree was associated with an increased odds of staff supporting affecting health equity (AOR, 2.39; p <.001) and the built environment (AOR, 1.68; p <.001) in their jurisdiction. LHD population size and public health tenure were not significantly associated with either health equity or built environment.

Discussion

This study examined the relationship between public health manager and supervisor workforce skills (*data and systems-thinking* and *community collaboration*) and their perceived support for their agency's involvement in affecting health equity or the built environment in their jurisdiction. In accordance with a small, emerging area of public health systems research, we hypothesized that increasing data use and community collaboration skill level would be associated with an increased odds of support for involvement in SDOH.[14,27] Our simple bivariate regression models supported this. This initial positive association between data use skill and support for SDOH is important, given the growing attention to public health's use of granular or county-level health outcomes data to better understand disparities related to SDOH.[23]

Community collaboration skill was also significantly positively associated with support for SDOH in our simple bivariate model and secondary model, before adding our interaction term. This is supported by the Office for Minority Health and Health Equity's Framework,[4] which emphasizes inclusion of community members in development and implementation of programs and health policies. This finding suggests a need to examine how community collaboration specifically garners support for affecting SDOH, and how this skill could be further cultivated in LHD leaders and within the larger community. If developing community partnerships helps public health staff recognize linkages between SDOH and health disparities, staff could be more motivated to implement upstream interventions and improve county-level disparities.

We did not expect for the interaction between *data and systems-thinking* and *community collaboration* to result in a negative association with support for SDOH. Although both skills were positively associated with support for SDOH in our bivariate regressions, these two skills

should not be examined separately for LHD Tier 2 staff. The effects of these skills are seemingly interactive and should be considered together when designing future trainings. Examining these skills separately could generate inaccurate conclusions about support for health equity or the built environment. Staff with a high level of community collaboration skill, such as public health nurses,[28] may think about and use data very differently than staff with higher data use skills, such as epidemiologists or other data scientists. Staff with high levels of both skills could also be more aware of the larger systemic factors shaping SDOH and may view it beyond a LHDs power to impact. Future studies should examine this relationship across different staff tiers and roles, and future research may benefit from using our latent class analysis approach.

Our unexpected findings could also, in part, be due to the specific skills comprising our new *data and systems-thinking* variable from our factor analysis. The items in this *data and systems-thinking* factor included a wide range of competencies including communication, data use, cultural humility, and one item on finance.[26] When we examined each item within this factor, we found one item was not significantly associated with the health equity outcome and three items were not significantly associated with the built environment outcome. Thus, it is possible that the mean variable derived from factor analysis did not specify the data use skill as precisely as we expected. Given data use for decision-making is a relatively new skill among some public health staff, our study suggests a need to better understand how staff believe data relate to their work, specifically regarding SDOH indicators, and their perceptions of the linkage between SDOH and disparities. Despite recent projects aimed at making data more accessible to LHDs,[8,14] and fostering a culture of data use, our study underscores the need to assure uptake and adoption of such informatics tools to address disparities and achieve health equity.

Education level was positively associated with support for addressing health equity and the built environment. This could reflect a greater amount of training on disparities and its linkage to SDOH in staff with higher degrees. A study finding discordance between non-supervisor, supervisor, and executive staff's support for various SDOH underscores the importance for LHD leaders to champion involvement in SDO.[29]

Age, race, ethnicity, public health tenure, and LHD size were not associated with either outcome and did not improve model fit. Given SDOH support is similar across different groups and settings, our model findings suggest a need to raise awareness for SDOH and their linkages to health disparities across public health staff. LHD staff may not yet see addressing SDOH as part of their role within public health[13] or may not yet have the necessary training[8] to carry out these complex solutions for health disparities, given their historical focus on surveillance and direct-service activities.[17]

Although our study has a large number of individual responses representing LHD staff nationally,[24] it has limitations. The most recent PH WINS data available at the time of this study were from 2017, prior to the COVID-19 pandemic and related disruptions to public health systems. Survey sample selection bias and the staff that choose to participate within an agency could influence representativeness and, thus, perceptions around SDOH and various public health skills. Knowledge of SDOH could also be a variable or mediator that we could not measure through PH WINS data. The distribution of our of health equity outcome variable was mediocre given that cross tabulation did show low cell counts for low levels of *data and systems-thinking* skill and our health equity outcome variable. This was perhaps a result of creating numeric averages from our categorical variable after our factor analysis. Finally, we could not

assess causal relationships between public health skill and support for SDOH in this cross-sectional study.

Practice & Policy Implications

This study examined LHD supervisor and manager staff, specifically, given their unique decision-making power over non-supervisor/manager level staff. Given their position to steer program and policy development, supporting their training needs is critical and could have important implications for county-level disparities. Although LHD leaders are restrained by certain mandated activities and limited funding,[6] if certain skills such as data use and community collaboration bolster support for affecting SDOH, these skills should be further examined, supported, and cultivated in LHD leaders. Given LHD directors had higher support for SDOH than non-supervisor staff,[29] leadership skills to cultivate health equity activities should also be nurtured. Addressing disparities and aligning with the Public Health 3.0 framework will require a workforce that reimagines and embraces different responsibilities across sectors; this may be a change from their more traditional roles and activities. If LHD leaders better understand health disparities and their causes, either through data or lived experiences in community collaboration, they may more readily develop upstream solutions aimed at structural change, rather than downstream interventions not focused on primary prevention.

Table 1: Factor analysis public health skills items

Question: "What is your current skill level for?"
Responses: (Not applicable, Unable to perform, Beginner, Proficient, Expert)

Tier 1 Items	Tier 2 Items	Tier 3 Items	Analysis Code*
22) Communicate in a way that different audiences can understand	23) As Tier 1	23) As Tier 2	1) T2_target_comm[1]
23) Communicate in a way that persuades others to act	24) As Tier 1	24) As Tier 2	2) T2_pursuade_comm[1]
24) Identify appropriate sources of data and information to assess the health of a community	25) As Tier 1	25) As Tier 2	3) T2_identify_data[2]
25) Use valid data to drive decision-making	26) As Tier 1	26) As Tier 2	4) T2_use_data_dm[1]
26) Apply evidence-based approaches to address public health issues	27) As Tier 1	27) As Tier 2	5) T2_apply_ebis[1]
27) Support development of a diverse public health workforce	28) As Tier 1	28) As Tier 2	6) T2_diverse_workforce[1]
28) Incorporate health equity and social justice principles into planning for programs and services	29) As Tier 1	29) As Tier 2	7) T2_incorp_he_sj[1]
29) Implement socially, culturally, and linguistically appropriate policies, programs, and services that reflect the diversity of individuals and populations in a community	30) As Tier 1	30) As Tier 2	8) T2_implement_cc[3]
30) Use financial analysis methods in managing programs and services	31) As Tier 1	31) As Tier 2	9) T2_fin_analysis[1]
31) Identify funding mechanisms and procedures to develop sustainable funding models for programs and services	32) As Tier 1	32) As Tier 2	10) T2_ph_funding[2]
32) Implement a business plan for agency programs and services	33) As Tier 1	33) As Tier 2	11) T2_business_plan[2]
33) Modify programmatic practices in consideration of internal and external changes	34) As Tier 1	34) As Tier 2	12) T2_inter_changes[2]
34) Assess the drivers in your environment that may influence public health programs and services	35) As Tier 1	35) As Tier 2	13) T2_ext_drivers[2]
	36) Integrate current and projected trends into strategic planning for programs and services	36) As Tier 2	14) T2_trends_stat_plan[2]
35) Describe how SDOH impact health of individuals, families, and overall community	37) Build cross-sector partnerships to address social determinants of health	37) Influence policies external to the organization that address SDOH	15) T2_sdoh_cs_part[3]
36) Participate in QI processes for programs and services	38) Apply QI processes to improve agency programs and services	38) As Tier 2	16) T2_qual_imp[2]
37) Describe the value of community strategic planning that results in community health assessments and community health improvement plans	39) Apply findings from a community health assessment or community health improvement plan to agency programs and services	39) As Tier 2	17) T2_apply_cha[3]
38) Describe your agencies strategic priorities, mission, and vision	40) Implement an organizational strategic plan	40) As Tier 2	18) T2_strat_mission[3]
39) Describe the importance of engaging community members in the design and implementation of programs to improve health in a community	41) Engage community members in the design and implementation of programs to improve health in a community	41) As Tier 2	19) T2_engage_comm[3]
40) Identify and engage assets and resources that can be used to improve health in a community	42) As Tier 1	42) As Tier 2	20) T2_comm_assets_res[3]
41) Collaborate with PH personal across agency to improve health across the community	43) Engage in collaborations within the public health system, including traditional and non-traditional partners, to improve the health of a community	43) As Tier 2	21) T2_cs_collab[3]
42) Describe your role in improving the health of the community	44) Assess how agency policies, programs, and services advance population health	44) Advocate for needed population health services and programs	22) T2_assess_pols[3]

*All questions in Tier 2 and 3 staff correspond to same analysis codes as Tier 1, unless otherwise noted.
[1]Items in data and systems-thinking skill variable
[2]Items in planning and management skill variable
[3]Items in community collaboration skill variable

Table 2. Tier Two Staff Descriptives Statistics Table

Characteristic	N = 2,770[1]
Education	
Bachelors or less	1,558 (57%)
Masters/Doctoral	1,193 (43%)
Unknown	19
Public health tenure	
>5 years	2,253 (83%)
0-5 years	459 (17%)
Unknown	58
Data and systems-thinking	4.00 (3.71, 4.14)
Planning and management	3.71 (3.29, 4.00)
Community collaboration	3.75 (3.25, 4.00)
LHD Size	
LHD Below 250k pop	653 (24%)
SHA-CO	0 (0%)
LHD Above 250K pop	2,117 (76%)

[1] n (%); Median (IQR)

Table 3. Bivariate Models of 2017 PHWINS public health skills and support for health equity and the built environment (N = 2748, 2747)

	Health Equity						Built Environment					
Characteristic	OR[1]	95% CI[1]	p-value	OR[1]	95% CI[1]	p-value	OR[1]	95% CI[1]	p-value	OR[1]	95% CI[1]	p-value
Data & Systems-thinking	2.21	1.57, 3.10	<0.001				1.29	1.08, 1.55	0.006			
Community Collaboration				2.00	1.55, 2.60	<0.001				1.58	1.38, 1.82	<0.001

[1] OR = Odds Ratio, CI = Confidence Interval

Table 4. Multivariate logistic regression parameters estimating 2017 PHWINS staff support for addressing health equity and the built environment (N = 2679, 2678)

	Health Equity			Built Environment		
Characteristic	**OR[1]**	**95% CI[1]**	**p-value**	**OR[1]**	**95% CI[1]**	**p-value**
Data & Systems-thinking	20.2	5.39, 74.3	**<0.001**	1.74	0.72, 4.20	0.2
Community Collaboration	33.4	7.83, 137	**<0.001**	5.12	2.00, 13.1	**<0.001**
Data & Systems-thinking x Community Collaboration	0.45	0.32, 0.64	**<0.001**	0.77	0.61, 0.97	**0.026**
Education						
Bachelors or less	—	—		—	—	
Masters/Doctoral	2.39	1.64, 3.57	**<0.001**	1.68	1.41, 2.01	**<0.001**
Public Health Tenure						
>5 years	—	—		—	—	
0-5 years	0.90	0.61, 1.39	0.6	0.88	0.71, 1.09	0.2
Local Health Department Size						
LHD Below 250k pop	—	—		—	—	
LHD Above 250K pop	1.01	0.69, 1.45	>0.9	0.92	0.76, 1.12	0.4

[1] OR = Odds Ratio, CI = Confidence Interval

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The DASH Model: Data for Addressing Social Determinants of Health in Local Health Departments

Abstract

Recent frameworks, models, and reports highlight the critical need to address social determinants of health for achieving health equity. Data play an important role in better understanding community-level and population-level disparities particularly for local health departments. However, data-driven decision-making—the use of data for public health activities such as program implementation, policy development, and resource allocation—is often presented theoretically or through case studies in the literature. We sought to develop a preliminary model that identifies the factors that contribute to data-driven decision-making in local health departments and describe relationships between them. Guided by implementation science literature we examined organizational-level capacity and individual-level factors contributing to using data for decision-making related to social determinants of health and the reduction of county-level disparities. This model has the potential to improve implementation of public health interventions and programs aimed at upstream structural factors, by elucidating the factors critical to incorporating data in decision-making.

Keywords: data-driven decision-making, evidence-based public health, social determinants of health, health equity, data use, health informatics, workforce development

BACKGROUND

Despite local health department (LHD) leaders expressing a need for reliable data, trainings to use data, and data visualization tools,[1] less than 40% of LHDs prioritize resources for the reduction of disparities.[2] Social determinates of health (SDOH) and their influence on disparities and negative health outcomes in specific populations has a robust evidence base in the public health literature.[3–6] System-level constraints among LHDs, that include lack of accessible, relevant data to guide practice,[7–10] inadequate workforce capacity, and funding and infrastructure limitations hinder LHDs in their efforts to improve population health. In response to these barriers, public health leaders have urgently advocated for more accessible and higher quality data as this is deemed critical to improve their population health decision-making.[1,11,12]

Several public health frameworks and emerging literature suggest factors such as data use,[13–20] understanding or knowledge of SDOH,[21–23] community collaboration and partnership,[20,24,25] and cross-sector collaboration[19,26,27] are important in reducing health disparities and achieving equity. The Public Health 3.0 framework, for example, emphasizes timely, reliable data and cross-sector partnerships across communities as a means for LHDs to be more effective in advancing population health.[13] The Center for Disease Control and Prevention's (CDC's) revised Ten Essential Public Health Services framework centers health equity in terms of public health services and emphasizes effective communication and improving health through evaluation, research, and quality improvement in its model depicting public health services.[28] Recent publications have identified equity and SDOH as being increasingly integrated into public health activities and infrastructure, with workforce capacity being a critical component to its integration.[29–31] The Consolidation Framework for Implementation Research (CFIR) comprises constructs from a myriad of published implementation theories and was

established for implementation researchers to examine aspects most relevant to their particular study setting and to guide assessment for implementation processes and evaluation. The CFIR framework, although not specific to population health outcomes, highlights organizational capacity and related factors in implementing change.[32] The National Academy of Science's Future of Nursing Report 2020-2030 also focused on the SDOH as a means to achieve healthy equity, particularly emphasizing nurses as well-positioned change leaders both inside and outside of the healthcare setting.[4]

Addressing large structural barriers to alleviate disparities may be a change from LHDs' more traditional public health roles and interventions, and there is debate over how they can and should intervene.[33] Historically, data collection on structural and social factors has not always been a top LHD activity or spending priority.[34,35] Additionally, public health staff have varying perspectives on the depth of involvement they should have in their participation with other governmental sectors and areas such as housing, transportation, and the economy.[36,37]

While it has been identified that data use, such as generating data visualizations in dashboards[14] or data sharing across public sectors,[38,39] (e.g., between a public health agency and the county transportation department) could impact resource allocation or policy development, it is unclear how to fully support this process. Further, the implementation, effect, and impact of data use in public health decision-making is infrequently described, examined, or cited in the literature. A gap, thus, remains regarding what concepts are integral to the implementation process of data-driven decision-making (DDDM) and the relationship between these concepts in public health.

The Data-driven decision-making process

Although efforts and interventions to build capacity for DDDM and SDOH in LHDs have recently been developed, the factors critical to the implementation process of DDDM are not well described or investigated in the literature. Development of dashboards, such as the CDC's Data, Trends, and Maps dashboard,[14] the City Health Dashboard,[16] and a rural-specific dashboard—Solutions in Health Analytics for Rural Equity in the Northwest (SHARE-NW) Dashboard,[40] have been described in the literature. However, generating evidence of their implementation and utility are still in their early stages.

In the data science literature Provost and Fawcett[41] highlight taking available data and then applying data-analytic thinking to the data, to be critical steps in decision-making. The education field also supports this process, by underscoring the need for staff capacity to "formulate questions, select indicators, interpret results, and develop solutions,"[42] when working with data. Public health literature offers the related term *knowledge translation* defined as, "the exchange, synthesis, and ethically sound application of knowledge."[43] A scoping review examining knowledge translation strategies in public health found four main strategies—evidence-based public health interventions, adapting interventions, evaluating public health activities, and developing policy related to public health.[44]

Staff and organizational capacity to interpret and understand data, particularly SDOH and disparities, are critical for advancing DDDM in public health. Studies examining cultural competency trainings' impact on staffs' understanding of drivers of health inequities, have found increases in staff's understanding of disparities and how to eliminate them.[21,23] However, for DDDM processes to take place, staff must also view addressing SDOH as a part of their public health role.[21,37,45] A health disparities leadership training series found "creating an urgency"

surrounding disparities and "shaping organizational culture," including increasing SDOH understanding, to be key themes in participants' responses on ways to address disparities in their work.[23]

Model Objective

Given gaps in the literature and practice-based understandings of decision-making in public health, and the need for guidance that supports data use and health disparities knowledge utilization, we sought to develop a model that would identify the factors critical to DDDM for public health interventions aimed at addressing SDOH. The development of this model aimed to further understand the implementation factors, processes, and related gaps to enabling DDDM in LHDs to address SDOH.

METHODS

As a means of developing and supporting this DDDM model, our methods included both incorporating prior evidence from the literature (via a literature review) and generating empirical evidence from recent analyses conducted by our team regarding specific aspects of our model. Based on existing literature focused on DDDM in public health, we developed a preliminary conceptual model (Figure 1). In this preliminary model we examined the following types of factors: individual- and organizational-level, broader environmental, and contextual. From this preliminary model we identified specific gaps and narrowed our final model to include only individual and organizational-level factors (Figure 2). We then conducted two quantitative analyses that were a factor analysis of public health skills and a multivariate linear regression analysis to empirically test elements of our proposed theoretical model and refine relationships in our final model. Lastly, we incorporated evaluation findings from a training series for public

health practitioners that was focused on data use and health disparities knowledge attainment to further support relationships between certain concepts in our model.

Literature Review

First, we focused our literature review on public health decision-making, data use, readiness for change, and evidence-based public health. Our model development was informed by the CFIR framework[46] including concepts within "inner setting" and "individual characteristics."[32] We found CFIR concepts most useful given the focus of our model and implementation science's focus on the "uptake of innovations into routine use,"[46(p3)] rather than their health impact. Additionally, Bronfenbrenner's Ecological Systems Theory was relevant in considering both individual, organizational, and environmental-level factors in the implementation process of DDDM.[47] We used the Ecological Systems Theory[47] to help determine what level or sphere we would focus our model on. This allowed us to narrow our focus from the broader contextual and environmental factors to narrower factors, including LHD staff and organizational-level factors.

Our final model (Figure 2) reflected a deeper examination and understanding of the "LHD staff" box from our preliminary model (Figure 1). In Brofenbrenner's model, our "microsystem" corresponded to public health workers and their interactions within their LHD. Although DDDM could be considered a systems-level change or intervention, it also requires individual-level data use and understanding of SDOH data.[32,41] The immediate setting, which in our model included staff-related factors and organizational-level factors, is described by Brofenbrenner as the most influential level of the ecological systems theory.[47] Although vital to LHD performance,[48] broader environmental factors related to the community and/or public health agency such as population size served, rurality, and budgets, for example, would be

considered among the "exosystem" and were not a focus in our model development. Given what little is understood regarding the DDDM process in the current literature, we focused on identifying the individual and organizational-level factors.

Factor Analysis and Regression Analysis

Our model was also informed by a factor analysis of public health skills and subsequent regression analysis.[49,50] Both of these quantitative studies used data from the 2017 Public Health Workforce Interests and Needs Survey (PH WINS) that assessed public health workforce perceptions of training needs, work place environments, job satisfaction, perceptions about national trends, and workforce demographics.[51] PH WINS includes data from staff across all 10 Health and Human Services regions in the US (including LHDs from all states) with 47,604 responses in 2017 and an overall response rate of 48%.[52] Staff came from large, mid-sized, and state health departments. Survey sampling and design details are discussed elsewhere.[52] These data are available from a third party (de Beaumont Foundation) upon request. This study was considered exempt from Human Subjects review by the University of Washington and data were managed in accordance with University of Washington's privacy and security standards.

We used an exploratory factor analysis approach to determine underlying latent structures present in public health workforce skills among three staff tiers: non-managers, managers and supervisors, and executive-level staff.[49] We aimed to better understand whether data use skills grouped together under a similar latent structure and what other skills grouped with these data use skills. Then, our multivariate logistic regression aimed to better understand gaps in the literature related to public health staff's support for addressing SDOH in their jurisdictions.[49,50]

Training Evaluations

Our DDDM model concepts and relationships were also supported by pre- and post-evaluation responses from public health staff participating in a training series conducted by the Northwest Center for Public Health Practice. The series included 3 SHARE-NW online modules and 2 live trainings covering 3 topics: using data to understand health disparities, leveraging SDOH data for public health decision-making, and utilizing data visualizations.[53] Each module consisted of one self-paced, problem-based learning activity delivered one time. The live training consisted of both didactic learning and problem-based scenarios discussed in break-out groups over 2 sessions.

RESULTS

Overview of the model

Figure 2 depicts key concepts surrounding DDDM and how each concept is related and justified. Two of the five CFIR framework domains include inner setting and individual characteristics. In our model these CFIR domains correspond to Organizational-level Factors (inner setting) and LHD Staff Modifiable factors (individual characteristics). We examined concepts and relationships between concepts as falling into one of these two domains. Organizational-level factors are depicted and outlined towards the model's left side and LHD Staff Modifiable factors are outlined towards the middle (Figure 2).

Literature Review

Organization-level factors

The CFIR framework describes the inner setting as the "structural, political, and cultural contexts through which the implementation process will proceed."[54(p 698)] The framework

recognizes the complexity and multi-level nature of implementation, where organizational-level processes and individual-level behaviors heavily influence each other.[32] Within the inner setting, implementation climate in CFIR includes the sub-constructs resource availability, trainings, relative priority, and readiness for implementation or change.

In our model **resource availability** includes ***SDOH data***. Having available, relevant, and usable data is considered a preliminary step in DDDM.[12,41,42] Dashboards such as the CDC's Data, Trends, and Maps dashboard,[14] the City Health Dashboard,[16] the SHARE-NW Dashboard,[1,40] and the Prevention Impact Simulation Model (PRISM)[55] have aimed to increase data availability surrounding SDOH as a means to improve SDOH decision-making such as resource allocation, program implementation, and community-level assessment. Similarly, a standardized data reporting system of public health services delivery, developed by Bekemeier et al.[57] allows U.S. local and state health departments to compare and evaluate their spending against other health departments and better estimate program and prioritize resource allocation. More recently, Bekemeier et al. developed the SHARE-NW Dashboard which emphasizes SDOH data and a focus on rural LHDs across four Northwest states, to build capacity for DDDM in rural public health systems.[10] Better access to and use of data such as these examples have been found to influence the activities that LHDs take on, as one study found that the number of information systems LHDs implemented significantly increased the odds of performing health disparities activities in their jurisdiction ($OR = 1.22$, $p < .01$).[2]

Studies suggest ***trainings*** on data use and SDOH could influence data use skill, community collaboration, and staff's support for addressing SDOH.[21,23,58,59] Trainings are complex in public health practice, encompassing a variety of disciplines and not tied to one specific discipline.[60] In order to facilitate data use for decision-making, specifically SDOH

decision-making, trainings should incorporate content related to health disparities, SDOH, and data use[1] in order to improve how public health staff conceptualize and initiate upstream interventions.

Trainings integrating data, information systems, and scientific reasoning into decision-making have been shown to have high satisfaction among participants, satisfaction with course instructors, and a high percentage of staff reporting they would use these principles in their daily work.[61] Such trainings have focused on teaching public health practitioners to interpret surveillance data rates and select appropriate public health programs[61] or policy initiatives. They have also aimed to show how data can be used to establish health priorities in program development[62] and determine appropriate policies.[61] Participants have reported that training helped them make more informed decisions at work,[61–63] including understanding reports and communicating evidence to coworkers.[63] These studies examining trainings and their effectiveness are further supported by a review of organizational factors that facilitate research use in public health policy-making, citing internal capacity-building, including trainings, support integration of evidence-based decisions.[64]

Relative priority in our model is defined as individuals' shared perception of the importance of the implementation process of a site-specific intervention within the organization.[32,65] In qualitative interviews, LHD leaders have expressed a need for improved data quality and trainings on data use, data visualization, and health disparities for their staff.[1] Sellers et al. found training related to SDOH to be a top training need among LHD staff across the country.[66] This is further supported by a review of public health staff's health informatics training needs, citing using and interpreting quantitative data, designing and running reports from

information systems, and using geographical information systems as top training needs expressed by staff.[67]

The relative priority of data use skill and focus on SDOH appears high in public health. As a result, staff may be more likely to engage in available trainings and data dashboards and implement upstream interventions. For example, one study found work units with a strong commitment to health equity were more likely to suggest use of evidence-based decision-making (OR=2.6, 95% CI=1.7, 4.0).[22] They were also more likely to engage in cross-sector collaboration (OR=3.9, 95% CI=2.6, 5.8), and had a decreased likelihood of workforce skill gaps (OR=0.3-0.7, $p < 0.05$). Conversely, if staff believe data or data dashboard displays are cumbersome or unimportant to their immediate work, they may have little motivation to attend data-related training or use a dashboard. At an organizational level, relative priority of DDDM also reflects LHD leadership buy-in[32,60] and a high level of organizational value placed on research-informed practice[68] and health equity.

Readiness for change has also been theorized to play a role in effective implementation of organizational change.[69] When readiness for change is high, organizational members are more likely to "initiate the change, exert greater effort, exhibit greater persistence, and display more cooperative behaviors."[70(p1)] Shea et al. describes the two dimensions of readiness for change as change commitment and change efficacy. Change commitment is described as an organization's members' "shared resolve to implement change," and change efficacy is defined as, "staff's shared belief in their collective capability to implement change."[70(p2)] The relationship between readiness for change and data use is further described below.

LHD Staff Modifiable Factors

Although individual behavior has a complex interplay with organizational-level factors, organizational-level change begins with individual behavior.[32] Evaluation responses from trainings aimed at addressing health disparities and increasing ***SDOH knowledge,*** have found that training can increase staff's knowledge of health disparities and their understanding of strategies to address them.[23,71] In the Disparities Leadership Program training, executive staff attend a year-long program of education on the root causes of disparities, create a strategic plan within their organization to address them, learn change management skills, and attend regular conference calls to achieve their disparities project goals.[23] In another example, interviews with equity and health system leaders suggested that training can help staff to better understand influences of explicit and implicit biases on disparities, although knowledge attainment was not assessed.[72] Finally, pre-post test results from a workforce readiness training for community health workers emphasizing SDOH in their care services, showed an average 34% increase in knowledge acquisition.[71]

The CFIR framework notes ***self-efficacy*** as one of the most widely measured concepts related to individual change.[73] Self-efficacy emphasizes staff's beliefs in their own ability to attain [data use and SDOH, in our case] skills,[73,74] and could, therefore, impact data use by public health staff. Two reviews of self-efficacy in other areas of health research support knowledge attainment by the individual through education or training as contributing to positive outcomes such as increased knowledge and self-management behaviors.[75,76] This concept has not been studied as widely in the literature on public health workforce as it has in chronic disease prevention or self-management or behavior change sciences. However, literature suggests that, similar to chronic disease self-management education, increasing knowledge through training

could impact public health staff's belief in their own capabilities to carry out tasks or behaviors,[75,76] including data-driven tasks, and specific decision-making actions. This is further discussed below in our training evaluation responses.

Closely related to self-efficacy is staff's ***motivation*** and belief surrounding implementing change.[32] Berstein et al. specifically highlights the need for individual-level motivation in addressing SDOH, and recognition by public health staff of their role in addressing upstream factors.[21] Berstein et al. target motivation to address SDOH by depicting SDOH to be of personal relevance to staff (n = 23). Berstein's training included a case study on minimum wage policy and the health department's role in passing the minimum wage law to encourage critical thinking among participants. Evaluation responses found promising preliminary results on learning objectives and staff motivation and confidence in addressing SDOH (n = 23). Motivation is also supported by a review of factors facilitating use of research for policy-making in public health staff that found that, among individual-level factors, motivation and perceived usefulness were most often cited to support research use among staff.[64]

Within our model, ***support for SDOH*** is conceptualized in part by staff's beliefs regarding SDOH. Concepts of the CFIR framework include knowledge and beliefs as "individual's attitudes and value placed on the intervention,"[(p9)] with positive or negative value enhancing or lowering intention to change.[32] In order for public health staff to implement upstream interventions or reallocate resources, SDOH and equity concepts and strategies need to be personally relevant or at least perceived as important. The training discussed above by Berstein et al., describes personal relevance as public health workers needing to see or believe SDOH to be a part of their job,[21] yet staff vary in how they view this role.[45] Support for SDOH has been explored in the national PH WINS survey of public health staff, which found varying

degrees of support for addressing different SDOH such as transportation, housing, and social support networks among participants.[36] One study using PH WINS data found varying levels of support among different staff *tiers*, which could be impacted in part by knowledge of SDOH and its linkage to health disparities, as well as by varying degrees of decision-making authority or autonomy in their unique roles.[77]

The specific relationship between support for SDOH and potential outcomes [SDOH-related decision-making], such as resource allocation, targeted interventions for acting on underlying SDOH, or policy-implementation, has not been well described in the literature, which is, thereby, indicated by a dotted and dashed line in our model (Figure 2).

The specific steps and implementation processes of ***data use***—including obtaining data, analyzing data, understanding health disparities within the context of the data, and finally making decisions that utilize data—are not well described in the literature either and are indicated by dotted and dashed lines in our model. However, recent developments in the creation of dashboards suggest that data use could facilitate better allocation of resources, the delivery of interventions specifically aimed at populations in greatest need, and the implementation of policies. For example, data use and its relationship to SDOH decision-making is exemplified through the CDC's Data, Trends, and Maps dashboard.[14] This CDC dashboard aggregates data on nutrition, physical activity, breastfeeding, and obesity from various surveillance data bases, policy sources, and environmental data sources, presenting the data on one single platform. Organized data, along with data visualizations, produce knowledge that allows public health staff to synthesize information and communicate it to policy makers and community partners. Public heath staff are also then better equipped to carry out activities and make decisions such as, citing disparities in new grant applications, better identifying geographical areas and specific

populations for interventions,[15] fostering community partnerships,[78] prioritizing certain health areas,[38] and developing policy surrounding nutrition and physical activity access.[14]

Factor analysis and regression analysis

Data use skill and community collaboration skill were supported by our literature review and our exploratory factor analysis of public health workforce skills conducted in a separate study and described elsewhere.[49] To examine latent structures underlying public health skills we used 2017 data from PH WINS. Three factors were identified – *data and systems-thinking, planning and management,* and *community collaboration*.[49] Our data and systems-thinking factor included skills such as "identifying appropriate sources of data and information to assess the health of a community, using valid data to drive decision-making" and cultural humility items such as "implementing socially, culturally, and linguistically appropriate policies, programs, and services that reflect the diversity of individuals and populations in a community," and "supporting development of a diverse public health workforce." Literature similarly describes data use as using valid data for decision-making[2,79] and describing data use, as a component of evidence-based public health approaches.[60,80]

Establishing cross-sector collaboration and partnerships[80,81] is also frequently cited as a core competency in public health and fundamental to promoting population-level health. In our factor analysis, community collaboration skill included items such as, "engaging community members in the design and implementation of programs to improve health in a community" and "building cross-sector partnerships to address social determinants of health." A collection of case studies highlights LHD collaboration on upstream health interventions aimed at SDOH and involving partners, such as enacting living wages and preventing mortgage foreclosures, although population-level health outcomes were not measured.[30]

In a regression analysis that included the latent factors we had identified above, we found significantly positive bivariate associations between data use skill and support for SDOH (OR = 2.21, *p value* <.001) and between community collaboration skill and support for SDOH 1.29; *p value* <.05).[50] When we modeled an interaction between data use skill and community collaboration skill, however, there was a significantly negative association with support for SDOH at the mean value of each skill (health equity: AOR, 0.45, *p value* <.001; built environment: AOR, 0.77, *p value* <.05). Cross-sector collaboration, an aspect of collaboration, is still somewhat of an emerging concept being explored by investigators in public health and is a shift in paradigm from the traditional role of LHDs.[26,29,82] These findings suggest a need for further examination of the relationship between these two skills.

Training evaluation responses

Our SHARE-NW training evaluation pre- and post-survey responses further support various aspects of our model including readiness to implement organizational change for DDDM and its relationship to data use, as well as the relationship between training and data use skill and training and self-efficacy. In our pre-training survey (n = 103), staff responded to various change commitment and change efficacy items in "thinking about using data for decision-making in their LHD." Change commitment for DDDM was quite high, with 70-90% responding 'agree' or 'strongly agree' across various change commitment items. Change efficacy was slightly lower with 70-90% of staff responding, 'neither agree nor disagree' or 'agree.' This could suggest that at the organizational-level, participants appeared motivated to implement DDDM, however, they may not have perceived their organization to have the resources and capabilities to carry out this change.

Although post-training survey response rates for the whole series were low (n = 17), staff appeared to have relatively high confidence levels related to having met the training objectives. For confidence in performing the following learning objectives after completing the series of 3 SHARE-NW online trainings and 2 live training sessions, 88% of respondents indicated either 'agree' or 'strongly agree' for "considering how community data can be used to support decision-making to address health inequities," 93.8% responded 'agree' or 'strongly agree' for "applying tools and methods to prioritize public health policy options for addressing health inequities," and 87.5% responded 'agree' or 'strongly agree' for "describing how data visualization can be used for decision-making for addressing community health inequities." Although not statistically robust, these evaluation findings suggest there could be a positive relationship between data use skill and self-efficacy and SDOH knowledge and self-efficacy.

Our training participants also noted several ways information from the SHARE-NW trainings could be applied to their day-to-day work. Written responses included communicating with boards of health, utilizing data visualizations to engage with Federally Qualified Health Centers, and using data for community health assessments. In discussion with a training participant with one of the authors, the practitioner stated that, "there's a struggle to find trainings that really help people learn how to *use* data to make decisions. It's a subtle difference from helping people learn to use data *in general*. But there's this extra, slightly different topic regarding how you use those data to really drive decisions."

Potential Outcomes

Theoretically, the goal of the DDDM process in public health is to positively impact SDOH and alleviate health disparities. While potential outcomes of DDDM, or improved SDOH-related decision-making, is not well described in the literature; the literature does describe LHD

activity as ultimately aimed more upstream with DDDM. This includes improved resource allocation,[14] targeted interventions for populations in greatest need,[45] and policy development or implementation.[78]

DISCUSSION

One can theorize that with increased data availability, skills, and staff support for addressing SDOH, DDDM could lead to improved resource allocation, program implementation, and policy development. However, currently, the factors critical to the DDDM process are discussed only in abstract terms in the literature. Thus, we sought to identify and define concepts within the implementation process of DDDM and examine relationships between concepts in our model. We also aimed to describe associations between concepts we tested within our DDDM model.

Our model for DDDM to address SDOH in LHDs, describes concepts crucial to DDDM and the relationships between these concepts. Bronfenbrenner highlights the immediate setting (individual-level factors in our model) as the most influential level of the ecological systems theory. Moreover, implementation science targets factors at these individual and organizational-levels for organization change interventions. Evaluation of our own trainings related to DDDM in LHDs suggests that, at least in our small sample, readiness for change for DDDM was present among most of our public health training participants, and that trainings on health disparities, data use, and data visualization could potentially improve self-efficacy around these skills and knowledge of SDOH. Overall, our model supports the continued need for trainings in both data use and health disparities, and the role of potential moderators such as self-efficacy and SDOH knowledge on data use.

Some relationships between concepts, such as self-efficacy and data use were not well described in the literature or highlighted in our data analyses and merit further investigation. This is not surprising, given DDDM is an emerging and not yet well understood process within public health. Although well described in other areas of health research,[76] *self-efficacy's* relationship to *data use skill* and *data use* needs further examination. In other areas of research, self-efficacy is related to increased skill,[76] however, increased skill could also further reinforce self-efficacy. Furthermore, these relationships in public health are complicated, as they not only involve data use skill, but also an understanding of SDOH and health disparities, to result in actual data use that ultimately facilitates SDOH-related decision-making. Nevertheless, self-efficacy could play a role, potentially mediated by motivation among public health staff. For example, if staff better understand (from data) how SDOH are related to health disparities, they could then be more motivated to collaborate with specific community partners to implement appropriate upstream interventions, programs, and policies.

Lastly, the relationship between *support for SDOH* and *potential outcomes*, such as resource allocation, targeted interventions, and policy development is often more theoretically described in the literature, than formally evaluated. Studies describe efforts such as aggregated data and data sharing across public sectors to lead to tangible, equitable outcomes, such as, targeting breastfeeding interventions in populations with particularly low breastfeeding rates.[14] However, the specific process of how they reached this implementation decision is not evident in the literature we explored. Similarly, very little literature has evaluated data use skill in public health staff, and whether it relates to their data use. However we do know that data are still a fundamental tool in preliminary decision-making in public health regarding resource allocation, such as for COVID-19 disparities data, for example.[23,83] Future studies could examine this

implementation process, using a process-mapping method or task analysis with a think aloud protocol, as a means to understand the DDDM process from data retrieval to final program or policy implementation.[84] This would allow researchers and public health practitioners to better understand barriers, facilitators, and specific steps for staff to examine and appraise data, prioritize certain issues, and make decisions formulated to implement effective programs or achieve specific outcomes.

In terms of both research and practice, this model is important for advancing the effectiveness of the public health workforce and their LHDs. The model itself can be used as a tool for determining staff and organizational DDDM capacity gaps. Lastly, the model can also be used to guide DDDM implementation assessment since this is a complex process involving data availability, staff skills and knowledge, staff perceptions, and organization-level resources.

Limitations

Our paper has some limitations. Other related terms in the literature may exist that could be relevant to DDDM, which we did not explore given we focused our search around CFIR framework concepts. Also, response bias could have existed among our training evaluation responses and due to our limited post-training sample.

Conclusion

Our model addresses data use within the broader goal of reducing county-level disparities and achieving health equity in LHDs, adding to the body of knowledge of public health systems research and public health workforce development. Not understanding the linkage between SDOH and health disparities could lead LHDs to limiting themselves to individual-level interventions such as diabetes self-management or self-efficacy for nutritional behavioral changes. Understanding that SDOH disproportionately and negatively impact health outcomes in

certain under-resourced groups,[6] which creates health disparities, could motivate LHD staff to collaborate with their communities and create interventions that are 1) aimed toward specific groups or geographical locations where SDOH more negatively impact health outcomes and 2) aimed at upstream factors such as food access, housing, transportation, or economic stability. Bringing data to community members to help facilitate interventions and programs that are evidence-based *and* culturally appropriate for a community[78] could foster more effective collaboration. Furthermore, data use skill combined with SDOH knowledge could bolster LHD engagement in health disparities and SDOH activity through improved visualization of where these disparities exist in a jurisdiction. Our model could allow LHDs and other healthcare organizations to better implement DDDM and interventions aimed at health equity and reducing disparities. Staff's data use, knowledge of SDOH, and surrounding organizational capacity for change are key to LHDs continuing to drive population-level health outcomes and assure effective distribution of limited public health resources.

Figure 1. Preliminary Data-driven Decision-Making Model

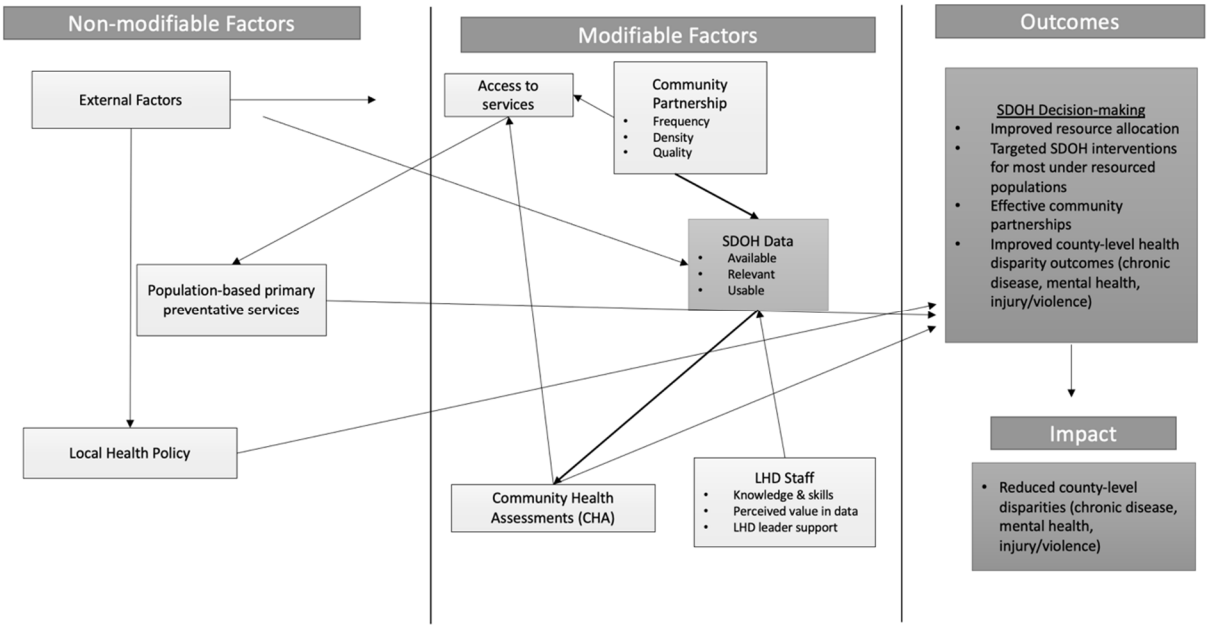

Figure 2. LHD Data-driven Decision-making Model

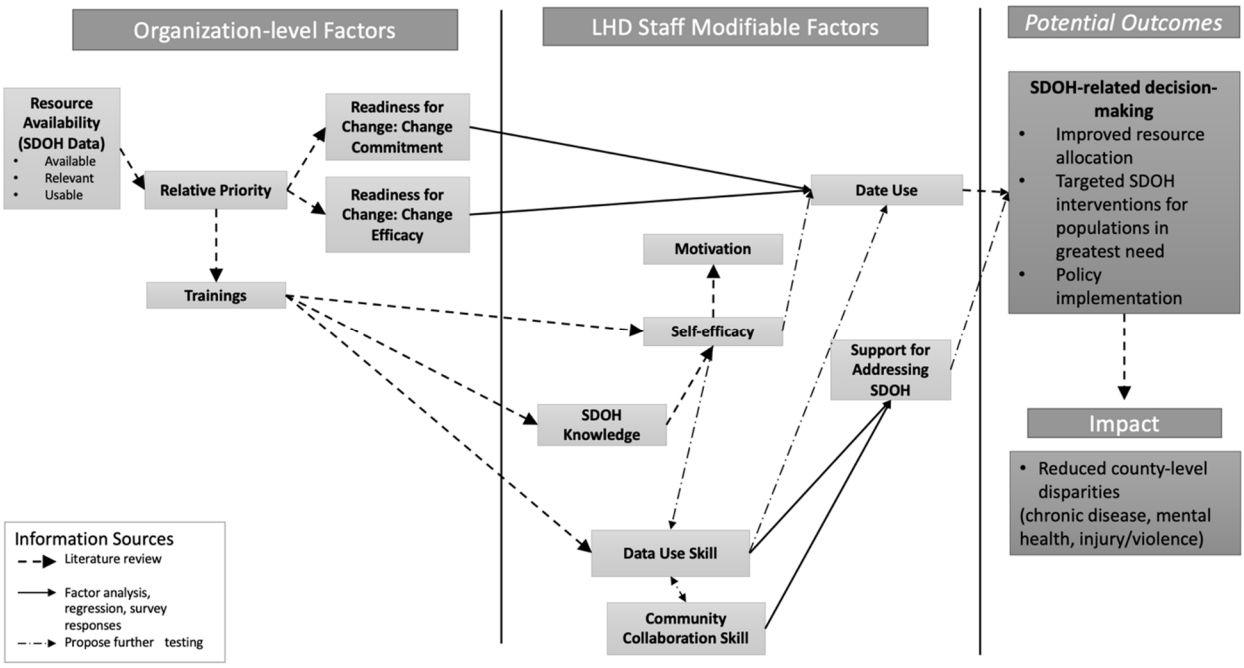

TABLE 1. Data Sources for LHD Data-driven Decision-making Model

Data source #1 - CFIR framework concepts:		
Year(s)	Model concept generated	Data supporting concept formation
2007-2022	• Resource availability	32. Damschroder, 2009; 42. Park, 2021; 41. Provost, 2013; 12. Ikemoto, 2007; 14. Lange, 2019; 16. Gourevitch, 2019; 10. Bekemeier, 2019; 40. Backonja, 2022; 55. Kuo, 2016; 57. Bekemeier, 2019(2); 1. Shah, 2019
2003-2019	• Training / workforce capacity	32. Damschroder, 2009; 21. Bernstein, 2019; 22. Furtado, 2018; 23. Betancourt, 2017; 59. Morrison, 2003; 61. O'Neall, 2005; 62. Maylahn, 2008; 63. Dreisinger, 2008; 64. Jakobsen 2019
2008-2014	• Readiness for change	32. Damschroder, 2009; 70. Shea 2014; 69. Weiner; 2008)
2009-2019	• Relative priority	32. Damschroder, 2009; 65. Gershon 2004; 10. Bekemeier 2019; 66. Sellers, 2015; 67. Massoudi, 2016; 22. Furtado, 2018; 60. Brownson, 2009
Data source #2 - Literature review:		
2017-2021	• SDOH knowledge	23. Betancourt 2017; 71. Lee 2021; 72. Doherty 2021
	• Motivation	32. Damschroder, 2009; 21. Bernstein 2019; 64. Jakobsen 2019
1977-2019	• Self-efficacy	74. Bandura 1977; 73. Grol 2007; 75. Náfrádi, 2017; 76. Jiang, 2019
2018-2022	• Data use	14. Lange 2019; 15. Chishtie 2020; 78. Owens, 2022; 38. Humphries 2018
Data source #3 - PH WINS data:		
2017	• Data use skill	*Q: What factors exist in public health competencies among LHD staff?* Three factors identified: data and systems-thinking, community collaboration, planning and management (*N*=15,173). Slight variation in item loadings existed between Tier one and Tier two and three staff analyses, suggesting workforce skills and training needs differ among public health staff groups.
2017	• Community collaboration skill	*Q: What factors exist in public health competencies among LHD staff?* Three factors identified: data and systems-thinking, community collaboration, planning and management (*N*=15,173)

2017	• Support for addressing SDOH	*Q: Are data use and community collaboration skills related to support for addressing health equity and the built environment among LHD staff?* Bivariate model showed data use skill was positively associated with support for addressing health equity (*N*=x, OR = 2.21, p value = <.001) and the built environment (*N*=4,829, OR = 1.29, p value <.05). Bivariate model showed community collaboration skills was positively associated with support for addressing health equity (*N*=4,829, OR = 2.0, p value = <.001) and the built environment (*N*=4,829, OR = 1.58, p value <.001).
Data source #4 - SHARE-NW Training evaluation:		
2021	• Change commitment*	*Is change commitment related to data use among LHD staff?* Change commitment for DDDM was high, with 70-90% responding *'agree'* or *'strongly agree'* across various change commitment items (*N*=103).
2021	• Change efficacy*	*Is change efficacy related to data use among LHD staff?* Change efficacy was slightly lower with 70-90% of staff responding, *'neither agree nor disagree'* or *'agree'*(*N*=103).
2021	• Data use	Open-ended responses from participants (*N*=17).

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Chapter 5: The future of data-driven decision-making

Introduction

Public health organizations have a duty to protect population-level health. Local health departments (LHDs) must form effective strategies to address the health disparities that create inequities. Although data are only a small factor in the complex process of population health improvement, data are nonetheless critical for guiding public health leaders and other staff making important programmatic and policy decisions. These decisions ultimately impact the well-being of individuals' lives in the communities LHDs serve. Support for data-driven decision-making (DDDM) across public health settings is growing.[1–4] Data dashboards and health informatics tool development are creating an opportunity to better understand the implementation of the DDDM process,[5,6] including the barriers, facilitators, feasibility, dissemination, and reach related to implementing data in LHDs.[7]

Many effective interventions in health services research ultimately fail to be translated into practice and meaningful public health outcomes. Some estimate that up to two-thirds of organizational efforts to implement change fail.[8] A recent qualitative study conducted of public health leaders' perspective on mis-implementation and the inappropriate continuation of programs or policies found participants considered programs ineffective for numerous reasons, including, if they were not evidence-based or did not fit well in the population and if the program did not reach those who could most benefit from that program.[9] It is evident that public health leaders recognize the influence SDOH have on health disparities to some degree,[9,10] however, mis-implementation of solutions appears to continue to be a barrier to LHDs effectively promoting health equity. Moreover, large societal barriers such as racism, sexism, transphobia, and poverty continue to drive policies that negatively impact communities and their health.

Although a national focus has begun to shift towards upstream interventions in nursing and public health,[11] centering health equity with every programmatic and policy decision should become the standard of practice. Data could be a part of the solution to intervention mis-implementation in several ways. For example, data could help LHDs better visualize where disparities lie, and thus where interventions are most needed. Data could also be shared with community partners to facilitate collaboration and align LHD prevention activity with community priorities.

This dissertation, in part, aimed to investigate the implementation process of DDDM by examining related skills, staff perceptions surrounding SDOH, and evaluation of trainings on health disparities, data use, and data visualization. Although our study elucidated constructs related to DDDM, the step-by-step by process of DDDM should be further investigated to gain insight into what data are still needed or can be improved upon, and what factors, both individual and organizational, best facilitate data use for SDOH-related decision-making. Qualitative interviews and process-mapping, for example, could help better clarify the psychology of decision-making for public health staff. Hierarchical linear models could also help better explain to what degree LHD factors such as budgeting, leadership, and political climate impact DDDM for SDOH-related activities in LHDs.

Public Health Staff's Perceptions and Knwoledge of SDOH

Epistemological barriers to addressing SDOH among public health professionals exist[12] and DDDM cannot likely be implemented effectively until staff see addressing SDOH as a part of their role and understand the linkage between access to various SDOH and health disparities. A study finding lower support for SDOH such as quality of housing versus social support systems suggests a lack of depth in understanding among some SDOH concepts, such as

transportation, housing, and the built environment and health disparities—critical system-level components related to promoting health equity.[13] This dissertation found that higher data use skills were not necessarily related to a higher likelihood of staff supporting the addressing of health disparities, a finding which merits further investigation into staff perceptions of data and SDOH and facilitatation of data integration for decision-making.

Staffs' perceptions and the degree to which staff are receptive to tools such as dashboards or other data-related activity implementation could also, in part, be related to COVID-19. Significant associations between exposure to COVID-19 among front line staff and burnout, anxiety, and depression[14,15] could impact workforce capacity, specifically related to staffs' motivation and ability to sustain organizational change in an already rapidly changing environment. For example, if LHDs are attempting to implement SDOH data use or data dashboards, but staff are burnt out or have competing priorities related to COVID-19 or other public health crises, organizational change may be difficult to implement or sustain. The current need to prevent COVID-19 has, at times, restricted public health staffs' focus to communicable disease and more secondary and tertiary care efforts. Nonetheless, change leaders, such as nurses, could help guide DDDM implementation in LHDs—decision-making that is necessary for effectively addressing disparities associated with COVID-19 and much more in communities.

Change Leaders of DDDM

Nurses are taking on leadership roles and nurse-led alternative models of care[11] and are particularly well-positioned to address the intersection of data use and addressing health inequities related to SDOH. A quantitative study found, for example, LHDs led by nurse public health directors, as opposed to non-nurse public health directors, were more likely to have completed a community health assessment and to engage in policy activities.[16] This could, in

part, be due to the holistic lens nurses bring to their leadership and public health roles.[17] Nurse public health director interviews found their "other-focused"[17(p4)] approach to nursing applied to their leadership-related work in addressing structural inequities. Qualities foundational in nursing, such as empathy, inclusivity, and integrity lend themselves to addressing SDOH. Given nurse's holistic approach to care and consideration of factors beyond biological or behavioral factors, nurses may be particularly well equipped to understand how SDOH relate to health disparities and what interventions could be most effective at the community-level. In using that knowledge, they can be change leaders who apply SDOH data to programmatic and policy decision-making, including intervention selection and targeting specific geographical locations for intervention implementation.

It would also seem important that LHD leaders be collaborative in relation to DDDM, as community collaboration appears to be an important factor to consider in DDDM. Our study also supported this finding. Even if the data suggest certain programmatic areas to be of high importance, if the topics and issues captured in the data are not of high priority to community members, they may not be appropriate to address, and related interventions may not even have a positive impact on health outcomes.[9] For example, a study examining rural health priorities compared community member's priorities and LHD health priorities.[18] While community members' top priorities were health care/insurance costs, obesity, and prescription cost, LHD top priorities included physical activity and nutrition, smoking, and unintentional injury. Community members, particularly in marginalized communities most negatively impacted by SDOH, infrequently have a 'voice at the table.' Participatory design or 'cocreating' health equity policy facilitates community members' buy-in and a sense of ownership, which could lead to more sustainable internventions.[19] A study of participator policy prioritization, termed policy

'codesign,' in eight geographically diverse counties was found to be a feasible approach to policy development.[19] Similarly, Owens et al. used codesign to develop a jail-based re-entry program for adults with opioid use disorder in a rural Washington state county.[20] LHDs could integrate community collaborations into their DDDM processes by combining community input and creativity with valuable SDOH data to cocreate upstream policy and program solutions that are grounded in both community need and evidence-informed practice. Moreover, community members could offer a valuable insight into SDOH-related disparities seen in the data to LHD leaders and staff through their lived experiences. Lastly, data could also be made more available for community members allowing them to better modify their own programs.[21]

Prioritizing Health Disparities

Although public health activities aimed at upstream factors are arguably more complex in their design and implementation than tertiary health interventions, they create far greater reach and longer lasting positive population-level health outcomes. Begun et al. developed an ordinal scale to assess whether a hospital's community programs promoted population level health, with higher scores indicating greater impact.[22] The levels included acute care/tertiary prevention (e.g., medical care); (b) secondary prevention (e.g., post-acute care services/screening/safety net programs); (c) primary prevention (e.g., immunization clinics/programs that promote healthy lifestyles and behaviors); (d) social determinants of health (e.g., housing, education, environment, access to resources and services); and (e) social determinants of equity (defined as population-level decision-making systems that influence SDOH). Scoring and determining a program's impact could be used by LHD's as well and taken into account when LHDs prioritize certain programs or policies. This kind of prioritization, in combination with SDOH data accessibility and PH capacity to understand and communicate these data, could help promote

health equity and more long-term positive health outcomes in communities. Data do not operate alone, however, they can help guide SDOH-related decision-making for more targeted and effective programs and policies.

Closing

Reliable, timely data are fundamental for public health workers (nurses, epidemiologists, program managers, and supervisors) to make decisions and to utilize limited resources and staffing. Understanding factors that contribute to DDDM and relationships between these factors is an important component to implementing interventions and policies related to SDOH. Data can inform interventions, but should be well-aligned with community need and properly communicated by skilled LHD leaders to be rendered effective. Examining the science of DDDM, generating related evidence for practice, and supporting related workforce development can enable LHD leaders and staff to be better prepared to carry out the DDDM processes in and with their communities that are needed to promote health equity.

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