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Digital Transformation in Measuring Social Determinants of Health:
A Systematic Review

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ABSTRACT

Digital transformation in public health has been implemented by governments and has significantly improved the accuracy and timeliness of public health management. Digital transformation in measuring social determinants of health is an emerging research area that has drawn significant scholarly attention. To assess how digital information influences the measurement of social determinants of health, this study performs a systematic literature review. The paper first discusses the background, definitions, conceptual framework, and research issues. Then it summarizes the research results with a focus on disruptions, strategic responses, changes that happened in the process, facilitators and barriers, and negative and positive impacts. After a discussion of the key findings, opportunities for future research are presented along with the conclusion.

KEYWORDS

Digital Transformation, Health Management, Public Health, Social Determinants of Health

INTRODUCTION

Digital transformation (DT), which has been implemented in various domains of public health, has significantly improved the accuracy, speed, efficiency, and cost-effectiveness of public health management (Brewer et al., 2020; WHO, 2019). To further improve public health outcomes, international and regional public health agencies have issued strategic frameworks in DT. For example, the Strategy on Digital Health 2020-2025 provides guidance and coordination on global digital health transformation (WHO, 2021).

In recent years, social determinants of health (SDOH) have gained attention in public health arenas. Research shows that SDOH have more significant effects on population health than healthcare alone (Barnard & Hagos, 2022; Bradley et al., 2016; Talbert-Slagle et al., 2016). Traditional measurements

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of SDOH are generally based on national surveys. Although reliable, the traditional methods are not timely (Elias et al., 2019). The far-reaching impacts of COVID-19 further underscore the need for prompt surveillance of SDOH to efficiently identify vulnerable groups and reduce health inequalities (Thorpe et al., 2022). Post-pandemic, social activities (e.g., working, studying, shopping) continue to shift to remote operations. This shift will continue to increase with the development of information technologies (Franken et al., 2021).

Thus, it is essential to implement DT in measuring SDOH. In fact, this emerging trend is drawing significant attention from scholars and officials. For example, the Centers for Disease Control and Prevention (CDC)'s Public Health 3.0 Call to Action asks political and local public health leaders to address SDOH and health equity issues with timely, reliable, granular, and actionable resources (DeSalvo et al., 2017). Studies of DT in measuring SDOH have been conducted across multiple disciplines. Most studies are seen in public health (e.g., Lasser et al., 2023), information systems (e.g., Macha et al., 2021), and sociology (e.g., Siira & Axel, 2022). To the best of the authors' knowledge, there are eight literature reviews in related fields. Four of the reviews examine SDOH measurement in the context of electronic health records (EHRs; Berg et al., 2022; Chen et al., 2020; Patra et al., 2021; Wark et al., 2021). Kino et al. (2021) focused on studies that measure SDOH with machine learning. Thorpe et al. (2022) theoretically discussed and summarized digital data sources for the monitoring of SDOH. Craig et al. (2021) and Cossio (2023) conducted a literature review of articles that leverage novel datasets and digital technologies to collect and measure SDOH. Still, both fail to adopt a clear theoretical framework to guide the review lens, resulting in a weak and incomplete analysis.

Accordingly, the current study conducts a comprehensive, deep systematic literature review on the ability of DT to measure SDOH based on a widely accepted DT process framework. The remainder of this article is organized as follows. First, it explains related definitions, the conceptual framework, and research issues. Second, the study describes research methods. Third, the results are presented. Fourth, the study offers recommendations for research agendas and discusses the article's contributions.

DEFINITIONS AND CONCEPTUAL FRAMEWORK

Definition of Measuring SDOH

Healthy People 2020 defines SDOH as:

Conditions in the environments in which people are born, live, learn, work, play, worship, and age, that affect a wide range of health, functioning, and quality-of-life outcomes and risks. (USDHHS, 2017, p. 1)

This definition is the basis of the SDOH measurement. It is divided into key domains with 19 subcategories per the U.S. Department of Health and Human Service (2017):

1. **Economic Stability:** This domain reflects on the connection between a person's financial resources (e.g., income, cost of living, and socioeconomic status) and their health. Issues include poverty, employment, food security, and housing stability.
2. **Education Access and Quality:** This domain reflects on the connection between a person's education and their health or well-being. Issues include high school graduation, enrollment in higher education, language and literacy, and early childhood education and development.
3. **Healthcare Access and Quality:** This domain reflects on the connection between a person's access to and understanding of health services and their health. Issues include access to health care, access to primary care, and health literacy.
4. **Neighborhood and the Built Environment:** This domain reflects on the connection between where a person lives (e.g., housing, neighborhood, and environment) and their health or well-

being. Issues include access to healthy food, quality of housing, crime and violence, and environmental conditions.

5. **Social and Community Context:** This domain reflects on the connection between a person's social environment (e.g., social support, family circumstances, and community engagement) and their health or well-being. Issues include social cohesion, civic participation, incarceration, and discrimination.

Definition of DT

Many differences can be found in research on the definition of DT (Vial, 2019). The current study adopts the following definition of DT:

A process that aims to improve an entity by triggering significant changes to its properties through combinations of information, computing, communication, and connectivity technologies. (Vial, 2019, p. 9)

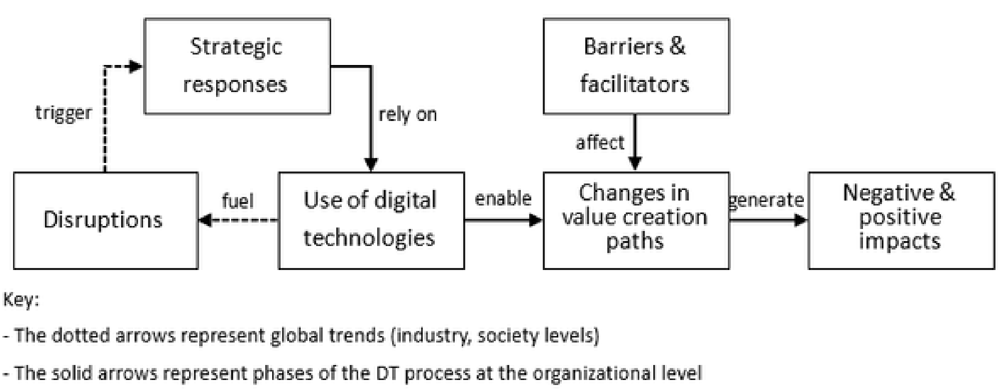
This definition is constructed on 23 extant definitions using semantic analysis methods. It also includes a comprehensive and in-depth description of the nature of DT.

Conceptual Framework and Research Issues

Vial (2019) presented an induction framework summarizing current DT knowledge to explain the process of DT. The authors adapted this framework to guide the literature review research (see Figure 1). The framework describes DT as a process in which digital technology plays a central role in creating and reinforcing disruptions at the social and industry levels. These disruptions also trigger strategic responses at the organizational level. Organizations apply digital technologies to transform value creation paths used to stay competitive. To this end, they must implement structural changes and overcome obstacles to their transformation efforts. At the same time, these changes have positive and negative impacts on organizations, industries, and society.

The arrow neither represents a statistical relationship nor the causal relationship in the variance model. Instead, it details the overall sequence of relationships described in the DT literature (adapted from Vial, 2019, p. 122).

Figure 1.



Thus, the following research questions are proposed:

1. What disruptions occur when DT is applied to measuring SDOH?
2. What strategic responses are proposed by industry associations or governments to facilitate DT when measuring SDOH?
3. What changes occur when measuring SDOH in the context of DT?
4. What negative and positive impacts could changes bring to organizations, industries, or society?
5. What are the facilitators and barriers at the organizational level in the process of measuring SDOH in the context of DT?

METHODS

Search Strategy

The current review is guided by PRISMA 2020 (Page et al., 2021). First, the study performs a search of full papers in the Scopus and PubMed databases. The search queries consist of three areas, focusing on titles and abstracts (see Table 1). The keywords in the public health domain are extracted from the Healthy People 2030 SDOH framework. Year of publication is set from 2013 to 2023. The final search was performed on May 1, 2023. If the databases provide studies within the reference list of previous literature reviews and papers, they will be screened to ensure the extent of coverage. In addition, the study searches for "digital transformation in measuring social determinants of health" on Google Search and Google Scholar. Then, it evaluates the results of the first 20 pages.

Study Selection Criteria

Table 2 lists the inclusion and exclusion criteria for this study. These criteria are iteratively developed by the authors based on a random sample of 20 abstracts. The study excludes research that meets any of the 10 exclusion criteria. It includes research that meets only the inclusion criteria. The authors follow this strategy to screen the abstract. If the authors hold differing opinions, the abstract is discussed until a consensus is reached. Then, the full text is reviewed for included articles. The authors filter the full text according to the selection criteria in Table 2.

Table 1. Search queries

Building Block	Keywords	
Information technology	"Digital" OR "Digital transform" OR "Information system" OR "Informatics" OR "Computer system" OR "Technology" OR "Big data"	AND
Public health domain	"Social determinants of health" OR "SDOH" OR "Public health 3.0" OR "Housing instability" OR "Poverty" OR "Employment" OR "Food insecurity" OR "Enrollment in higher education" OR "Early childhood development and education" OR "Language and literacy" OR "High school graduation" OR "Access to primary care" OR "Health literacy" OR "Access to health services" OR "Environmental conditions" OR "Quality of housing" OR "Crime and violence" OR "Access to foods that support healthy dietary patterns" OR "Social cohesion" OR "Discrimination" OR "Incarceration" OR "Civic participation"	AND
Characteristics	"Measure" OR "Assess" OR "Detect" OR "Surveillance" OR "Collect" OR "Identify" OR "Quantify" OR "Assess" OR "Impact" OR "Quantify" OR "Policy" OR "Disruption" OR "Strategic" OR "Change" OR "Impact" OR "Facilitator" OR "Barrier"	

Table 2. Selection criteria

Exclusion Criteria	1. Study that explores the new SDOH generated in the digital context. 2. Study that records SDOH information using digital techniques. 3. Study that assesses the importance of SDOH using digital techniques. 4. Study that teaches SDOH-related classes using digital techniques. 5. Study that predicts disease using SDOH data. 6. Study that discusses traditional measurement strategies for SDOH. 7. Study that uses digital techniques to solve SDOH-related problems. 8. Study that discusses barriers or facilitators of digital transformation in measuring SDOH. 9. Papers without full text. 10. Literature review papers.
Inclusion Criteria	1. Study that explores disruptions that have occurred when DT is applied in measuring SDOH. 2. Study that explores strategic responses that have been proposed by industry associations or governments to facilitate the DT of measuring SDOH. 3. Study measuring SDOH with one or multiple digital data sources. 4. Study measuring SDOH with one or multiple digital techniques. 5. Study exploring the negative or positive impacts of DT in measuring SDOH. 6. Study exploring the facilitators and barriers at the organizational level in the process of measuring SDOH in the context of DT.

Data Screening, Extraction, and Synthesis

The screening took place in two stages. Following the removal of duplicates, studies were screened independently by two authors (on title and abstract). Conflicts were resolved by a third reviewer. In the second phase, full text articles were screened independently by two authors. Conflicts were resolved by a third author. Data extraction was performed by two reviewers. Differences were resolved by a third reviewer.

The extracted data contained the following characteristics of each study: publication year; publication region; publication name; research theories; research approaches; research contexts; and samples. Data were also extracted pertaining to five research issues: (1) disruptions; (2) strategic responses; (3) digital data/technologies used; (4) negative/positive impacts; and (5) facilitators/barriers.

Extracted data were imported into a Microsoft Excel spreadsheet and a narrative synthesis was conducted. The qualitative and quantitative data were tabulated and classified according to five research questions. Frequency and proportion were calculated to examine the characteristics of studies.

RESULTS

Descriptive Quantitative Analysis

Overall Growth

A total of 73 papers (62 journal papers, five book chapters, three conference papers, two working papers, and one report) were included in the review. Figure 3 illustrates the annual number of published articles on DT in measuring SDOH. According to the results, over the last decade, researchers have continued to pay attention to DT in measuring SDOH. In fact, most of the articles were published after 2016.

Research Regions

Figure 4 shows the geographical scope of the included research. It is identified as the first affiliation of the article in this study. A total of nine countries were involved. Among them, the United States ranks first (with 61 publications). This is followed by the United Kingdom (4), and Australia (4). Portland.

Figure 2.

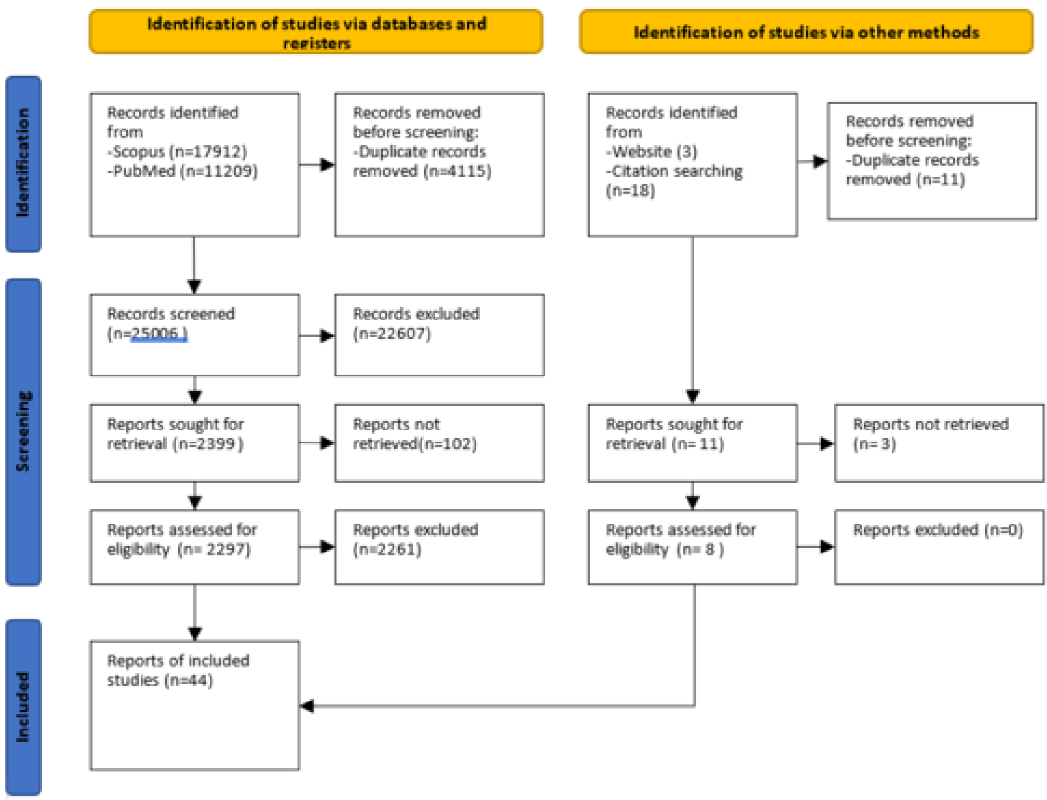


Figure 3.

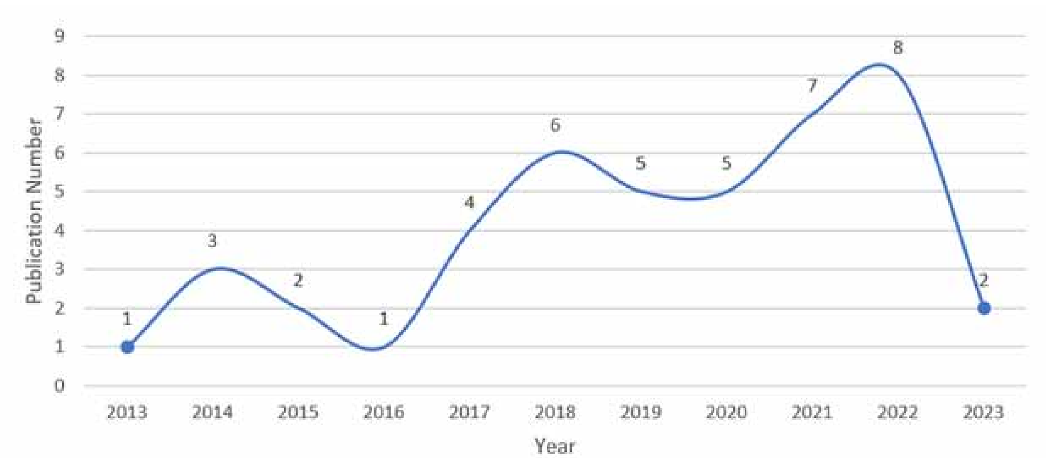
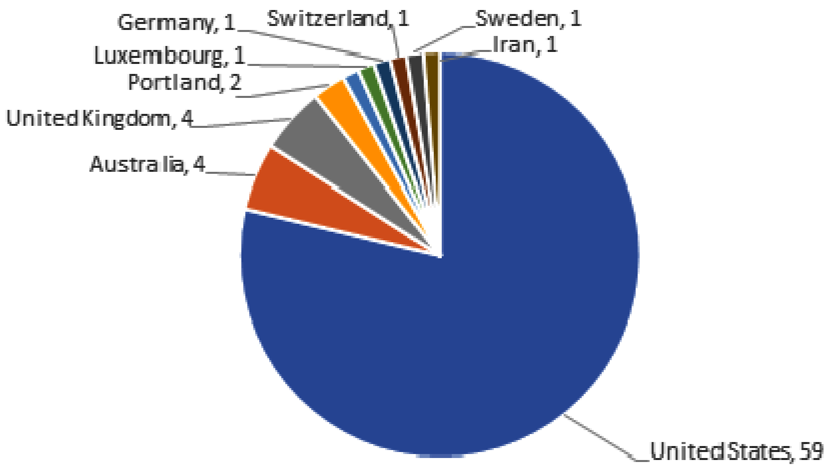


Figure 4.



Publication Sources

Furthermore, selected articles were distributed across various disciplines (e.g., information systems, public health, medicine, social science, and computer science). Publications with three or more articles include the American Medical Informatics Association Annual Symposium Proceedings (five articles), Journal of Biomedical Informatics (three articles), Journal of the American Medical Informatics Association (three articles), NPJ Digital Medicine (three articles), and American Journal of Preventive Medicine (three articles).

Research Theoretical Basis

Most studies did not employ a theory or framework to guide research. Only three studies adopted a specific theory or framework (social network theory, Bourdieu's forms of capital theory, and the biopsychosocial model). Table 3 summarizes the theories/models and their descriptions.

Research Approaches

Twenty-three of the included articles belong to review/comment papers. The remaining 49 research papers used six approaches to answer research questions. Secondary data analysis (n = 35) was the dominant method in the digital measuring of SDOH. Secondary data used in this method is usually obtained from publicly available data sources (e.g., Lybarger et al., 2021) or third party (e.g., Melody

Table 3. Overview of the theoretical foundation of included studies

Theory	Description	Study
Social network theory	The theory holds that each person is embedded in a social network of relationships that can influence health through diet, exercise, and other lifestyle habits (Scott, 2012).	Dhand et al. (2022)
Biopsychosocial model	The model states that in every healthcare task, three dimensions (biological, psychological, and social) must be considered (Engel, 1977).	Conic et al. (2021)
Bourdieu's forms of capital theory	Social class is a social group defined by the possession and utilization of various kinds of capital (economic, cultural, and social capital) in social space (Bourdieu, 1986).	Baum et al. (2012)

et al., 2022). The remaining five methods were case study (n = 5), survey (n = 5), observation experiment (n = 2), interview (n = 1), and focus group (n = 1). Table 4 summarizes the research approaches adopted in the research papers.

Disruptions

Expanded Measurement Framework

DT calls for a new understanding of the concepts of SDOH measurement. The most significant disruption in the SDOH measurement framework has been expanded. Two new indicators, digital literacy and digital access, are suggested for inclusion in the SDOH measurement framework (see Figure 5) as super determinants of health. This is because they are essential factors that impact all other SDOH (Bauerly et al., 2019; Clare, 2021; Early & Hernandez, 2021; Golder et al., 2010; Kickbusch et al., 2021; Sieck et al., 2021).

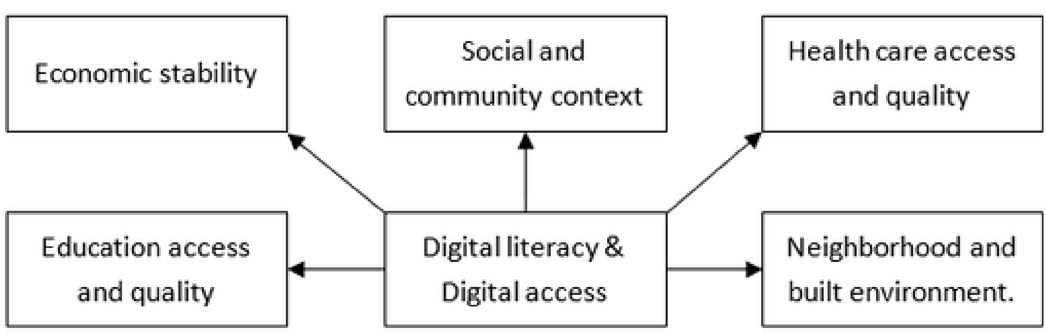
Digital literacy refers to the ability to search, evaluate, create, and communicate information via information and communication technologies (American Library Association, 2017). Digital access refers to the appropriation process in the form of information and communication technologies. These forms are mainly computers and the internet. Sometimes, smartphones and other digital hardware and software are included (Van et al., 2017).

Few studies present digital health literacy as the super determinant of health instead of digital literacy (Gillie et al., 2022; van Kessel et al., 2022; Richardson et al., 2022). However, the relationships among digital health literacy, digital literacy, and health literacy in the SDOH measurement framework have not been identified. More empirical research is needed to support this opinion.

Table 4. Overview of the research approaches of included studies

Method	Frequency
Secondary data analysis	35
Case study	5
Survey	5
Observation experiment	2
Interview	1
Focus group	1

Figure 5.



Digitally Recorded SDOH Data

Increased activities have shifted online as DT is embedded into broader healthy, political, societal, and economic processes. As a result, SDOH-related data can increasingly be collected from digital data sources, such as electronic health records or other digital health information storage and management systems (Adler & Stead, 2015; Backholer et al., 2021; Bazemore et al., 2016; CRSBDMEHR, 2014), real-life digital trails (Thorpe et al., 2022), and virtual digital trails (Rowe, 2021).

Proposed Strategic Responses

A digitally inclusive strategy is most proposed in responding to DT when measuring SDOH. This generally includes improving citizens' digital connectivity (e.g., providing equipment, reducing network costs, providing technical support) and digital literacy (e.g., providing digital literacy training) (Chakkalakal et al., 2014; Gold et al., 2017; Graham et al., 2016; Ray et al., 2017). Another strategy is through the creation of SDOH collection tools and record standards (BPHPHP, IoM & CRSBDMEHR, 2015; Friedman & Banegas, 2018).

In addition to efforts to create new collection and integration tools, a potential source of SDOH data already exists in electronic medical records. Thus, the International Classification of Diseases (10th edition) clinically modified Z codes (Z55-Z65) to document patients' SDOH-related socioeconomic, occupational, and psychosocial environments (CMS, 2018).

Changes in the Process of Measuring SDOH

Changes in the process of measuring SDOH in the context of DT can be divided into three streams. First, as mentioned, the measuring framework of SDOH has been expanded to six domains with 21 subdomains. Then, an overview of the SDOH domain measured in selected studies was completed (see Table 5). The results show that housing instability and social cohesion are the most watched indicators. Other indicators, measured by more than 10 articles, are poverty (n = 10), access to primary care (n = 11), and environmental conditions (n = 12). However, indicators of high school graduation, incarceration, and civic participation are only mentioned in two papers. Among the five SDOH domains, economic stability captures the attention of scholars. Social and community contexts gain the least attention.

The second stream of research places emphasis on seeking novel digital data sources (see Table 6). Among these data sources, electronic health record (EHR) is the first to receive attention. It is still the key component of digital sources for measuring SDOH (n = 28). Particularly, unstructured EHR data, such as physician notes (Navathe et al., 2018) and nursing notes (Topaz et al., 2019), have attracted increased attention from scholars. Other digital data sources explored in selected articles contain online activity data (n = 3), mobile device data (n = 4), and online survey data (n = 4). However, online survey data are self-reported by research subjects. Other data are passively collected, which makes data more objective and accurate.

The third stream of research highlights technology innovation (see Table 7). Technologies that emerged from the analysis include digital analytic technologies (e.g., natural language process [NLP]), geographic information system (GIS), machine learning (ML), image processing (IP), digital display technology, and digital collection technologies.

There is a degree of overlap between research streams. For example, some studies that extract SDOH from novel data sources also try to innovate in data analysis methods (e.g., Gundlapalli et al., 2013; Lybarger et al., 2021; Navathe et al., 2018). In addition, with the deepening of research in related fields, increased studies will innovate in both data sources and collection/analysis methods.

Forty-four papers measuring SDOH with digital data resources and digital technologies have used different types of research samples. Table 8 lists the common research samples used in the selected research. Fourteen of the 44 identified studies use general patients as samples. Samples of four studies are general individuals. However, more studies select specific objects as research samples, such as participants with a specific disease, participants of specific age, participants with a specific

Table 5. Overview of SDOH domains in included studies

SDOH Domains		Frequency
Economic stability	Housing instability	14
	Poverty	10
	Employment	9
	Food insecurity	3
Education access and quality	Enrollment in higher education	6
	Early childhood development and education	3
	Language and literacy	3
	High school graduation	2
Healthcare access and quality	Access to primary care	11
	Health literacy	8
	Access to health services	7
Neighborhood and built environment	Environmental conditions	12
	Quality of housing	6
	Crime and violence	4
	Access to foods that support healthy dietary patterns	3
Social and community context	Social cohesion	14
	Discrimination	3
	Incarceration	2
	Civic participation	2
New domains in the context of DT	Digital access	6
	Digital literacy	1
	Digital health literacy	1

Table 6. Overview of digital data sources used for measuring SDOH

Categories	Study
EHRs (n = 28)	• Structured data (Blosnich et al., 2020; Caryn et al., 2014; Downs et al., 2019; Feller et al., 2019; Kepper et al., 2023; Lasser et al., 2023; Rogers et al., 2022; Sills et al., 2016) • Unstructured data (Bejan et al., 2018; Bhavsar et al., 2020; Bucher et al., 2019; Conic et al., 2021; Feller et al., 2018; Goodday et al., 2020; Gundlapalli et al., 2013; Gundlapalli et., 2014; Hatef et al., 2021; Hatef et al., 2022; Hazlehurst et al., 2014; Lybarger et al., 2021; Navathe et al., 2018; Reeves et al., 2021; Shoenbill et al., 2020; Stemerman et al., 2021; Topaz et al., 2019; Winden et al., 2018; Yu et al., 2022; Zhu et al., 2019)
Mobile devices data (n = 4)	• Mobile location data (Macha et al., 2021) • Wearable camera data (Gemming et al., 2015; Schrempft et al., 2017) • Sensor devices data (Dhand et al., 2022)
Online survey data (n = 4)	Allison et al. (2022), Elin and Axel (2022), Greg et al. (2018), Prather et al. (2017)
Online activities data (n = 3)	• Online consumer data (Melody et al., 2022) • Social media and search engine data (Melody et al., 2022; Nguyen et al., 2017; Rachel, 2021)

Table 7. Overview of digital technologies used for measuring SDOH

Category		Study
Digital analytic technologies (n = 26)	NLP (n = 17)	Gundlapalli et al. (2013), Hazlehurst et al. (2014), Gundlapalli et al. (2014), Winden et al. (2018), Navathe et al. (2018), Feller et al. (2018), Bejan et al. (2018), Zhu et al. (2019), Topaz et al. (2019), Bucher et al. (2019), Goodday et al. (2020), Bhavsar et al. (2020), Shoenbill et al. (2020), Hatef et al. (2021), Conic et al. (2021), Hatef et al. (2022), Yu et al. (2022)
	GIS (n = 5)	Kolifarhood et al. (2015), Masho et al. (2017), Greg et al. (2018), Zhang and Schwartz (2020), Siegal et al. (2022)
	ML (n = 2)	Lybarger et al. (2021), Stemerman et al. (2021)
	IP (n = 2)	Gemming et al. (2015), Schrempft et al. (2017)
Digital display technologies (n = 1)		Pettit and Howell (2016)
Digital collection technologies (n = 1)		Friedman and Banegas (2018)

Table 8. Overview of the research samples of included studies

Sample		Frequency
Characteristic	General individual	4
	General patient	14
	Participants with specific disease	ICU (n = 1); COVID-19 (n = 1); Cardiovascular (n = 1); Gestational Diabetes Mellitus (n = 1); Mental Illness (n = 3); HIV (n = 2); Eye Loss (n = 1); Hypertension (n = 1); Lung Cancer(n = 1); Tuberculosis (n = 1)
	Participant with specific age	Live Birth Baby (n = 1); Children (n = 1); 4-17 years old (n = 1); Adult (n = 2); > 65 years old (n = 1)
	Participant with specific occupation	Military veterans (n = 2); Patients (n = 1)
	Participant with specific gender	Woman (n = 1)
Scale	> 100,000	10
	10,000 - 100,000	12
	1,000 - 10,000	9
	< 1,000	8

occupation, or participants with a specific gender. Among these samples, mental illness patients, human immunodeficiency virus (HIV) patients, adults, and military veterans have gained attention.

The scale of selected samples varies from 15 (Schrempft et al., 2017) to 240 million (Rachel, 2021). It is evenly distributed across four intervals through this review (see Table 5). Choice of sample size is closely related to research method. Research conducted by case studies, surveys, or observation experiments usually selects small-scale samples. The data collection and initial processing may need to be carried out manually by selecting a small-scale sample, making the research more feasible. The research using the secondary data analysis method generally chooses large-scale samples as they will result in more accurate research results. Finally, current computer technology has the ability to process large-scale data and unstructured data.

Two studies select longitudinal samples to follow individuals over time to measure changes in SDOH and health outcomes (Bucher et al. 2019; Feller et al., 2019). This type of sample is useful for understanding the impact of SDOH on health over time.

Facilitators and Barriers at the Organizational Level

Two types of facilitators emerged from the analysis. The first, the rapid adaptation of SDOH documentation tools in health information systems, includes EHR (Gottlieb et al., 2015; Wang et al., 2021). The second notes that unstructured SDOH data could be effectively captured and utilized with the development of technologies (Dorr 2019).

Meanwhile, studies found that a lack of interoperability is a key barrier to measuring SDOH in the context of DT (Cook et al., 2021; Lehne et al., 2019). Interoperability is the ability to exchange and use information shared between two or more systems or components (IEEE Standard Computer Dictionary, 1991). This requires a shared technical, legal, and organizational framework, which is a prerequisite for digital tools and data-driven technologies to realize their potential in public health (Lehne et al., 2019). However, combining data sets and running a comprehensive analysis is a longstanding challenge due to unstructured data and isolated data infrastructures (Cook et al., 2021).

Although SDOH is highly correlated with health, screening or conversations about SDOH are not a standard part of clinical communication (Gottlieb et al., 2015; Winden et al., 2018). For instance, the existing standard for recording SDOH (e.g., ICD-10-CM Z codes) has been found to have a low rate of utilization (Guo et al., 2020; Truong et al., 2020).

Negative and Positive Impacts

Impacts have been extensively discussed in the literature on DT measuring SDOH. The consensus is that the implementation of DT in measuring SDOH could reduce costs and improve efficiency (Siira & Wolf, 2022). It also poses a set of novel ethical and human rights challenges, such as privacy, equity, fairness, and safety (Bincoletto, 2020; Cantor & Thorpe, 2018; Kickbusch et al., 2021; Wood, 2020).

The studies yield inconsistent findings about the accuracy of digitally measuring SDOH. Several studies found that leveraging digital technologies and data in measuring SDOH could improve accuracy (Greer et al., 2022; Macha et al., 2021; Rowe, 2021). However, several scholars indicate biases in algorithmic development and data collection (Wood, 2020), as well as the growing digital divide (Baum et al.,2012). These factors could, in turn, magnify the monitoring deviation.

DISCUSSION

DT in measuring SDOH continues to gain attention from scholars and officials. However, a unified and systematic understanding of current knowledge is lacking. Therefore, based on a widely accepted DT process framework, this study reveals the current situation of related research from the aspects of disruptions, strategic responses, changes happening in the processes, facilitators, barriers, and negative and positive impacts. This section uses the observations and findings to discuss gaps in research and future opportunities.

First, the authors recommend discussions on how to expand the SDOH measurement framework in the context of DT. A preliminary consensus has been reached about expanding the measurement domain of SDOH in the context of DT. However, the exact number, name, and relationship of indicators are being discussed. For instance, which indicators should be adopted in the new measurement framework (digital health literacy, digital literacy, or both)? What is the logical relationship between digital health literacy, digital literacy, and health literacy if they are all included in the measurement framework? Besides, most current research on new indicators belongs to conceptual discussions. Therefore, more empirical research is needed to support the development of a measurement framework.

Second, future research directions should develop new digital data sources because the existing development of data sources is limited. The current research shows that the digital data sources used in existing research focus on EHR. Thus, they lack exploration of other digital data sources, especially passively collected data. There is rich research on digital public health surveillance using digital data. In addition, it is proven to be effective and feasible (Dredze, 2014; Șerban et al., 2019; Drew et al., 2020; Menni et al., 2020).

Besides, the measurement of SDOH belongs to the category of digital public health surveillance. Therefore, most digital data sources used in the research of digital public health surveillance (i.e., sensor data, social media data, search engine data, and online news data) are theoretically feasible for the detection of SDOH. Future research can learn from existing studies on digital public health surveillance and, in turn, develop more effective digital data sources to measure SDOH.

Furthermore, extant literature has not compared the differences among data sources used in measuring SDOH. Future research could investigate questions around which type of data could measure SDOH more accurately (active presentation data or passively collected data).

Third, the authors aim to further measure the SDOH with less attention. The current study shows that the measurement of SDOH in existing research focuses on few indicators, including housing ability, social cohesion, power, access to primary care, and environmental conditions. There are still many SDOH indicators to be measured. For example, future research could investigate how to measure civic participation or discrimination with digital data sources and technologies. The measurement of health literacy, digital literacy, digital health literacy, and digital access, as relatively new concepts with evolving definitions, should also be explored (American Library Association, 2017; Berkman et al., 2004; van Kessel et al., 2022).

Fourth, future research should explore new methods for SDOH measurement. The current study shows that most existing studies adopt secondary data analysis as a research method. This lacks in-depth exploration of other research methods. With the rapid development of sensor technology, real-time and specific data collection of research objects will become increasingly convenient. Therefore, observation experiments will have more space in SDOH measurement research. Future research should give more attention to observation experiments and other research methods, including how to use sensor technology to capture and categorize the environmental and social context of individuals.

Fifth, the current research shows that many studies are conducted in the U.S. The sample is too strong to effectively promote research results. Future research should include more extensive samplings in different regions of the world to expand the range of existing research and increase the universality of results. Furthermore, the research could compare the accuracy of the monitoring of SDOH through social media data in different countries.

Last, prior studies yield inconsistent findings regarding the influence on the accuracy of measuring SDOH in the context of DT. Most empirical studies support that leveraging digital technologies and data sources in SDOH measurement could improve accuracy. Macro factors like algorithmic biases (Wood, 2020) and the digital divide (Baum et al., 2012) would magnify the monitoring deviation. Thus, future research should explore the differences and interrelationships among these accuracy impact factors. Furthermore, there exists a tipping point to which macro factors (e.g., digital divide) have been improved. Thus, relevant disputes will no longer exist.

CONTRIBUTIONS

This study makes three main contributions. First, guided by PRISMA 2020, this study uses a rigorous method to review and analyze the published research on digital measurement of SDOH. Then, it determines the trend, theoretical basis, method, and background. Second, this study applies and adapts the DT process framework presented by Vial (2019) to explore the current situation of related research from five aspects (disruptions occurred, strategic responses, changes that happened in the processes, facilitators and barriers, and negative and positive impacts). Third, based on the discovery and analysis, the authors identified six future research directions.

However, this study is not immune to the common limitations of the literature review. For example, although this study does not restrict the search language, there are no non-English studies in the final review. Additionally, the keywords in the literature search need to be covered in more detail to search the literature more comprehensively. Further studies can improve the search keywords.

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