Received: 15 November 2023 | Revised: 9 September 2024 | Accepted: 10 December 2024

DOI: 10.1002/asi.24973

RESEARCH ARTICLE

JASIST WILEY

Using the S-DIKW framework to transform data visualization into data storytelling

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Abstract

Communicating insights from data effectively requires design skills, technical knowledge, and experience. Data must be accurately represented with aesthetically pleasing visuals and engaging text to effectively communicate to the intended audience. Data storytelling has received much attention lately, but as of yet, it does not have a theoretical and practical foundation in information science. A data story adds context, narrative, and structure to the visual representation of data, providing audiences with character, plot, and a holistic experience of narrative. This paper proposes a methodological approach to transform a data visualization into a data story based on the Data-Information-Knowledge-Wisdom (DIKW) pyramid and the S-DIKW Framework. Starting from the bottom of the pyramid, the proposed approach defines a strategy to represent insights extracted from data. Data is then turned into information by identifying character(s) facing a problem, adding textual and graphic content; information is turned into knowledge by organizing what happens as a plot. Finally, a call to wise action—always informed by cultural and community values—completes the storytelling transformation to create a data story. This article contributes to the theoretical understanding of data stories as emerging information forms, supporting richer understandings of a story as information in the information sciences.

1 | INTRODUCTION

Communicating information from data meaningfully requires an innovative blend of data visualization and storytelling approaches, which bridge the gaps between raw data, actionable knowledge, and good actions. Data storytelling has received much attention lately, but as of yet, it does not have a theoretical and practical foundation in information science. A data story adds context, narrative, and structure to the visual representation of data, providing audiences with character, plot, and a holistic experience of narrative. By transforming a visualization into a data story, its communicative power is enhanced, enabling the audience to understand complex information more effectively to know what to do and why (Dykes, 2019).

This paper proposes a methodological approach to transforming data visualizations into data stories, drawing inspiration from information theory, including the classic Data-Information-Knowledge-Wisdom (DIKW) pyramid (Rowley, 2007) and the more recent S-DIKW Framework, which uses storytelling to operationalize the process of bridging the epistemological gap between empiricism and social constructionism (McDowell, 2021).

The DIKW pyramid represents a hierarchical model that outlines the journey of data from its raw form to wisdom, with each level building upon the previous one. In this article, a new version of the S-DIKW framework integrates storytelling elements with the data visualization process. Defining data stories requires a combination of visual and textual elements that are developed by gradually working through the S-DIKW steps.

Data are necessary but not sufficient for communicating effectively. For example, communicating social justice issues requires both information and emotion, along with wisdom about sensitively representing suffering. The S-DIKW framework emphasizes the importance of engaging the audience. Narratives are developed systematically as they interact with and come to have meaning through text and visualization. Operationalizing the transition from data to story avoids the common pitfalls of creating stories without empirical substance or communicating data without meaning. To demonstrate the feasibility of the proposed methodology, the paper also details a practical case study related to the problem of homelessness in Italy, starting from the raw dataset. The S-DIKW Framework is applied to guide its representation as a data story, and further potential case studies are described in the discussion.

In this paper, we will use the S-DIKW Framework to create and edit a data story. This approach allows readers who are technically proficient with data visualization to grapple with why their data storytelling succeeds or fails, how to consider audiences as sense-making groups, and how to take responsibility for connecting data to the best actions to take and why.

The paper is organized as follows: first, we describe the related research in data visualization and data storytelling. Next, we define the concept of data story with characters and plot and then we explain and elaborate on the S-DIKW Framework in relation to the DIKW Pyramid. The following section explains the proposed approach, focusing on each step of the S-DIKW framework and how to interpret it in data visualizations and accompanying narratives. The next section describes a practical case study, which illustrates the practical application of the proposed approach. Discussion and conclusion sections elaborate on the role of the storyteller, potential future case studies, wisdom, and limitations.

2 | RELATED RESEARCH

A vast amount of literature exists on data visualization and data storytelling. Compared to the existing literature, in this paper, we combine concepts and practice to define a methodology for the practical construction of data stories. In the remainder of this section, we describe some of the most relevant work in data visualization and data storytelling. While the true scope of this literature is beyond any article-length literature review, we distill here some of the most important literature for understanding the methodological approach we propose. We start with the technical details of data visualization and expand with data storytelling. The objective here is to reveal the need for a more rigorous connection of theory and practice in the emerging area of data storytelling.

2.1 | Data visualization

Over time, research on data visualization has focused on different aspects. First, many researchers have focused on *design and principles* for data visualization. The most relevant works include the effort by Cairo to merge function, beauty, insight, and enlightenment, which, taken together, provide a set of guiding principles for data visualization (Cairo, 2012, 2016, 2023). Other important works highlight data analysis and visualization techniques commonly used to study science and technology (Borner, 2015), represent quantitative (Franconeri et al., 2021) and qualitative data (Henderson & Segal, 2013), how to distinguish between data and models (Midway, 2020), how to use the science of perception in data visualization (Ware, 2013), and the development of a framework to improve data visualization literacy (Börner et al., 2019).

A second research field includes investigating how data visualization can help *amplify human cognition and persuasion*. One of the pioneering works in this field is by Card et al., who suggest that data visualization expands the memory and the resources available, reduces the search for information, improves pattern detection, enables perceptual inference operations, and uses perceptual attention mechanisms for monitoring and encoding information in a manipulable medium (Card et al., 1999). In addition, visual representations can impact how efficiently we perform tasks (Norman, 2014) and minimize the time users need to understand data (Stasko, 2014). Other studies have focused on user modeling related to the cognition abilities in data visualization tasks, distinguishing between eye-tracking (Gingerich & Conati, 2015) or interaction methods (Conati et al., 2020). Following a completely different approach, Pandey et al. conducted an empirical study on the persuasive power of data visualization. They discovered that the persuasive power of data visualization depends on the initial attitude of the audience (Pandey et al., 2014).

The third field of research investigation relates to *technical aspects and tools* (Wilkinson, 1999). Qin et al.

survey the techniques data visualization tools require to make visualizations more efficient and effective, specifically focusing on efficient and scalable data manipulation and mapping (Qin et al., 2020).

Other fields of study in data visualization are Artificial Intelligence (Wu et al., 2021), the Internet of Things (Protopsaltis et al., 2020), Cultural Heritage (Windhager et al., 2018), and Big Data Analytics (Ali et al., 2016; Mani & Fei, 2017). In librarianship, creative metaphors from sculpture and design reflect the high level of variation among and between different libraries, with concepts for guiding data exploration and infographic creation (Magnuson, 2016).

2.2 | Data storytelling

Simply presenting charts with data points is insufficient to engage and enlighten viewers memorably. To truly captivate an audience and enable them to grasp the significance of the data, it is essential to transform a visualization into a compelling data story (Pica, 2023; Rodríguez et al., 2015). Data storytelling is a relatively recent field of study, so the distinction between data visualization and data storytelling is not completely clear yet. Schröder et al. systematized the understanding of the role of storytelling in visualization by conducting an extensive literature review, noting that the domain is still developing (Schröder et al., 2023).

One of the pioneering works on the topic of data storytelling is the book *Data Storytelling with Data* by Knaflic, who defines some creative strategies for visualizing data (Knaflic, 2015), such as the use of chart decluttering to communicate a message through a chart effectively. Following the same line are the books by Ryan using specific platforms like Tableau (Ryan, 2018) and Kriebel & Murray, who provide many existing visualizations as examples to create engaging charts (Kriebel & Murray, 2018). The Data Storytelling Workbook extends data visualization for applications in civic media spaces to "co-create effective ways of engaging with sensitive social issues through data analysis and communications" (Feigenbaum & Alamalhodaei, 2020, p. 2).

Studies on data storytelling have also focused on the classification of data stories using some criteria, such as the genres (Segel & Heer, 2010) and the story type (Davenport, 2014; Gray et al., 2012; Ojo & Heravi, 2018) similar to efforts during 19th-century colonial periods to classify all the world's stories (Clarkson & Cross, 1980). In higher education, new courses on data storytelling are being developed in information science (IS), library and information science (LIS), journalism, and other disciplines (D'Ignazio & Bhargava, 2018; Getz & Brodsky, 2022; McDowell & Turk, 2024).

Other recent publications focus on the processes of creating data stories, albeit predominately from specific industries or applications, including many how-to guides for business, journalism, librarianship, and science. In the book *Effective data storytelling*, three elements—data, narrative, and visuals—are developed in a four-step storyboarding process aimed at crafting compelling business data visualizations and developing data literacy more broadly (Dykes, 2019). Only a few works recognize the importance of the story structure with plots and characters (Dasu et al., 2024; El Outa et al., 2020). In particular, Dasu et al. acknowledge the importance of character, especially given the constraint of stories "rooted in non-alterable non-fiction" and argue that "we should think of abstract visual representations as data characters" (Dasu et al., 2024, p. 100). Claiming that data storytelling "is not storytelling with data," another framework for health-focused data storytelling posits a structural approach to story construction, "focusing on the novelty they introduce and the assumption they violate" (Matei & Hunter, 2021, p. 312). Pica focuses on the importance of communication in data storytelling by providing different strategies for data communication, including presentation planning, story structuring, and brainstorming (Pica, 2023). As a specific field of application of data storytelling, research on data journalism has focused on what distinguishes between simple journalism and data journalism. Weber et al. have identified seven key features of data journalism stories: data, communicative function, the textual–visual relationship, structure, and design of a story, interactivity, and the meta-story (Weber et al., 2018). Other studies on data journalism investigate how to engage readers more by exploiting user beliefs about data to build more engaging data-driven articles (Nguyen, 2019) and using data visualization to capture the readers' attention (Dukalska-Hermut & Dziwak, 2021).

Some approaches to data storytelling claim to have achieved an "automatic generation process of data stories by utilizing data science principles and software engineering methods." (Daradkeh, 2024) Other efforts have been devoted to the emerging field of combining data storytelling and generative Artificial intelligence (Li et al., 2024; Lo Duca, 2024b). While storytelling may be possible to automate at a surface level, automated storytelling—and related engineering or AI approaches—will require human judgments to reach and engage audiences effectively (Brooks et al., 2023). The need for human judgment in data storytelling is further demonstrated by problems of bias in data that can impact stories and storytelling. Recent work in data science has challenged the presumed neutrality of data, finding that social biases are routinely replicated in search engine results (Noble, 2018), large data sets (Crawford, 2013),

and coding practices (Benjamin, 2019). This has implications for all data visualization that go well beyond technical aspects. Taking data about underrepresented and frequently misrepresented groups of people can cause social harm, and remedies involve a complex humanistic set of epistemologies that center values and ethics (D'Ignazio & Klein, 2020). In other words, wisdom is necessary for effective data science and data storytelling. Table 1 summarizes the literature review on data visualization and data storytelling by highlighting the different fields of investigation.

TABLE 1 Summary of literature review.

Related work	Contributions
Data visualization	Design and Principles: Cairo (2012), Henderson and Segal (2013), Ware (2013), Borner (2015), Cairo (2016), Börner et al. (2019), Midway (2020), Franconeri et al. (2021), and Cairo (2023)
	Human Cognition and Persuasion Amplification: Card et al. (1999), Norman (2014), Stasko (2014), Pandey et al. (2014), Gingerich and Conati (2015), and Conati et al. (2020)
	Technical Aspects and Tools: Wilkinson (1999) and Qin et al. (2020)
	Application to Specific Domains: Magnuson (2016), Wu et al. (2021) (AI), Protopsaltis et al. (2020) (IoT), Windhager et al. (2018) (CH), Ali et al. (2016), and Mani and Fei (2017) (Big Data Analytics)
Data storytelling	Enhanced Data Visualization: Knaflic (2015), Ryan (2018), Kriebel and Murray (2018), and Feigenbaum and Alamalhodaei (2020)
	Data Stories Classification: Segel and Heer (2010), Gray et al. (2012), Davenport (2014), and Ojo and Heravi (2018)
	Data Storytelling Courses: McDowell and Turk (2024), D'Ignazio and Bhargava (2018), and Getz and Brodsky (2022)
	Data Narrative: Weber et al. (2018), El Outa et al. (2020), Dykes (2019), Nguyen (2019), Dukalska-Hermut and Dziwak (2021), Matei and Hunter (2021), Schröder et al. (2023), Dasu et al. (2024), Pica (2023), and Rodríguez et al. (2015)
	Data Storytelling and AI: Brooks et al. (2023), Li et al. (2024), and Lo Duca (2024a, 2024b)

3 | DEFINING DATA STORY

A data story is anchored to data, having some scientific basis in reality. However, at the same time, to be recognizable as a story, language must convey meaningful content in a structured way (Rayfield, 1972), which is based on two main concepts: central character and plot. The central character or protagonist is often the hero of the story; Joseph Campbell drew on structuralist analysis and psychology to define the hero as a narrative archetype based on analysis of major sacred, religious, and mythological stories. The hero is "the man or woman who has been able to battle past his personal and local limitations" to become a "perfected, unspecific, universal man" (Campbell, 1949, p. 20). In structuralist literary theory, Roland Barthes drew on semiotics to define a set of codes that structure narrative, including the enigma or hermeneutic code that defines the "intelligible progression" of plot as "a series of enigmas, their suspended disclosure, their delayed resolution" and a conclusion (Barthes, 1974, p. 29). We use these two theories from narratology, based on myth and fiction, to define what a data story is: Joseph Campbell's theory of the hero's journey (1949) informs the data story character definition, and Roland Barthes' theory of narrative semiotic codes (Barthes, 1974) informs the plot definition.

3.1 | The character

Character is adapted from Joseph Campbell's definition of a hero as a protagonist who sets out on a journey, struggles through obstacles, and completes the journey having transformed (1949). Data can serve as a character with an adapted understanding of the term "hero" as a type of main character. A data character is created from a pattern or trend in the data. It must be someone or something the audience cares about, which may range from an abstract representation to a person (Dasu et al., 2024). An effective data story character will relate, directly or indirectly, to people's experiences.

Example characters are:

- The number of people experiencing homelessness in a region.
- Incidence of disease by population.
- Temperature measurements that reflect climate change.
- Measurements of how well a new product solves a common problem.

The first two have direct connections to people, while the last two are connected indirectly, relating to the quality of people's lives. In each example, the main character

has an implied desire, such as to provide homes for people or maintain a habitable climate. Adding a human face to data can further refine the character, adding emotional appeal or zooming in on people impacted.

3.2 | The plot

In data stories, the audience discovers and tracks an adapted hero's journey, from data to wisdom. How these transformations occur is the foundation of the plot. Plot is defined as an adaptation of Roland Barthes' definitions of codes that constitute the structure of narrative (1974). Barthes identified five codes in narrative, from the cultural to the symbolic, that drive the reader to engage with the narrative. This definition adapts the hermeneutic code, which is the repeated process of encountering an enigma or mystery followed by disclosure of a solution or discovery throughout a narrative. The sequence may be causal, but it must be factual. The process of learning more is the narrative momentum in the hermeneutic code. E. M. Forster claimed that a story may be sequential but plot is causal (Forster, 1927). Data stories reflect correlations or causations as the data and context indicate, through a plot driven by investigation that draws the audience in like a mystery story.

Creating a story is the process of defining the characters and the plot, while the editing phase adapts the story to the audience and selects the order to tell the scenes, whether to cut some, add other details, etc., just as happens in creating a film. The creation phase of the story can include the classic division into three acts of a story: in the first act, the hero and the context in which they live are presented. The second act introduces the problem they have, and the third act describes if and how the main character hero solved the problem and possibly what to do next (Vogler, 1998).

Data stories can be energizing, inspiring people to change their actions based on the story. Data stories are told with the goal to persuade audiences to take action. What action to take and why must always be defined in relation to local events, situations, cultural values, and wisdom traditions. Therefore, while we can demonstrate several cases of how to transform data into wisdom through visualization, it is crucial that creators of data visualizations bring their judgment—professional and humanistic—as they develop data stories that convey information, knowledge, and wisdom.

4 | DIKW AND THE S-DIKW FRAMEWORK

DIKW stands for data, information, knowledge, and wisdom; this pyramid appears regularly in IS textbooks as "one of the fundamental, widely recognized and 'taken-for-granted' models in the information and knowledge literatures" and is often "used implicitly in definitions of data" (Rowley, 2007). T. S. Eliot is often credited with inspiring DIKW with his 1934 poem The Rock: "Where is the wisdom that we have lost in knowledge?/Where is the knowledge that we have lost in (Cite Eliot, 1962) information?" DIKW has alternately been called the information hierarchy, the knowledge hierarchy, or the wisdom hierarchy. While there are multiple ways of understanding and visualizing DIKW, all acknowledge the set and sequence of data, information, knowledge, and wisdom (Ackoff, 1989; Baškarada & Koronios, 2013; Bellinger et al., 2004; Bernstein, 2019).

The S-DIKW Framework adapts DIKW for theoretical and practical applications in narrative and storytelling. In this framework, each level relates to human abilities to derive stories from data, to interpret data with context as information stories, to take action based on those information stories, and to enact wisdom based on what they know.

- S-Data Basis of information in story.
- S-Information Data interpretation with context as story.
- S-Knowledge Actionable information in story.
- S-Wisdom Which story to tell when, how, to whom, and more.

It is important to distinguish between the broader definition of knowledge as a defining element of knowledge commons and s-knowledge as used here, which is derived from the narrower definition in the DIKW framework of actionable information (Rowley, 2007). In relation to S-Wisdom, this definition is likely only partial but provides a launching point for information fields to more actively and deliberately grapple with wisdom as a concept (McDowell, 2021, 2024). In this project, we move beyond that launching point and into an illustrated proposal for moving from data to wisdom in visual data storytelling.

5 | THE PROPOSED APPROACH

Transforming a data visualization chart into a data story consists of extracting characters and plot from the data (story creation with the three acts structure) and showing them to an audience through an enriched visualization (story editing). In simple terms, a data story raises questions and provides answers that connect data with context, and these connections constitute the plot. The audience engages a discovery plot that allows them to

TABLE 2 The mapping between the S-DIKW framework and the visual elements in a chart.

S-DIKW framework	Visual elements
S-Data	Choose the chart type describing the problem the hero has (Act II of the story)
S-Information	Add textual or graphic context describing the initial situation before the problem occurs (Act I of the story)
S-Knowledge	Define the enigma, disclose what happens, explain how/if the hero solves the problem and what to do after the story is ended (Act III of the story)
S-Wisdom	Tailor the story to the specific audience (Story editing)

learn, with support of visuals and text, the meaning of the data. In data story, the plot is then the process of discovering meaning based on data, moving from data to information, knowledge, and wisdom. To guide this transformation, we use the S-DIKW framework, which can represent the journey from the data character to the audience. A data story starts at the level of data, with a simple chart representing the problem the character has (II Act). In this scenario, the problem is a relevant insight extracted from raw data. Then, the story is enriched with new elements as it transforms into levels of information (I Act), knowledge (III Act), and wisdom (story editing). When the enrichment reaches the last level, wisdom, the chart is converted into a powerful data story, adapted to a specific audience. While there are many debates about how to understand the terms "knowledge" and "wisdom," for these purposes, we mean to operationalize these concepts as an illustrated guide to moving through this transformation process from data to story.

Table 2 shows the mapping between the S-DIKW framework and the visual elements to add to a chart to transform it into a data story. The remainder of this section describes each step separately.

5.1 | S-Data: Extracting and representing relevant facts

Data points form the basis of what ultimately becomes the visualization and its narrative. The choice of these data points depends on the specific research or analytical objectives, ensuring that the selected data aligns with the problem that the main character faces. In applying the S-DIKW framework to visual data storytelling, S-Data is the visual representation of facts relevant to something people care about, which becomes the main character. Transforming data into S-Data means building the setting of our data story, which should be represented through a clear chart that selects enough data to be informative but not so much that it overwhelms the audience with detail.

Raw data can be provided as tables stored in comma-separated-data (CSV) files, basic output from a dashboard, and JSON or SQL objects. Before representing data through a visualization chart, researchers should ensure they have permission to represent them. In addition, data should be of high quality (Moses et al., 2022), respect data privacy policies (Jarmul, 2023), and be fair and non-discriminatory (Davis & Patterson, 2012; Dignum, 2019). Data that represent people deserve additional consideration so that they cause no harm to anyone they represent.

Various data analysis techniques can be applied to extract facts that could be the basis of a story, such as descriptive statistics, inferential statistics, data mining, and machine learning (Khalil, 2024). These techniques enable the identification of patterns, relationships, and trends within the data. In the case of big data analytics, problems related to uncertainty should also be considered, including noisy data, high volumes of data, ambiguity in words and so on (Hariri et al., 2019). In his book *Seeing what others don't*, Gary Klein looks at data analytics from a more psychological viewpoint, by identifying four main strategies to identify a tension, obstacle, or challenge that can help to build a data story: connections, coincidences, curiosity, and contradictions (Klein, 2013). The connection strategy involves identifying the main points of data and then interpreting them to identify a story. The coincidence strategy involves searching for repeated events in data, disregarding isolated events while looking for longer-term patterns that suggest a relationship. The curiosity strategy searches for a wide range of phenomena in data, including outliers, missing data, data gaps across time or space, sudden shifts or trends, unexpected patterns, or any phenomena that raise new questions toward exploring the underlying factors contributing to the observed patterns. Finally, the contradiction strategy searches for two or more beliefs or pieces of evidence that conflict with data, creating an inconsistency. This model starts from the point of complete interpretation, when a pattern with potential to become a data story has been identified.

The first step to create a data story visually is to identify a problem (Act II) and choose an effective technique to represent the data. Note that the story development process occurs differently than the chronological story presentation, with Act II before Act I. In many cases, the visual representation of data stops at data visualization, without becoming a story. Identifying a character and plot is the difference between an audience being able to

TABLE 3 Suggested charts based on the information to convey.

Information to convey	Description	Suggested charts
A single piece of information	A single number representing critical information	• Big Number (BAN) • Donut Chart • 100% Stacked Bar Chart • Waffle Chart
Parts of a whole	The components contributing to the entirety of a system, object, or concept. The sum of all components must be 100%	• Pie Chart • 100% Stacked Bar Chart • Multiple Waffle Chart • Donut Chart
Comparison among entities	The similarities and differences between multiple entities to establish relationships and distinctions	• Bar Chart • Column Chart • Slope Graph • Dumbbell Chart • Table
Trend	The behavior of an entity over the time	• Line Chart • Small Multiple Line Chart • Stacked Area Chart • Stacked Column Chart
Outcomes of a survey or a questionnaire	Answers to questions contained in a survey or a questionnaire	• Stacked Bar Chart • Column Chart • Multiple Bar Charts
Distribution	Spread of values across a dataset, indicating how frequently different values occur	• Histogram • Pyramid • Box Plot
Relationship	Association, connection, or correlation between different entities to identify patterns, trends, and dependencies	• Scatterplot • Bubble Chart • Heatmap
Spatial information	The behavior of an entity over the space	• Choropleth Map • Dot Density Map • Proportional Symbol Map • Heatmap
Flow	Represent a process	• Sankey • Chord

infer information from a visualization and a fully developed data story, with a main character and plot raising questions that lead the audience to discover meaning that is informative, imparts knowledge, and points toward wisdom. While these differences can be a matter of degree in analyzing data representation, the main point here is to compose effective data stories, which starts with selecting a visualization strategy.

Data stories require effective visual representation that depends on the data type (Dykes, 2019). For quantitative data, common chart types include bar charts, line charts, scatter plots, and histograms. Qualitative data is often represented using charts like pie charts, stacked bar charts, and word clouds. These visual representations provide a concise and intuitive means of conveying information, facilitating comprehension. Comprehensive review of data representation is out of the scope of this paper. For convenience, Table 3 recommends which chart to use based on the information to convey. The list of described charts is not exhaustive, and imagination and expertise can be used to build new charts by combining elements of these techniques or inventing new ones.

5.2 | S-Information: Adding context to the story

The next step of the S-DIKW is information, describing the initial situation before the problem occurs (Act I). Turning data into information is adding details related to the story to introduce the audience to the problem (as the basis of the plot) and to engage them with the main character. This may also mean revising the data visualization with appropriate design that includes scaling adjustments, color contrasts, or even a different layout so that the initial situation is visually clear. From here, we can add textual and graphic content further describing the initial situation before the problem occurs. This is analogous to the setting in a story, but is more than just place because it may also include definitions of terms or additional images that represent contextual elements of the initial situation.

At this stage, using a too-detailed visualization for a general audience could distract them from the important information. Instead, we adapt the data visualization so that there is a place, both visually and in language, to begin following the character in the data story. Following Horn, who distinguishes three general classes of graphic symbols (shapes, words, and images) (Horn, 1998) we propose to add the following visual elements to the chart:

- *Commentary*: a textual description of the data, or the context around data, such as events, past situations, or conditions.
- *Annotation*: a short text focused on a specific data point or set of data points.

- *Symbol*: a visual element, such as a circle, an arrow or a line, that helps the audience focus the attention.
- *Image*: a picture, an illustration, or a photo that helps the audience give a face to the people behind the data.

Elements like these help to specify the character and anchor the opening of the plot by evoking curiosity to investigate. Adding context to a chart also involves crediting images and data sources by providing a reference to the image and data providers, which may include the name of the author or creator, a reference to the website, and any other relevant information that allows the audience to locate the source and continue to discover more of the data story.

Crediting images and data sources in a chart is an ethical responsibility because we show respect for the work of others and provide them with the recognition they deserve. In addition, proper citation ensures that the information presented is accurate, reliable, and credible. The audience can verify the accuracy of the information which supports their ability to critically assess information and promotes data literacy.

5.3 | S-Knowledge: Adding the climax and the story resolution

A good data story does not merely present the data, but interprets it as information toward knowledge of what to do next. With a defined initial situation and data character, the plot now develops to discover meaning at the level of knowledge of the problem, the enigma or mystery and disclosure of what happens, and whether or not the data character solves the problem. In a presentation, these steps occur sequentially; in a chart, these steps are designed to be followed visually. These representations together create a full picture of what to know, understand, learn, and/or what to do based on this data story. Knowledge in this context may be explicit or tacit, involving a "a mix of information, understanding, capability, experience, skills and values" (Rowley, 2007, p. 174). Knowledge also means knowing how to accomplish a goal, learning about how a problem might be solved (Ackoff, 1989), in this case, from the obstacles faced and steps followed by the data character. Knowledge helps the audience to consider what they could do, meaning both what actions to take and what they might do next with the story they have learned. Again, the below potential actions based on knowledge are not exhaustive, and imagination and expertise may combine forms or invent new ones. Table 4 shows some of the most popular potential actions based on S-Knowledge (Lo Duca, 2024a, 2024b).

Recent work analyzing patterns in social justice storytelling revealed patterns of calling out a problem and/or calling in an audience to act or learn more (McDowell & Cooke, 2022). Similarly, data stories developed to communicate knowledge may call out a problem by providing different options or enabling free interaction to explore the problem; or they may call in an audience by asking for support, proposing a plan, learning more, or sharing. For any specific data story, developing knowledge from data and information will depend on the history of best practices, research, and other factors that could demonstrate the benefits of a solution.

In a presentation, it would be valuable to justify the proposed next steps with research about best practices of other organizations that have been effective in addressing similar problems in other places.

Summarizing, the visual and textual elements to add to the story at this stage are:

- Commentary, annotation, or additional charts stating the main problem and the solution.
- Proposed next steps.
- Pointer to outside resources, such as a link, which reinforces the proposed next steps.

5.4 | S-Wisdom: Tailoring story to audience

Wisdom involves editing by selecting actionable insights tailored to a specific audience. We modify an element, like the title or a caption at the bottom, to be explicit about the goal to take action. The call to action must leave time for the audience to process the message. If too little time is left for the audience to elaborate on the message, the risk is to arouse denial, frustration, or depression (Kübler-Ross, 1969).

Wisdom entails complexity, including "contextual wisdom about audience, wisdom about story (selection), and self-reflective wisdom about the storyteller's own purpose, positionality, or bias" (McDowell, 2021). At this level the data character is informed by a set of values, and the plot connects the data, information, and knowledge to a larger purpose based on wisdom, such as the value of democratically addressing social problems. This stage of story development includes story editing, tailoring the data representation to our audience.

The most popular types of audiences can be grouped into three categories with some intersection: the general public, executives, and professionals. The general public includes individuals from various backgrounds and levels of knowledge who require precise language, focused on the most relevant insights. Executives are typically

TABLE 4 Potential actions based on knowledge.

Category	Description	Purpose	Example
Ask for support	Ask the audience to support the story in some way	Leverage the audience's competencies to solve the problems highlighted in the story	A text inviting the audience to participate in a survey
Provide different options	Provide the audience with potential alternatives to proceed	Help the audience's decision-making process	A list of possible alternative next directions: A, B, C
Interact Freely	Leave the audience the possibility to freely interact with the story	Let the audience analyze the data and draw conclusions	An interactive chart or dashboard
Learn more	Encourage the audience to delve deeper into the topic or insights presented in the data story	Direct the audience to additional resources, articles, studies, or references for a more comprehensive understanding	A link to an in-depth analysis report
Propose a plan	Propose a plan outlining the sequence of actions to be taken next	Let the audience continue working on the story after its end	A list of possible sequential next steps
Share	Encourage the audience to share the data story, for example, on their social networks	Leverage the audience's networks, foster discussions, and increase visibility to amplify the reach of the data story	A social media post sharing the story

high-level decision-makers in organizations who rely on data-driven insights to make essential business choices. They often have limited time and need concise and actionable information, and so need key findings, trends, and recommendations upfront. Professionals have specific domain expertise and a deeper understanding of data, and so they require more analytical information. Professionals need the methodology of the data analysis, making explicit any assumptions or limitations so that they are well-positioned to communicate their expert insights to executives. Table 5 summarizes the requirements and what to represent based on the audience type.

Wisdom is, at least in part, the audience empowered by the story. The audience develops the potential to act wisely, because they understand the story correctly, with attention to the real people affected by the data. They can learn from the story and retell it to others, so that the audience becomes the storyteller and amplifies the data story over time (Table 6).

Wisdom is ultimately as complex as the many human cultures and value systems through which wisdom spans long histories and generations. For data storytelling, telling a story wisely requires understanding what the audience needs to see, read, hear, and follow. Enacting S-Wisdom will require insights about audience roles, goals, and cultural value systems, all of which must be approached with cultural humility (Hurley, 2022) on the part of the storyteller, who will not entirely know how the audience interprets and retells the story (McDowell, 2018, 2020). Wisdom is the aim, even when we fall short, because stories told from data have profound consequences for human life.

TABLE 5 Requirements and what to represent based on the audience type.

Audience type	Requirements	What to represent
General Public	Understand data	An appealing overview of insights
Executives	High-level overview of data trends to aid strategic decision-making	Highlight critical metrics and trends influencing business outcomes
Professionals	Detailed insights to understand the phenomenon behind data	Add numbers, statistics, and helpful information to understand insights deeply and communicate them effectively

6 | A CASE STUDY: THE HOMELESSNESS PROBLEM IN ITALY

This section applies the concepts described in the previous sections to a practical case study: the homelessness problem in Italy. Let us suppose that we work for a humanitarian organization that wants to apply for funding from a Foundation to help reduce the homelessness problem in Italy. Humanitarian interventions can be applied to up to four Italian regions, and these regions are the character of the data story. The call for funds involves preparing a data visualization chart motivating the selected regions and why to fund the proposal. We

TABLE 6 The knowledge and the goal of each audience type.

Audience	Knowledge "before the story"	Goals or strategies "after the story"
Public	Lower knowledge levels	More variation of attitudes, but the goal is to persuade for democratic support
Executives	High knowledge levels but may lack a detailed understanding of data	Decision-making power and how they can be persuaded but also retell the story to others to justify decisions
Professionals	High knowledge level, most detailed understanding of data	Persuade executives as decision-makers, but they do not need to persuade the public

start a web search for possible datasets on homelessness in Italy. After several searches, we find the ISTAT dataset on homelessness in 2021 (ISTAT, 2021). We download the dataset and start analyzing it. Table 7 shows a simplified version of an extract of the homelessness dataset. The original dataset column names are in Italian. We have translated them into English to improve readability.

To transform the raw data into a data story, first, we identify the main character and the plot and then apply the S-DIKW framework. The story's main characters are the four regions with the highest presence of people experiencing homelessness, and the plot is about their desire to be funded to reduce the homelessness problem. The problem the main characters must deal with is that they are the worst regions in the country in terms of numbers of people experiencing homelessness. Once we have identified the main characters and the plot, we can apply the S-DIKW framework to transform raw data into a story, as shown in Table 8.

6.1 | S-Data

After defining the character and the plot, the following step involves choosing the best chart to represent our data. Due to the geographical nature of our dataset (Italian regions), we can adopt a choropleth map to represent data (Figure 1). However, this visual representation is not entirely sufficient for our purposes because it does not clearly show the top four regions of concern as the story characters.

As an alternative, we use a simple, ordered bar chart highlighting the top four regions to be funded (Figure 2). At this level, the chart simply describes a relevant fact in our data: the presence of four regions (Lazio, Liguria, Piemonte, and Sardegna) which are four characters people care about, each needing attention and a measurement of the need.

6.2 | S-Information

During this phase, we must tailor the chart by adding textual and graphic context describing the initial situation before the story occurs. This will engage the audience to support their process of discovery as plot.

During this phase, we add the following visual elements to describe the context (Figure 3):

- *Commentary*: a textual description of the people experiencing homelessness and a description of what the chart shows (immediately under the title). This commentary should help the audience understand the chart content and the situation of people experiencing homelessness in these regions so that they better grasp the struggles of these regions and the implications of the problem.
- *Annotation*: the percentage values associated with each bar. This increases chart readability.
- *Image*: two photos representing people associated with data (people experiencing homelessness). Images of people should never be used without permission, so these are not real people but instead are placeholder images that have been generated via AI. Represented people are characters that live in these regions as real people affected by the data, helping to reinforce the character function by personalizing the issue, emphasizing the urgency to act and do something on emotion, and the people whose lives can improve if these regions can make changes. At the same time, an organization doing this work well will likely have connections with real people who might be persuaded to lend their image to such a cause.

This phase captures the initial situation effectively, with enough additional information for the audience to understand what people there face.

6.3 | S-Knowledge

S-Knowledge requires explaining how or if the main character solves the problem, defining the possible next steps to follow. To explain how the problem is solved, we add the following elements to the chart (Figure 4):

- *Commentary* highlighting why the top four regions should be funded compared to the other regions.
- *Pointer to outside resources*, containing references to policy documents from Italy or related regions that have

TABLE 7 An extract of the ISTAT dataset on homelessness in 2021.

ITTER107	Territory	Sex	Age	Citizenship	Value
ITC1	Piemonte	M	TOTAL	ITL	4218
ITC1	Piemonte	F	TOTAL	ITL	1496
ITC2	Valle d'Aosta	M	TOTAL	ITL	41
ITC2	Valle d'Aosta	F	TOTAL	ITL	17

Note: ITTER107 is the region ID, Territory is the region name, Sex is one of Male (M), Female (F), Total (T), Age is one of Total (TOTAL), under 17 (Y_UN17), between 18 and 34 (Y18-34), between 35 and 54 (Y35-54), and greater than 55 ('Y_GE55), Citizenship is one of Italian (ITL), Foreign (FRGAPO), Total (TOTAL), Value is the actual number of people experiencing homelessness.

TABLE 8 How the S-DIKW framework is applied to the homeless case study.

S-DIKW framework	Story character and plot	Visual elements
S-Data	The main characters of the story are the top four regions, and the problem they have is high levels of homelessness (Act II)	A chart showing the top four regions and the comparison with the other regions
S-Information	Describe the homeless situation independently from the comparison among the regions (Act I)	Add commentaries, annotations, and pictures explaining the homeless situation
S-Knowledge	Describe why the top four regions should be funded and the next steps after funding (Act III)	Add a commentary and a pointer to outside information highlighting the motivation of funds and some charts for the next steps
S-Wisdom	Tailor the story to executives	Adapt language and tone of text and add other details, if needed

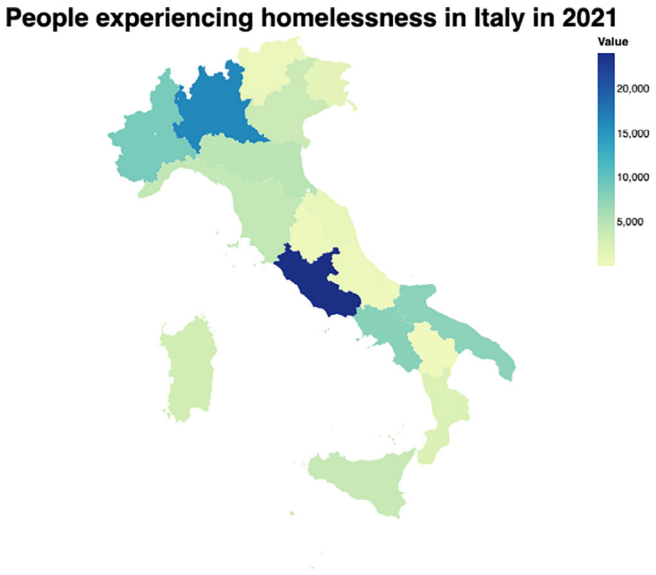

FIGURE 1 A preliminary representation of data using a choropleth map.

similar issues and resources that research outcomes or state best practices for reducing homelessness.

- *Next steps*, describing how funds will be used to address homelessness. For example, using 35% of the funds for shelter and housing, 25% for job training, etc. demonstrates that the funders have a clear plan to address the problem and provides the audience with knowledge about how to be effective in making a difference.

6.4 | S-Wisdom

S-Wisdom includes tailoring the story to the specific audience. This requires adding to the data, information, and knowledge of what to do a call to action that clarifies why this particular effort draws on the best available wisdom. In our case, the audience comprises executives from the Foundation who are able to allocate funding. The selected charts are easy to understand for executives, but they would be better suited to the audience by enriching them through the following steps. We modify the title to be explicit about the goal to take action: *Together, Let's Make a Difference: Support Our Project to Reduce Homelessness!* Another possible tailoring element could be the choice of colors, adapted for the specific audience, or the refinement of the pictures and the emphasis or tone of text in commentaries and annotations (bolded keywords). Figure 5 shows the final chart containing a full data story.

In other cases, depending on the audience, it might be wise to adapt for visual accessibility or readability by alternative reading devices, for those with visual impairments. Other audiences might require less detail, for example, if addressing a public audience then the goal at this stage might be to simplify the visualization. Similarly, if the audience includes people without homes and

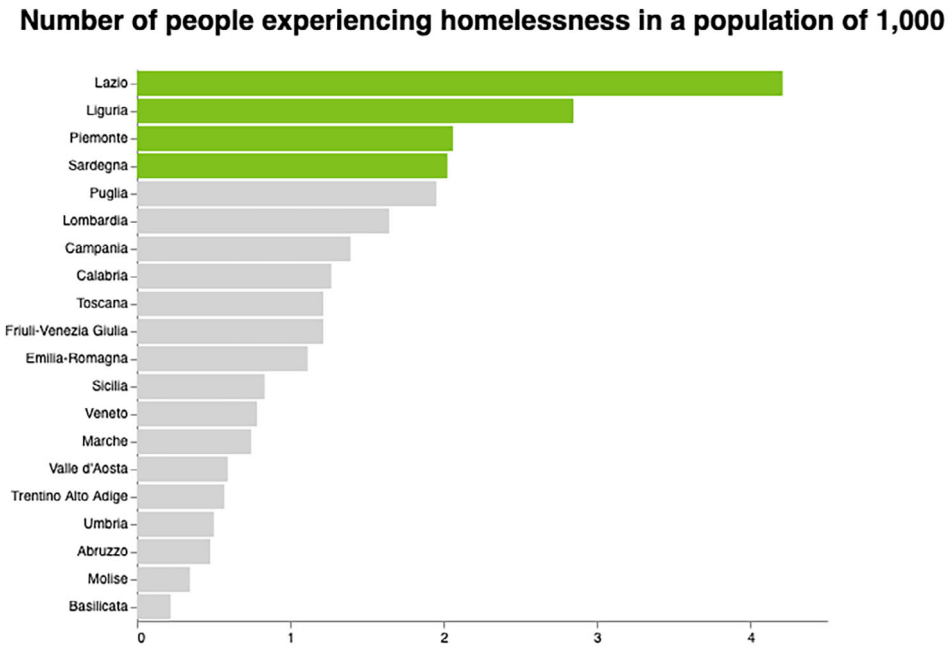

FIGURE 2 S-Data: A clear, ordered bar chart highlighting the top four regions to be funded.

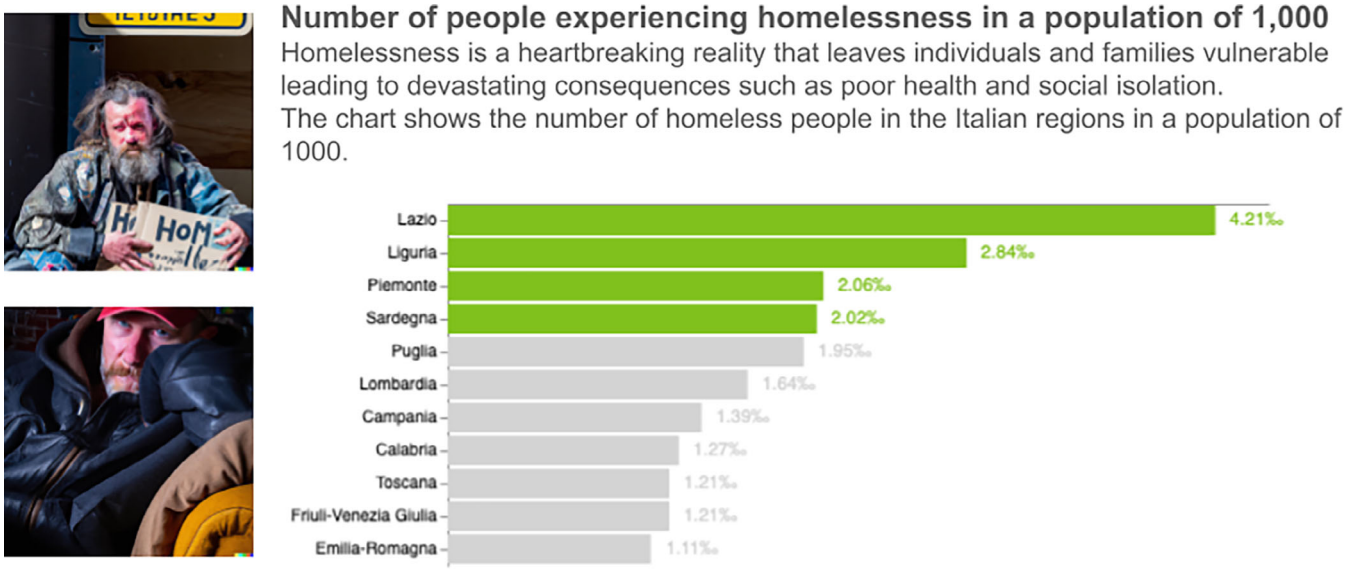

FIGURE 3 S-Information: The bar chart enriched with context (text and images).

the storyteller has not experienced this, then the presentation should emphasize humility. Further ideas about wisdom appear in the discussion section.

This completes the plot process of discovering the meaning of the data. The audience can see these regions as characters struggling with an issue and real people affected as characters. They learn the magnitude of the problem of homelessness. They gain knowledge about homelessness and its additional consequences that might not be immediately evident. Finally, they see a proposal for use of resources that indicates the wisdom of multiple forms of intervention and support.

7 | DISCUSSION

In the previous sections, we have illustrated how to use the S-DIKW framework to create a data story. Using this framework enables us to become aware of the essential parts of a data representation with attention to the story functions of character and plot and without adding unnecessary elements. S-DIKW helps the data storyteller to reason gradually about what elements to include so that the audience will emotionally engage and learn.

The storyteller plays an essential role in communicating a message to an audience, crafting meaningful

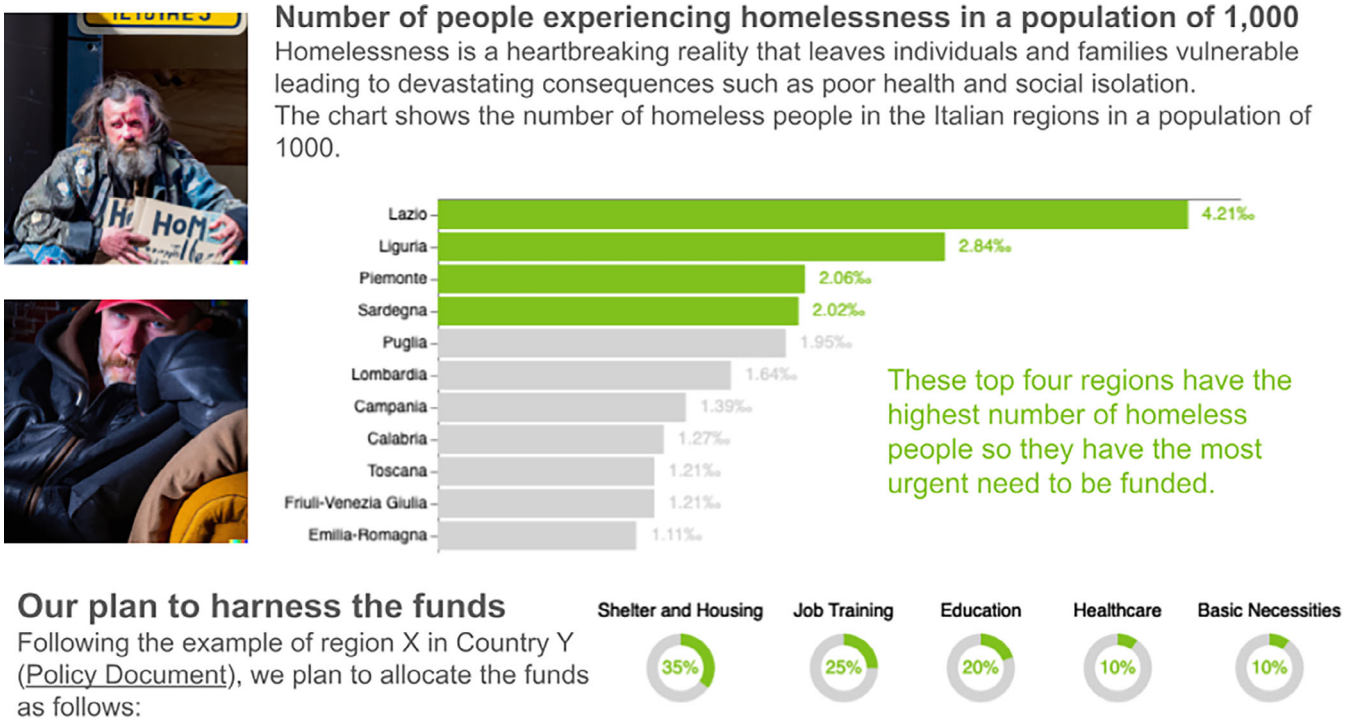

FIGURE 4 S-Knowledge: The bar chart enriched with problem solution, pointer to outsider resources, and next steps (a commentary and donuts charts).

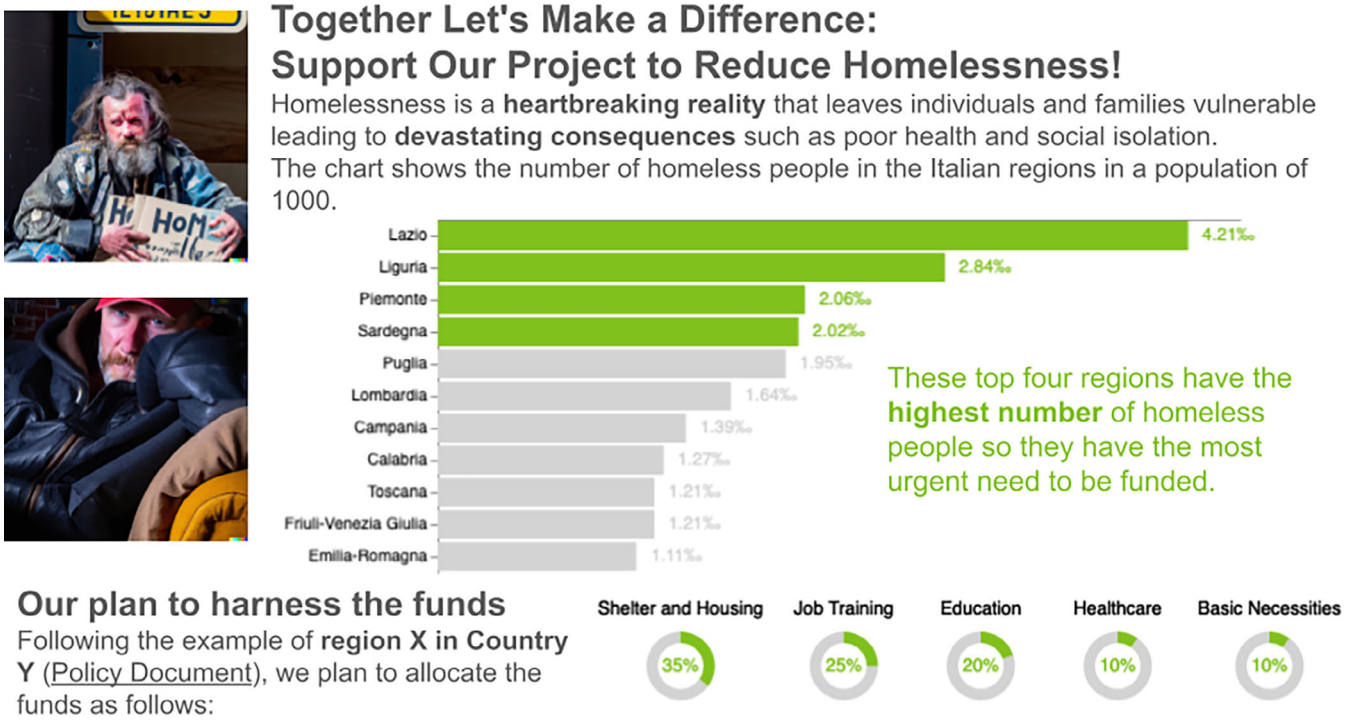

FIGURE 5 S-Wisdom: The bar chart converted into a data story.

stories around the data through representing their insights via chart selection, effectively conveying an initial situation, revealing a pattern or trend in the data as character, and organizing plot as a series of exploration steps and insights, with relevance to an audience.

This article details one practical case study, but many others would be possible. Three examples, based on

earlier possibilities for data characters, are incidence of disease by population; temperature measurements that reflect climate change; and measurements of how well a new product solves a common problem. Incidence of disease by population could become a data story with a trend of increasing disease as the foundation of data character and exploration of a secondary set of factors, such as temperature and humidity that influence the trend over time, leading to knowledge of how to prevent disease transmission and wisdom of how to communicate this effectively from a public health official to the public. Temperature measurements that reflect climate change could become a data character trend linked to greenhouse gas emissions, knowledge of how to reduce emissions, and wisdom of how the story should matter to executives who control manufacturing that produces greenhouse gasses. Measurements of how well a new product solves a common problem could serve as a data character, following a trend of how the new product compares to older ones connected to knowledge of why the product works and wisdom of what a group of professionals need to know to continue to design effective products.

Data storytellers must take responsibility for connecting data to what the best actions to take are and why. The complexity of drawing on values and finding ways to connect with an audience will require wisdom, and a full definition of wisdom goes beyond any case study and challenges us to think beyond any specific theory and into long traditions of human wisdom. Wisdom means aspiring for a virtuous chain that starts from the data and travels to an audience who acts and shares the story with another audience. As this communication flows, each type of audience subsequently takes on the role of storyteller when they retell the story to another audience. During a successful retelling, the components at the top of the S-DIKW framework will change, progressing from information (S-Information) to wisdom (S-Wisdom) while maintaining S-Data accuracy as a constant reference point. In other scenarios, we could decide to modify the Knowledge level but keep the others constant, and so on. Ultimately, if S-Data accuracy is maintained, then using S-DIKW enables us to decouple each level of the framework from the others to build accurate and flexible stories tailored to the specific audience and situation.

Wisdom requires the combination of cultural values with experience. S-DIKW can be used to communicate the same story to different cultures and societies, and yet the storyteller may not be able to evaluate whether the audience later acts wisely. Using the S-DIKW framework helps us to link each data story to its ultimate goal, wise action, while considering the people behind the data and anchoring the meaning to ethical principles.

8 | CONCLUSIONS, LIMITATIONS, AND FUTURE RESEARCH

In this paper we have described a theoretical approach to adapt the S-DIKW framework to data visualization to transform simple charts into data stories. We have identified a mapping of this framework to data story building and a practical case study showing how to apply it to an actual scenario. Our findings highlight the potential for data visualization to transcend its traditional role as a static information display tool and progress toward rich data storytelling. Data can anchor dynamic storytelling, enabling a deeper engagement with data for different purposes and types of audience.

The S-DIKW framework is limited in that it will require adaptation for applications in different situations, and its use will always require consideration of cultural and social context. Further investigations of adaptation to specific applications will support development of this and related frameworks. Further research will be important for future data storytelling needs as this is a rapidly changing area. Additionally, the conceptual process of identifying character(s) and transforming data into plot relies on the data storyteller investigating not only the data but also additional effective visualization or narrative techniques that, in specific cases, may go beyond the scope of this model. Nevertheless, defining data storytelling with a conceptual foundation and practical steps in visual data story building contributes to theoretical understandings of wisdom.

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How to cite this article: Lo Duca, A., & McDowell, K. (2025). Using the S-DIKW framework to transform data visualization into data storytelling. *Journal of the Association for Information Science and Technology*, *76*(5), 803–818. https://doi.org/10.1002/asi.24973