Tangible Data Exploration: Creating Card Games for Sensemaking

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***Abstract*—Participatory sensing has largely focused on the collection and dissemination of data, paying little attention to the fact that people often struggle to use the data and relate it to their daily lives. However, data is strongly connected to the context, environment and community within which it is gathered, whether by human or machine. Thus, those who are local to the data - especially those who participate in its collection - can bring valuable insights and can themselves gain value from interpreting it. This paper offers an approach for designing interactive narrative games with civic datasets, which are designed to make data easier to interact with, discuss and share in informal settings. It describes the planning and execution of a public data exploration event based around these activities. This work will be of use to people who are designing civic interfaces to support participatory sensemaking from data, especially in informal settings.**

I. Introduction

Participatory Sensing (PS) - often also referred as citizen science, crowd-sensing or crowdsourcing - is a type of civic technology created to support civic participation and encourage exploration of the physical environment through the collection and interpretation of geospatial data about issues of shared concern [1]. Local communities bring important knowledge to both defining and finding solutions to the issues that concern them. They also have important local knowledge for making sense of the collected data. All data, especially geospatial data, are local and have complex attachments to the place from which they are derived [2], [3]. Thus, PS is powerful when used by communities to not only gather evidence, but to participate in the interpretation of data and to bring in their understanding of the local context. This in turn facilitates the general public to use data as evidence to advocate for change or to contribute to urban planning and decision-making.

Yet, even when they have a role in the collection of data, most people still struggle to participate in its interpretation and make sense of it in relation with their daily lives. Where once the majority of research around PS concentrated on the technologies to support data collection [4] and ways to engage volunteers in sensing initiatives [5], very recently the focus is beginning to shift to how this data can be made more usable by the general public, especially those who lack expertise in these types of activity [6].

This paper describes one approach to overcoming barriers to using data for urban change, by *using narrative principles and game mechanics to make geospatial data both easy and enjoyable to interact with and make sense of* [7]. We also consider how to support *participatory sense-making* from the data. In other words, how to foster the sharing of ideas amongst the community from which the data came (both those who contributed to its collection and those who did not) in order to draw on their different experiences, knowledge and goals. In this way, where PS harnesses the collective efforts of the community, so might the interpretation of the data also benefit from communal wisdom.

The setting for the work described here is an 'in the wild' study [8] of a civic data exhibition that was designed to engage the public with data that had been previously collected through a participatory sensing initiative, in which members of the local community had used an app to monitor their local area, by finding and marking abandoned or 'lost' items, invasive species and nice places to visit. In this event, the public would engage informally with the datasets, driven by their own interests and time constraints. Therefore, the data had to be presented in a way that would grab attention and be easy to engage with, even in a very limited time-frame. The approach we have taken is to frame a number of individual *data games* which are designed to familiarise people who are visiting the exhibition with the different datasets that have been collected, in a short time frame. These games are designed so that they adapt existing techniques for presenting data in narratively coherent ways [9] whilst introducing an element of interactivity to the data stories. We also explain how we designed the space to lead people on a journey of increasingly unconstrained exploration of data, increasing the agency that the visitors have in creating their own stories from data, while reducing narrative constraints.

The questions we aimed to answer during the design and running of this event, were:

1) Can narrative data games engage visitors with data in informal settings and within time constraints?
2) Does the design of the space and activities support participatory sense-making?

II. Related Work

Data on its own has little intrinsic value; the value is created by its use and by the meaning that people place on it in a given context. But data can be hard to find and use [10]. Thus, open data is often under-utilised, especially when considering its use by citizens [11] and participatory sensing initiatives may find that people are not using the data as much as expected [6], [12], [13].

A range of research has looked at how to improve the data literacy of the general population [14], [15], [16], [17] to create a citizenship more able to understand and use data. Whilst definitions vary, data literacy is generally considered to be more than simply learning a set of technical skills, but also includes the ability to use data for civic empowerment [18], [19]. Data literacy skills support people to ask and answer questions from data, taking into account its possible limitations, the hidden assumptions behind the data and possible bias [20]. However, there are *limitations* to the data literacy approach. Many data literacy initiatives are designed for formal settings, such as in schools, where people have time to learn new concepts, tools and data literacy techniques. In a public setting where time is short a different strategy may be needed to help people who are not data professionals to make sense of large, or complex data sets. An alternative approach to building data literacy is to make the data itself easier to read and interact with [7]. Narrative principles are one approach to structuring new experiences in a way that helps people to make sense of them. The NAPA cards [21] are a set of design patterns that use narrative principles to structure data so that it can be presented in the form of *data comics*, made up of individual panels which they describe as 'a narrative element that captures a moment in the narration and focuses the readers attention'. Another approach to promote interaction with data is via games. Two fairly recent examples of this are the Datopolis board game designed by the Open Data Institute and the Datascape board game, designed to support learning how to match data and problems [22].

Based on the related work and given the goal of engaging people with data in a very short timeframe, our intentions were not to build data literacy but instead to reduce the need for data literacy skills by making the data easier to use and make sense of. We wanted to design data experiences that would a) entice the general public to explore the data collected during the monitoring initiative b) facilitate sensemaking of the data. We chose a *gamification* approach to engender the initial engagement and the use of *narrative* for sensemaking.

III. Designing Narrative Data Games

We utilised design patterns [9] to create individual narrative elements (or *panels*), presented as playing cards, that would frame the data in ways that highlighted the *key dimensions* (table 1). Instead of presenting cards in a fixed narrative, the goal was to design game mechanics in a way that would support people to find and tell stories from the data in an interactive manner. Narrative coherence was provided by fixing either the spatial or temporal aspect of the data within any given game and allowing the player to navigate only along one dimension at a time.

The following describes three different data games that were created based on the above principles. We also describe how they were presented in the context of the data exhibition.

Game	*Data Dimension*	*Design Template*
A	Type of data collected	Narrative (Expose)
B	Data collected across time	Temporal
C	Data collected across space	Faceting and Spatial

TABLE I
Data dimensions

Fig. 1. Speed data-ing. The player must turn the last card and read quickly.

A: Speed data-ing is designed to help visitors to get to know the different collected datasets. Visitors have only 30 seconds to get to know each of the three main data types that were monitored, these being lost items, invasive species and nice places. A similar approach was used by [23] with personal data, revealing how this might change the relationship that people had towards data and the way they engaged with and questioned it. A short time period is used, as positive time based stress helps people to focus on most important aspects and as such helps productivity too [24]. Key information on the cards is a) the name and icon used to consistently identify the dataset in the platform and in the exhibition b) the locations where most instances of the data can be found c) the most likely time periods containing data. This game is very low in interactivity with the narrative presentation of data.

Fig. 2. Shark-bytes. The first 3 cards are shown face up, the player predicts the next two

B: Shark-bytes is based on the US television show Card Sharks (Play Your Cards Right in the UK). The game normally starts with a random playing card and the player has to guess if the subsequent card (facing downwards) would be higher or lower. In our version, each game focuses on one of the data types and each card shows one weeks worth of data. Players predict whether the value for that datatype went up, or down (in total) in each following week. A player 'wins' by getting to the end of the line of cards without error. We anticipated that players would discuss how they base their prediction, using their knowledge both of the city and also knowledge of human behaviour. For example, by knowing popular holiday weeks, a player might predict lower values because the people participating in monitoring might be away. The aim of Shark-bytes was to support visitors in thinking about the importance of finding and analysing data trends - but also to cause reflection on how data is collected and how this may lead to errors or bias in data. To support the players memory, we also created a timeline of events in the city during the monitoring period captured by the playing cards and also an average of the weather conditions for each week. While Shark-Bytes can be played alone, we were also interested in the types of reasoning that people might bring to making a guess and whether people would collaborate and discuss how they made their predictions. This game maintains a fixed spatial aspect but supports the player to navigate the data across time. The player interaction slowly reveals the narrative, which is presented in a fixed order.

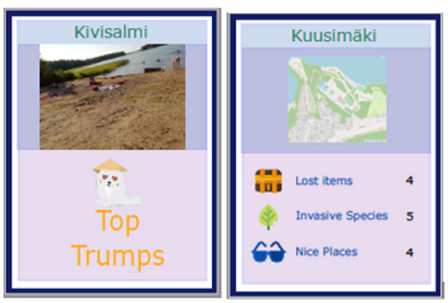

Fig. 3. Data Trumps, showing back of Kivisalmi card and front of Kuusimäki card, from which the player picks the category they think will 'win' the round

C: Data Trumps is based on the original Top Trumps card game. Data Trump cards relate to places in the city where the monitoring took place. Attributes are the three main data types that were monitored (lost items, invasive species and nice places) and the values are the total for the designated period (in this case, 5 weeks of monitoring). This game is designed to teach data comparison skills. Images taken by participants in the monitoring were used on the back of cards, to give a clue to the place (as even locals will not be familiar with all areas of the city). In addition, a map of the region was printed on the front of the card, along with the attributes and values. This is a competitive game, that is played in pairs. Each player takes a card and the player whose turn it is chooses an attribute that they think will have a higher value than their opponent. This game maintains a fixed temporal aspect but allows the player to navigate all three types of data across space. It has a much higher narrative interactivity than the previous two games, given the random nature of the cards and the player choice in choosing which attribute to find out about from the opponent.

A. Designing the visitor experience

As the card games were designed to be displayed and used in a public setting, it was important to consider the visitor's overall experience of visiting the exhibition space. Our approach was designed to lead the public through several distinct phases of interaction with data, starting with a high level of narrative constraint and low interactivity, leading to increasingly less constrained data exploration with lower narrative constraints imposed and higher agency for the visitor to find their own stories from the data. These stages are shown in Figure 2 and are now described in more detail, along with the activities within each.

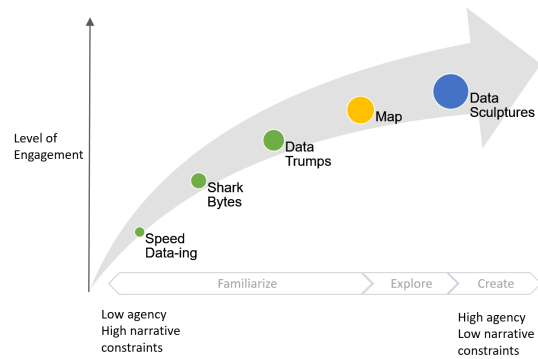

Fig. 4. Staged data exploration for increasing data engagement

Familiarise: The familiarisation stage consisted of the three interactive games; i) speed data-ing ii) shark-bytes and iii) top data-trumps, for visitors to the data exhibition to play. All three card games were presented in tangible form. There was an alternative digital version of the Data Trumps game that was made available on an Apple Mac Computer placed directly next to the physical version. The choice to present as cards that could be picked up and played was based on the premise that tangibility leads to deeper levels of engagement.

Explore: The exploration stage was designed to give visitors free access to the data, via a map-based interface presented on a large display over which they could easily collaborate. The map supported actions such as selecting:

1) One or more data sets to look at;
2) A geographical region (with panning and zooming);
3) A time period.

Create: The creation stage provided visitors with an artwork creation space to reflect a story they wanted to tell about what they had seen. Craft materials were provided, inspired by the data sculptures approach of D'Ignazio and Bhargava (https://databasic.io/en/culture/).

B. Guiding the visitor experience and capturing feedback

In the data exhibition, knowledge of museum curation strategies were used both to stage individual activities and to configure the layout to guide visitors along the intended path towards greater interactivity and storytelling from data. However, each activity was also designed to be self-contained and to make sense even if visited out of order.

Capturing feedback in a public place designed for fun can be problematic if it begins to detract from enjoyment of the overall experience of being in the place. As participation in the data exhibition was based on semi-structured activities, evaluation could not happen in a controlled way. Also, attending the event and all engagement actions were entirely voluntary. Since intervening with questions or questionnaires could distract the attention from participation, the data capture was designed to be unobtrusive and directly fitted to event themes. There were two primary methods of collecting data. Firstly, directly from visitors and secondly through observation.

C. Visitor contributed

Each visitor was offered the opportunity to take a sheet which had a place for a stamp and a place to mark some feedback on a 5 point scale. The scale was presented as faces to make it appealing and easy to use, knowing in advance that there would be several schools visiting on that day. Visitors who collected stamps for all the activities were able to take a lollipop when they handed them in. Stamps with different colours and patterns were placed at each activity station. In this way, data could be collected about the order in which visitors did the activities.

D. Observation

The second method through which data was collected was by direct observation. This type of observation can be extremely challenging in a public space, especially when it is conducted in real time. The purpose of the observation data was to provide some additional support for the visitor contributed data. Observation data was captured directly onto maps of the exhibition layout. To measure engagement, we adapted a number of individual behaviour measures from Falk [25] to fit our context and then weighted them according to the levels of engagement within the Visitor Based Learning Framework (VBLF) developed by Barriault and Pearson [26]. Both scales were created to measure engagement within informal settings, such as museums.

Level	*Description*
1A	Doing activity in passing
1B	Doing activity somewhat completely
1C	Doing activity completely, but no further exploration
2	'Purposefully' watching others engaging in activity
3	Repeating the activity
4	Expressing positive emotional response
5	Referring to past experience while engaging in the activity

TABLE II
VBLF MEASURES

IV. Results

A. Visitors

A total of 158 visitors (80 female, 78 male) indicated their presence at the exhibition by placing a LEGO piece onto a LEGO bar graph, used for capturing demographics. Breaking this down further, there were 28 visitors between 0-10 and 122 between 11-20, showing that children make up most of our sample. This is due to a number of schools bringing students to the event during the morning. Not everyone placed a piece

Level	*Description*	*Weight*
L1	Irrelevant behaviour (messing around, eating)	0
L2	Focusing attention on game cards, or map display	0
L4	Interacting randomly	0
L5	Visitors negotiate what to do or discuss the activity	1
L6	Visitors take turns in doing the activity	1
L7	Playing game as intended	1
L8	Two visitors do the activity at the same time	1
L9	Playing again, changing variables	2
L10	Smiling, pleased with exhibit	3
L11	Stronger signs of enjoyment	3
L12	Obvious signs of eagerness to participate	3
L13	Relating the activity to own life	4
L14	Can't tell	0

TABLE III
INDIVIDUAL BEHAVIOURS AND WEIGHTS

of LEGO and this was particularly true of older visitors, so the true picture is not quite as out of balance as it appears here. Figure 5 shows pictures from the exhibition.

Fig. 5. Exhibition set up

The stamp sheets were analysed to evaluate the level of engagement visitors had with the different activities. 149 visitors completed a stamp sheet, meaning that they placed at least one stamp or one rating onto the sheet. While we do not have information about who completed these sheets, it was observed that the majority of these were from the under 20 demographics. 5 sheets were removed because the visitors had not understood where to get stamps and had visited other stalls within the carnival area and written feedback about those. 5 further sheets were removed as it was observed that the visitors had given feedback without engaging in the activities first. This left a total of 139 sheets for analysis. Analysis of these sheets revealed that 71 of the 139 visitors went to each activity in the intended order, 1-5, which is just over 51 percent of the sample. A further 5 visitors started in order and then did not complete remaining activities. In some of the remaining cases, there is only slight disruption in the ordering, for example visiting in the order 51234, or 15234. Others are completely disrupted (6 people visited in the order 53214) whilst 3 people visited everything in reverse, going 54321. Some disruption can be explained by the busy times, when there were lots of visitors at once and people tended to visit the activity that had less people waiting. Only 16 people did not complete all 5 activities.

Each activity was rated between 1-5, where one was least enjoyment and 5 was maximum enjoyment. Not all stamped activities received a rating, leaving a number of missing values. Interestingly, it was usually the last rating that was left out, indicating a type of post-completion error where visitors were focused on the goal of collecting stamps and not on the rating that they gave. The activities were:

1) Speed Data-ing
2) Shark Bytes
3) Data Trumps
4) Map Interface, with questions
5) Data Sculptures

The mean ratings for the activities 1-5 (in order and with SD in brackets) were 4.2813 (1.03825), 4.3789 (0.67128), 4.4719 (0.61865), 4.4028 (.67989) and 4.5068 (.7092). The significance of the difference between ratings on the different activities was calculated using Wilcoxon Signed Ranks Test. A Bonferroni correction gives a significance level of 0.05. This showed a significant difference between the mean rating for activity 1 and activity 3 (Z = -3.050, p= .002), and also between activity 1 and activity 5 (z = 3.162, p = .002), but not between the other activities. To investigate this further, the same tests were conducted between the ratings given by people who encountered activities in intended order and those who did not. This showed a significant difference in ratings when people did activities 1 and 3 *in order* (z = 2.882, .004) but not when they did them in reverse, e.g. 3 and then 1. This result indicates that the ordering of at least these activities is important for fostering engagement.

Detailed observations of engagement were made by trained observers. In total, 39 people were observed, 20 female and 19 male. 8 were estimated to be over 20 and 31 were under 20. 16 participants visited the activities in the order 12345, a further 3 started in order but did not finish. Several of the observed visitors only completed one activity, which was the 4th activity (interactive map).

Each activity received an engagement rating between 0-4. This was calculated as a weighted average from the set of individual behaviours, adapting the equation used by Falk to obtain a weighted measure of engagement:

$$B_i = \frac{\sum_j b_j w_j}{n_i}$$

where:
b_j = the score for the behavioural category j
w_j = weighting for category b_j
n_i = total incidences of behaviour annotated for that activity

The mean ratings for the activities 1-5 (in order and with SD in brackets) were 0.6682 (0.65715), 0.8362 (0.72627), 1.1591 (0.67726), 0.9931 (.91204) and 1.1375 (.68704). The low mean scores are due to individual behaviours L1-L4, which in quantity can bring the overall engagement rating down. Given the age of the visitors and the fact that they were visiting in groups, there were many times when a visitor under observation was distracted from the activity. Another issue is that it was difficult for observers to identify L13 behaviour, where visitors related the experience to their own lives, without intruding on conversations.

However, the important finding is that the overall trend of the observation data is similar to that found from the self reported engagement and so for the purpose of being used to validate the accuracy of the self reported data, these findings do lend confidence. From both measures, activities 3 (Top Trumps) and 5 (Data Sculptures) were the most popular. The sample size of the observed data is quite small, therefore the more detailed comparison looking at order effects would not be reliable and so was omitted for this data.

V. Discussion

In answering the question *can narrative data games engage visitors with data in informal settings and within time constraints?* the self reported engagement measures, which were validated by formal and informal observation, showed a good level of engagement across all activities. The staged exploration did appear to support visitors to make sense of the data, this was shown through the effects of ordering on engagement. The explanation for these order effects could be that familiarisation with the datasets through the Speed Data-ing task prompted deeper types of engagement with the data via familiarisation when subsequently playing Data Trumps, rather than just focusing on surface elements of that task if coming to it without getting to know the data types first. However, Speed Data-ing itself was the least popular activity. This was the most narratively constrained activity, suggesting that the interactive elements were important in fostering engagement. In fact, there was a slight trend towards increasing engagement as agency increased, which was disrupted by the Data Trumps game. This was the last activity that had both game-like elements and structured narrative, lending credence to their importance.

Next we consider the question *How does the design of the space and activities support participatory sense-making?* While there was evidence of sense-making, it is harder to identify with any certainty whether this was individual or participatory, for reasons we now explain. We have taken the view that participatory sense-making is a form of collective intelligence that emerges from interaction between people, in this case around the collected data. While methods for formally measuring collective intelligence have been developed and used in laboratories and in online settings [27], there is no easy method available for capturing and measuring it at such a public event as the data exhibition. Another approach is to consider whether the conditions for collective intelligence were met. James Surowiecki [28] considers four conditions, which are: diversity, independence, utilization of decentralized knowledge, and effective aggregation of dispersed knowledge.

Within the data exhibition, there is evidence that people did try to relate the data to their daily lives, especially in the Shark-Bytes game. There may not have been diversity of age, but almost certainly a diversity of thinking across the school-age population of the city who visited with their schools. We can also assume that people would arrive at the exhibition with some level of independence of thought. From this, we might conjecture that we have conditions from which collective intelligence might emerge. But without mechanisms for formally measuring the extent to which this has caused dispersed knowledge to be aggregated, we have failed to recognise whether or not is was realized. This needs further and more formal study from which to draw concrete conclusions about what was occurring and why.

VI. Conclusions

This paper has described a data exploration event that has shown that gamified interactive data narratives can act as a first step towards supporting engagement and possibly participatory sense-making. Interfaces to data are important and should be appropriate to the setting. A data exhibition in a public place is better enjoyed through tangible and creative activities rather than through a screen. The novel contribution is in demonstrating how principles used to balance interactivity against narrative constraints for creating engagement can be applied to *data* storytelling as well as more conventional narrative forms. We also show how to use game elements to foster engagement and support narrative interaction, which can be particularly useful when there is only a short time in which people can engage with the data. Possible uses for this could be in empowering the general public to make sense of data and to bring their local and collective knowledge to its interpretation, for example in participatory sensing or citizen science activities.

VII. Acknowledgements

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References

[1] S. Heggen, "Participatory sensing: repurposing a scientific tool for stem education," *interactions*, vol. 20, no. 1, pp. 18–21, 2013.

[2] Y. A. Loukissas, *All Data Are Local: Thinking Critically in a Data-Driven Society*. Mit Press, 2019.

[3] A. S. Taylor, S. Lindley, T. Regan, D. Sweeney, V. Vlachokyriakos, L. Grainger, and J. Lingel, "Data-in-place: Thinking through the relations between data and community," in *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*. ACM, 2015, pp. 2863–2872.

[4] C. Golsteijn, S. Gallacher, L. Capra, and Y. Rogers, "Sens-Us: Designing Innovative Civic Technology for the Public Good," in *Proceedings of the 2016 ACM Conference on Designing Interactive Systems*. ACM, 2016, pp. 39–49. [Online]. Available: http://dl.acm.org/citation.cfm?id=2901877

[5] I. Iacovides, C. Jennett, C. Cornish-Trestrail, and A. L. Cox, "Do games attract or sustain engagement in citizen science?: a study of volunteer motivations," in *CHI'13 Extended Abstracts on Human Factors in Computing Systems*. ACM, 2013, pp. 1101–1106.

[6] S. Coulson, M. Woods, M. Scott, D. Hemment, and M. Balestrini, "Stop the noise! enhancing meaningfulness in participatory sensing with community level indicators," in *Proceedings of the 2018 on Designing Interactive Systems Conference 2018*. ACM, 2018, pp. 1183–1192.

[7] S. Kuznetsov and M. Tomitsch, "A study of urban heat: Understanding the challenges and opportunities for addressing wicked problems in hci," in *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*. ACM, 2018, p. 563.

[8] Y. Rogers and P. Marshall, "Research in the wild," *Synthesis Lectures on Human-Centered Informatics*, vol. 10, no. 3, pp. i–97, 2017.

[9] B. Bach, Z. Wang, M. Farinella, D. Murray-Rust, and N. Henry Riche, "Design patterns for data comics," in *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*. ACM, 2018, p. 38.

[10] M. Janssen, Y. Charalabidis, and A. Zuiderwijk, "Benefits, adoption barriers and myths of open data and open government," *Information systems management*, vol. 29, no. 4, pp. 258–268, 2012.

[11] A. Wolff, A.-M. Valdez, M. Barker, S. Potter, D. Gooch, E. Giles, and J. Miles, "Engaging with the smart city through urban data games," in *Playable Cities*. Springer, 2017, pp. 47–66.

[12] K. Boehner and C. DiSalvo, "Data , Design and Civics : An Exploratory Study of Civic Tech," in *Proceedings of the 2016 ACM Conference on Human Factors in Computing Systems*. San Jose, CA: ACM, 2016.

[13] M. Balestrini, T. Diez, and F. Kresin, "From participatory sensing to making sense," in *Proceedings of the Workshop" Environmental Infrastructures and Platforms 2015–Infrastructures and Platforms for Environmental Crowd Sensing and Big*, 2015.

[14] S. Williams, E. Deahl, L. Rubel, and V. Lim, "City digits: Developing socially-grounded data literacy using digital tools," *Journal of Digital Media Literacy*, 2014.

[15] C. Anslow, J. Brosz, F. Maurer, and M. Boyes, "Datathons: an experience report of data hackathons for data science education," in *Proceedings of the 47th ACM Technical Symposium on Computing Science Education*. ACM, 2016, pp. 615–620.

[16] C. D'Ignazio, "Creative data literacy," *Information Design Journal*, vol. 23, no. 1, pp. 6–18, 2017.

[17] R. Bhargava, R. Kadouaki, E. Bhargava, G. Castro, and C. D'Ignazio, "Data murals: Using the arts to build data literacy," *The Journal of Community Informatics*, vol. 12, no. 3, 2016.

[18] C. D'Ignazio and R. Bhargava, "Approaches to building big data literacy," in *Proceedings of the Bloomberg Data for Good Exchange Conference*, 2015.

[19] A. Wolff, D. Gooch, J. J. Cavero Montaner, U. Rashid, and G. Kortuem, "Creating an understanding of data literacy for a data-driven society," *Journal of Community Informatics*, vol. 12, no. 3, pp. In–press, 2017.

[20] S. Hautea, S. Dasgupta, and B. M. Hill, "Youth perspectives on critical data literacies," in *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems*. ACM, 2017, pp. 919–930.

[21] B. Bach, M. Stefaner, J. Boy, S. Drucker, L. Bartram, J. Wood, P. Ciuccarelli, Y. Engelhardt, U. Koeppen, and B. Tversky, " narrative design patterns for data-driven storytelling," in *Data-Driven Storytelling*. AK Peters/CRC Press, 2018, pp. 125–152.

[22] A. Wolff, M. Barker, and M. Petre, "Creating a datascape: a game to support communities in using open data," in *Proceedings of the 8th International Conference on Communities and Technologies*. ACM, 2017, pp. 135–138.

[23] C. Elsden, B. Nissen, A. Garbett, D. Chatting, D. Kirk, and J. Vines, "Metadating: exploring the romance and future of personal data," in *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems*. ACM, 2016, pp. 685–698.

[24] E. Salmela, A. Happonen, M. Hirvimäki, and I. Vimm, "Is time pressure an advantage or a disadvantage for front end innovation–case digital jewelry," *Journal of Innovation Management*, vol. 3, no. 4, pp. 42–69, 2016.

[25] J. H. Falk, "Time and behavior as predictors of learning," *Science Education*, vol. 67, no. 2, pp. 267–276, 1983.

[26] C. Barriault and D. Pearson, "Assessing exhibits for learning in science centers: A practical tool," *Visitor Studies*, vol. 13, no. 1, pp. 90–106, 2010.

[27] D. Engel, A. W. Woolley, I. Aggarwal, C. F. Chabris, M. Takahashi, K. Nemoto, C. Kaiser, Y. J. Kim, and T. W. Malone, "Collective intelligence in computer-mediated collaboration emerges in different contexts and cultures," in *Proceedings of the 33rd annual ACM conference on human factors in computing systems*. ACM, 2015, pp. 3769–3778.

[28] J. Surowiecki, "The wisdom of crowds: Why the many are smarter than the few and how collective wisdom shapes business," *Economies, Societies and Nations*, vol. 296, 2004.