Edo: A Participatory Data Physicalization on the Climate Impact of Dietary Choices

Kim Sauvé, Pierre Dragicevic, Yvonne Jansen

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Kim Sauvé
Lancaster University
United Kingdom
kim.sauve@lancaster.ac.uk

Pierre Dragicevic
Université de Bordeaux, CNRS, Inria, LaBRI
France
pierre.dragicevic@inria.fr

Yvonne Jansen
Université de Bordeaux, CNRS, Inria, LaBRI
France
yvonne.jansen@inria.fr

ABSTRACT

A participatory data physicalization, or PDP, is a physical visualization that allows people to physically participate in the creation of the visualization, by directly encoding their data. PDPs offer a way to engage a community with data of personal relevance that otherwise would be intangible. However, their design space has only begun to be explored, and most prior work shows relatively simple encoding rules. Therefore, we present a design exploration of different ways of faceting contributed data: by week, day, or person. Specifically, we designed Edo, a PDP that allows a small community to contribute their data to a physical visualization showing the climate impact of their dietary choices. In this pictorial, we elaborate on the design process of Edo and reflect on the findings of a three-week deployment of different layouts of Edo. Fabrication instructions and data are available under CC-BY 4.0 at osf.io/q5fr6.

Authors Keywords

Participatory Data Physicalization, Packed Bubble Chart, Climate Change Communication

CSS Concepts

• Human-centered computing~Visualization~Empirical studies in visualization

Figure 1. Edo: a participatory data physicalization on the climate impact of dietary choices.

INTRODUCTION AND RELATED WORK

Participatory data physicalization (PDP) is a subset of physical data visualization or *physicalization* [9]. Although a wide variety of work exists within the larger area of data physicalization [3] and a variety of different PDPs have been proposed by design practitioners (see Figure 2), not much research has explored the potential of PDP. Currently, there is no single clear definition offered yet, hence we refer to PDP as *"a physical visualization that allows for a co-located audience to physically participate in the creation of the visualization by directly encoding their data while following predetermined rules"*. In other words, the audience participates in the construction of the physical visualization and they contribute data by physically adding, subtracting, and/or reorganizing their data points to the visualization. As a PDP is situated [2], it unites the physical location of data collection and consumption, physically representing people's activities in a particular physical space over time.

Looking at related work and literature, PDP has been previously advocated as *"an intriguing and playful practice that has an incredible potential in informing and engaging a local public on specific issues"* [16]. As the data is immediately transferred into a visualization, it provides a reification of personal opinions and/or behavior for others to see. As a consequence, a PDP could inherit benefits similar to *situated visualizations* [2] supporting social engagement and collective reflections on an otherwise intangible topic. *Input visualizations* [8], which are visual depictions that collect (and represent) data from viewers rather than from a pre-existing dataset, show common ground with PDPs as both allow for direct input by viewers. However, the difference is that PDP is inherently physical (whereas input visualization can be digital), it focuses on the viewer contributing as well as consuming the data (whereas input visualization can be data collection only), and multiple people participate in its creation (whereas input visualization can be a single person undertaking). Finally, Dragicevic et al. [4] acknowledge that physicalizations in public spaces could possibly facilitate people engaging in data collection and construction, instead of merely the consumption of data.

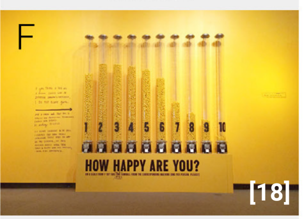
Looking at existing work from practitioners [3], PDPs come in many different forms (Figure 2), varying in topic (e.g., sleep (C), happiness (F), or political opinion (A)), visualization type (e.g., bar chart (I), matrix (B), or parallel coordinates (G)), and interaction mechanism (e.g., stacking disks (B), spanning a wire (E), or placing differently shaped tokens (K)). For the majority, the data collected is relatively simple such as answering a yes/no question (e.g., Figures 2A and 2J), selecting from a set of categories (e.g., Figure 2H), or ranking (e.g., Figures 2C and 2F). In contrast, Cairn [5] (Figure 2K) is one of the few examples which shows high data complexity, as it asks for people to contribute multiple attributes about their practices in a fabrication lab (such as duration, frequency, motives, activities, and learning practices). Similarly, the aim of this work is to explore the design of PDPs with more complex data encodings and how this influences the user experience with data.

In the remainder, we first explain the final design of Edo, after which we elaborate on the design process. Finally, we discuss the deployment of three different layouts of Edo and the implications for future work.

Figure 2

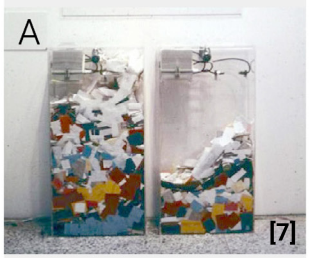
Exemplar participatory data physicalizations from the List of Physical Visualizations [3] illustrating the variety in data complexity. For each we included the Context, Question(s) asked (Q), and (a selection of) possible Answers (A).

Exhibition



Q: How happy are you? *A: On a scale from 1 - 10 (inverted bar chart)*

Museum exhibition



Q: Would the fact that Governor Rockefeller has not denounced President Nixon's Indochina Policy be a reason for your not voting for him in November? *A: Yes, No*

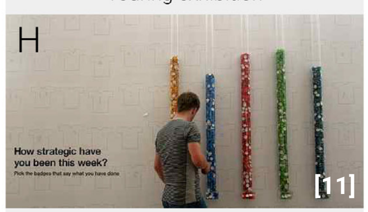
Art fair

Q: Demographics *A: Country, gender, age, status, height, L/R handed, weight*

Prevention and health event

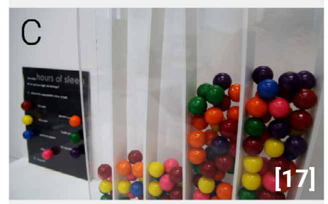
Q: Can you guess which are good prevention practices or controls that allow cancer to be diagnosed at an early stage for different age groups? *A: Prostate examination, Breast self-examination, Colonoscopy, etc.*

Touring exhibition



Q: How strategic have you been this week? *A: I made mistakes, I saw the big picture, I thought then acted, I acted then thought, I used PowerPoint (inverted bar chart)*

University campus



Q: How many hours of sleep do you get per night on average? *A: Hours of sleep by university population type (color)*

Ice-cream truck driving around

Q: When is it justified to use "dirty" speech? *A: No problem with that, that is how they talk today; Only when the argument is heated; When they hurt me; Never, just clean speech*

University cafeteria

Q: How did we serve you today? *A: Satisfactory, Unsatisfactory*

Streets of London

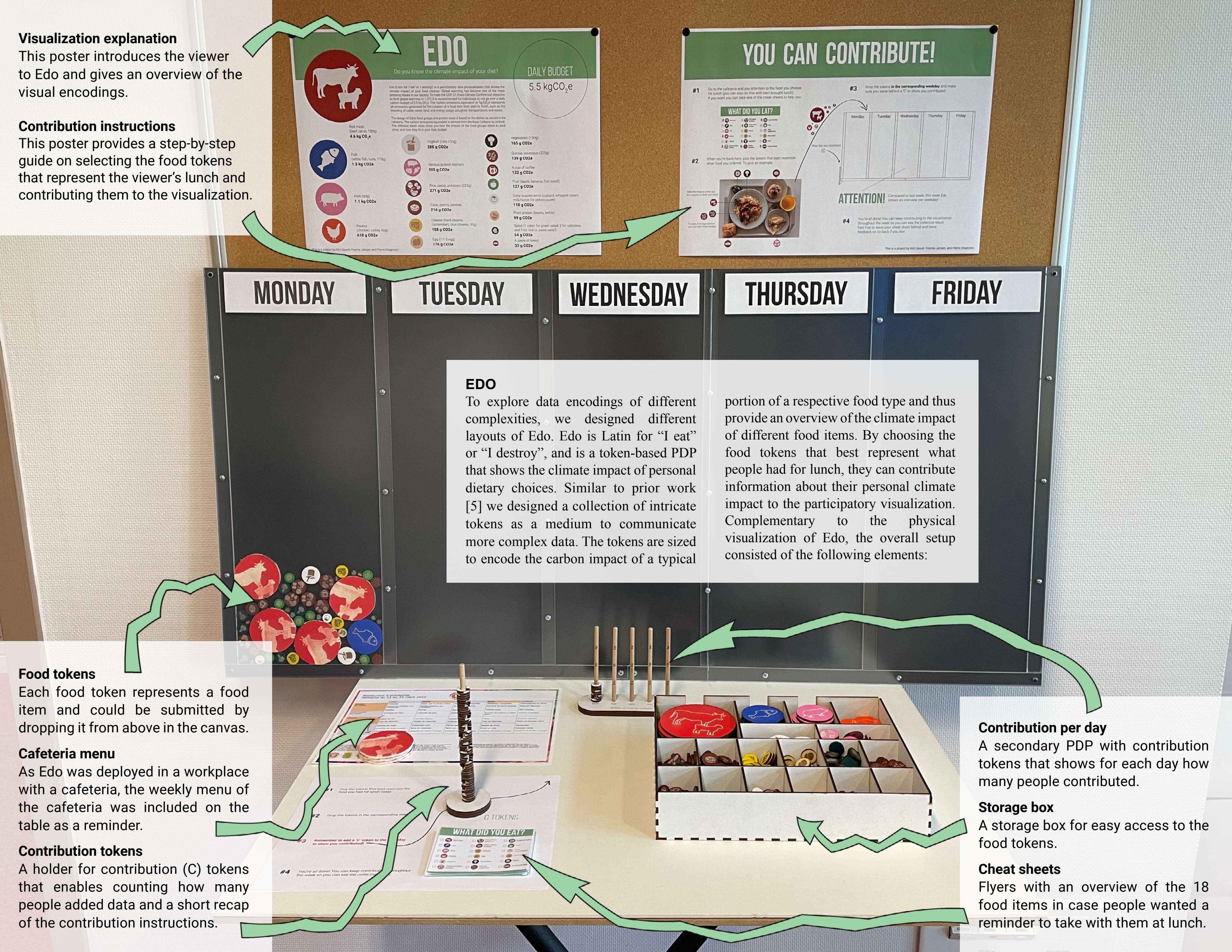
Q: Is Brexit OK? *A: Yes, No*

Public design exposition

Q: What made you think? What made you create? What made you angry? What made you happy? What made you change? *A: Music, Neighbor, Internet, etc.*

Fabrication lab

Q: Can you provide details of your FabLab activities today by stacking pieces on the table? *A: Duration, frequency, motives, activities, learning practices*



EDO

To explore data encodings of different complexities, we designed different layouts of Edo. Edo is Latin for "I eat" or "I destroy", and is a token-based PDP that shows the climate impact of personal dietary choices. Similar to prior work [5] we designed a collection of intricate tokens as a medium to communicate more complex data. The tokens are sized to encode the carbon impact of a typical portion of a respective food type and thus provide an overview of the climate impact of different food items. By choosing the food tokens that best represent what people had for lunch, they can contribute information about their personal climate impact to the participatory visualization. Complementary to the physical visualization of Edo, the overall setup consisted of the following elements:

EDO

From Data to Visual Encoding

We focused on the climate impact of food because we were looking for something that everyone can engage with and which involves daily decisions or actions. More specifically, we focused on the carbon impact of different food items consumed daily by a small community in a university workspace. Similar to the disks used in the Econundrum project [19] we used surface areas of different sizes to communicate relative climate impact. The focus of our work is different though: Econundrum is not a PDP but used a smartphone app to enter data and consisted of one disk per person that descended depending on the sum of items consumed over a day, thus clearly showing the impact per person; our work explores how direct interaction with and different faceting of tokens (see page 5) affect how people engage with a PDP. For the curation of the dataset that served as the basis for designing the food tokens, we took four steps:

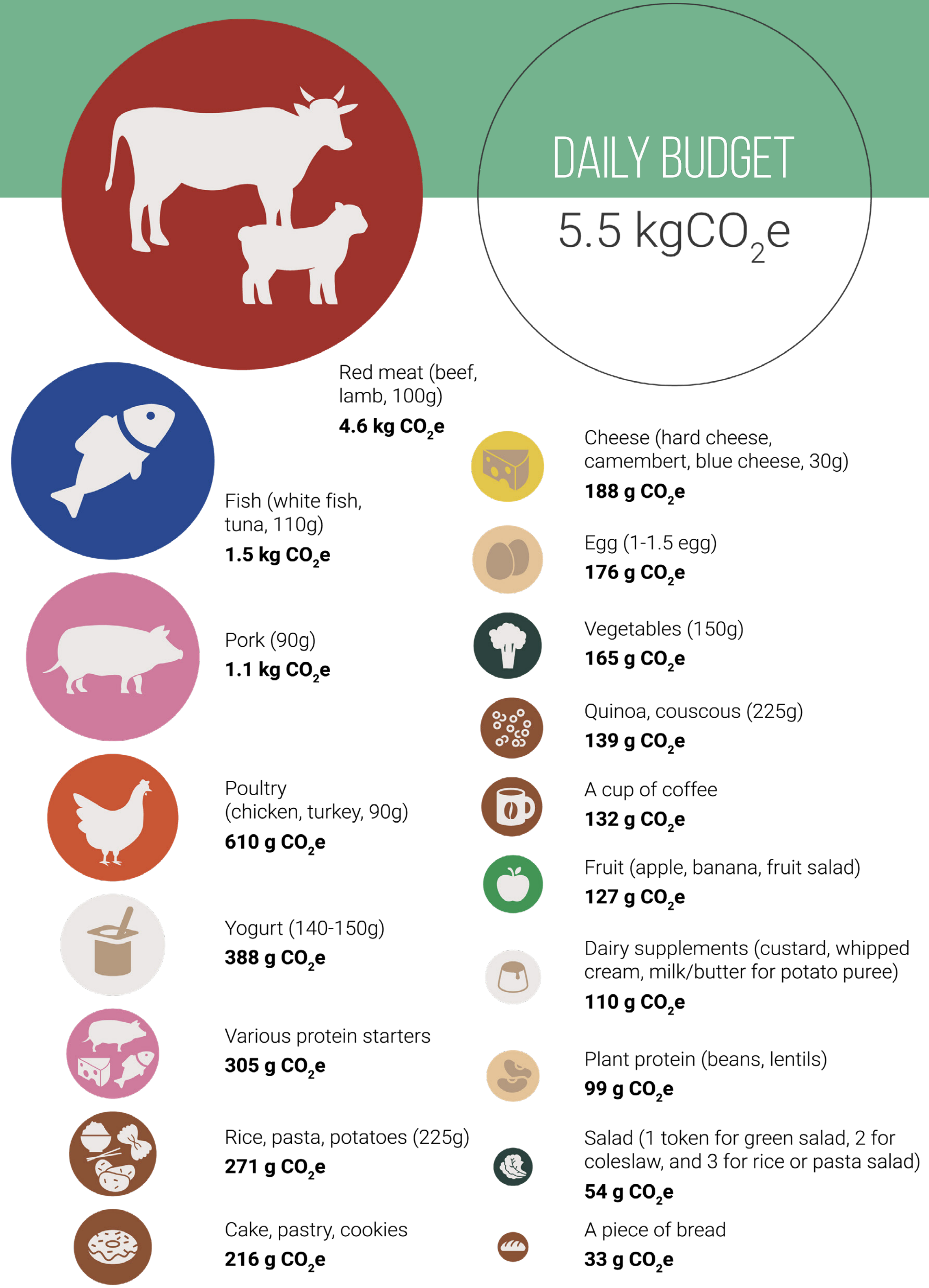
Step 1: We analyzed the weekly menus of the cafeteria at Centre Inria de l'université de Bordeaux and curated a list of food items commonly served.

Step 2: To estimate portion size, we used the same source[1] as the university cafeteria used for the preparation of food.

Step 3: To express the climate impact of each food item, we took as measurement unit the commonly used 'carbon emissions equivalent' or 'kg CO_2e', which represents all emissions generated for the creation of a food item from start to finish, such as the breeding of cattle, energy usage, slaughter, transportation, and waste. For the calculation of the carbon footprint (kg CO_2e), we consulted the Base Carbone[2] and used the AGRIBALYSE® life cycle inventory (LCI) database[3]. We cross-referenced portion size and carbon footprint to calculate the carbon footprint per portion of each food item.

Step 4: The carbon footprint per portion was used as input for the surface area calculation of the different circles. For example, the surface area of the fish token (1.5 kg CO_2e) was three times smaller than the red meat token (4.6 kg CO_2e). Food items of similar carbon footprint were grouped together, resulting in a final list of 18 items. We used a set of icons and a semantically resonant color scheme [15] to make the different food groups easy to recognize and differentiate (e.g., pink for pork, white for yogurt) and allow people to determine different sources of climate impact at a glance. Finally, on the poster we included a circle representing a reference to a daily budget of 5.5 kg CO_2e based on the COP21 (Paris Climate Conference) objective, so people could compare how their food items fit within this budget (see top right of this page).

The icons and descriptions on this page are illustrative of the visual encodings used on the poster to explain Edo to viewers.

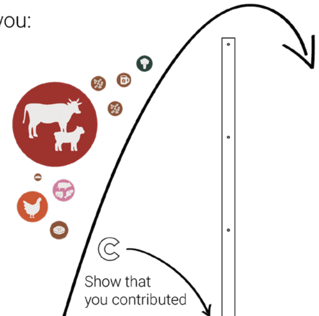


[1] Annexe 2.2. Retrieved from https://www.economie.gouv.fr/daj/recommandation-nutrition

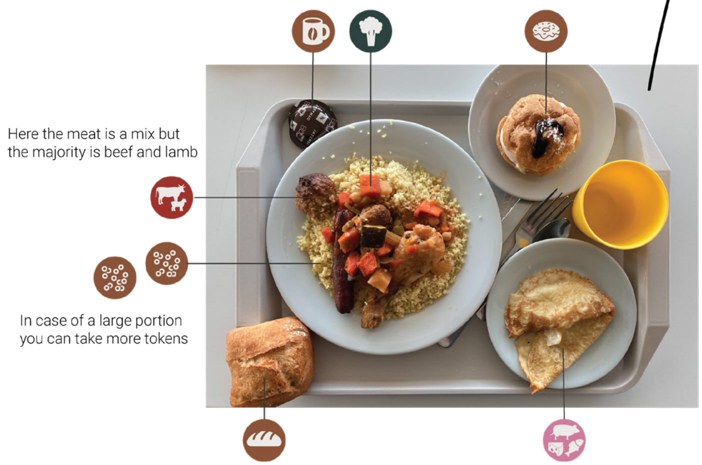
[2] https://bilans-ges.ademe.fr/en/accueil/contenu/index/page/bc_introduction/siGras/0

[3] Database 3.0.1 (Excel format). Retrieved from https://doc.agribalyse.fr/documentation/acces-donnees

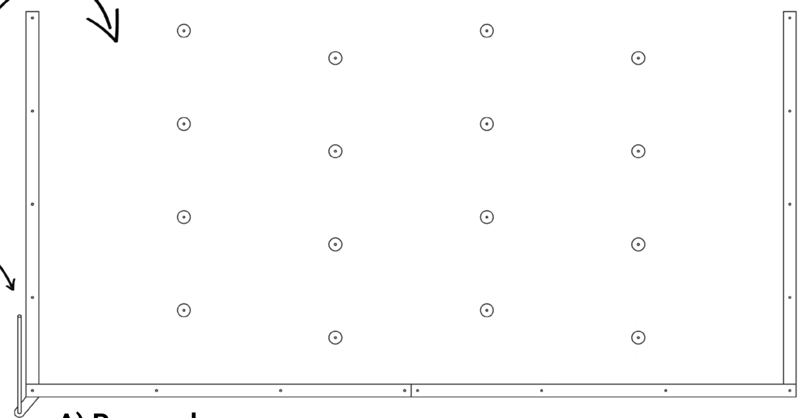
#1 Go to the cafeteria and pay attention to the food you choose for lunch (you can also do this with own brought lunch). If you want you can take one of the cheat sheets to help you:



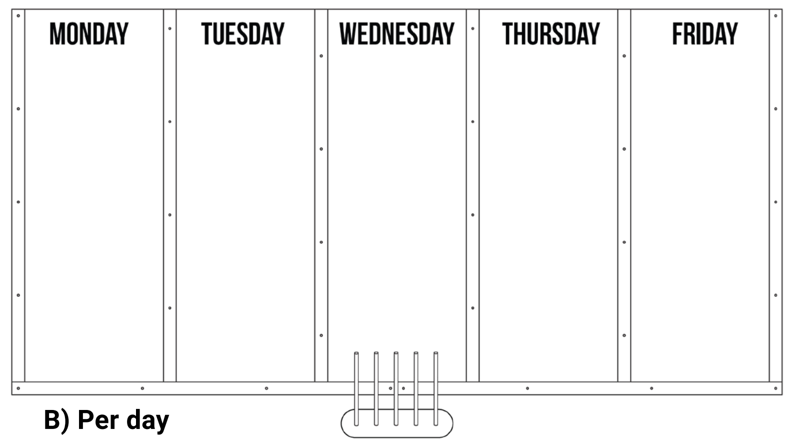
#2 When you're back here, pick the tokens that best resemble what food you ordered. To give an example:



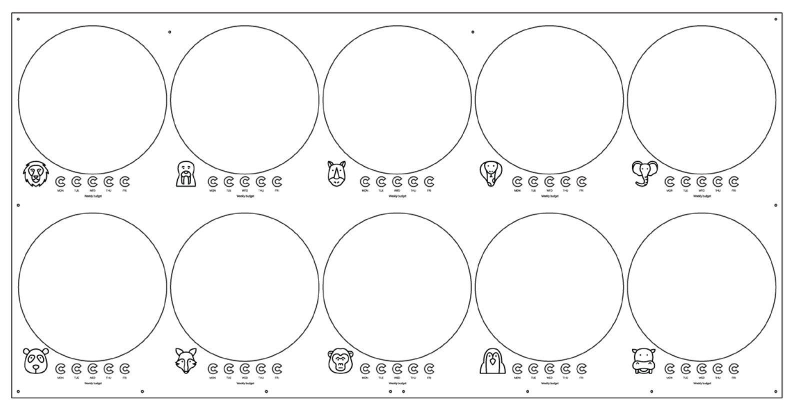
#3 Drop the tokens **anywhere in the visualization** and make sure you leave behind a 'C' to show you contributed.



A) Per week



B) Per day



C) Per person

Legend design

To make Edo easy to learn and use, we developed instructions and legends that people could refer to while entering data (for a complete overview of the Edo setup see page 3). The illustration on this page includes the main elements of the 'You can contribute!' poster which guided people step by step on the interpretation (#1), selection (#2), and submission (#3) of tokens to the physical visualization.

Visualization configuration

To explore how visual encodings of different complexities would influence the interactions with the PDP, we designed three different layouts of Edo, each with different levels of faceting:

Per week (A)

The first layout faceted the food tokens per week. As this layout was displayed for a single week, the entire surface of the visualization was dedicated to that week. This surface area roughly corresponds to 80 daily budgets.

Per day (B)

The second layout faceted the food tokens per day of the workweek. This layout was again displayed for a week, and so the surface was divided into five areas, from Monday to Friday. The surface area per day corresponds to about 15 personal budgets.

Per person (C)

The last layout faceted the food tokens per person. The surface area per person is equivalent to 5 personal budgets (so one work week). To allow people to remain anonymous yet enable them to recognize and discuss their personal budgets we marked each with avatars of wild animals (5 carnivores and 5 herbivores). This layout was again displayed for a week.

Contribution tokens

To extract the number of people that contributed to each layout, we introduced 'contribution tokens', which were C-shaped tokens that people were asked to add to the visualization when submitting their lunch info. For the layout per week, a single contribution token holder was attached to the bottom left. For the layout per day, we placed a contribution holder in front of the visualization that allowed people to indicate their contribution per weekday. Finally, for the layout per person, each personal budget had five slots (for each weekday) for the contribution tokens.

Visual encoding

The general visual encoding used to visualize the aggregate climate impact of dietary choices was the circle packing [22] (also called packed bubble chart) of differently sized food tokens with the token surface area encoding the representative carbon emissions. We used 18 token units of different sizes so that people only needed to take one token per food item and not needed to count out how many single-size tokens correspond to high impact items (e.g., red meat would otherwise have required 139 tokens).

In contrast, the faceting of the food items and contribution tokens was different per layout of Edo as illustrated in Table 1. All three layouts visualized the food items consumed across a week and the collective climate impact of the group. Additionally, layout 2 faceted the food items consumed per day, whereas layout 3 faceted it per person. Regarding the contribution tokens, all three layouts visualized the contributions across the week, whereas layout 2 faceted contributions per day, and layout 3 faceted them per person and day.

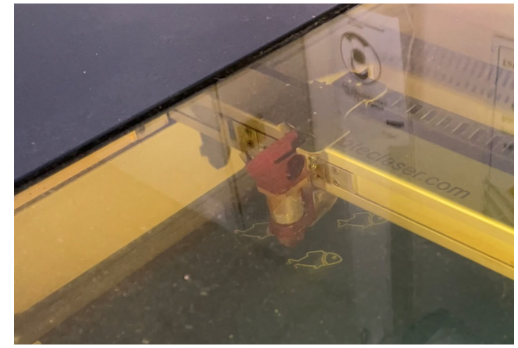
	Layout 1	Layout 2	Layout 3
Food tokens			
Food items consumed per week	x	x	x
Food items consumed per day		x	
Food items consumed per person			x
Collective climate impact	x	x	x
Personal climate impact			x
C tokens			
Contributions per week	x	x	x
Contributions per day		x	x
Contributions per person			x

Table 1. Data encodings of the food and contribution tokens per layout (layout 1-3).

Fabrication

The overall visualization of Edo was made of a black Medium-density fibreboard (MDF) back wall, connected to a 1mm transparent acrylic sheet via lasercut spacers of 4mm thickness, so the tokens of 3mm would fit comfortably between the layers. The back wall mechanism was designed in such a way that it was transformable between layouts, hence the circular spacers could be replaced with vertical rectangular spacers to create the layout per day. For the layout per person, the acrylic sheet and spacers were replaced altogether by a thicker 4mm layer. As this final layout allowed people to place the tokens freely in the open circles, we placed this back wall at an angle, to minimize tokens dropping out.

Engraving: To realize the tokens, we experimented with primer, acrylic paint, and different levels of engravement. We used a deeper engraving on lighter colors (e.g. yellow) so the icons showed up darker, whereas for darker colors (e.g. red) we used a light engraving only removing the top layer, revealing the white primer layer.



Laser cutting: All tokens were laser cut out of 3mm MDF sheets, except for the larger red meat tokens, which were created from 3mm cardboard pulp sheets to reduce their weight.

Fabrication: We produced all 18 token types in 10 different colors.

Back wall: Every Monday early morning we transformed the layout of Edo for the upcoming week.

Interaction design: For layouts 1 and 2, the food tokens could be dropped into the visualization, whereas the C tokens were placed around a placeholder, respectively for the entire week (left) or per day (middle). In contrast, for layout 3 (right), the food tokens could be placed freely into the visualization, and the C token slots were also integrated.

Storage: As the tokens needed a space to exist before entering the visualization, we designed a storage box that allowed for easy access and could be placed near the visualization.

Figure 3. Resulting visualization for each layout (L1-3), after day one (D1) and day 5 (D5). Enlarged pictures are available under CC-BY 4.0 at osf.io/q5fr6.

DEPLOYMENT

To see how a community in context would use Edo, we placed it in the common area of a research group at Centre Inria de l'université de Bordeaux and deployed it there for three weeks. Each week, we presented one of the three layouts of Edo and anyone passing by the common area was free to submit their lunch info throughout the deployment (see Figure 3 for the resulting visualization after every week).

Data collection & analysis

Throughout the three weeks, we took daily pictures of Edo to capture the change in contribution and food tokens over time. Additionally, we performed sporadic in-situ observations of the interactions with Edo and between people in close proximity to the visualization. During the last week of the deployment, we also organized a 1.5-hour focus group with 12 people who contributed to Edo over the three weeks, to ask them about their overall experience with the visualization. The only data collected during the deployment phase and the focus group were summary counts of tokens put into the PDP per week (see Table 2) and written, anonymized notes by the three authors, which were later analyzed using inductive thematic analysis. In the following, we report a summary of our findings. When we use 'R#', we refer to comments made by people present at the focus group; The identity of respondents was not recorded during in-situ observations. As this type of research is broadly considered exempt from IRB review, we did not seek IRB approval from our institution.

	Mon	Tue	Wed	Thu	Fri	Total
Layout 1	10	21	8	9	3	51
Layout 2	11	12	15	13	5	56
Layout 3	8	10	5	6	4	33

Table 2. Number of contributions per day across the 3 layouts.

FINDINGS

Overall, we observed that people quickly understood how Edo works and how to add data to it. Doing so seemed to encourage reflection on dietary choices and facilitate comparisons between different options (carnivore, pescatarian, vegetarian, vegan), but also consider approaches like removing red meat from one's diet to eliminate the largest impact. Generally, people preferred layouts that facilitated some form of comparison, for example across days or between people.

Quantitative data

We refer to the set of food tokens representing a single meal as a contribution. Looking at the numbers of total contributions per layout (Table 2), we observed a total of 51 contributions for layout 1 (per week), 56 for layout 2 (per day), and 33 for layout 3 (per person; which could be due to half of the research team switching to working remotely because of illness). Interestingly, for layouts 2 and 3, we observed, respectively, 4 and 2 instances in which people contributed not only their lunch of the present but also the previous day. Finally, upon a forced-choice vote in the focus group, the majority of respondents reported a preference for layout 2 (7 votes), followed by layout 3 (4 votes), and layout 1 (1 vote).

Qualitative data

Herein, we will elaborate on the reported user experience of the three different layouts through 9 themes.

Food tokens

Generally, respondents reacted positively to the aesthetics of the food tokens, and the colors allowed them to easily extract from the visualization which categories were eaten most and/or were the most impactful. For example, R12 mentioned that the design, color, and icons on the tokens made the activity playful and allowed them to reflect on the impact of different food items. R10 commented that after a short learning curve, the use of circles made it easy to compare carbon footprints between different food categories and that the drawings (icons) on the tokens helped them remember which category they represented. However, the categorization of 18 food items was not always straightforward in use. R1 explained that sometimes they were unsure which tokens to choose, for example when contributing a lunch dish that did not clearly fit the food items in terms of quantity (e.g. choosing between a protein starter or main portion) and/or kind (e.g. when bringing their own lunch that did not correspond with the cafeteria menu). As a possible solution, we observed how a respondent used a token of a similar color but larger size to accommodate for a food item not specifically on the list (i.e., 1 couscous token instead of 3 bread tokens to indicate a larger pita bread). During the focus group, R3 suggested having different sizes of tokens per category so people can submit different numbers to get to the corresponding impact, or as R2 suggested, to have completely blank tokens for items that do not fit in the existing categories. Finally, for week 2 veal was served, which had a different climate impact than the categories we anticipated. Hence, we improvised veal tokens of the correct size (by cutting existing red meat tokens; see Figure 4) before the first lunch of that week.

Circle packing

The use of circle packing had as a result that depending on the token sizes, there would be a variable amount of space between tokens in the visualization. During the focus group, some respondents wondered how to interpret this empty space. For layout 2, R4 commented that as long as the empty space was consistent across weekdays, they did not see a problem in using circle packing, as it is about relative differences anyway. Moreover, R5 mentioned that depending on the aim of the visualization (e.g. to reduce carbon emissions), it is actually not a bad thing to get an upper estimate.

Figure 4. Improvising veal tokens by cutting existing red meat tokens to size.

Legends

During the focus group, 11 out of 12 respondents indicated having used the visualization poster when contributing to the visualization. However, we observed during the deployment that respondents often did not read the posters in detail, as several details of use were overlooked, such as the salad token explanation, and the explanation of the daily budget. R10 suggested including the daily budget circle on the table surface so they could check how their lunch tokens fit within this budget. Lastly, respondents generally did not make use of the cheat sheets.

Contribution (C) tokens

During the first week of deployment, it already became apparent that respondents experienced some difficulty using the contribution or C tokens. In particular, they tended to forget to submit them. One respondent showed initiative on the second day of week 1 and created a reminder so others would not forget to submit a C to show they contributed (Figure 5). The design of the C tokens was meant for both researchers and respondents to follow the number of contributions over time, but we observed that it was not necessarily insightful for the respondents, as it was unclear how to compare the height of the C token stack with the food tokens in the visualization. Following the first week, we designed a reminder for the C tokens on the table in an attempt to make the C token more obvious and easy to remember. In contrast to layouts 1 and 2, layout 3 integrated the C token into the visualization, which made it easier to extract the number of food items as a result of the number of contributions and to remember to submit the C tokens in the designated slots. During the focus group, R5 suggested including a physical mechanism to unlock the token storage box so people would not forget to indicate their participation.

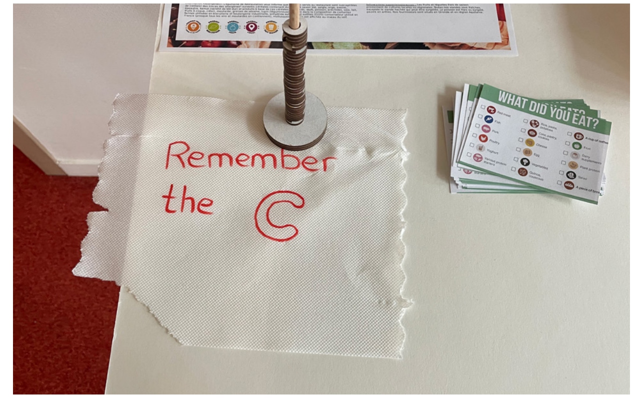


Figure 5. One respondent took the initiative to include a reminder for contributing the C token.

Canvas scale and axes

For layouts 1 and 2, we observed that the size of the canvas as a whole was too large in relation to the individual contributions of the group. As a result, after a week, the canvas was not even filled for 50% and the differences in height across the days were small. In contrast, layout 3 was scaled according to a weekly personal budget, which simplified the comparison of climate impacts. During the focus group, multiple respondents also proposed including a reference in the y-axis, such as showing how many personal budgets correspond to a certain height (R4), providing a reference to an average week or previous week (R9), or including a weekly budget for 10 people as a comparison (R11).

Comparison and frame of reference

Comparing the three layouts during the focus group, respondents had a preference for layout 2 (7 votes) as it showed collective impact but also allowed for comparison across days. Layout 3 (4 votes) was the second most popular, as respondents could compare themselves with others, but it also made it more personal (e.g., more judgment of personal diet due to less anonymity). Layout 3 was the most direct in showing individual impact, which was insightful, but also more confronting. Moreover, it was perceived as less collaborative as respondents' contributions had no impact on the 'team contribution' (R9), hence it was

Figure 6. Different interactions were observed: collecting tokens on the table surface (top left), collecting tokens in the hand (bottom left), and balancing a fish token on one of the spacers.

perceived as more suitable for personal use (R11). Both layouts 2 and 3 still introduced some complexity as there was not the same participation rate from one day to another (R1) or from one person to another (R12), hence, respondents did not exactly know how to make more detailed comparisons. Finally, layout 1 was the least popular (1 vote) because no frame of reference was included in the visualization. Therefore, it was not easy for people to extract how their total impact changed over time, hence there was a lack of comparison altogether.

Physical interactions

The very first data entry to Edo was ambiguous as respondents did not realize that the tokens could go inside the canvas (no tokens were inside the canvas yet). Hence, the researchers had to draw the respondents' attention to how the tokens fit between the canvas layers.

Respondents described the act of dropping the tokens in the visualization as satisfying and easy to use. R7 particularly enjoyed how the tokens bounced off the spacers of layout 1 as it increased randomness and compared it to Pachinko (a Japanese gambling game).

Throughout the deployment, we observed that the strategies to submit tokens to Edo were consistent within, but different between respondents. Some respondents applied the strategy of picking tokens and submitting them one by one, whereas others would collect them first (either on the table surface or in their hand; Figure 6), and then submit them all at once. We also observed uses beyond the mere submission of data, for example R10, who used the tokens and the cafeteria menu to plan out their meals of the week, to anticipate their prospective climate impact (Figure 7).

For layouts 2 and 3, we observed 6 instances of respondents submitting their lunch for the previous day in addition to their lunch for the present day, as they got remembered they forgot a prior submission. Moreover, for layout 3 we observed richer interactions because, in contrast to layouts 1 and 2, respondents could freely touch and manipulate the tokens after submission. Therefore, the faceting was not as final, and we observed it facilitated other interactions such as R3 temporarily altering the circle of R6 to validate how many red meat tokens fit in a weekly budget (Figure 8). This also allowed respondents to correct errors, such as R5 who was able to recover a C token submitted on the

Figure 8. R3 using the circle of R6 to try out how many red meat tokens fit in a weekly budget.

wrong day using a toothpick. Finally, we observed other miscellaneous explorations of the use of tokens, such as balancing a fish token on one of the spacers during layout 1 (Figure 6), or R7 who tried to aesthetically stack their tokens throughout layout 3 (Figure 9).

Social interactions

We observed that Edo was mainly used immediately after the lunch break when the research group would come together in the common area for a coffee break and gather around the visualization. In addition, some respondents would contribute to the visualization throughout the day when passing the common area.

Figure 7. R10 planned out their meals of the week to anticipate prospective climate impact.

Figure 9. Throughout the work week, R7 tried to aesthetically stack the food tokens in their weekly budget circle.

Especially during the first days of deployment, respondents had regular questions directed at the researchers who happened to be present in the common area, such as the accuracy and sources of the calculations behind the visual encoding of the carbon footprint, explanation of the personal daily budget, and confirmation of which food tokens to choose to represent their lunch. Respondents even suggested that it could be intentional to have a representative next to the visualization at least for the first days, to facilitate interactions and answer questions. Moreover, Edo was a conversation starter among respondents on a myriad of topics more or less related to climate impact, such as diet and nutrition, animal cruelty, and other factors that might influence the impact of different food items (e.g. deforestation, overfishing). On the other hand, based on the visualization, R9 inferred the occupancy of group members, as it was more likely to have higher participation on days of weekly meetings (Tue/Thu), and lower when people tend to work from home (Fri). Lastly, respondents had discussions on the applicability of a visualization such as Edo for other topics (e.g. food waste, health), use by other audiences (e.g. one visualization per research group or as educative use for children), and/or use over time (e.g. let the visualization circle among different groups or common areas).

For layout 3, the faceting per person and inclusion of avatars resulted in additional social interactions. For example, respondents wanted to pick their (favorite) animal, discussed their diet in the context of their avatars' diet (e.g. a respondent commented that the lion did not really have a carnivorous diet like a lion; Figure 10), tried to guess who was who by paying attention to the diet and attendance of others, and expressed feelings of similarity and camaraderie with colleagues who shared a similar diet (e.g. vegetarian).

Figure 10. An example of a carnivorous avatar (lion) that did not consume any meat in their diet.

Thinking or acting differently

As a result of using Edo, respondents had different reflections more or less related to climate impact. The majority of respondents described the realization (and surprise) of the disproportionate impact of meat items (especially red meat) over other food items and their considerations in choosing food items of lower impact in the future. Additionally, respondents reflected on the different climate impacts as a result of the cafeteria menu, such as R10 who realized that the accumulation of many smaller meat tokens can still create a large impact (Figure 3; the pork tokens on Wednesday in L2D5).

Multiple respondents commented on the possibility of a visualization such as Edo resulting in social pressure, especially for layout 3, but did not report experiencing this themselves. However, we did observe instances of thinking and/or acting differently based on the visualization of Edo. For example, R6 expressed notions of guilt when consuming red meat. Another respondent described how they had to think fast when queuing up for the cafeteria lunch, and chose fish over beef because they did not want to have to submit the red meat token.

Finally, after the deployment, the lead researcher left the university and was not co-located with the research group anymore. However, upon request of the research group we left Edo in the common area, in layout 2 (per day). Interestingly and to our surprise, from there on the research group self-organized and used Edo for 11 more weeks. The participation was halved relative to the three weeks of deployment. After that period, engagement and interest waned.

DISCUSSION

Herein, we reflect on the three-week deployment of Edo and discuss the challenges and opportunities when designing a PDP with more complex encodings than prior work has explored so far. Although a wide variety of prior work exists on data physicalization, the potential of PDP has been underexplored. Some of our reflections below are transferable to physicalization design more generally (e.g., frame of reference, encoding and uncertainty), whereas other concepts are more specific to PDPs (e.g., encoding of contributions). Future work on PDP design could further mature this subset of physicalizations, but also be informative for other interactive or participatory forms of physicalization.

Encoding the number of contributions

In contrast to many prior PDPs [3], Edo introduced more complexity in the encoding since a contribution could consist of multiple tokens, and each contributor could contribute multiple times. Therefore, we observed some challenges in interpreting the relation between the number of contributors and the collective impact, especially in layouts 1 and 3. More specifically, you need to know how many people contributed to extract collective impact and need to make sure that people do not forget to indicate that they contributed. We found that layout 3 (per person) provided some integration of the C tokens in the visualization, which made it easier for respondents to remember to indicate their contribution.

Looking at related work, Cairn [5] is an example of a PDP that allows the viewer to extract how many contributors (wooden pins) contributed what information (tokens piled on each pin). However, extracting the collective result of individual stacks might be a bit more challenging. Other solutions to facilitate indication of contributions could be, for example, a PDP canvas or token storage box that only becomes accessible after someone indicated they want to contribute. Apart from integration, the PDP designer can also provide more reminders in strategic locations in relation to the tokens to further facilitate the contribution of data.

Design consideration #1: *When introducing more encoding complexity in a PDP (e.g., multiple tokens per contribution and/or multiple contributions per person), consider how to relate the number of contributors to the data in the visualization.*

Adapting the PDP to audience size

We observed that the size of the overall canvas of Edo in relation to the tokens was not at scale with the number of contributors. Therefore, the contributions did not populate the majority of the canvas, leading to less striking visualizations. In contrast, if the canvas would have been too small, it could have overflown. Hence, there is a tradeoff between canvas and token size in relation to the target audience. Dependent on the type of visualization this will have more influence on the resulting data. To give an example, for a parallel coordinates visualization (e.g. Figure 2G), individual contributions will populate the majority of the canvas, whereas for a bar chart visualization (e.g. Figure 2I) an individual contribution might add little to the vertical height. Moreover, if a visualization is based on the subtraction of tokens (e.g. Figure 2F), the number of tokens is limiting the contributions (and creates ambiguity in the visualization). Hence, it is important to consider if there are design choices that make a PDP more resistant and/or adaptive to different use case scenarios. Especially if the designer does not know the size of the audience, it might be not so much about matching a particular context, but more to design for adaptability over time (e.g. a vertical dimension that can be shortened/lengthened dependent on contributions).

Design consideration #2: *Take into account the ratio between the overall visualization canvas, individual data tokens, and the target audience.*

Situatedness and environmental awareness

We collected insights from a local deployment and focus group focusing on the interactions with the different layouts of the PDP. Therefore, more formal studies in different settings would be required to explore Edo's capacity of raising lasting awareness and understanding of the climate impact of food (which was outside our scope). Moreover, this could give more insights into what level of situatedness is appropriate for PDPs that aim for more environmental awareness. Prior work described that situatedness can manifest through different *levels of indirection* [23]. *Spatial indirection* [23] refers to the distance between the physical referent (e.g., consuming food at a university cafeteria) and the PDP, whereas *temporal indirection* [23] refers to the temporal distance in time between the referent and the moment the PDP is interacted with (e.g., contributing tokens to Edo). Future work could further explore how lower or higher indirection of a PDP influences environmental awareness. For example, the PDP could be in closer proximity to where food is consumed, which would lower spatial indirection, but might be more intrusive. Another exploration could be to use the PDP to let people construct anticipatory climate impact of their meal before eating, rather than reflect in hindsight.

We envision PDPs such as Edo as temporal interventions, as we observed that Edo became redundant over time: people seemed to have gained some level of intuition of the impact of their food choices. More in-depth studies will be required to evaluate if that intuition can easily be applied to different meal compositions, or to test if it wanes over time. Therefore, PDPs for environmental awareness are most useful in (semi-)public spaces where they can be used more than once (e.g., at cafeterias, restaurants, or educational settings). Future work could further investigate how deployments in different settings over time could spark conversations around the climate impact of dietary choices, foster personal reflection, or even behavior change.

Design consideration 3: *Consider the influence of different levels of temporal and/or spatial indirection on the interactions with and takeaways from the PDP.*

Facilitating meaningful comparison

For layouts 1 and 2, there was no particular meaning ascribed to the surface area of the canvas, preventing the respondents to make meaningful comparisons with their data. In line with this observation, prior work [19] discussed the use of a *historical or social frame of reference*, i.e. providing a comparison to data from a prior week, average week, or similar community. Looking at prior examples of PDPs, most often the comparison lies within the audience contributing to it, but there are opportunities in going beyond that. For example, for Cairn [5] (Figure 2K) it could be valuable to compare their practices by week, or for a university population (Figure 2I) it could be insightful to compare themselves with another university campus.

Finally, regarding the layout within the canvas, for Edo there was a preference for a faceting by day, which provided enough reference and ability to compare, without making the visualization too personal. Looking at prior PDPs, the majority only include categorical

FOOD FOR THOUGHT

Encoding of contributions: when using multiple tokens per contributor, how can we clearly show the relationship between the number of contributors and the collective result in the visualization of a PDP?

Situatedness: how does the spatial and/or temporal distance between the physical referent and the PDP influence the interactions with and takeaways from the PDP?

Frame of reference: how can we include frames of reference within a PDP visualization in relation to the contributing audience, to allow for meaningful comparisons?

Signposting: how can we design legends surrounding a PDP visualization to facilitate the consumption and contribution of data?

Encoding and uncertainty: when designing the encoding of a PDP, how can we consider the different levels of uncertainty in the data and communicate these to the viewer?

Flexibility of interaction: the layout and faceting of a PDP dictate to what extent the visualization is freely accessible and/or accessible over time. To what extent should a PDP allow for reversible and temporal interactions and/or reporting of past behaviors/opinions?

Physicality of encoding: as a PDP provides a physical representation of complex information, what are the tradeoffs between the precision of the visualization and simplicity of interaction?

comparisons, and do not add a temporal axis. For any PDP (with more encoding complexity), it is important to choose a faceting that is objective enough (e.g., per category or time interval), while allowing for comparisons of some sort.

Design consideration #4: *Consider how to include frames of reference within the PDP visualization so that the contributing audience can make meaningful comparisons.*

Signposting

The visualization of Edo was accompanied by a variety of legends and signposting to facilitate the *consumption* and *contribution* of data. However, during the deployment we observed that respondents did not necessarily read all instructions in great detail, resulting in them sometimes missing out on crucial information and reaching out to each other or the researchers for help. Hence, when designing a PDP it is important to repeat information at relevant places to facilitate people through the contribution and/or consumption process. To give an example, for the people merely consuming (i.e. observing) the PDP it might be more beneficial to have the information available at eye height, whereas for prospective contributors it is more useful to have explicit instructions (e.g. the C token reminder) in close proximity of the tokens. This is especially important if the PDP is intended for standalone and/or long term use, as the design needs to be self-explanatory.

Design consideration #5: *Consider repeating crucial information and locating it strategically surrounding the PDP to facilitate the contribution to and consumption of the visualization.*

Encoding and uncertainty

We observed that at times respondents struggled to recall their lunch, or were not sure what representative tokens to choose. This was not necessarily problematic as it persuaded people to reflect for themselves and it was a conversation starter. A possible solution from the focus group was to include blank tokens to provide some freedom and flexibility to contribute alternative food items. However, apart from the inherent uncertainty that comes from self-reporting – and is a challenge for any PDP – there are additional levels of uncertainty to consider when designing one.

First, a source of uncertainty and imprecision that was very specific for Edo was the conversion of several data sources into a physical form (tokens of different sizes). Without this conversion, all tokens would have been of the same size – similar to the majority of existing PDPs [3] – and Edo would have purely been a categorical recording of what people ate. Instead, Edo converted an individual's set of food items into their carbon footprint. Hence, there is an additional imprecision and uncertainty introduced by this conversion, when estimation is involved (e.g. portion sizes) or when there are multiple data sources for the topic at hand (e.g. carbon footprinting). Looking at existing PDPs, there is no other example we know of using such a conversion. For the design of any future PDP that introduces a conversion (e.g. for Figure 2C converting hours of sleep to the size of the gumballs) it is important to be aware of the additional challenges it brings.

Second, there is ambiguity in reading the PDP. In the case of Edo, the circle packing leaves gaps between circles which made respondents question how to interpret these. A limitation of the current design of Edo was that uncertainty was not communicated as part of the visualization – e.g. how to interpret gaps in circle packing – hence researchers provided clarifications when asked. Prior work [5] also discussed ambiguity in reading the 'code' of the visualization.

To summarize, it is not necessarily about ruling out as much uncertainty on the different levels when designing the visual encodings, as in many cases this will be impossible, but about acknowledging and conveying the uncertainties to the people participating in the PDP.

Design consideration #6: *Be mindful of the different levels of imprecision and uncertainty that can be involved in the design and interpretation of a PDP, and try to convey them.*

Supporting pragmatic and epistemic actions

We observed that respondents had different interaction patterns when contributing data to Edo. Moreover, we observed instances in which respondents reverted their contributions (e.g. in case of an error), made temporary alterations to the visualization to answer a question (e.g. how many red meat tokens fit a daily budget), or created temporarily constructs to anticipate implications of their contributions (e.g. the climate impact of the cafeteria week menu). As discussed by Kirsch et al. [12], we can differentiate between *pragmatic* and *epistemic actions*. Pragmatic actions have a specific purpose (e.g. contribute tokens to the PDP), whereas epistemic actions do not have a specific end goal but help with the sense-making of information (e.g. create temporary token constructs). As a result, if there is more room for reversibility in the PDP, there is likely also more room for epistemic actions as part of the contribution process. Likewise, more reversibility might also create opportunities for playful or even vandalic actions. Hence, different design considerations could facilitate epistemic actions more as part of the process of contributing data to the PDP. Moreover, designers can actively target epistemic actions or prevent potential misuse from happening by designing the layout and/or faceting in a more or less restrictive manner [21]. For example, for the layout per day, prior days could be locked off in case reporting of past behaviors is not desired, or any other day than the present day could be locked off to prevent errors by respondents. Looking at related work, existing PDPs show different levels of reversibility, which influences the potential for different interactions to occur.

Design consideration #7: *Consider the variety and type of actions that will be facilitated by the PDP (e.g. pragmatic and/or epistemic) and adapt the layout, faceting, and physical constraints accordingly.*

CONCLUSION

In this pictorial, we aimed to explore a PDP with more complex encodings than prior work. Therefore, we designed Edo, a PDP of the climate impact of personal dietary choices and deployed it in three different layouts with a research group. We found that there were trade-offs between showing more or less collective faceting of the contributed data. To conclude, we contribute a set of future considerations when designing a PDP with more complex visual encodings, such as how to encode contributions, adapt the PDP to audience size, facilitate meaningful comparisons, include signposting, and support epistemic interactions.

ACKNOWLEDGMENTS

This research was funded in part by the ANR grant ANR-19-CE33-0012.

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