A Design Space of Animating Data-Driven Transitions in Data Videos

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ABSTRACT

Data video is an increasingly popular genre of narrative visualization. To distill a data story into a video, designers need to draft a sequence of data facts and visually connect them by animated transitions. Such animated transitions are critical for illustrating data changes and enhancing narrative coherence; however, their design still lacks systematic guidance. To fill this gap, we developed a design space by collecting and analyzing 89 high-quality data videos. The design space characterizes the design of animated transitions under three dimensions: narrative relation, data change, and transition animation. We conducted an online design workshop with 14 participants to evaluate the effectiveness of our design space on designing transitions. The results show that the design patterns summarized in our design space can be used to efficiently guide the transition designs in data videos.

Index Terms: Data video, Transition

1 INTRODUCTION

Data videos represent data stories with visualizations and motion graphics [5,7]. They provide an intuitive approach for data communication, thus have attracted increasing attention from the visualization community (e.g., [7,38]) and have been commonly used in various domains, such as journalism [45] and advertising [15]. A data video consists of a sequence of data-driven clips [7] or visualization states [20] that demonstrate a piece of the data story [20,37]. Creating a compelling data video requires not only finding insightful data facts and crafting narratives that connect insights into a story, but also designing smooth transitions between insights that help convey the flow of narratives to the audience.

Given the complexity of creating data videos and the broad skill sets required for video designers, researchers have been exploring ways to automate video creation. Previous work has introduced techniques for automatically finding data facts [46] and linking data facts into coherent stories [37]. There are also tools with templated charts and animations that are developed to alleviate the hassle of designing and editing data videos [1,7]. However, there is not much existing research on automation for the last step of data video creation – transition design. One of the biggest challenges of doing so is the lack of systematic review of the design patterns and actionable guidance to leverage for either heuristic or model-based solutions.

While animated transitions are considered complex and difficult to craft in data video [7], it is the key to bridge succeeding data facts and smoothly convey the narratives. Prior studies have suggested that an effective animated transition design can illustrate the underlying narrative relation between data facts, facilitate the communication of data insights, and improve the engagement of the communication process [6]. Due to its importance, many research efforts have been devoted to designing effective transitions in data visualizations. Heer and Robertson [18] introduced a taxonomy of transitions in visualizations, inspiring research on transition effectiveness [13,34], authoring tools [16,26], and the design space [44]. However, these studies on animated transitions were mostly conducted out of the context of data videos and storytelling narratives. Recent research efforts have started focusing on transitions in data videos [7,43], but little effort has been put into studying the transition methods for revealing the changes of the underlying data in a visual narrative.

To better understand transition design in data storytelling and create guidelines for designing transitions in data videos, this paper introduces a design space by investigating the current design practice of animated transitions based on a corpus of 89 high quality data videos. We summarize the frequently used and effective design patterns into a three-dimensional design space that reveals how a ***narrative relation*** could be implemented via certain ***data changes*** and represent by expressive ***transition animations***. In the design space, we adopted the cinematography terminologies [12,31,42] to define visual transition animations and leverage a well-established taxonomy from linguistics [47] to classify different types of narrative relations. To understand and capture the change of the underlying data regarding a narrative relation, we introduced a set of data changes, through which one can manipulate the raw data to generate a proper data-changing flow for presenting a given narrative relation. Based on the three dimensions, our design space summarizes 26 frequently used transition patterns. To facilitate training and exploration, we further designed a set of design pattern cards and an online website[1] for designers to explore the cards. We evaluated the proposed design space via an online design workshop with 14 designers followed by semi-structured interviews. The evaluation results showed that our design space successfully summarized a set of useful design patterns and efficiently guided the transitions design in a data narrative. The contributions of the paper are as follows:

- We introduce a design space that summarizes design patterns and guidelines to help author meaningful visual transitions based on a study of 89 high-quality data videos.
- We evaluate the design space via an online design workshop with 14 designers and discussed our findings and implications.

2 RELATED WORK

2.1 Narrative Visualization and Data Videos

Narrative visualization has been an emerging topic given its ability to efficiently communicate data and insights with general audiences [35]. Prior research has studied how to organize data facts into narratives through, for example, understanding the sequential patterns of data narrative structures [5,20,27,37] and narrative linearity [28]. Another thread of research focuses on understanding human perceptions of different visual story representations [35]. Hullman and Diakopoulos [19] illustrate the rhetorical effect of various design tactics in narrative visualization. McKenna et al. [32] identify seven

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[1] https://transitionexplorer.github.io

factors that can improve the flows of visual narratives. Shu et al. [41] proposed a design space for data-GIFs, with a user study showing different designs having different impacts on user interpretation of GIF narratives.

Following the research trend of studying the communication of data stories with visual narratives, in this work, we target data video [35]. Previous research has studied how animation and pictographs affect the engagement of audiences in data videos [6] and how to use different animation techniques for different narrative strategies [38]. Complementing the design spaces proposed in previous studies, our work aims to fill in the missing design component – transitions – of data videos and provide animation design guidelines around it. Tang et al. [43] touched upon this research topic by proposing a taxonomy of transitions in data videos. However, this taxonomy does not guide transition design under certain narrative structures and data changes. For example, an animation transition between two similar data facts should be designed differently from another transition between two contrasting data facts. The former one may be smoother, and the latter one can be more intense. Thus, our work focuses on how to represent different narratives in animating these data-driven transitions.

2.2 Animation in Visualization

Animations are commonly used in visualization to enhance expressiveness and improve user engagement. Researchers have identified benefits of incorporating animations in visualizations, such as improving graphical perception [18], outperforming static uncertainty visualizations in trend inference [24], and facilitating visual comparison [33]. There are also downsides to animations when not designed properly. Robertson et al. [34] found that the usage of animations in visualizations is often error-prone, which leads to less effectiveness compared to static plots and small multiples. Chevalier et al. [13] found staggering, a common animation technique, might harm the tracking performance of multiple objects. These studies reflect the importance of careful animations in visualizations.

Animation is considered powerful in context preserving and is often applied in visual storytelling. Shi et al. [38] presented a design space for understanding the use of animations for presenting individual data facts with different narrative strategies. They identified eight common visual narrative strategies and created a design space that summarized the use of 43 animation techniques. Compared to their study, our work focuses more on the transitions that bridge the changes between different data facts in data videos.

2.3 Transitions in Cinematography

The design of film transitions is mainly founded on the continuity style [10, 42], which consists of a suite of continuity editing rules for transiting the narrative from shot to shot and scene to scene seamlessly [42]. Brown summarized six groups of continuity editing rules [12], including the content cut, the action cut, the Point-of-View (POV) cut, the match cut, the conceptual cut, and the zero cut. The narratives behind the scenes play a decisive role in the selection of editing rules in a transition. For example, if a character walks from one place to the other, the action cut may be used to illustrate the motion; if a character is looking at something, the POV cut may be used to show her attention [42]. The theory and practice of transition designs in cinematography inspired us to adopt a similar methodology to understand transitions in data videos. We adopted terminologies from cinematography resources [2–4, 12, 31, 42] to define the transition animations and explored the ability of these transition animations in representing data narratives.

3 Design Space

In this section, we first introduce our methodology for collecting the corpus of 89 data videos, summarizing design patterns, and developing the design space. Then, we illustrate the three dimensions of our proposed design space: ***narrative relation***, ***data change*** and ***transition animation***. Lastly, we connect three dimensions and illustrate in more detail how *narrative relation* can be implemented via certain *data change* and represented by *transition animations* to provide concrete guidelines on transition designs in data videos.

3.1 Methodology

To understand how transitions are designed to assist narrations in data videos, we collected a corpus of data videos and analyzed each video to identify its transition types and the corresponding narrative structure. The collecting procedure of the video corpus consists of two stages. In the first stage, we selected some candidates from public datasets of previous studies [12, 38, 48]. In the second stage, we further explored the recently published data videos from some reputable video producers (e.g., Vox, The New York Times) and have a high number of views. For each selected data video, we ensured that the video (1) is data-driven, (2) contained at least two data facts that are presented by visualizations, and (3) included at least one transition. We ended up with 42 data video candidates after the first stage of collection, and we further expanded our corpus to 89 data videos in total after the second stage. The complete list of data videos in our corpus is in the supplementary material. To build a design space that can best characterize the use of animated transitions in data videos, we analyzed the data video through an initial coding phase, followed by validation and refinement of the initial coding through pilot studies.

3.1.1 Coding

Two visualization researchers (also authors of this paper) coded the data videos independently using thematic analysis [11]. One coder has over two years of research experience in visualization while the other is proficient in designing narrative visualization.

Effective transitions can promote the development of narrative and bridge data facts smoothly [12, 32, 43]. Thus, we established our initial dimensions by coding the *narrative relation* and *data change* of data transitions in our corpus, which occur where data facts change in the videos. We then analyzed the design of animations for these transitions. In particular, we referred to a well-established taxonomy from linguistics [47] to identify the types of *narrative relation*. To capture the underlying data changes of each transition, we first coded the starting and ending data facts of a transition with the five-tuple definition given in [37]. Then, we categorized and open-coded the change of data facts. We coded what fields of the five-tuple change in the transition and, if applicable, in what direction they change (e.g., expand or narrow down *subspace*). We grouped the frequently appeared data changes and initially derived six categories in the *data change* dimension. We further identified the transition animations of each transition with a group of predefined concepts curated from cinematography resources [2–4, 10, 12, 42] to formulate the *transition animation* dimension.

The coding process took over weeks. After completing initial coding independently, two coders frequently discussed and reached a consensus on the categorizations. ' This stage resulted in the identification of 36 design patterns. Each pattern represents a transition design that reflects a *data change* under a *narrative relation* through a *transition animation*, appearing in at least two different data videos in our corpus. These patterns cover 72.7% of transitions in the corpus. We excluded frame-based animations (covering 23.0% of the transitions in the corpus; see Sec. 3.2.3) as they are universal and not strongly connected to narrative relations and data changes.

3.1.2 Validation and Refinement

While the initial design space is derived from the video corpus, the transitions in these videos are not always well-designed or generalizable. To validate and refine the design space, we conducted a pilot study with four data video designers (D1-D4). These designers are

Figure 1: Some transition animations in our initial design space

postgraduate students from design schools with at least one year of data video design experience. We first introduced each dimension of our design space in detail. Then, we provided them with the 36 design patterns, which were laid out similarly to Figure 4 (to be discussed in Section 3.3). Each design pattern is depicted using six sequential key frames. Designers can explore the design pattern by successively selecting the *narrative relation*, the *data change*, and the *transition animation*. We provided designers with six data facts about obesity extracted from an online data video [39], and asked each designer to design a data video with at least three transitions using our design space. After the video design is completed, we conducted a semi-structured interview with each designer to collect their subjective feedback on the design space regarding the utility and usefulness.

We distilled the following findings from the study. First, finding *transition animations* based on *narrative relation* and *data change* turns out to be intuitive and natural to designers. D1 shared that, "*These two data facts* [before and after the transition] *are very similar, and* [the data] *are also of the same dimension, so I used morph to change its* [the visualization component] *size*". D2 and D4 also described their usage experience with our design space as using a "*dictionary*" and having a "*design book*", respectively.

Designers also raised some concerns regarding some *transition animations*. Three designers mentioned that it is difficult to imagine a usage scenario of *arc shot* (Fig. 1) (1)). The *cross cut* (Fig. 1) (2)) had the same issue. Hence, we decided to remove the two *transition animations* from our design space for better generalizability. Also, *lap dissolve* and *contrast cut* (Fig. 1) were found to be very similar, both laying out the two data facts in one scene for better comparison. Hence, we merged these two animations.

After the validation process, we arrived at the design space with six *narrative relations*, six *data changes* and 12 *transition animations*. Besides, we have 26 **design patterns** that can be interpreted as combinations of items in the three dimensions. The **design patterns** are organized in Figure 4. We introduce the definitions for each dimension, and discuss how designers can choose **design patterns** that fit their design intention from Figure 4 based on the *narrative relation* and *data change* in later sections.

3.2 Design Space of Transitions in Data Videos

Our proposed design space of data-driven animating transitions in data videos consists of three dimensions: 1) a ***narrative relation*** dimension describes the narrative structure of the corresponding data facts during the transition, 2) a ***data change*** dimension that captures the underlying data changes, and 3) a ***transition animation*** dimension depicting the frequently occurred animation techniques.

3.2.1 Narrative Relation

An animated transition bridges two consecutive data facts in a data video. Based on the underlying narrative intent, the design of the animated transition can be different [28]. To guide designers in choosing the effective animations for conveying the narratives, our design space uses the *narrative relation* dimension to capture the differences of animated transitions regarding the narrative logic from one data fact to the other. We adopt the categorization of prior research on narrative visualization [20, 37] and linguistic [47], and include six *narrative relations* in the design space:

- **Similarity** The two data facts share similar narrative logic;
- **Contrast** The two data facts are in contrast to each other;
- **Elaboration** The latter data fact adds more details on the top of the previous data fact;
- **Generalization** The latter data fact is an abstraction from the previous one;
- **Cause-Effect** There exist a causal relation between the two succeeding data facts;
- **Temporal Sequence** The two data facts occur in a specific temporal order.

The taxonomy of *narrative relation* in our design space is capable of explaining nearly every transition's narrative structure in our corpus. There are exceptions where the two succeeding data facts show limited logical connections, which is referred to as "joint" [30] in the narrative relations. We omit "joint" in our design space as it does not embed strong semantic information to guide the design of animating transitions.

3.2.2 Data Change

The development of a data story is driven by the change in underlying data, which, suggested in prior research [20], greatly impacts the choice of animated transitions. Effective transitions in a data video can illustrate the evolution of data more clearly and smoothly. Therefore, our design space incorporates the *data change* dimension to capture the relation between data changes and the design of transitions. Our review of the past studies in narrative visualizations [20, 27] gives us an initial understanding of how to characterize the change of underlying data in visualization sequences, and we borrow terminologies like "dimension walk" as well as "measure walk" from these work to name some categories in the *data change* dimension of our design space. We define *data change* as operations that can transform one data fact into another data fact. Each data fact is characterized by the 5-tuple definition (*type, subspace, breakdown, measure* and *focus*), which was commonly applied in previous narrative visualization research [37, 46]. We further define each *data change* as the modification of the fields in the 5-tuple. From the analysis of our corpus, we identify six types of *data changes*. We elaborate on each type of data change with an obesity dataset that comprises six data facts (Fig. 2).

- **Filter Walk+** indicates an expansion of the *subspace* of a data fact. *Data Fact 1* is about the calorie consumption data in 2015. After a *Filter Walk+* to *Data Fact 2*, the *subspace* "Year" expands to {1975, 1995, 2015}.
- **Filter Walk-** refers to narrowing down the *subspace* of a data fact. For example, from *Data Fact 3* to *Data Fact 4*, the data range in *subspace* "Year" is shrunk down to {2015}.
- **Dimension Walk** indicates a substitution of the *subspace* value of a data fact. For example, *Data Fact 5* changes to *Data Fact 6* by changing the *subspace* value {"2015"} to {"2000"}.
- **Measure Walk** indicates updating the *measure* of the data fact. For example, *Data Fact 2* is transformed to *Data Fact 3* by changing the *measure* from "calories consumed" to "obesity rate" in the population.
- **Drill-Down** refers to subdividing the *breakdown*. For example, we can introduce a new *breakdown* on the "countries" level to transit from *Data Fact 4* to *Data Fact 5*.
- **Roll-Up** is the reverse of *Drill-down*, which aggregate the low-level *breakdowns*. For example, by merging the "countries" in the data, *Data Fact 4* can be changed into *Data Fact 4*, which show the data of the world.

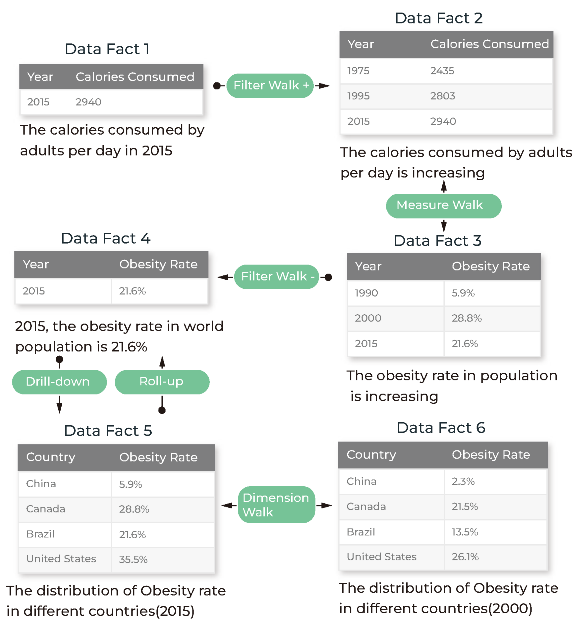

Figure 2: The obesity dataset to illustrate the *data changes* dimension

Note that our proposed taxonomy is not intended to exhaust all possible data changes. Instead, we focus on the data changes that are often applied in data storytelling. The six types of data changes in our design space can cover most data-driven transitions we observed in our corpus. We excluded some transitions in our corpus that use the composition of multiple data changes, as previous studies suggested such transitions are high-cost and may harm viewers' understandability [20].

3.2.3 Transition Animation

The *transition animation* dimension identifies a set of animation techniques to transform one visualization into another coherently. Video designers tend to apply design suggestions that align with their editorial behaviors [38]. Therefore, we utilize a set of *editorial layers*, which characterize the steerable elements in an animation, to categorize the *transition animations* in our design space. Four of the *editorial layers* are based on a prior work [38]. We add an additional layer called "frame", a common concept in video editing [2] (Fig 3 (9)-(12)). In particular, the definition of five *editorial layers* is as follows:

- **Visualization elements**, representing data-driven visual marks such as bars, lines, points, etc. Operations to these elements refer to changing visualization elements' color, size, shape, and position.
- **Auxiliary elements**. One can change the color, size, shape, and position of textual or graphical elements that are not bound with data. Such elements are often seen in data videos.
- **Camera**. Operations to camera refer to changes in the video camera's perspective and configurations (e.g., focal length, aperture, focus, exposure, etc.).
- **Timeline.** Operating timeline refers to changing the duration, delay, easing, and staggering [13] of the animations to create transition variants.
- **Frame.** A video comprises a sequence of static images, each of which is considered a frame. A frame is in a particular timestamp and consists of all elements (including *visualization elements* and *auxiliary elements*) in the scene. The frame's transparency, brightness, position, rotation, etc, can be changed.

Every transition animation in our design space can be implemented via manipulating one to three editorial layers, as presented in the second column of Figure 3. We leveraged terminologies on film cuts and transitions from cinematography to determine the main categories of *transition animations* in our video corpus. As a result, we identified 12 types of transition animations (Figure 3).

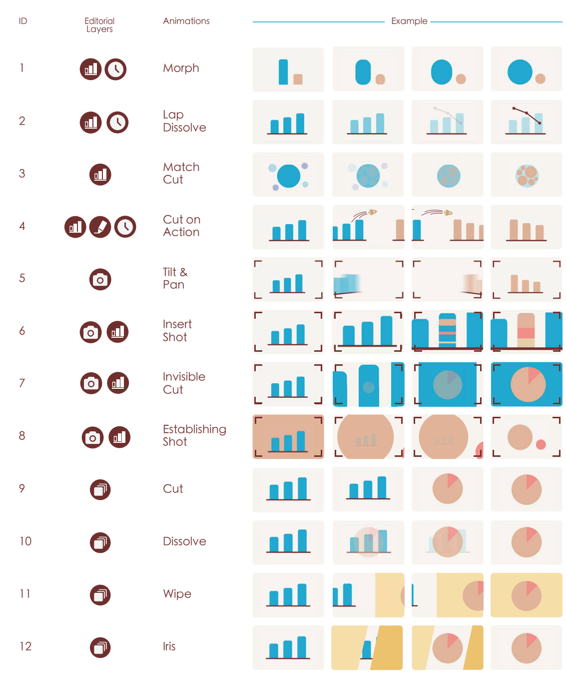

Figure 3: The 12 types of transition animations in our design space

While previous works also provide a summaxrization of *transition animations* in data storytelling [18,43,44], our analysis of animations is situated in the context of *narrative relations* and *data changes*, through which our proposed design space is capable of providing more actionable guidance on what animations to use in a specific narrative and data context. Note that while most of the transitions in our design space are closely tied to particular *narrative relations* and *data changes*, the last four animations (Figure 3, 9–12) can be applied to any case. They are also popular in other mediums, such as presentation slides. In the next section, we depict the eight transition animations and how they should be applied in transition designs for data videos.

3.3 Design Patterns of Data-Driven Transitions

In this section, we present 26 transition design patterns that offer actionable guidance for creating transitions in the contexts of narrative relations and data changes. Visual expression in data stories often evolves alongside the narrative [29, 37, 38, 48], so we focus on narrative relations to introduce these patterns. In each subsection dedicated to a specific narrative relation, we first explain which data changes can support it. Next, we describe the transition animations applicable within the constraints of each combination of narrative relation and data change, forming the design patterns.

3.3.1 Similarity

The change of data facts that reflect similarity is typically minor. For example, when the first data fact describes the economic trend of country A, the following two cases both present similarity relations: changing to country B that has a close economic trend (*dimension walk*) and changing to another economic measure while the trend does not change much (*measure walk*). Viewers' perception of

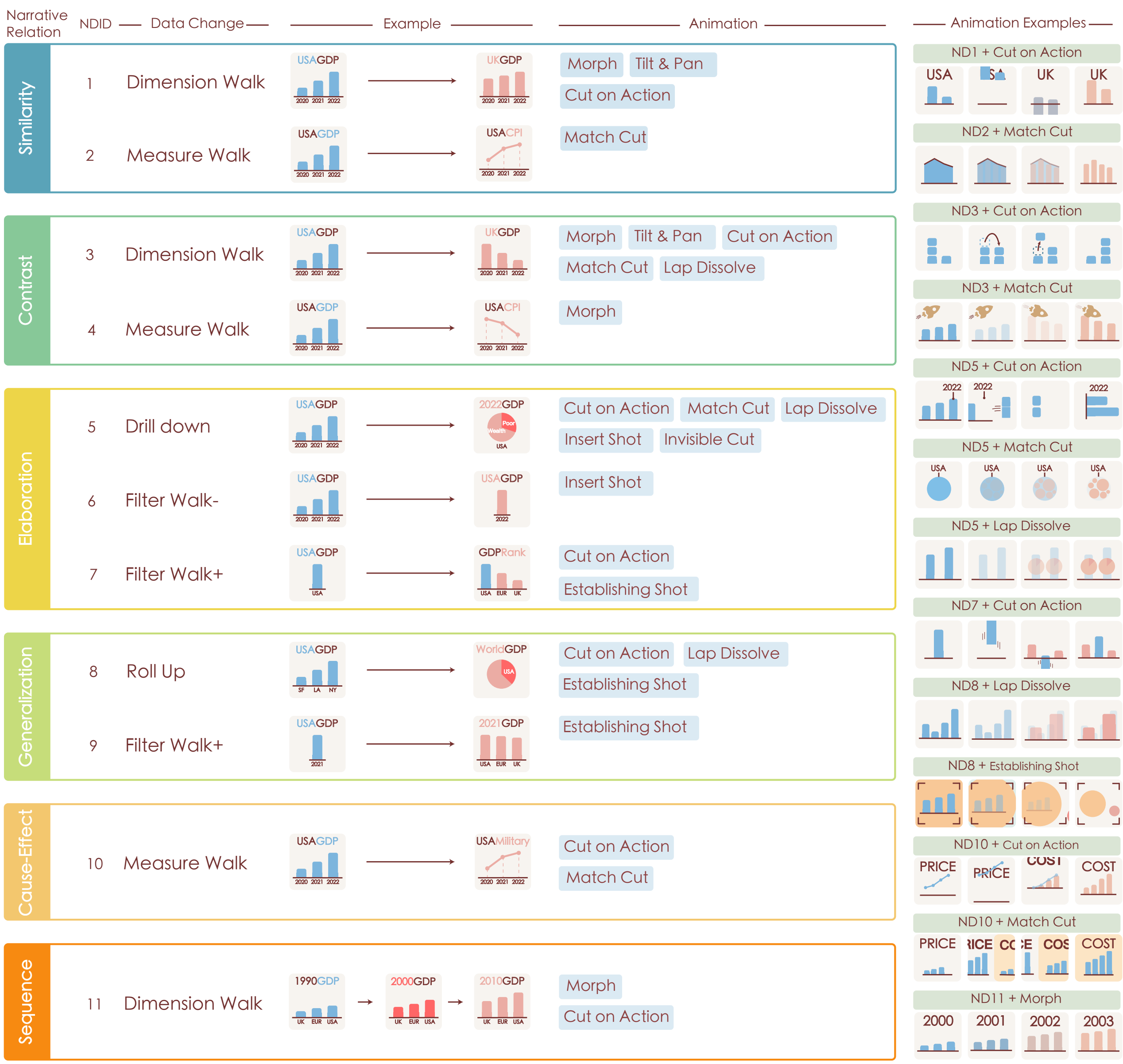

Figure 4: The design space offers actionable guidance for transition designs. Each *narrative relation* aligns with specific *data changes* and examples to illustrate their application. Each combination of *narrative relation* and *data change* is indexed by "NDID" (i.e., narrative relation-data change index) and linked to appropriate *transition animations*. The far-right examples demonstrate how these transitions support specific NDIDs.

visual changes is expected to be unobvious, hinting that the data and narrative logic do not change much. For example, *morph*, which gradually changes the shape of the visualization elements, is often used with the *dimension walk*. For *measure walk*, where the visual encoding of different measures is often different (e.g., from bars to lines), *match cut* can be the option. As shown in Fig. 4 [*ND2+Match Cut*], the visualization elements are updated, and designers try to maintain a similar overall shape, color, and position. Nevertheless, designers sometimes do not want viewers to ignore what changes during the transition. With *dimension walk*, the main subject of the data fact changes (e.g., from USA to UK in Figure 4). In this case, *tilt & pan* can be used, where the camera pivots to move the viewpoint away from the original visualization to the new one. *Cut on action* is another option, where the movement of either visualization elements or auxiliary elements can indicate, for example, "we are discussing another country" (Fig. 4 [*ND1+Cut on Action*]).

3.3.2 Contrast

Transition patterns under contrast appear most frequently in our video corpus, accounting for 29% of transitions. The data changes with contrast are often significant. For example, after explaining country A's increasing economic trend, the next data fact illustrates the decrease in its population (*measure walk*). *Dimension walk* can lead to "contrast". In the previous example, if the subsequent data fact depicts the economic decrease of country B, it is a *dimension walk*. For both *dimension walk* and *measure walk*, *morph* can be used to emphasize significant data fact changes, which often involve exaggerated shape deformation like transforming the largest visualization elements to the smallest one. For *dimension walk*, another four *transition animations* are suitable. *Tilt & pan* and *cut on action* can be used to highlight what is changing. We also observed *cut on action* are often implemented in ISOTYPE charts with contrast, where pictographs perform large motions (Fig. 4 [*ND3+Cut on Action*]). *Match cut* is another option for *dimension walk* under contrast. Typical *match cut* matches meaningful metaphors shared by the two data facts while updating the visualization with "pulse" or "shake" [38] to highlight the changes (Fig. 4 [*ND3+Match Cut*]). *Lap dissolve*, as a variation of *dissolve*, overlays (or juxtaposes) the new visualization elements to the old one for contrasting and eases the difficulty of finding the difference in between (Fig.3 No.2).

3.3.3 Elaboration

The most common *data change* reflecting elaboration is *drill-down*. For example, the data fact showing the economic growth of the US can transit to another presenting the distribution of wealth in the US in a certain year. Similarly, *filter walk-* reduce the data volume to the essential data point for elaboration (Fig. 4 ND.6). *Filter walk+* can be another alternative: from a data fact showing the economy of the US to another showing the world's economic ranking, detailing the US economic situation.

For transitions with *drill-down* or *filter walk-* for elaboration, elements in the latter data fact often logically belong to one or more elements in the former data fact. Such a relationship is what transitions need to depict visually. The *insert shot* (Fig. 3 No.6) takes the camera close to the visualization element of interest, where new visualization elements may appear within the close lens. Another similar animation, *invisible cut* (Fig. 3 No.7), brings the camera so close to the element of interest that it makes the original scene invisible to viewers, where the new visualization takes the chance to cut in. This kind of animation has great affordance of digging into details, thus may not be applicable for *filter walk-*, where the two succeeding data facts are at the same level. Besides manipulating the camera, *cut on action* can also present elaboration with *drill-down*. For transition in Fig. 4 [*ND5+Match Cut*], the bar representing the year 2022 can *fly* to a new scene and *split* to a new bar chart about low-level information. As shown in Fig. 4 [*ND5+Match Cut*] and [*ND5+Lap Dissolve*], *match cut* and *lap dissolve* serves for similar purposes. However, designers need to carefully curate the visualization so that the visual marks can match between the two data facts (Fig. 4 [*ND5+Match Cut*]).

Elaboration by *filter walk+* is often demonstrated by *cut on action* and *establishing cut*. By *filter walk+*, the newly added data points work as a foil. *Cut on action* fits in this purpose by moving the to-elaborate element to a new scene with more data points (Fig. 4 [*ND7+Cut on Action*]). For *establishing shot*, the camera moves away from the to-elaborate element and has a broader view containing more data points.

3.3.4 Generalization

Roll-up and *filter walk+* are the two most used data changes for generalization. The former raises the data hierarchy, while the latter increases the data volume. By moving the camera for a broader perspective, *establishing shot* can intuitively present the "raising up" idea for the two kinds of data changes. For "roll-up", *cut on action* and *lap dissolve* are often used. With *cut on action*, for example, by merging visualization elements representing states in the US, the visualization can be transformed to encode country-level data. *Lap dissolve* works by using new visualization elements that represent high-level data to gradually overlay on corresponding low-level data (Fig. 4 [*ND8+Lap Dissolve*]). These two animations are less used with *filter walk+*. The possible reason is that increasing the scope of the data is much more intuitive than merging the breakdowns of the data. Thus, there is less need for designers to use complex animations to illustrate *filter walk+*.

3.3.5 Cause-Effect

Measure walk is often used for explaining causal relations. For example, the former data shows an increase in vaccinations, and the next data shows a decrease in the number of infected cases. The narrator may state that the epidemic situation improves due to vaccinations. To express the *cause-effect*, designers can coordinate the actions in two data facts to illustrate that the action from the former data fact causes the action in the latter. For example, in Figure 4 [*ND10+Cut on Action*], the line representing the price trend drops to the top and pulls up the bars representing the cost trend. *Cut on action* that manipulating the visualization elements is applied in this example. The movement of line (*cause*) introduces an up-ward force to the bars(*effect*) visually. Another example is *match cut*. Some cases of *match cut* are matching on the action, instead of matching on shape in most cases. While animating some elements in the former data fact (e.g., bars are rising up), some other elements in the latter data facts show up and also animate in the same direction (Figure 4 [*ND10+Match Cut*]). In such a transition, the moving elements in the former (*effect*) are like chasing the moving elements of the latter (*cause*), implying the former cause the latter.

3.3.6 Temporal Sequence

A sequence of data facts that keep chronological order often appears in data videos. Such sequence is used to illustrate a trend in one domain (e.g., economic trend in Figure 4). The transition involved in such sequence is *dimension walk* in the time dimension. To illustrate the trend, *morph* is often used, which smoothly transforms the visualization elements through timestamps. Another available animation is *cut on action*. Considering the change of scatter plots along the temporal pace, circles move over time (similar cases for bar charts, line charts, etc.).

4 Evaluation: Design Workshop

We held a 4-hour online workshop to evaluate the effectiveness of our design space in guiding the transition design in data videos. We seek to answer two questions: (1) is the design space useful? and (2) how can the design space be utilized by video designers when they create data videos? We adopted a quasi-experiment design. In the workshop, participants were trained to use our design space through a three-phase process with three prepared datasets. In the first phase, we asked participants to make their first data video design based on the first dataset after introducing the basic concepts and examples. We then introduced the 12 types of transition animations summarized in our design space in the second phase and asked them to design a new data video based on the second dataset. In the last phase, we detailed the entire design space and asked the participants to make their final design based on the third dataset. The three datasets were used among the participants in a counterbalanced order. After each phase of design, we asked the participants to make a self-evaluation by (1) rating their satisfaction with their own designs and (2) estimating the degree of engagement for designing each data video. At the end of the workshop, they were asked to rank their three designs. These results were recorded for analysis.

4.1 Participants

Upon recruitment, we informed the participants that they would need to design data videos in the workshop and had the required skills. We received 22 valid registrations, and 14 participants (8 females), aged 20 – 34 years, showed up on the workshop day. Six participants had design backgrounds, while others are from computer science, education, and psychology. Participants joined our workshop out of interest, and no compensation was given.

4.2 Material

In the following, we introduce the materials we used in the workshop, including the datasets we provided to participants for video creation, a design space explorer we developed for participants to easily browse the transitions in our design space, and a storyboard for participants to demonstrate their design of data video.

4.2.1 Datasets

To make participants focus on the design of transitions, participants were directly provided with a set of data facts as the material for creating data videos instead of raw data. The data facts were collected from public datasets and existing data videos. We prepared three different datasets – wealth distribution in America [40], Netflix movies and TV shows [22], and US election 2020 [23] – for different design phases. In particular, we extracted seven data facts from each dataset. Examples of the data facts include: "In 2018, there were 705 billionaires in the United States, ranking first in the world", and "The elective votes of Biden received is higher than that of Trump.". The orders of the three datasets used by the participants are counterbalanced with a balanced Latin Square design: each participant was randomly assigned to one of the six possible orders of datasets.

4.2.2 Design Space Explorer

To help participants understand and use the design space, we developed a web app, *Transition Explorer*. The explorer consists of two pages with different links to support the second and third rounds of the design, respectively. The first page contains cards representing the 12 transition animation types, designed by following the practice of the NAPA [9] and IDEO Method Cards [21]. Each card includes the transition animation name, a GIF demo, and descriptions regarding how it can be used and why it can benefit story narratives. Two or three examples are provided so that participants can understand various forms of each type of animation. The second page, as an interactive version of Fig.4, contains 26 cards, corresponding to the 26 patterns. By selecting a narrative relation, applicable animations will be presented, which are indexed by data changes that can illustrate the selected narrative relation. The cards are colored based on their narrative relation. Each card includes a GIF demo from the data videos in our corpus that illustrates how the animation works under the corresponding data change and narrative relation.

Participants were encouraged to browse the website when designing transitions in the last two rounds of the study. While the two pages were separated for use in different rounds of study, we combined the two web pages into one website after the study for the demonstration purpose of this paper, which can be accessed through `https://transitionexplorer.github.io`.

4.2.3 Storyboard

Storyboard is a sketchy graphical tool that organizes a sequence of scenes in the order of narratives and is widely used in filmmaking and motion graphics [17]. It is also commonly used in design studies [5, 38] for participants to illustrate designs. To allow participants to present their transition animation designs, we designed the storyboard as a series of cells intersected by solid and dashed boxes, as shown in Fig. 6. Participants were asked to design data visualizations to present data facts in the solid boxes and illustrate the transitions between data facts in the dashed boxes. Participants can also describe the transition in more detail using the text form at the bottom of the dashed box.

4.3 Procedure

We delivered storyboards in digital forms to participants days before the workshop. They were asked to print out three or more copies of the storyboard and prepare drawing tools in advance. Alternatively, they can use tablets and digital pens. The workshop had three rounds of design. First, we introduced the basics of data videos, transitions, and storyboards in 20 minutes. We used an example data video to illustrate how to design data videos with a given dataset and storyboards. Next, we presented participants with two data facts and asked them to design a transition between these two data facts for practice. Then, we delivered one of the three datasets (see Sec 4.2.1) to each participant. Participants were given 40 minutes to complete the design before we collected the storyboards. The second and third rounds of the workshop are similar to the first round. The only difference is the tutorial. In the second round, we introduced the 12 types of transition animations with detailed explanations and examples; in the third round, we presented the complete design space, including narrative relations and data changes. We also provided an extra animation-making tutorial and encouraged participants to select one storyboard they liked most to create a real data video.

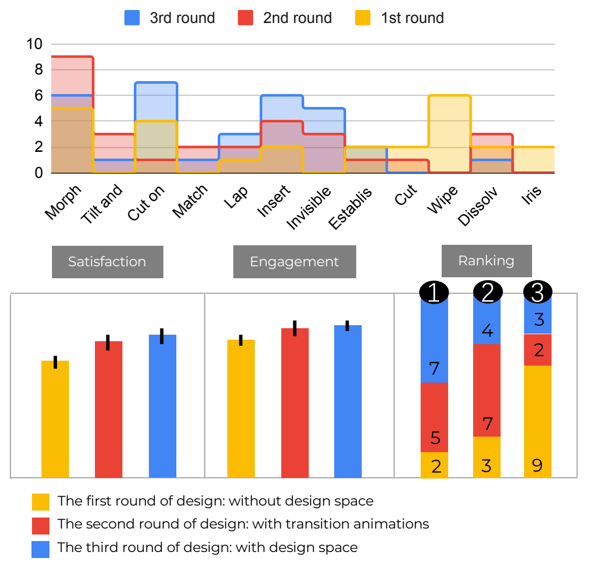

Figure 5: Top: the *transition animations* used in each round; Bottom: The results of the post-study questionnaire. The error bars represent the 95% percent confidence interval.

Participants were asked to fill in a post-task questionnaire after each round of design regarding their satisfaction with their designs and engagement during the process [25]. After completing all three rounds, participants were asked to complete a survey regarding the ease to learn, usefulness, ease to use, and helpfulness of the design space [8, 38]. We also asked them to rank their designs in the three rounds. We further conducted semi-structured interviews guided by questions such as how they perceived the usefulness of the design space, and what challenges they encountered during the designs. Due to the difficulty of coordinating the participants' schedules, we arranged interviews through online meetings within three days after the workshop. Upon agreement from the participants, we recorded the videos of the interviews for subsequent analysis.

4.4 Results

4.4.1 Usefulness of the Design Space

Overall, the participants agreed that our design space provides clear guidance on transition design 1 7 (M=5.71, SD=1.49) and supports their ideation process 1 7 (M=5.93, SD=0.92). Specifically, the usefulness of the *narrative relation* dimension was rated 1 7 (M=5.71, SD=1.07), the *data change* dimension was rated 1 7 (M=5.43, SD=1.22), and the *transition animation* dimension was rated 1 7 (M=5.64, SD=1.33).

We further compared the three rounds (Fig. 5). Friedman Tests suggest significant differences in participants' reported satisfaction with the design outcomes in the three rounds of design (χ^2=9.962, p=0.007). Conover's post-hoc comparisons with Holm correction reveal that participants' satisfaction level with their design in the last round is significantly higher than that in the first round (p=0.016). There is marginal significance found by comparing the satisfaction of the first and second rounds (T=2.262, p=0.065), and no significance between the second and the third rounds (T=0.787, p=0.439).

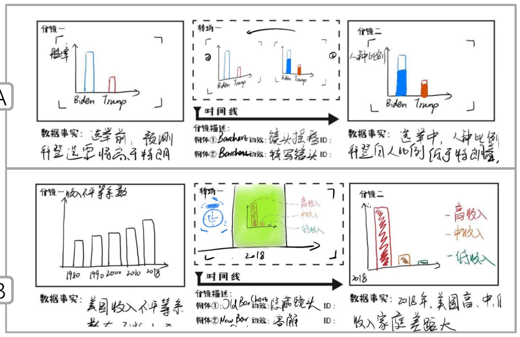

Figure 6: P12's two transition designs. (A) is his design in the second round, which transits from Trump and Biden's voting comparison to their voters' distribution in races; (B) is his design in the third round, which transits from an inequality trend to the wealth distribution in 2018.

These results show that our design space can help participants better design the transitions; but showing them a taxonomy of *transition animations* is not enough, guidance on what *transition animations* to use under a combination of *narrative relation* and *data change* is more helpful. Additionally, we did not find significant results by comparing participants' engagements in three rounds of design.

Compared with designing without the design space, participants emphasized how the 12 types of transition animations helped them in ideation during the interview, "*I have a clearer feeling for how to change elements during the transition*" (P04). Besides the taxonomy of animations, participants highlighted the importance of having *narrative relation* and *data change* in the design space, "[narrative relationship and data changes] *makes my logic clearer and more ideas on how to design appropriate animation to tell stories*" (P12).

4.4.2 Ease of Use

In general, our design space was rated positive regarding ease to learn 1 7 (M=5.61, SD=0.92) and ease to use 1 7 (M=5.92, SD=0.86). We found the design space to be intuitive to participants. The two dimensions, *narrative relation* and *data change*, in our design space can match some stages of participants' design in the first two rounds where these two dimensions hadn't been introduced," *In the first two rounds, I already thought about the relationship between them* [the two data facts bridged by the transition] *and then, how to explain such logic or such a data change*" (P13), "*In the second round of design, I was thinking about what scene each transition animation should fit into*" (P05). Participants also raised some concerns. Some struggled between their design intuition and the given design space, *"Sometimes I found there is no animation in similarity that I want; but, I found a good one in contrast. I don't know whether to follow my own ideas or follow the table."* (P08)

4.4.3 Design Space Usage

Each participant contributed two transitions in each round. As a result, we collected 14 storyboards with 28 transitions in each round. We coded these transitions based on our design space. For any vagueness, we asked participants in the interviews for explanations. Participants mainly used the frame-based *transition animations* (Fig. 3 (9)-(10)) in the first round (12 out of 26) (Fig. 5). In the second and third rounds, transition designs were more diverse. Nevertheless, participants in the second round still used one particular *transition animation* a lot (morph, 9 times); in contrast, participants in the third round tried more design alternatives (e.g., cut on action, 7 times; insert shot, 6 times; invisible cut, 5 times).

We found more differences in the combinations of the three dimensions of their designed transitions. Most transition designs in the third round follow our concluded design patterns in Fig. 4 (29 out of 32), while the percentage is much lower in the second round (14 out of 29). Combining the three dimensions that do not belong to the 26 design patterns weakens the narrative and illustrates the data change. P12 designed a transition in the second round (Fig. 6 A), which should be the *elaboration* relation with *drill-down* according to our design space. However, he applied *tilt & pan* in his design, which has little connection with the storytelling. Instead, in his third round of design, he applied the *invisible cut* for another transition with *elaboration* and *drill-down*, which clearly illustrate that the narrative goes from yearly trend to the detailed data in one year.

In addition, participants showed creativity in their designs. Several participants leveraged one or more metaphors throughout the storyboards and designed transitions around these metaphors. For example, P04 used an envelope with a ballot in her data video design around the US election. Her first transition is taking an *insert shot* to the envelope, which is accompanied by one candidate's election data. Her second transition applies *cut on action* to have the envelope fly from one candidate to another. Centering the data video around a metaphor helps the narrative logic to be more fluent.

5 Discussion

In this paper, we proposed a design space combining *narrative relation*, *data change*, and *transition animation* to guide the design of animating data-driven transitions in data videos. Although our work focuses on transition designs in data video, the design space can be further extended to other genres of narrative visualizations such as data comics [8] and scrollytelling [36] that contain multiple data facts and is with linear storytelling. They share similar design goals as data videos, such as maintaining continuity, explaining data flows, and shaping narratives in transitions.

Our study also reveals some underexplored directions. First, we found that a number of data videos utilize animating metaphors in transitions (e.g., coins when data is about wealth, and football when data is about sports). This suggests the creation of data videos is not only tied to data. Designers often borrow design experience from motion graphics and inject auxiliary elements into the illustration of data facts. How to design these elements and how their animation supports storytelling can be an important direction. Also, the role of animation in a sequence of visualizations may be underestimated. Previous studies discuss the cognitive load for viewers to understand transitions that involve significant data change [20, 27]. However, these studies did not consider animating transitions. Incorporating the transition animations with specific data changes opens up a research space for further investigating whether animations can make viewers comprehend the complex data change in a sequence of visualizations better. Moreover, traditional authoring tools for transitions, such as Adobe After Effect [14], have support for visual effect design and offer sufficient transition presets. However, these tools typically lack data-oriented support, which builds barriers to designing data-driven graphics and animations in data videos. There is still a lack of effective authoring techniques for creating animated videos to support the needs of novice users. Our design space can serve as the foundation for future animating transition authoring and empower novice designers to tell the stories out of the data.

Despite the fact that our video corpus has a decent number of data videos we compiled and extended from previous literature, it may not cover all existing transition design techniques for data videos. We expect the design space can be further refined and extended by analyzing more data videos collected from a wider range of resources in the future. What's more, We conducted an online workshop instead of onsite due to the local COVID-19 policy. Participants can be less focused and less engaged. An in-person workshop can better evaluate our design space and show its effectiveness.

6 Conclusion

Based on 89 high-quality data videos, this paper summarizes 26 commonly used design patterns of animating data-driven transitions into a three-dimensional design space, which comprise narrative relation, data change, and transition animation. The evaluation results show that our design space can effectively support designers in creating innovative transitions to facilitate data communication.

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