Interpreting the Effect of Embellishment on Chart Visualizations

Tiffany Andry
tiffany.andry@uclouvain.be
Université catholique de Louvain,
Louvain, Belgium

Christophe Hurter
christophe.hurter@enac.fr
ENAC, Université de Toulouse,
Toulouse, France

François Lambotte
francois.lambotte@uclouvain.be
Université catholique de Louvain,
Louvain, Belgium

Pierre Fastrez
pierre.fastrez@uclouvain.be
Université catholique de Louvain,
Louvain, Belgium

Alexandru Telea
a.c.telea@uu.nl
Utrecht University,
Utrecht, Netherlands

ABSTRACT

Infographics range from minimalism that aims to convey the raw data to elaborately decorated, or embellished, graphics that aim to engage readers by telling a story. Studies have shown evidence to negative, but also positive, effects on embellishments. We conducted a set of experiments to gauge more precisely how embellishments affect how people relate to infographics and make sense of the conveyed story. We analyzed questionnaires, interviews, and eye-tracking data simplified by bundling to find how embellishments affect reading infographics, beyond engagement, memorization, and recall. We found that, within bounds, embellishments have a positive effect on how users get engaged in understanding an infographic, with very limited downside. To our knowledge, our work is the first that fuses the aforementioned three information sources gathered from the same data-and-user corpus to understand infographics. Our findings can help to design more fine-grained studies to quantify embellishment effects and also to design infographics that effectively use embellishments.

CCS CONCEPTS

• **Human-centered computing** → Empirical studies in HCI.

KEYWORDS

infographics, embellishments, interpretation, gaze detection

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1 INTRODUCTION

Infographics, defined as visual representations of information, aim to present information quickly and clearly [70] and are an established communication tool in science and society. At one extreme, minimalist-style infographics directly and unambiguously encode underlying data [98] to maximize the number of data items shown on a given screen space, or the data-ink ratio [98]. At the other extreme, infographics, like the ones present in mass media, use many graphic elements that do not encode data proper (*e.g.*, shadows, background textures, icons, and complex layouts) but 'merely' *embellish* the display [89]. The effect of embellishments is not fully understood: Minimalist design argues that they only complicate data understanding and, in the limit, are 'chart junk' [97, 98]. Others argue that embellishment has added value, *e.g.*, in memorization and recall [6, 14, 16, 49] and in engaging users to study and understand the infographic [24, 58, 102]. All above works show that embellishment affects low-level perception, *e.g.*, the time needed to decode a given data variable from the infographic, complete a quantitative task (*e.g.*, sort some values), or how well data values are memorized. Less is known on how embellishments affect how people *assimilate* the entire *message* conveyed by an infographic, which goes beyond decoding data values and includes making sense of what the story these values tell. We refer to this process next as assimilation, to avoid potential confusion with the narrower meaning of sensemaking as used in *e.g.* visual analytics [84].

Kennedy and Hill [67] outlined human and emotional factors that influence people engagement. The beauty-emotion link is obvious: Beauty, through aesthetic pleasure, arouses emotion [33], so a key goal of designers using embellishment is to make a visualization look aesthetically pleasing. Yet, how embellished infographics fare here *vs* minimalistic ones is not fully clear. Understanding such higher-level aspects is important for choosing (or not) for embellishment in a given context.

We aim to gain more insight in how embellishment affects infographics assimilation along three dimensions: (1) aesthetics, (2) intelligibility, and (3) engagement. Questioning embellishment on these dimensions relates to an iterative interaction between visual perception [44], comprehension [71], and gap-bridging [34]. We do this by an experiment where 40 digital communication professionals study 19 embellished infographics and 19 standard counterparts created by minimalist design rules, by three types of user feedback (questionnaires, semi-structured interviews, and eye-tracking data), to answer six questions:

Q1: Do people find embellished data visualizations more beautiful than standard ones?

Q2: Do people prefer embellished visualization to standard ones?

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Q3: What is the effect of embellishment on clarity, compared to standard visualization?

Q4: Does embellishment affect interest and understanding?

Q5: Are finding a visualization beautiful and liking it correlated?

Q6: Which embellishment elements stimulate emotions and how does that affect reading a visualization?

These questions have, *in isolation*, been studied so far. Yet, this was done using different datasets, users, and feedback types, and on subsets of the above questions. A study combining all these elements and also showing relationships between the different questions is, to our knowledge, still lacking. We perform such a joint study, leading to several novel insights. Summarizing these: If not excessive and not changing traditional layouts, embellishments have an overall positive effect in engaging people to (put effort into) reading the visualization in many interconnected ways; and help, overall, making sense of the data encoded in the visualization.

2 RELATED WORK

2.1 Chartjunk and visual embellishment

Embellishment analysis: While lacking a unique formal definition, embellishments cover shadows, lighting, color gradients, icons, complex shapes, and background images. They can be seen as pictorial or metaphorical additions to, or modifications of, the visual variables that encode data, elements that "are not essential to understanding the data" [6], or more extremely, "chartjunk", which "seeks to attract and divert attention by means of display apparatus and ornament" [98]. Following Tufte [98], embellishments relate to artistic efforts that have no place in graphic design, as they only emphasize the pleasant and creative in visualizations, while transparency and truth is revealed by the data and not the data-containers. Many other authors [30, 35, 40–42, 47, 90, 95] have similar, albeit more nuanced, viewpoints. Embellishment contradicts classical chart design [9, 97, 98] which asks for maximum simplicity to ensure that the message is perceived as faithfully as possible. While embellishment goes beyond what is acceptable in terms of effectiveness for Tufte [98] and Bertin [9], most authors agree that it is not just an addition to a raw chart. Rather, embellishment is an *explicit* part of a chart's design process. Many studies have shown that using decorative visual elements benefits the visualization reception. Hence, embellishment is neither good nor bad *per se*. Bateman *et al.* [6] argue that embellishment, seen as the addition of icons and background images and touching upon features that encode data, helps memorization. For Skau *et al.* [93], embellishment focuses on additions and modifications to a raw chart, and not on aesthetic elements with a purely decorative aim. Borgo *et al.*[14] argue that embellishments go further, being a form of non-linguistic rhetorical figures that is often seen in visual and performing arts, advertisements, cultural symbols, color symbolism, and graphical user interfaces, and show benefits on long-term memory. Borkin *et al.* [16] showed that a low data-ink ratio, the use of objects recognizable by the human eye, and a high visual density increased memorization. Similarly, Haroz *et al.* [49] showed that icons improve memorability and also recall. Hill *et al.* [50] and Inbar *et al.* [65] believe that the graphic minimalism advocated by Tufte can be detrimental to users who have never encountered it before. Other investigations have shown that stylization in visualizations may not have a significant effect on data perception and understanding [10, 100]. Quispel and Maes [88] tested embellished and standard visualizations on two user samples (graphic design professionals and laypeople) to find how they rate attractiveness, clarity, and general appreciation of the visualizations. They found that professionals value embellishment more than laypeople in all aspects but clarity. Researchers are now trying to put into practice knowledge found on visual embellishments and are developing tools that produce embellished visualizations, allowing different benefits to be taken advantage of [28, 31].

Role of user: When arguing against chart junk (which can be seen as an extreme form of embellishment), Tufte focuses mainly on how to encode information in the clearest way. The user's role in the reception is left somehow on a secondary plane. Yet, many characteristics of users (human and emotional factors *e.g.* self-confidence, beliefs, opinions; statistical, language, and computer skills) and/or their environment affect a visualization's reception [67]. Aspects such as data source, visualization appearance, or subject matter can also influence how users *understand* and *engage* with a visualization. Importantly, *emotions* play a key role in the reception. They can be aroused by the appearance of a visualization, in particular by visual embellishments, in line with Norman's [79, 80] emotional design principles, for whom "simplicity is not the answer".

Our contribution: All authors agree that embellishments *affect* how an infographic is perceived – either negatively for the execution of certain tasks and/or the amount of information that a chart conveys, or positively regarding the traces that the displayed information leaves in the reader's long- or short-term memory, and reader's interest. We show additional insight in how embellishments affect the end-to-end infographic assimilation process, beyond studying how embellishments affect more 'local' aspects like decoding individual variables or memory.

2.2 Gaze analysis

Most studies discussed in Sec. 2.1 use questionnaires and interviews to gauge the users' responses. Eye tracking technology is also effective in capturing and analyzing user attention [36, 52] and visual behavior in a factual way. Eye-tracking systems (*e.g.* Tobii Studio [3], Blickshift [1], Eyevido [2]), open source [103], and web-based [19]) create datasets of fixation points linked by paths (saccades), next aggregated and visualized to extract user patterns via heatmaps [13, 69], scanpaths [46, 52] and Areas of Interest (AOIs) [11, 12, 20, 53]. Heatmaps, scanpaths, and AOIs can answer questions such as where on the stimulus image (and when), has the user focused most. Yet, they cannot, in general, extract more complex and/or fine-grained patterns such as *reading order*, which are important in many contexts, *e.g.* improving air traffic control tools [59–61, 64, 81]. *Trail bundling* groups similar eye trails to find and show such patterns. Different similarity definitions using spatial proximity, trail direction, and/or time stamps, emphasize different aspects in the eye-tracking data.

Many bundling algorithms exist [76, 106]. Explicit methods construct an intermediate control structure from the trails to group these along this structure, much akin to a clustering process. Control structures include compound graphs [23, 29, 45, 54, 104], trees [18, 82, 86, 101], Voronoi diagrams [32, 73], and Delaunay triangulations [32, 87]. Given such a control structure, trails are routed along it, using various forms of smooth curves, *e.g.* B-splines [23, 45, 54, 83, 104]; Bézier splines [17]; NURBS [87]; and cubic curves [48]. Explicit methods offer high control over the bundling, but require creating the above-mentioned control structure, which is not always easy. Implicit methods let trail fragments 'self-organize' into bundles, either in a geometric setting [21, 55, 77, 78, 92] or by using faster, GPU-parallelized methods [63, 76, 81, 99]. Implicit methods are easier to use than explicit ones, as they do not require a control structure. Hence, implicit methods have been the choice for producing simplified visualizations of eye-tracking datasets. In Sec. 4.3.2 we show how we adapt such methods to our analysis aims.

3 EXPERIMENTAL DESIGN

We now detail the experiments we conducted to understand how embellishments affect infographics assimilation. We next describe the data and participants (Sec. 3.1), exposure to data (Sec. 3.2), and post-exposure interviews (Sec. 3.3). Figure 1 outlines our workflow.

3.1 Data and participants

Data: We collected 19 embellished visualizations $E = \{E_1, \ldots, E_{19}\}$ in an inductive manner: We chose different types of visual embellishments, *e.g.*, pictographs arranged next to simple graphics, icons that constitute the data-ink, or fanciful graphic design. We gathered these from websites [94], blogs and social media, *i.e.*, places where citizens often read visualizations. We restricted ourselves to designs that can be seen as bar and pie chart variations, as these designs are the most easy to understand (decode) [27]. We restricted ourselves to stories (about the shown data) which were simple and understandable by the grand public, *e.g.*, most popular touristic places on Instagram (E_8). Figure 2 shows snapshots of the collected E_i. The green captions summarize the stories told by these images.

Standardized visualizations: We created simplified versions S_i of the embellished visualizations E_i, leading thus to a set $S = \{S_1, \ldots, S_{19}\}$ of additional visualizations (similarly to [6]). For brevity, we next refer to the embellished and standardized visualizations as *E-type*, respectively $S - type$. We produced S_i using Microsoft Excel following Bertin and Tufte's design principles [9, 97, 98], as follows: (1) When possible, we used the same type of bar or pie chart in S_i as in the original E_i. (2) We used a monochrome design in S_i, unless when E_i used categorical color coding, in which case we used the same categorical color palette. (3) We used an overall neutral font (Arial or similar) for all annotations. (4) All elements in E_i not encoding data, *e.g.* icons, color gradients, background images were removed. Figure 2 shows the S_i visualizations to the right of their E_i counterparts. We can see S_i as 'standardized' but not strictly speaking minimal, following Inbar *et al.* [65] and Hill *et al.* [50] according to which minimalism disturbs users who are not used to it. Following Kennedy and Hill's human and emotional factors [67], information on the sources of, or conclusions about, the data, was removed from E_i, and not shown in S_i, so as to not bias the users. We translated all annotations into French, to avoid language issues, given the population of our study (described next).

Users: Forty participants were involved in our study. All work as digital communication professionals, aged 23 to 55 years (mean: 29). They graduated from a Master in Communication Strategy and Media (web-oriented) or had a University Certificate in Web Communication, which covers digital communication strategies, including the use and manipulation of digital data for communication goals, *e.g.*, Google Analytics and data journalism. The users had varying amounts of experience years but had the same professional objectives, knowledge of communication purposes, and are digitally literate, given their occupation and studies. We did not further consider age and demographics in the selection. Hence, our user selection qualifies under what is known as reasoned sampling [8, 43].

Study set-up: All forty subjects came to our lab to take part in the study (about 1h30 per person). The study conditions (room, computer equipment, procedure) were identical for all subjects. Subjects could not communicate concerning the study aims, neither before nor during the study. For the eye tracking part of the study (see Sec. 3.2 next), we checked that subjects were not wearing hairstyles that obstructed vision or glasses that interfered with the eye tracking (wide frames or thick lenses). Participants were rewarded with a gift certificate.

3.2 Exposure to data corpus

Each participant in the study was shown 19 of the 38 total visualizations $E \cup S$, one at a time, on a display at 2048×1152 resolution. In this selection, we avoided pairs (E_i, S_i) showing the same data, so as to avoid learning effects and related biases. The order of presentation of the visualizations was different for each participant. To achieve this, we used the Latin square randomization method [91]. This experiment phase lasted 12 to 20 minutes depending on the participant.

Participants were asked to observe (read) each visualization and click to signal when they felt they *understood* it. Note that this (implicit) task is very different, and higher level, than explicit tasks used in related studies [6]. During this, we used an eye tracker to collect gaze data (discussed separately in Sec. 4.3.1). After signalling completion, each participant filled in an online questionnaire to show their agreement level, on a 5-point Likert scale (strongly disagree to strongly agree), with the following statements:

A1: I found the visualization *beautiful*;
A2: I found the visualization *interesting*;
A3: I found the visualization *clear*;
A4: I found the visualization *understandable*;
A5: I *liked* the visualization.

The formulation of A1..A5 links to our view of how assimilation works, thereby jointly addressing the questions Q1..Q5. When reading a visualization to make sense of it, one goes through three connected stages: Visual perception [44] (A1,A3,A4); comprehension [71] (A3,A4); and personal judgment [34] (A2,A5). These link to the three dimensions outlined in Sec. 1: aesthetic taste (A1, A5), intelligibility (A3, A4), and engagement (A2, A5).

3.3 Semi-structured interview

After doing the experiment in Sec. 3.2, each user undertook a semi-structured interview in a separate lab room (30 to 60 minutes), aiming to elicit the users' *own impression* on how they read and

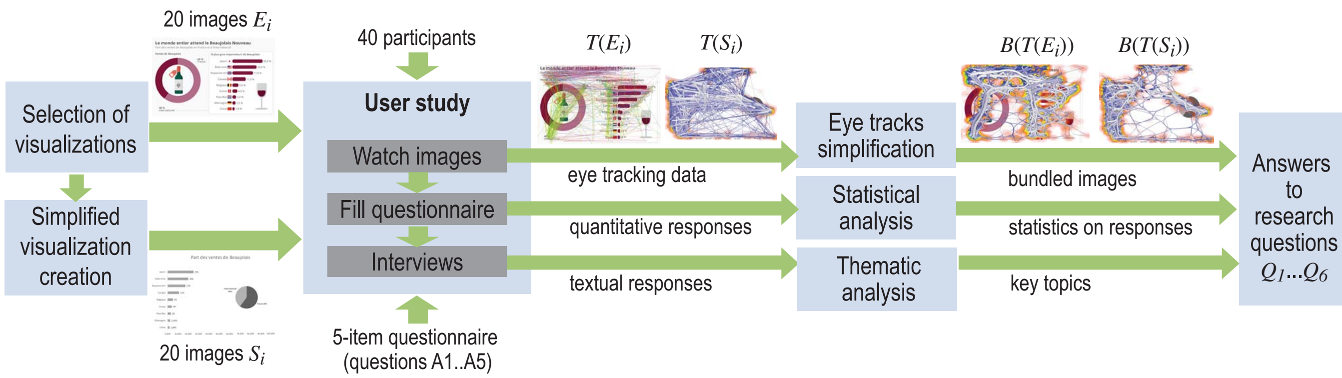

Figure 1: Pipeline of conducted user experiments and subsequent data analysis. For details, see Sec. 3.

understood the visualizations and which visual elements invoked which meanings, accounting for their personal characteristics and giving importance to emotion expression and the person's habitus, all while addressing certain themes. While the questionnaire data tells us *what* participants found of a visualization, interviews refine this by telling us *why* they gave those scores and *how* they read the visualization to score that way. This phase, in line with our vision of assimilation, corresponds to the very personal, subjective, and emotional components of people who feel engaged with a visualization [34, 67].

Figure 3 shows the interview workflow. We started with the same question: "Which visualization made the most impression on you?". We then asked to elaborate on why they named *that* visualization (denoted V_i in Fig. 3). If one mentioned a visualization that impressed *positively*, we then asked which other visualization V_j had impressed them *negatively*, and conversely. This elicits one positive-impression and one negative-impression visualization. In the interview, we used both a set of fixed (predefined) questions, following Kennedy and Hill [67], *e.g.*, "Do you feel comfortable when you observe this chart? Does this topic interest you?" and free questions, driven by the discussion flow, *e.g.*, "Do you value ornaments of this type? What did you think of all the images you just saw? What do you think of the use of color? If you could change something in this visualization, what would that be?" This style of interview allowed us to delve more deeply into topics mentioned by participants. While all interviews addressed all themes, not all questions used were identical, their actual choice being left to the interviewer's competence and experience [66].

We used the questionnaire results (available on a tablet) to guide the interview: We identified high differences in the scores for questions A1..A5 and asked users to comment on why they gave those scores. We searched for five classes of events (Fig. 3): high aesthetics but low liking (A1++, A5- -); high aesthetics but low clarity (A1++, A3- -); high aesthetics, clarity, understandability but low liking (A1++, A3++, A4++, A5- -); high aesthetics but low interest, low liking (A1++, A2- -, A5- -); and cases where scores were either all high or all low. When the discussion focused on whether or when one looked at a specific visual item, we used playbacks of the eye-tracking data to check and analyze that together with the user. However, we did this opportunistically, *i.e.*, not for every user. This is far lighter than full-blown think-aloud retrospective eye-tracking, as it can be disturbing for some people to watch a gaze replay for the first time [38].

This interviewing method (for full details, see [5]) allowed conducting interviews dynamically and efficiently and stimulated users to speak about important tensions reflected by their questionnaire answers. For instance, if one found a visualization very beautiful (high A1 score) but not clear at all (low A3 score), we would ask about this tension, using the same fixed-free question mix as reported earlier. We next show two fragments of our interviews (*I*: interviewer; *R*: subject; full texts are in the supplementary material [96]):

I: *This visualization was not very nice according to you but it was clear and well understood. Why? What would you change in it?*
R: *Yes, I would have added... I don't know what, images of men sleeping, partying, ... I would have "dressed up" this chart a bit.*

I: *I can see that you found this visualization beautiful, interesting, very clear, you understood and liked it... Why was it so perfect to you?*
R: *Star Wars is something that interests me more than the rest since I was a kid, so I'm not very objective. Like I said, it's got colors and it's eye-catching. The subject interests me so necessarily it's good and on the side you can see more or less a calibration of how many lightsabers have what color. The visualization is clear and it says what it is.*

All interviews ended with identical questions: "What is your job? Are you often in contact with data visualizations? How old are you? Is there anything else you want to add?" Asking such questions at the end likely made interviews less formal, and thus more natural, for the participants.

4 RESULTS

We next discuss the analysis of the three types of data we collected, *i.e.*, self-reported appreciations from questionnaires (Sec. 4.1), interviews (Sec. 4.2), and eye-tracking data (Secs. 4.3, 4.4).

4.1 Analysis of self-reported appreciations

Questionnaires (Sec. 3.2) hold the answers to questions A1..A5 of 40 participants for 19 visualizations each. After removing invalid answers, we were left with 741 of the $40 * 19 = 760$ total answer-sets. Figure 4(A1-A5) shows these answers aggregated per visualization.

Figure 2: Overview of the embellished visualizations E_i and their standardized (minimal) counterparts S_i used in our experiments (Sec. 4.1).

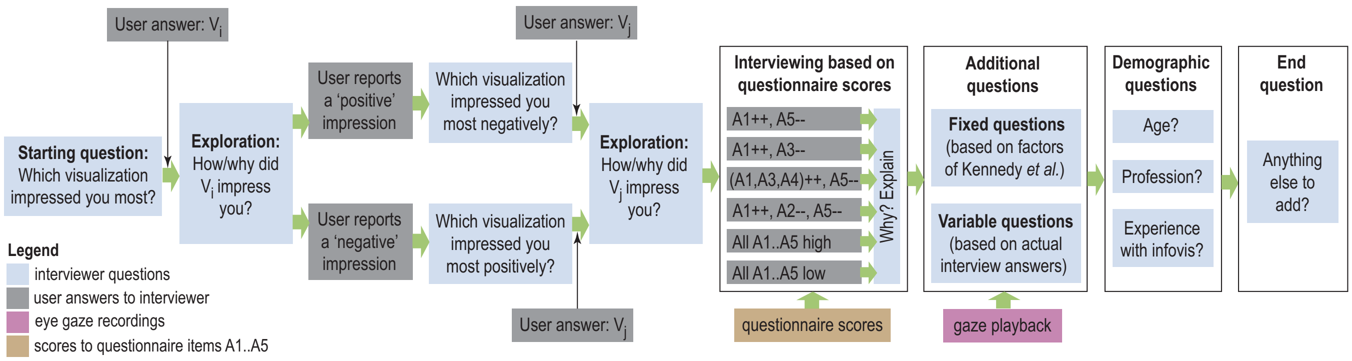

Figure 3: Pipeline of semi-structured interview. See Sec. 3.3.

The top and bottom halves of these five charts show the results for the *E*, respectively *S*, visualizations. Each row is a stacked bar whose segments show how many answers on the five-point Likert scale – strongly agree (dark green) to strongly disagree (dark red) – a question got for a visualization. Bars are horizontally aligned to their neutral-answer (neither agree nor disagree) points, so bars shifted to the right show questions with overall more in-agreement answers, and conversely for bars shifted to the left. These charts give us several insights:

A1 (Aesthetics): Nearly all *E* visualizations were found more beautiful than the *S* ones. Section 4.2 next explores how this can influence engagement with a visualization.

A2 (Interestingness): Varies largely over both visualization types, with no clear difference between them. Interestingness seems to depend much on the actual visualization (what it shows) and how the users relate to that topic. We explore this further in Sec. 4.2.

A3 (Clarity): As for A2, clarity varies widely intra-type and inter-type. Yet, most visualizations (both types) are ranked more often clear as unclear. This is important to know – if most visualizations were unclear, further analysis would bring little added value.

A4 (Understandability): Even more than clarity, nearly all visualizations were found to be (very) understandable, with no marked difference between the two types.

A5 (Liking): *E* visualizations are overall liked more than *S* ones, though the inter-type difference is less marked than for A1. The intra-type variability is smaller for *S* than for *E* visualizations – users liked *S* visualizations similarly but had more diverging linking of the *E* ones. We explore this further in Sec. 4.2.

The bottom-right image in Fig. 4 summarizes the first five charts by aggregating scores for each question A1..A5 over all 19 visualizations. We see here more clearly that *E* visualizations were found more beautiful than *S* ones (A1) and were also liked more (A4). Clarity (A2), understandability (A3), and interestingness (A4) scored similarly for the two types.

We found differences between the two visualization types beyond what Fig. 4 shows using statistical analysis, as follows. A first idea was to compare answers aggregated per visualization type, *i.e.*, *E vs S*, using Mann-Whitney's non-parametric test, which finds whether the medians of two groups are close. Yet, the distribution of our data (frequency of answers in each of the 5 Likert classes for A1..A5) is not normal, also seen from the aggregated scores in Fig. 4. Also, the variances of these distributions were not homogeneous, so the Mann-Whitney test preconditions were not satisfied. Hence, we used the Brown-Forsythe test (which does not require homogeneous variances) on the rank means of our data. If rank means are similar, we can tell whether there are statistical differences in the ratings for A1..A5.

Statement	Significance	Mean ranks *S*-type	Mean ranks *E*-type
A1: Aesthetics	0.000	237.98	503.65
A2: Interestingness	0.385	364.35	377.62
A3: Clarity	0.010	390.45	351.59
A4: Comprehension	0.102	381.87	360.15
A5: Liking	0.000	305.97	435.84

Table 1: Brown-Forsythe test for equality of rank means for the questionnaire results for statements A1..A5.

Table 1 shows the significance values for the Brown-Forsythe test for the answers to A1..A5. Using these, we test the null hypothesis (H0) that the mean ranks of *S* items equals the mean ranks of *E* items, *i.e.*, whether users find *S* and *E* visualizations similar, for a minimal significance level of $p = 0.05$. Adding to this the analysis of the actual mean ranks (Tab. 1, rightmost two columns) allows us to answer Q1..Q5 as follows:

For A1, A3, and A5, H0 is *rejected* ($p < 0.05$). Mean ranks for *S* and *E* visualizations are not equal for these statements: For A1, *S* mean ranks strongly exceed *E* mean ranks – users strongly find *E* visualizations more beautiful than *S* ones (Q1 answered positively). The same happens for A3, *i.e.*, users find *S* visualizations clearer than *E* ones (answer to Q3). For A5, *E* mean ranks strongly exceed those for *S* ones, so users prefer *E* visualizations to *S* ones (Q2 answered positively).

For A2 and A4, H0 *cannot* be rejected: We cannot say that users find *S* visualizations more (or less) interesting than *E* ones, nor that they find one type easier (or harder) to understand than the other. Hence, we cannot (yet) clearly answer Q4.

To answer Q5, we ran a Kendall Tau b test on the variables A1 (aesthetics) and A5 (liking). We obtained a rho coefficient of 0.578, *i.e.* a strong correlation between finding a visualization beautiful and liking it (Q5 answered positively). This is in line with the results of [50]. However, [50] studied only *simplified* visualizations, with no embellishments, focusing on the effect of the ink-data ratio.

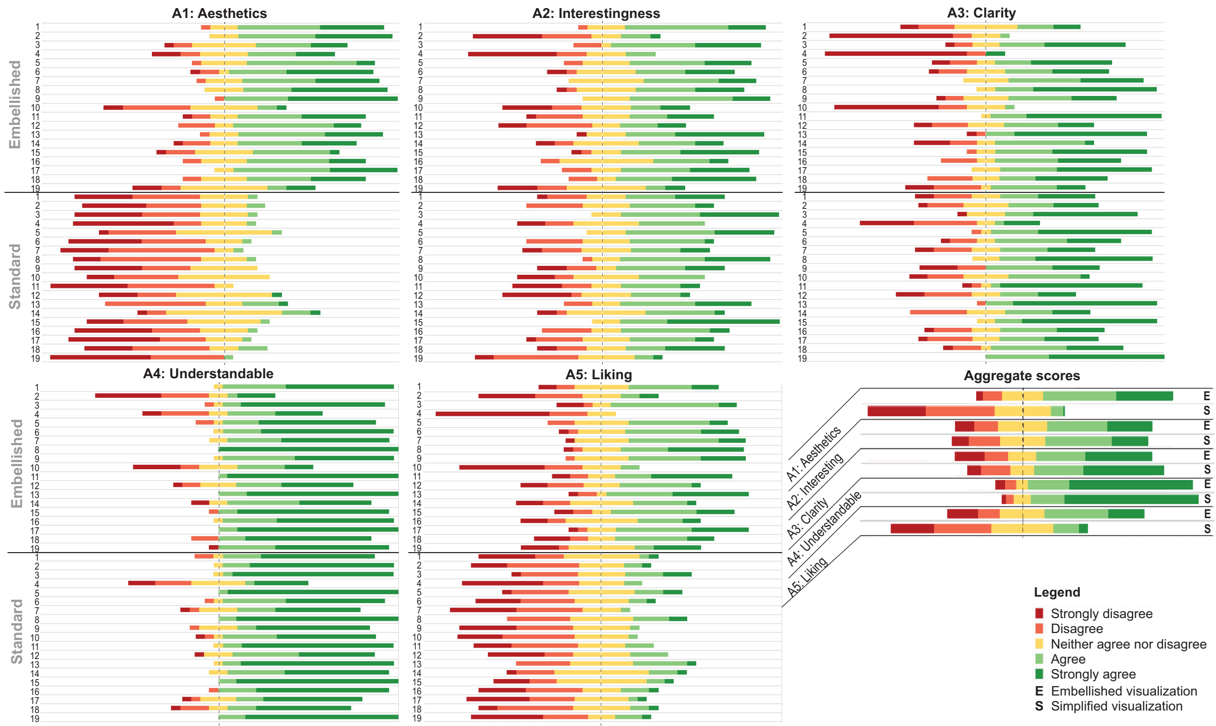

Figure 4: Scores for questions A1..A5 for embellished (top) and corresponding standard visualizations (bottom). Bottom right: Aggregated scores.

Moreover, we add questions on understanding (A4) and linking (A5) which were not considered in [50].

4.2 Thematic analysis of interview data

To further understand the quantitative results emerging from the self-reported appreciations (Sec. 4.1), and the reasons behind the subjects' responses, we explored the semi-structured interviews by a thematic analysis, searching for *codes* present in each interview. A code signals the presence of a theme, and can be a phrase, group of words, or recurrent discussion topics. We coded the interview transcripts manually using QDA Miner [85] rather than using automatic topic-mining tools [4, 7, 56], so we could better control how codes (topics) appear in the presence of synonyms, different phrasing, and other language variations. For a detailed overview of the coding procedure, see [39].

We found 122 codes in total (see supplementary material) which we ranked by their frequency, *i.e.*, number of times a code was found in all 40 interviews. For ease of analysis, we grouped codes in five main *categories*: *reception* (codes related to the participants' assimilation actions and thoughts – make an effort, understand easily without reading all numbers, complicated visuals that need to be simplified, habit of reading these visuals), *emotions, personal statements, and visual factors* (as defined in [67], and *user engagement* (as defined in [74, 75]). Table 2 shows the most-frequent codes by category, their frequency, and in how many interviews they appeared. As seen from their names, the codes show that the interviews capture (much) more user concerns than the questionnaires.

We analyzed the interview texts containing these most-frequent codes to get several insights:

Category	Codes	Frequency	Cases (%)
Reception	Clarity, comprehension	212	40 (100%)
	Incomprehension	117	38 (95%)
	Confusion	116	35 (88%)
	Reduced effort	63	25 (63%)
	Effort required	55	27 (68%)
Kennedy factors: Emotions [67]	Beautiful	125	36(90%)
	Negative judgment	92	37(93%)
	Positive judgment	81	35(88%)
	Funny aspect	77	30(75%)
	Ugly	69	29(73%)
Kennedy factors: Personal statements [67]	Subject matter	110	35(88%)
	Personal commitment	41	18(45%)
Kennedy factors: Visual [67]	Color	105	37(93%)
	Visual overload	91	33(83%)
	Pictograms, icons	65	29(73%)
	Simple	60	23(58%)
	Embellishments	56	25(63%)
User engagement [74, 75]	Raises interest	110	35(88%)
	Recall/remember	58	25(63%)
	Useless	49	26(65%)
	Immersed in story	46	21(53%)

Table 2: Most-frequent codes found from the interviews' thematic analysis, grouped per category.

- All users are *interested* in the stories told by the visualizations. This is important to know as, otherwise, a further interpretation of the embellishments' effects would not be very valuable; they felt particularly involved in visualizations related to their *interests*, *e.g.*, country comparisons including their own, or related to their work or hobbies;
- There is a feeling of *effort* needed to read overloaded visualizations, *i.e.*, highly embellished ones but also *S* ones that show much data; yet, the feeling that a visualization is *beautiful* creates a pleasant sensation that reduces this effort;

- Users appreciate that *embellishments*, in particular icons (for their suggestive simplicity) remind them of the visualization's *topic*, increasing their feeling of being 'immersed'.

Regarding Q4: All above tell us that embellishments *do* affect how users *relate* to visualizations in subtle ways, connecting aesthetics, interestingness, clarity, comprehension, and liking (A1..A5). While a full analysis is the scope of a separate paper, we can already say that embellishments have a *positive* impact on reading a visualization, by (1) reducing the adverse feeling of effort needed to read the data and (2) engaging the reader with the visualization topic.

4.3 Gaze data analysis: Data and methods

Statistical analysis (Sec. 4.1) shows significant differences, *e.g.*, E visualizations are found more beautiful (Q1) and are preferred to standard ones (Q2). Thematic analysis (Sec. 4.2) showed that understanding (Q4) and personal characteristics and emotion (Q6) topics are salient in most interviews. Yet, this does not tell us how exactly embellishments *affect* these topics, which is important for Q4 and Q6. We next use eye tracking techniques to collect data to better answer Q4 and Q6. Compared to questionnaires and interviews, gaze data (1) shows where, and in which order, users look at a visualization (so it shows which embellishments can actually influence them); (2) is less susceptible to user bias when reporting past events; (3) describes the complex process of reading a visualization in detail and with high precision, allowing finer-grained analyses than questionnaires and interviews. Analyzing this data (Sec. 4.4) strengthens the results of the statistical and thematic analyses and also bring new insights. We next describe how we acquired gaze data (Sec. 4.3.1) and how we visualized its main patterns by an adapted trail bundling technique (Sec. 4.3.2).

4.3.1 Gaze data capturing and cleaning. We captured the gaze of the 40 users who watched the embellished and simplified visualizations E_i and S_i on a 17-inch screen at 2048 × 1152 resolution with a Tobii Pro X3-120 tracker with standard 5-points calibration [37]. Watching times were 28 seconds (average) with 18 seconds standard deviation. This yields eye trail-sets called next $T(E_i)$ and $T(S_i)$. These are sets of 2D points with timestamps $T = \{(\mathbf{p}_i, t_i)\}$, $\mathbf{p}_i \in \mathbb{R}^2$, $t_i \in \mathbb{R}^+$. We next cleaned the data to remove eye blinks and incoherent gaze locations and extracted gaze *fixation points* defined as $\mathbf{f}_i \in T$ where the gaze does not move for at least 60 ms [37]. All data processing was done using Tobii Studio with default parameter settings. Let $F = \{(\mathbf{f}_i, t_i)\}$ be the set of fixation points $\mathbf{f}_i$ and their timestamps t_i. The line segments $\mathbf{s}_i = (\mathbf{f}_i, \mathbf{f}_{i+1})$ denote the most salient eye *saccades*. We next use the simpler (and smaller) saccade-set F instead of the raw trail-set T as there is little information in the positions $\mathbf{p}_i$ recorded along a saccade [62, 76, 81].

4.3.2 Visualizing salient gaze-data patterns. Figure 5b shows the saccade-set F extracted from the gaze of a user who watched the visualization in Fig. 5a. To find patterns in F, we simplify F by *trail bundling*, akin earlier approaches for similar data [62, 81]: We use the Attribute-Driven Edge Bundling (ADEB) method that keeps fixation points in F blocked and bundles together spatially close saccades that have the same direction. Note that ADEB performs an extra step of saccade-point filtering and aggregation, which we do not use, to keep intact the information present in the fixation areas, and also to avoid delicate data-filtering decisions.

Figure 5c shows the bundling $B(F)$ of F with directional color coding and bundle density $\rho_{B(F)}$ mapped to opacity. Figure 5d shows the same result atop a density map ρ_F of the fixation points F. The main (longest, densest) bundles start and end in the six main fixation areas (dark blue and dark red in the density map). We compute ρ_F by Kernel Density Estimation (KDE, see [63] for details). For $\rho_{B(F)}$, we could use the trail density ρ_{KDE} which ADEB already computes. However, ρ_{KDE} is noisy at trail crossings. We next want to map density to bundle thickness, so we need a smoothly-varying density. For this, we compute $\rho_{B(F)}$ by smoothing ρ_{KDE} with a 1D Gaussian 10-pixel wide filter along each saccade in F.

Figure 5c shows clearer patterns than the raw saccade-set in Fig. 5b but is still cluttered by small low-density bundles that 'branch out' from the main ones, caused by fixation points roughly evenly spread over large areas, *e.g.*, over the visualization's title at the top. Such points are not compact, so bundling cannot group trails starting or ending there. Clutter is also created by overlapping bundles whose color-mapped directions are hard to see. To reduce clutter, we first simplify the bundled trails $B(F)$ using their density $\rho_{B(F)}$, which is low in areas where only few saccades merge into bundles. Such saccades correspond to weakly-recurrent gaze paths, *i.e.*, rarely occurring events in the user's reading of the image. We deem these less important and remove them from $B(F)$ as follows. Let $\rho^{max}_{B(F)}$ be the maximal value of $\rho_{B(F)}$ over $B(F)$. We say bundles in $B(F)$ to be sparsely populated if $\rho_{B(F)} < \kappa\rho^{max}_{B(F)}$, where $\kappa \in (0, 1)$ is a simplification factor. Next, we encode $\rho_{B(F)}$ into bundle thickness rather than opacity, and draw $B(F)$ in increasing density order. This way, important (long, dense) bundles appear *thick* and at the *top* of the image, thus more salient. Finally, we encode bundle directions by a chevron texture pointing in the direction of the bundled saccades.

Figure 5e shows the bundles $B(F)$ uncluttered as described above for $\kappa = 0.8$, color-coded on direction as in Fig. 5d. Compared to Fig. 5d, clutter is reduced. Recurrent gaze paths are easier to spot as thick and long bundles. Using $\kappa = 0.6$ makes the simplification even stronger (Fig. 5f). Figures 5e,f use color for bundle direction, fixation-point density, and background image, which can be confusing. Mapping direction to texture allows us to use a separate blue-luminance colormap to show the timestamps t_i (dark blue: early in the sequence; white: late in the sequence; Fig. 5g). We now see the salient bundles (thick), their directions (see textures), the reading order (luminance: title first, bottom-left legend, right bar-chart, and finally ring-chart subtitle), and fixation areas (hues). We use this design next to analyze our eye tracking data.

4.4 Gaze data analysis: Results

Table 3 shows the statistics of the trail sets produced by data cleaning. These are small (strongly simplified *vs* the raw eye trails), which next helps us to extract salient patterns.

Data	Minimum	Maximum	Average	Std deviation
Nodes	1280	8598	3371	1306
Saccades	640	4299	1865	661

Table 3: Statistics of the 741 eye trail-sets.

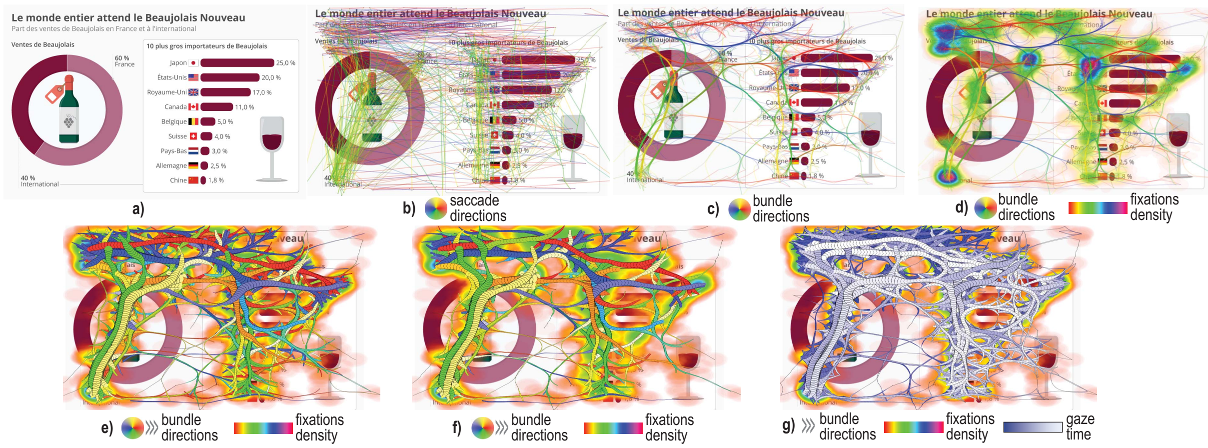

Figure 5: Simplified bundled visualization of gaze data for infographic E_{16}. a) Original image. b) Saccade set F. c) Bundled saccades $B(F)$ color-coded by direction. d) Like (c), with fixation density-map in background. e) Simplified bundling ($\kappa = 0.8$) with texture=direction and bundle-width=saccades density. f) Like (e) with more simplification ($\kappa = 0.6$). g) Like (e) with gaze timestamps shown by luminance. See Sec. 4.3.2.

O1	(General observation, not supported by specific interview text)
O2	I always first look at the title. Then I go through the picture, and go back to the title to see if I've understood what it's about. I know I do this systematically.
O3	Icons help to understand the subject! They are so integrated in the image that you can see them quickly. You don't need to look at them and linger on them to understand. As compared with the information where you have to stop and read.
O4	Usually, in such images there's a legend to the left. It's so much clearer with the numbers placed directly above the bars.
O4 (i)	There's nothing that tells you where to look first so inevitably you go a bit everywhere. The chart doesn't start and end at the same place. We don't know how to compare [the data items].
O5	I didn't like it because even if the information is visually understandable, the legend is small and all the way to the bottom, so we hardly pay attention to it. I would have put the legend next to the title and thus made it stand out.
O6	(General observation, not supported by specific interview text)

Table 4: User interview excerpts supporting observations O1..O6 based on the bundled gaze analysis (Sec. 4.4).

We could simplify each such trail set F, yielding 741 bundled images. Analyzing 741 images manually would not help finding salient and recurring patterns. Hence, we bundle together all trail sets of all 20 users who watched the *same* visualization, yielding 38 bundled images (19 for the embellished images E_i and 19 for the simplified ones S_i). Computation time is 8 seconds on average for one image. Given how the ADEB method works, and also our filtering of low-density patterns (which only a few users exhibit, Sec. 4.3.2), our proposed bundling emphasizes eye-movement patterns *common to all users* for one visualization.

We next analyze the 38 bundled images to find recurrent visual patterns (Fig. 6 shows selected images; all images in the supplementary material). This yielded six findings O1..O6 that support answering $Q6$, see next. Table 4 shows excerpts from user interviews that support our findings.

O1: Cyclic reading patterns: A visualization is read cyclically. After a first scan, the eye scans the various parts of an image several times in roughly the same order. See image O1: The gaze starts with the title (dark blue), then moves down to the data and other textual information. Following the light blue and white colored bundles, we see that the eye follows the same path several times during the same reading. We found this cyclic reading pattern in virtually all E and S visualizations. Other researchers have also shown that there are several reading cycles, though using coarser information (fixation points) than our finer-grained bundled trail data [22, 72]. During the reading of charts, one goes through two search stages followed by a reasoning stage. The visual search is almost identical in the search stages: The different target "nodes" for comprehension are located in the chart. In the third stage, the relationships between these nodes are visually established, leading to interpretation and understanding. Bundling shows something that is theoretically established by highlighting different reading cycles. Also, we show that visual embellishments do not prevent the appearance of reading cycles, except for the complex, visually charged, structures unfamiliar to the user (O4).

O2: Reading order: We found two patterns: (i) Reading starts and ends with the title, *e.g.*, in image O2(i), both the dark blue bundles (reading start) and the white ones (reading end) connect to the title area. (ii) Reading starts with the title but, when 'footnote' text exists below the image, it ends there, *e.g.* image O2(ii): Dark blue bundles start at the title. The white bundles end at the footnote. As for O1, we found these two patterns in both E and S visualizations.

O3: Icons and gaze path: Icons affixed to a traditional chart in an E visualization do not strongly affect reading paths. For example, in image O3 (i), we see that the gaze path does not go through any of the (small) character icons in that image. Similarly, in image O3 (ii), gaze almost does not touch the larger umbrella and balloon icons. Only when icons are very large *and* their placement affects the visualization layout do they affect reading order, see *e.g.* image O3 (iii). We found this pattern in most E visualizations. So, it seems that adding reasonably-sized icons to a given visualization layout is a degree of freedom that designers can exploit to *e.g.* engage users more, without adversely affecting where the user will focus on.

O4: Familiar structure causes simple reading patterns: By structure, we mean how the data is laid out. Familiar structures are Cartesian plots, axis-aligned bars, line charts, and pie charts. Complex structures correspond to atypical layouts. Image O4 (i)

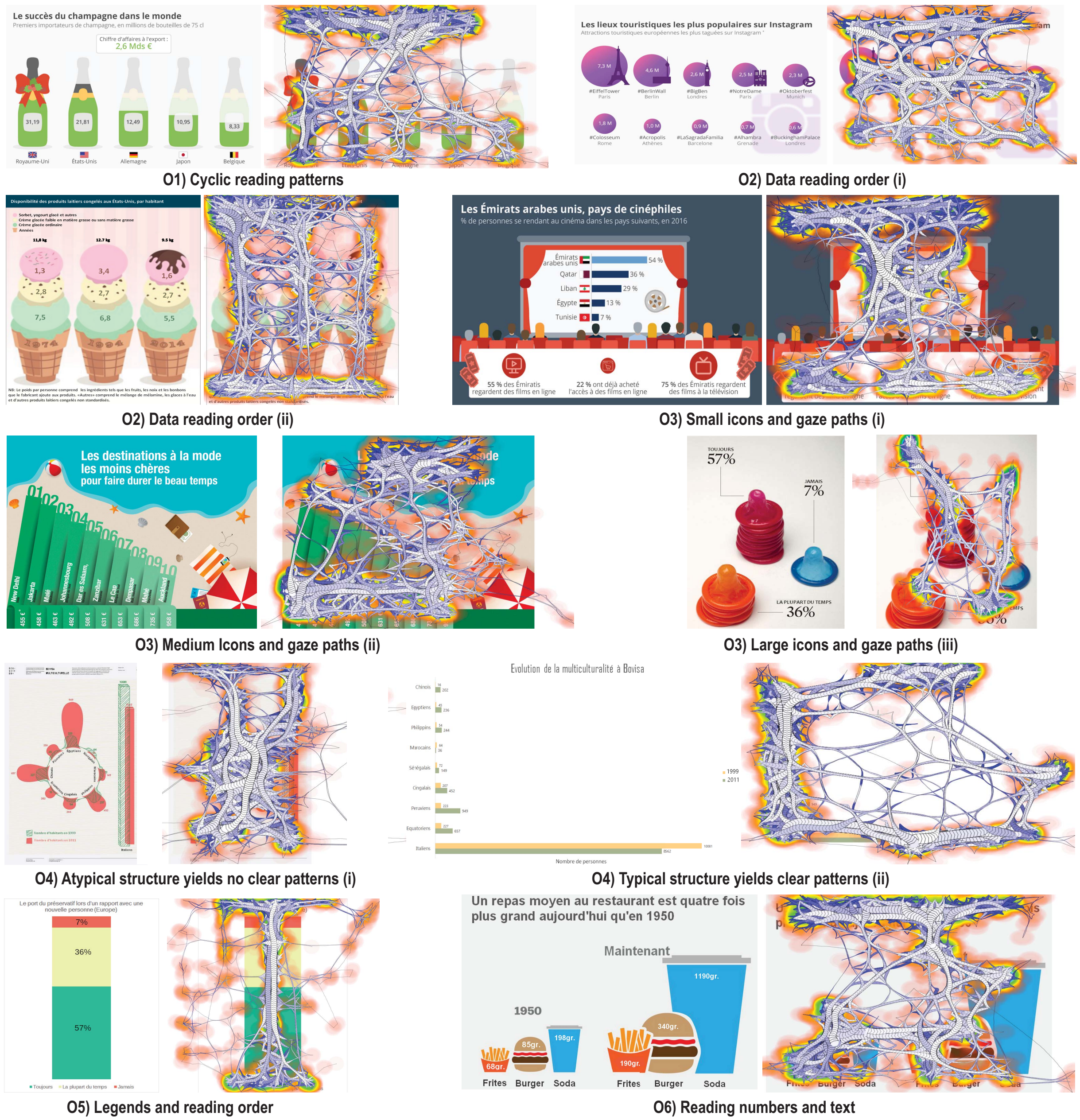

Figure 6: Examples of visualizations and their bundled eye-gazes supporting observations O1..O6. See Sec. 4.4.

is such an atypical layout, akin to a radial bar chart. The resulting bundles crisscross in all directions with no clear reading pattern. In contrast, image O4 (ii) is a classical horizontal bar-chart layout showing the same data, yielding far clearer reading patterns. We found this to be the case for both S and E visualizations. In other words, visually complex and unfamiliar designs hinder the appearance of a common reading pattern. This matches the statistical analysis of the self-reported appreciations (Sec. 4.1) that showed that participants describe such complex designs as unclear, difficult to understand, and occasionally even ugly (even the E ones).

O5: Legends and reading order: The legend position affects the gaze path. Users prefer legends placed close to the title, *e.g.*, S_{14} (Fig. 2; legends placed too far from the title make reading hard, *e.g.*, image O5 (Fig. 6). Here, the legend is placed at the bottom of the image, far from the title. We see two salient vertical bundles which confirm that users had to scan the image top-to-bottom and conversely to link the title and legend. Whether the infographic is embellished or not, the legend position is very important. Placing it close to the title seems to simplify the reading.

O6: Reading numbers and text: Numbers and text are the main attention-attracting elements in reading a visualization. We see this by the fact that bundles are 'anchored' to such elements. Image O6 shows a salient example: The reading pattern (bundles) pass through all the textual and numerical information. This is the case for both *E* and *S* visualizations. Hence, the embellishment level does not seem to adversely affect the reading of textual (quantitative) information. Borkin et al.[16] have already shown that the eye produces the most fixations on text and numbers, something that our density-and-bundle visualizations confirm.

Summarizing the above, and relating to Q6: Based on the full interview texts and gaze analysis, we conclude that embellishments – if reasonably sized and added as *decorations* to a familiar visualization layout – do not strongly affect the reading order of a visualization, which is mainly driven by the used layout (title and legend position, type of chart used). Key elements, such as text and figures, are always focused on in both *E* and *S* visualizations. Similar layouts yield quite similar reading patterns for both *E* and *S* visualizations. Finally, icons (in *E* visualizations) do have a positive effect in engaging the reader to read the visualization.

5 DISCUSSION

We now discuss the main results of our three-part study.

Main findings: Our study refines, and extends, earlier work in understanding the effect of embellishments along the following dimensions:

- *E* visualizations were found more beautiful than *S* ones (Q1 answered positively) and were preferred to them (Q2 answered positively); *S* visualizations were found clearer than *E* ones (answer to Q3); and we found a strong correlation between liking and finding a visualization beautiful (Q5 answered positively). In contrast, *S* visualizations were not found to be more (or less) interesting than *E* ones (partial answer to Q4).
- Embellishments – in particular, icons – have a positive impact on reading a visualization, by (1) reducing the adverse feeling of effort needed to read the data and (2) engaging the reader with the visualization topic (further answer to Q4).
- Using trail bundling, we identified and visualized six salient reading patterns related to cyclic reading (O1), reading order (O2), icons (O3), layout structure (O4), legends (O5), and textual annotations (O6), prominent across multiple visualizations *and* users. In answer to Q4 and Q6, we found the following: If reasonably sized and added as decorations to familiar visualization layouts, embellishments do not strongly affect these reading patterns. The visualization layout and text annotations are very important in creating a simple reading pattern and useful fixation points, respectively. These reading patterns further confirmed the useful effect of icons in engaging the user with the visualization.

Comparison to Bateman *et al.*: Our work shares many common points with the research goals and methodology of Bateman *et al.* [6]. However, we go beyond strengthening some of their findings, with the following main differences and contributions.

Questions: Bateman *et al.* pose two research questions – whether embellishments cause understanding problems (B1) and whether they may provide information that is valuable for the reader (B2), and answer them by measuring interpretation *accuracy* and infographics short-term and long-term *memorability*. We do not consider memorability at all, but refine B1 and B2 (via our Q1..Q6) as follows. Concerning B1, we do not cover *accuracy*, which is well studied by Bateman *et al.*'s four-question study. Rather, our questions Q1..Q6 'zoom in' the 'user preferences' part of Bateman *et al.*'s study. In their work, this was investigated by asking users to chose their preferred chart format (*S* or *E*) for 10 dimensions. Of these, dimensions most enjoyed and most attractive are similar to our dimensions A5 and A1, respectively (see Sec. 3.2). Our other dimensions A2, A3, and A4 have not been explored in their study. Also, it is important to stress that, in their study, users only had to *choose* the visualizations they found the best along each dimension. In contrast, we measured how *all* visualizations scored along *all* our dimensions A1..A5 (see Fig. 4 and related text).

Data: Bateman *et al.* use 14 infographics (and corresponding simplified visualizations) all drawn from a single source, the design work of Holmes [51]. More specifically, they intentionally chose "the most extreme type of visual embellishments [they] could – namely, the full cartoon imagery of Holmes." This was done as to best gauge how embellishments help recall. They however advocate the need to study different types of infographics, and specifically those using less extreme imagery, *e.g.*, textures, color, and abstract shapes. Our work goes in this direction: Our infographics come from multiple data sources and authors, and also cover a wide spectrum ranging from heavily embellished ones (*e.g.*, E_5, E_{10}, E_{19}, see Fig. 2) to less extreme ones (*e.g.*, E_9, E_{12}, E_{15}, E_{17}).

Analysis tools: Both Bateman *et al.* and ourselves use, at a high level, the same methodology – subjects view the *E* and *S* visualizations, after which they answer some questionnaires and their eye gaze data is further analyzed. However, important differences exist. Besides the structural differences in the tasks and questions (discussed above), a key difference is that we did not aim to only find *whether* embellishments affect certain aspects (liking, understanding, etc) but *why* this is so. Our interviews were thus structured differently – we started from identifying tensions in the users' answers, then zoomed in on these during the interviewing (Sec. 3.3, and finally analyzed the recorded answers thematically to identify causes of the aforementioned tensions (Sec. 4.2). This, we believe, significantly refines the insights in Bateman *et al.* Separately, our usage of eye tracking data is entirely different. Bateman *et al.* measure how long users looked at embellishment, data, both, or other areas, *e.g.*, white space, aggregated over all users and over all *S vs E* images. From this, only limited insights can be drawn. We cannot, for instance, say whether textual annotations, icons, or other graphics act differently, since they are all classified as embellishments (see Figs. 3 and 9 in [6]). Also, no analysis of gaze spatial patterns, *e.g.* their complexity, or the reading order, or amount of time spent on a specific visual item, is possible from this aggregation. Our use of trail bundling allows such analyses to be done separately for each visualization, leading to the observation of the six reading patterns O1..O6 discussed in Sec. 4.4. Separately, Bateman *et al.* also note that their aggregated time analysis would possibly lead to different results if users had limited viewing time – one may spend less time on data elements "assuming that they look at both data and image in an interleaved fashion." They could not test the latter hypothesis given the aforementioned data aggregation. Our bundling addresses this point, showing precisely that this interleaving, hypothesized by [6], *does* indeed take place (see Fig. 6 and related text).

Embellishment user impact: Our analysis shows that embellishments increase aesthetics (which correlates with liking), but decrease clarity somewhat (Sec. 4.1). Our thematic analysis shows that embellishments decrease the negative user-effort feeling and increases engagement, so positively impact reading a visualization (Sec. 4.2). This strengthens previous work showing positive effect of embellishments [6, 14–16, 49]. Finally, eye gaze analysis by bundling shows that embellishments do not strongly affect reading order (Sec. 4.4). We conclude that, if not excessively used, embellishments have overall more *added value* than adverse effects.

Bundling: To our knowledge, this is the first time that interviews and gaze data were correlated. Doing so, we found salient patterns that mutually reinforce these two investigation tools, joining insights that these tools, in isolation, could not bring. Also, we bundled and analyzed – to our knowledge, for the first time – the gaze data of *multiple* users looking at the same image, to elicit *cross-user*, thus statistically more significant, viewing patterns. Our bundling shows simplified views of per-user data. Our bundling is a global, static, technique that encodes time in brightness. Refinements are interesting to study, *e.g.*, adding selection or animation to better show time dynamics. While these are easy to do, the effort of examining the simplified bundled sequences may increase, and results may be too user-specific, thus less statistically relevant.

Limitations: Our results are subject to the limited number of visualizations and users tested and also to how we created the simplified versions (Sec. 3.1). Yet, as said, we chose to study a limited number of visualizations (19 embellished ones and their 19 simplified counterparts) and users (40) by three different procedures rather than studying more visualizations and/or users by a *single* procedure. While atypical in current studies, we think that more instruments (if yielding correlated results) only increase evaluation confidence. Concerning *tasks*, one may argue that our experiments do not have a clear, simple, task, such as comparing, sorting, or memorizing data. Our task is at a higher level – *understanding* the message behind the data (Sec. 3.2). We argue that this is ultimately the key task that any visualization should support.

User sample: Our study subjects were study digital communication professionals, who are used to designing messages and communicating them in an enjoyable way. Quispel and Maes [88] showed that graphic design professionals were more likely to find embellishment useful compared to laypeople. It is thus possible that the reception and assimilation of embellished infographics is different for different user types. This makes sense since character or identity traits influence engagement with data visualization [68]. Professional identity would thus be a trait to be accounted for when studying (embellished) visualizations. Yet, we believe that the situation is more nuanced. The study of Bateman *et al.* [6], which targeted university students having no particular design or digital communication background as users, also showed a clear preference for *E* visualizations. This can mean, among other possibilities, that (a) both professional and non-professional users prefer *E* visualizations; or (b) the bias for *E* visualizations shown in [6] is due to the reported fact that several users did not understand the minimalistic *S* visualizations, with which they were not familiar, therefore making the *E* visualizations (which are more explicit) stand out better. Our study thus *complements* the findings in [6] showing that the same preference for *E* visualizations happens for our more specialized users. In our case, this is definitely not due to the lack of understanding of *S* visualizations. What precisely makes a specific user group prefer *E* visualizations is, we concede, still unclear, and subject for future studies.

Intra variability of visual embellishments: Our data corpus is quite varied as it contains very different types of embellishments. Variations exist in icon positions (*e.g.*, at the bottom, at the top, centered or not); functions (*e.g.*, decorative background, marking values on the data, or annotating a legend); and size and complexity. The level of embellishments, ranging from familiar icons to a heavy visual design unfamiliar to the user also strongly varies. Our three analyses showed that such aspects of visual embellishments can influence the assimilation results. For example, we found that embellished visualizations where icons were placed next to the data were seen as clearer than visualizations where the icons represented the data itself, while producing a similar level of engagement.

Towards new perspectives: Our research has an interdisciplinary nature, as it originated in the humanities (communication sciences) but used several infovis techniques to analyze the data. Our goal was to show, at different levels of granularity, what is the influence of visual embellishments on the assimilation of the message contained in the data. Our research is more broadly part of a questioning of the meaning produced by the users. Starting from communication science, we wanted to go beyond simple message reception by focusing on different user-specific aspects. Likewise, sensemaking is a central concept in communication sciences which takes into account the social environment of individuals as well as their personal characteristics and experiences. We draw inspiration from this. Our method is based on three dimensions (visual perception, comprehension, and gap bridging [34]) and thus provides a rich overview of the assimilation of the message communicated by the data from a cognitive, perceptual, and also social viewpoint. This overview would not have been possible without the link between communication sciences and the infovis field.

Our experimental method is also exploratory. We knew upfront that we would obtain many, rich, results but these would not directly allow us to establish visual design rules in the strict sense. Yet, our results allow closing a debate that has been open for a long time: Is embellishing data visualizations "safe" for the understanding of the data? Given the variety of our studied corpus, our results allow us to assert that visual embellishments are of great added value for static infographics, while often being misused. This is why we now propose to qualify the embellishment of data visualizations as *practices*. As with any practice, embellishments must be mastered. Poor mastery will lead to negative effects, whereas good mastery will allow to exploit their benefits. The limits of our experiments allow us to glimpse new perspectives: By replicating the study on different corpi, one could further detail how personal characteristics such as profession influence the assimilation of the message contained in the data to further enrich the work of Kennedy and

Hill [67]. Similarly, creating a typology of existing visual embellishments and studying the influence of different types of ornaments on the data would allow developing design principles for the use of embellishments. Our work thus shows the extent of possibilities by asserting that visual embellishments must be considered as a practice rather than a problem or a neutral decoration aspect.

Finally, our findings can help the design of *customized* visualizations for specific user groups. For instance, personal visualizations (PV) and personal visual analytics (PVA) [57] study the creation of visualizations that show personally relevant data to the grand public. Given this personalization aspect, aesthetics is a major concern for PV and PVA. Our work can be relevant in this area. For instance, we can imagine that a user runs through the experiments described in this paper, and the PV/PVA system next creates visualizations based on the scores that the respective user has given to a number of visualizations. Thereby, each user is offered a different kind of visualization that best matches what he/she 'liked' during the study. A different direction would be to specialize so-called embedded visualizations – which project data atop of physical-world structures [26, 105]. One could create simplified versions thereof – using *e.g.* a real photograph of the embedding as background in an *E*-type visualization – to study how users perceive it, by running our experimental pipeline, prior to actually creating the more expensive embedding. In the same vein, one can consider using embellished data visualizations for their persuasive potential [25]. More engaging visual contents can possibly leverage designer ability to convey more persuasive messages through various media, *e.g.*, animated charts, data videos, or AR-VR experiences.

6 CONCLUSION

In this paper, we studied the impact of visual embellishment on data visualization with a corpus of 40 professional communication users. We selected a set of 19 embellished infographics and built their corresponding non-embellished counterparts. We combined three methods – self-reported appreciations, interviews, and gaze analysis – to capture and validate intrinsic characteristics of the two visualisation types. While parts of our extracted insights have already been identified in past research, we propose for the first time a methodology combining three tools from two different scientific communities (social science and data visualization) that is applied to the *same* data and *same* users. Furthermore, we used a set of six additional questions to gain a finer understanding of the subtle data assimilation differences between the two visualization types. This helped us to better grasp the impact of embellishments regarding data perception, gap bridging, and data retrieval.

Our analysis showed that embellishment reduces the user's feeling of effort and produces more engagement, engages users, and only marginally decreases understandability. Finally, edge bundling helps to depict the inherent reading structure of the visualization and find reading patterns that classical methods (eye fixation heatmaps) would not have revealed.

Our proposed method has shown validated results which can be extended with additional work. The same methodology can be replicated with some variations to extend and/or refine our conclusions. First, other user populations can be further studied, *e.g.*, non-professionals, to see how our findings generalize. Secondly, other infographics can be considered with a common set of data, to reduce possible bias related to the visualizations' topics *vs* the users' interests. Thirdly, additional types of simplified visualizations can be used beyond bar and pie charts. Such extensions can lead to a common corpus of design guidelines providing valuable help for designers to produce more effective, efficient, and engaging infographics for data communication and storytelling.

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