

ChartOptimiser: Task-driven Optimisation of Chart Designs

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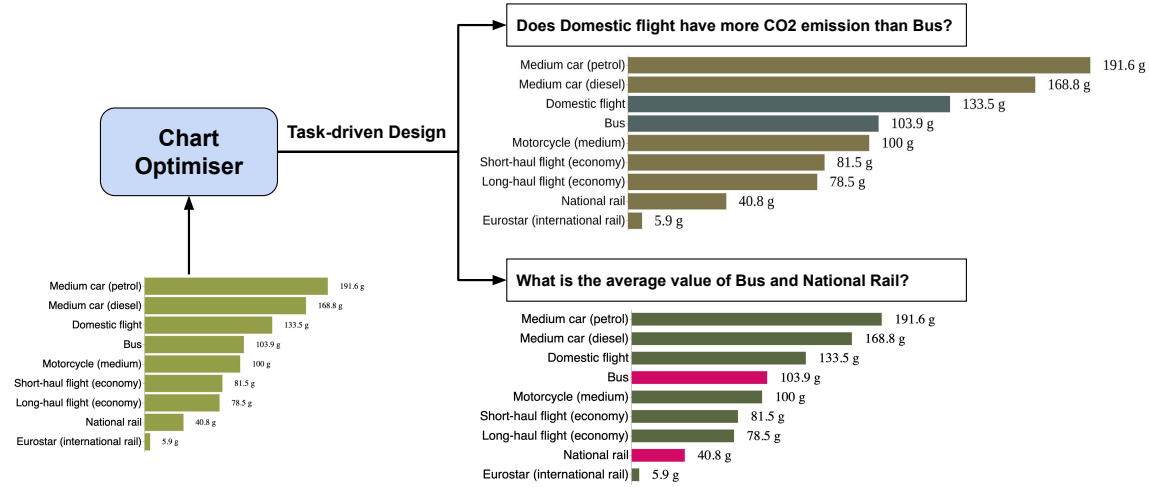


Fig. 1. ChartOptimiser is the first method to optimise parameters of chart designs for users' visual analytical tasks. Taking a plain chart and an analytical task as input, ChartOptimiser uses Bayesian optimisation to automatically adapt the chart design with respect to a novel objective function that combines four perceptual metrics.

Effective chart design is essential for satisfying viewers' information needs, such as retrieving values from a chart or comparing two values. However, creating effective charts is challenging and time-consuming due to the large design space and the inter-dependencies between individual design parameters. To address this challenge, we propose *ChartOptimiser* – a Bayesian approach for task-driven optimisation of charts, such as bar charts. At the core of ChartOptimiser is a novel objective function to automatically optimise an eight-dimensional design space combining four perceptual metrics: visual saliency, text legibility, colour preference, and white space ratio. Through empirical evaluation on 12 bar charts and four common analytical tasks – finding the extreme value, retrieving a value,

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comparing two values, and computing a derived value – we show that ChartOptimiser outperforms existing design baselines concerning task-solving ease, visual aesthetics, and chart clarity. We also discuss two practical applications of ChartOptimiser: generating charts for accessibility and content localisation. Taken together, ChartOptimiser opens up an exciting new research direction in automated chart design where charts are optimised for users’ information needs, preferences, and contexts.

CCS Concepts: • **Human-centered computing** → **Information visualization**; **HCI theory, concepts and models**.

Additional Key Words and Phrases: Information visualisation, task-driven optimisation, chart design optimisation, Bayesian optimisation

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1 INTRODUCTION

The ability to effectively communicate information through visualisations is crucial in the information age [6, 37]. For example, information visualisations on social media are designed to communicate the goals or intended messages of those creating them [14]. Well-designed charts not only satisfy viewers’ information needs by enabling, e.g., easy retrieval or comparison of data values, but they can also enhance overall comprehension and decision-making processes [4, 5, 61]. However, creating effective visualisations remains challenging and time-consuming – visualisation designers must navigate a vast design space in which each design choice impacts others.

One challenge of chart design is the inter-dependencies between various design parameters, such as colour schemes, chart types, data scaling, or labels. While the choice of parameters is crucial for the overall effectiveness of charts, these choices can also lead to misinterpretations if they are not carefully made. The need to balance functional clarity with aesthetics further increases the difficulty of chart design. Visual appeal can only be evaluated by "taking a look at" the chart, i.e., viewers produce the image only when evaluating it. Consequently, designers must understand visual perception principles and data characteristics to create understandable, informative, and effective visualisations. Finally, it is challenging to design visualisations for the various analytical tasks that users may face when trying to satisfy their information needs [44, 69]. Analytical tasks are among, if not the most important, factors influencing how viewers visually explore, make sense of, and extract information from visualisations.

The ever-increasing importance of information visualisations across various areas and the significant challenges in designing them call for automatic approaches that allow designers to optimise charts according to viewers’ needs. However, few previous works explored automatic *optimisation* of charts. Some works instead focused on automatically *generating* visualisations either using machine learning algorithms or user-defined rules and visual embellishments [68]. These methods have been studied in various application contexts ranging from extracting reusable layout templates from visualisations [11], over generating visualisations from natural language [26, 32], to optimising the layout according to various metrics [29, 65]. However, no previous work has integrated viewers’ visual attention into this optimisation process, even though attention is well-known to convey rich information about analytical tasks and memory recall [8, 9, 60], as well as decision-making processes [22, 54].

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Optimising visualisations to satisfy users’ information needs is usually an iterative process that requires evaluating the visualisations at each iteration, which is inefficient and costly because the problem of finding the optimal parameter hypercube is inherently challenging, and the design space is vast. Recently, Bayesian optimisation [45] has shown good performance in optimising costly black-box problems and has been demonstrated to be highly effective for various applications such as optimising map searching [13] and accelerating materials design [67]. Despite the effectiveness of Bayesian optimisation, it has not been explored for optimising visualisations.

We propose *ChartOptimiser* – a novel Bayesian approach for task-driven optimisation of chart design that considers human visual attention. At the core of ChartOptimiser is a novel objective function that combines four perceptual metrics to evaluate and automatically identify the optimal chart design parameters within an eight-dimensional design space: highlighting saliency, text legibility, colour preference, and white space ratio. We demonstrate the usefulness of our method on the sample task of optimising the design parameters of bar charts – a widely used chart type in information visualisation research and practice. Through empirical evaluation of our method on 12 bar charts and four common visual analytical tasks – find extremum, retrieve value, compare, and compute derived value – we show that these four objectives are sufficient for effective optimisation, contrasting prior work that required many more objectives [29]. We further demonstrate that our ChartOptimiser outperforms existing design baselines concerning task-solving ease and clarity of the resulting chart. Our method also shows competitive performance with human-designed charts in terms of aesthetics and surpasses all baseline methods, particularly in more complex analytical tasks that involve comparison or computing derived values. In summary, the contributions of our work are two-fold:

- (1) We introduce ChartOptimiser – the first automatic method to optimise chart design parameters to users’ analytical tasks. Our method uses Bayesian optimisation with a novel objective function that combines four perceptual metrics. We show that these metrics are sufficient for effective optimisation. We further discuss two sample applications that underline the practical usefulness of ChartOptimiser: designing charts for accessibility and content localisation.
- (2) We report an empirical comparison of ChartOptimiser with four baseline design methods that demonstrate our method’s superiority and the high similarity of the optimised visualisations to those created by human designers.

2 RELATED WORK

Our work is related to previous works on 1) Perceptual Metrics of Information Visualisation, 2) Automatic Visualisation Design, and 3) Visualisation Analytical Tasks.

2.1 Perceptual Metrics of Information Visualisation

It is indubitable that the effective use of colours is a key factor in any visual design, including information visualisations [38, 55]. Palmer and Schloss [35] proposed the weighted affective valence estimates (WAVE) score to quantify the colour harmony and aesthetics in visualisation design. [16] proposed an integrated technique for colour exploration, assignment, and refinement, which took colour harmony, visual saliency, and elementary accessibility requirements into consideration. Visual saliency, defined as a measure of the regions in a visual stimulus or scene that attracts viewer attention, has been extensively studied, leading

to the development of numerous effective saliency models in natural scenes [15, 20, 23]. However, saliency models have been found to perform poorly when applied to information visualisations, as highlighted in prior work [28, 59]. This triggered several research developing saliency models tailored for information visualisations in both free-viewing [28, 49, 59] and task-driven settings [62]. Some other perceptual metrics are specifically designed for information visualisations. Data-ink ratio quantifies the share of ink presenting data-related information in a visualisation [58]. Visual density rates the overall density of visual elements without distinguishing between data and non-data elements [5]. Sedlmair and Aupetit [43] evaluated how separable different classes were in projections of high-dimensional datasets. Micallef et al. [29] proposed three perceptual metrics devised for scatterplots, including the perception of linear correlation, image quality, and classes and outliers. As an integration of perceptual metrics, Shin et al. [50] proposed the Virtual Human Visual System, which provides accessibility, text, visual saliency, and visual density as feedback for iterative visualisation design, enabling designers to refine their visualisations better to align saliency with their design intentions. Although the Virtual Human Visual System is promising, the involvement of visualisation designers is inevitable. Instead, this paper builds a fully automatic layout optimisation pipeline using four perceptual metrics in the objective function.

2.2 Automatic Visualisation Design

Automatic design systems could enumerate design candidates within the design space and find the best layout to satisfy the needs of designers or users. It usually requires a utility or objective function to rank the design candidates. Researchers have proposed many systems [19, 25, 31] that recommend visualisations based on data structures and characteristics. Those systems focus on deciding the effective chart type, visual encoding, and data transformation. In addition to effectiveness, much research has optimised visualisations from other aspects. For example, Hopkins et al. [18] addresses data integrity by surfacing chart construction errors such as truncated axes. Previous works have automatically extracted reusable layout templates from visualisations [11], sketches [51], and infographics [24]. Other systems optimise the layout according to various metrics, such as similarities with user-input layouts [56], handcrafted energy terms, e.g. white space, scale, alignment, and balance [34], perceptual metrics [29], and crowdsourced layout quantifier [65]. Generating visualisations from natural language (NL2Vis) has been a trend of automatic visualisation for many years [26, 32, 52]. NL2Vis takes a tabular dataset and a natural language query as input, specifying tasks and visualisation type, and generates visualisations that meet the requirement [26, 32]. Recently, several works have demonstrated the superior performance of large language models (e.g. ChatGPT) for NL2Vis, highlighting their great potential under in-domain and cross-domain settings [10, 66]. However, current methods do not consider human perception feedback, such as visual attention. This work optimises chart design for a combination of four perceptual metrics, making the optimised charts closer to observation conditions and human perception.

2.3 Visualisation Analytical Tasks

Strong evidence has shown that tasks significantly influence how viewers interact with visualisations [36, 62]. Amar et al. [3] identified 10 low-level analytical tasks (e.g., retrieving value, finding extremum, comparison) while another study [17] highlighted high-level tasks such as background understanding, planning of analysis, and data exploration. Saket et al. [40] evaluated the effectiveness of basic types of visualisations in the 10

low-level analytical tasks. Elzer et al. [14] proposed a Bayesian network to identify the communicative signals for intention recognition on simple bar charts. Eye tracking data collected by Polatsek et al. [36] under three low-level analytical tasks demonstrated consistent gaze patterns within each task, with significant differences across tasks. Similarly, Wang et al. [62] found saliency metrics significantly varied across different tasks. Considering specific tasks is crucial, as visualisations can be designed to support a range of tasks based on the input data and can be evaluated by how effectively they enable task completion [42]. To support task execution in visualisations, some researchers have developed visualisations that explicitly highlight “data facts”, such as trends or comparisons [48, 53]. In this work, we take task saliency as a metric in the objective function of the optimisation pipeline.

3 ChartOptimiser

ChartOptimiser aims to automate the optimisation of chart design parameters for a given analytical task (see Figure 2). Our method operates on a design space consisting of eight dimensions and optimises these with respect to a novel objective function that combines four perceptual metrics. Bayesian optimisation is used to sample from the design space and maximise the objective function. In the following, we describe each of these components in more detail. Our dataset and code are publicly available at <https://xxx.xxxxxxxxxxxx.xx>.

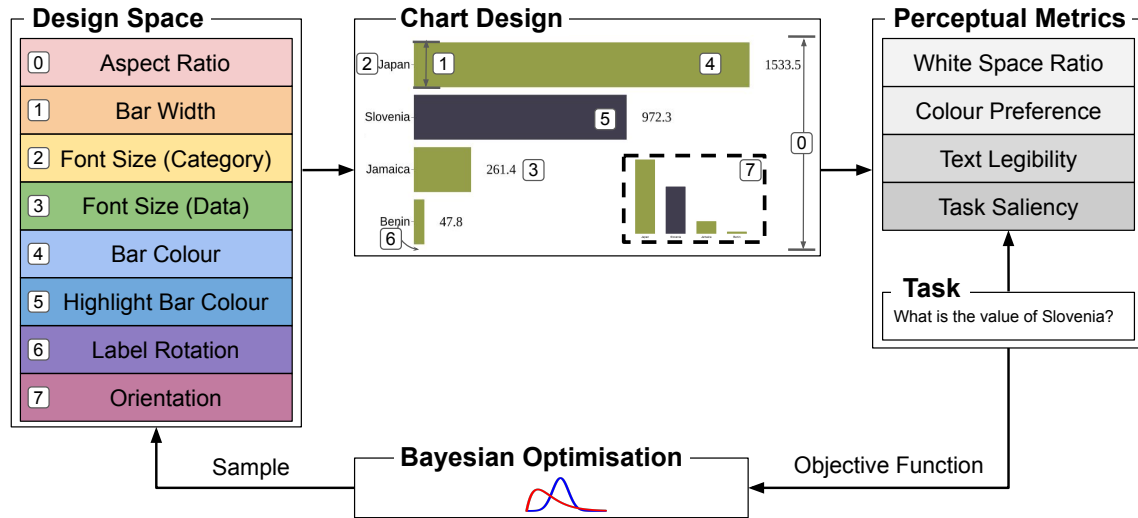


Fig. 2. Overview of ChartOptimiser. Our method operates on a design space with eight dimensions that it optimises with respect to an objective function consisting of four perceptual metrics. Bayesian optimisation is used to sample from the design space and to maximise the objective function, thus optimising the chart design for a given visual analytical task.

3.1 Design Space

The design of charts involves two main components [65]: 1) *visual encodings* that map data items to visual representations such as colour, position, and size, and 2) *visual styles* that specify data-irrelevant visual designs like orientation and bar width. This work focuses on chart design space for visual styles, specifically for bar charts. Bar charts are a widely used visualisation type, mainly for two-dimensional data. It divides

the categorical data values into distinct bars, with values encoded by the bar length. Thus, categorical labels on axes associated with each bar are essential to a meaningful bar chart. Moreover, data labels on or next to bars showing the exact value of bars are also commonly used.

For task-driven chart design, highlighting the bar(s) relevant to tasks was shown to facilitate task completion [14]. For this initial work, we only include single-group bar charts to reduce the design space to a reasonable size. Key parameters in the design space of bar charts are (see Figure 2): 0) the aspect ratio of the chart, the font size of 1) axis labels and 2) data labels, 3) the bar width and 4) colour, often a 5) highlight bar colour, 6) the label rotation, and 7) the orientation of the chart. This set of design parameters extends the design space proposed in previous work [65].

We used the Vega-Lite [41] grammar for interactive graphics to specify the data visualisations. Vega-Lite specifications describe charts as encoding mappings from data to visual properties of marks, which usually requires a given mark type and a set of one or more encoding definitions for the visual channels. Vega-Lite expects a relational table of records with named fields. The mark type specifies the geometric objects used to encode data records visually. Possible values include bar, point, area, line, and tick. Visual encoding determines how data values map to the visual properties of marks. An encoding uses a visual channel such as spatial position, colour, size, shape, or text. The Vega-Lite compiler will infer defaults based on the channel and data type if omitted. With the Vega-Lite descriptive grammar, the entire design space of charts is represented as

$$\mathcal{S} = V\mathcal{X}_1 \times \mathcal{X}_2 \dots \times \mathcal{X}_n, \quad (1)$$

where \mathcal{X}_1 to \mathcal{X}_n each denotes a dimension in the design space, such as aspect ratio and colour encoding. The V function is the Vega-Lite compiler that automatically renders a chart from certain design parameters and determines the default properties for missing components based on a set of carefully designed rules [41]. A certain parameter set $\mathbf{x} = x_1, x_2, \dots, x_n, x_i \in \mathcal{X}_i$ corresponds to one chart, denoted as $V_{\mathbf{x}}$.

3.2 Objective Function

The recent work [50] demonstrated that including text legibility, visual saliency, and visual density as feedback can significantly facilitate the design process for designers. However, Shin et al. [50] ignored the influence of tasks on chart designs. As the effectiveness of visualisations varied among different analytical tasks[40], we aim to include a visual saliency metric biased by analytical tasks. As a conclusion, our novel objective function combines four perceptual metrics, providing task-specific objective in the automatic design loop.

The first metric L_w is the *White Space Ratio (WSR)* [34], also known as area usage [63]. WSR is calculated as the ratio of pixels in $V_{\mathbf{x}}$ that are purely white (RGB value #FFFFFF) to the total number of pixels in $V_{\mathbf{x}}$. This metric is critical for quantifying the visual density of chart designs [39]. A high WSR suggests the presence of visual clutter, while a low WSR implies inefficient space utilisation. The WSR distribution $\mathcal{N}\mu, \sigma^2$, derived from human-crafted charts in the ChartQA dataset [27], is considered the golden standard. Any WSR that deviates significantly from this standard is penalised.

$$L_w V_{\mathbf{x}} = \begin{cases} 0 & WSRV_{\mathbf{x}} \in \mu - \sigma, \mu, \sigma \\ -|WSRV_{\mathbf{x}} - \mu| & \text{otherwise} \end{cases} \quad (2)$$

The second metric, *Colour Preference* (L_c), corresponds to the weighted affective valence estimates (WAVE) score [35]. WAVE reflects human colour preference by calculating the average affective valence of people's responses to objects associated with specific colours, weighted according to the strength of the association with each colour. Based on psychological studies, bright, saturated colours like red may evoke excitement or urgency, yielding a higher valence score. In contrast, softer colours like light blue yield a lower score.

$$L_c V_{\mathbf{x}} = WAVE V_{\mathbf{x}} \quad (3)$$

The third metric is the *Task Saliency* (L_s), i.e. mean visual saliency in the task-related areas of interest (AOIs). It represents the average task-driven saliency value across the AOIs $task_aoi_i V_{\mathbf{x}}$. A well-designed chart that supports task-solving should effectively direct viewers' attention to these regions. Thus, a higher L_s indicates more attention is drawn to the target region, suggesting better alignment with task objectives.

$$L_s V_{\mathbf{x}} = \frac{1}{N} \sum_i^i Saliency_{task_aoi_i} V_{\mathbf{x}} \quad (4)$$

The fourth metric, *Text Legibility* (L_t), evaluates the readability of text in visual designs [50]. A design fails if the texts are not readable due to small font sizes, text overlap, or misalignment beyond the image region. We employ Optical Character Recognition (OCR) [47] to automatically detect text characters in the rendered charts to approximate human perception. A penalty is applied when OCR fails to detect the text, indicating poor legibility successfully. For all M categorical and data labels, the OCR score equals 1 if a label $text_m$ is successfully detected and equals 0 if missing. To ensure a smoother objective function, we construct a P -level image pyramid, where $downsample_p V_{\mathbf{x}}$ is a downsampled version of the original image by a factor of p .

$$L_t V_{\mathbf{x}} = \frac{1}{PM} \sum_{p=1}^P \sum_{m=1}^M OCR_{downsample_p V_{\mathbf{x}}, text_m} \quad (5)$$

All parameters in the design space are constrained by at least one metric in the objective function (see Figure 3). The *WSR* controls the aspect ratio and bar width, preventing bar overlay or too far distances. The *Colour Preference* metric controls bar colours, making the colours in the chart more harmonious. The *Task Saliency* metric generally influences chart layouts (orientation, aspect ratio, bar width) and colour, improving colour harmony and bar distance. Finally, the *Text Legibility* constrains the font size of the category and data labels. For example, optimising for *Text Legibility* may influence the font size of categorical and data labels and the rotation of these labels, while optimising for *WSR* may influence the width and aspect ratio of the bars themselves. Optimising for both may influence all of these metrics jointly. The final objective function L is

$$L V_{\mathbf{x}} = w_w L_w V_{\mathbf{x}} + w_c L_c V_{\mathbf{x}} + w_t L_t V_{\mathbf{x}} + w_s L_s V_{\mathbf{x}} \quad (6)$$

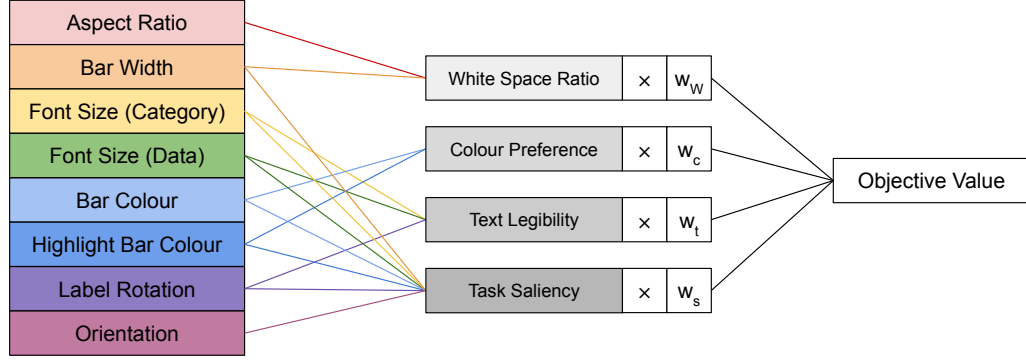


Fig. 3. Associations between weighted perceptual metrics (centre) used in the objective function (right) and parameters in the design space of bar charts (left).

3.3 Bayesian Optimisation

Evaluating charts poses significant challenges as identifying the parameter hypercube that yields the optimal value of the objective function is time-consuming. The challenges are threefold. First, identifying a “golden standard” for a specific design parameter is hard since the inter-dependencies between parameters are inherently black-box. Second, despite using descriptive grammars like Vega-Lite, the design space \mathcal{S} remains large, encompassing continuous chart design parameters such as bar width and colour. Third, each evaluation requires generating a visual representation of the chart, as all terms in the objective function depend on rendered images. For instance, saliency maps could only be predicted once images were rendered. Repeated image generation across iterations incurs substantial computational costs. These factors underscore the need for sample-efficient optimisation techniques to reduce the number of costly evaluations required to achieve an optimal layout.

Inspired by [13] that used Bayesian optimisation to refine 2D interface design in a map searching use case, we built a BO pipeline to balance efficiency and effectiveness. Bayesian optimisation [45] is a popular approach to optimise costly functions across various applications, which typically employs a probabilistic surrogate model to approximate the black-box function and estimate uncertainty. An acquisition function then utilises these estimates to determine the next query point. The surrogate model is often a Gaussian process (GP) [64], which uses a kernel or covariance function k to encode the prior belief for the smoothness of the black-box function f .

Let the perceptual metrics $f = L \circ Vega$ be the black-box function to optimise, we perform a sequential optimisation to find the optimal design parameters $\mathbf{x}^* \in \arg \max_{\mathbf{x} \in \mathcal{X}_1 \times \mathcal{X}_2 \dots \times \mathcal{X}_n} f\mathbf{x} = \arg \max_{V_{\mathbf{x}} \in \mathcal{S}} LV_{\mathbf{x}}$ based on the previously collected data, where in each iteration, we collect a new noisy observation $y_i \sim \mathcal{N}(f\mathbf{x}_i, \sigma^2)$. Given data $\mathcal{D}_n = \{\mathbf{x}_i, y_i\}_{i=1}^n$ that are collected up to n -th iteration during optimisation, the posterior prediction of a GP $pf\mathbf{x} \mid \mathcal{D}_n$ at a test location \mathbf{x} is specified by the mean function $\mu_n\mathbf{x}$ and the covariance function $v_n\mathbf{x}$:

$$\mu_n\mathbf{x} = \mathbf{k}_n\mathbf{x}^T \mathbf{K}_n \sigma^2 \mathbf{I}^{-1} \mathbf{y}_n, \quad v_n\mathbf{x} = k\mathbf{x}, \mathbf{x} - \mathbf{k}_n\mathbf{x}^T \mathbf{K}_n \sigma^2 \mathbf{I}^{-1} \mathbf{k}_n\mathbf{x}, \quad (7)$$

where $K_{nij} = k\mathbf{x}_i, \mathbf{x}_j$, $\mathbf{k}_n = k\mathbf{x}, \mathbf{x}_1, \dots, k\mathbf{x}, \mathbf{x}_n^\top$ and σ is the variance of the noise. $k\mathbf{x}, \mathbf{x}'$ is the similarity prediction based on a type of kernel k . We use radial basis function kernel in the experiment. \mathbf{k}_n is the vector containing all the similarity measures between input point \mathbf{x} and all other existing data x_1, \dots, x_n .

With the posterior prediction, we can compute the utility of a given point \mathbf{x} via an acquisition function $\alpha\mathbf{x}$. One of the most popular acquisition functions is the Expected Improvement (EI) [30], which has the form:

$$\alpha^{\text{EI}}\mathbf{x}; \mathcal{D}_n = \mathbb{E}_{f\mathbf{x}} \max f\mathbf{x} - y^*, 0 = \max f\mathbf{x} - y^*, 0 p f\mathbf{x} \mid \mathcal{D}_n d f\mathbf{x}, \quad (8)$$

where y^* is denoted as the best-observed value till step n . We can make a recommendation for the next iteration by maximising the acquisition function

$$x_{n1} \in \arg \max_{\mathbf{x} \in \mathcal{X}_1 \times \mathcal{X}_2 \dots \times \mathcal{X}_n} \alpha^{\text{EI}}\mathbf{x}; \mathcal{D}_n. \quad (9)$$

In summary, we use BO to find the optimal design parameters by treating the user's perceptual behaviour as a black-box function. We use a GP [64] to model the joint perceptual objective L based on four perceptual terms described in section 3.2. The chart design parameters are optimised by maximising the acquisition function iteratively.

3.4 Implementation Details

Tasks. Performing analytical tasks are common use cases when people read charts [14, 36]. Good chart designs should let viewers easily solve analytical tasks for efficient information communication. In this work, four common analytical tasks were studied (see Figure 1):

- *Find Extremum (FE)* [3]. FE tasks ask for the label of a data point with an extreme value of an attribute. Example task: Which mode of transport has the fewest CO2 emissions? To solve this task, participants must find the shortest bar in the chart and read the corresponding categorical label *Eurostar (international rail)*.
- *Retrieve Value (RV)* [3]. RV tasks ask for the data value given a specific target. Example task: *What is the value of Medium car (petrol)?* To solve this task, participants should look up the categorical labels to find Medium car (petrol), then read the data label for the value *191.6g*.
- *Compute Derived Value (CDV)* [3]. CDV tasks require participants to perform RV tasks to retrieve the value of given data points and then calculate the derived value. Example task: *What is the average value of National rail and Bus?* To solve this task, participants should look up the National rail and Bus values and then calculate the average of these two values.
- *Compare (CP)* [2]. CP tasks require participants to perform RV tasks to retrieve the value of given data points (usually two) and then make judgements about data properties. Example task: *Does Domestic flight have more CO2 emission than Bus?* To solve this task, participants should look up the values of domestic flights and buses and then judge whether domestic flights have more CO2 emissions.

Data Preparation. Implementing the proposed pipeline requires a vector-based chart dataset that supports customisable chart design parameters and includes task-based optimisation goals. We utilised the ChartQA dataset [27], a chart question-answering dataset comprising real-world charts and high-quality human-annotated questions. Each chart in ChartQA is associated with two human-annotated analytical tasks. We restricted our selection to single bar charts to simplify the design space. Since bar colours were changed in

the optimisation pipeline, we filtered out visual questions about bar colours, such as "What is the value of the yellow bar?" The final selection comprised 300 bar charts (207 horizontal and 93 vertical). These charts were recreated using the Vega-Lite grammar [41]¹, which allowed for declarative control over chart properties via key-value pairs in JSON format. This reduces the design space to a reasonable scale, consistent with previous visualisation literature [31, 65]. We created one horizontal and one vertical bar chart template with fixed design parameters in Vega-Lite and filled the JSON template with data values from the ChartQA annotations. In line with previous work [65], the chart height was fixed at 600 pixels, while the width was initialised to 600 pixels as well. Text elements were uniformly set to a font size of 15 pixels, bar widths were standardised to 40 pixels, and all bars were assigned the colour #949d48, a common hue in ChartQA. The orientation of each chart followed the original designs in ChartQA. The Vega-Lite compiler then rendered the JSON files into Portable Network Graphics (PNG) and Scalable Vector Graphics (SVG) formats.

Specification of Objective Functions. The implementation of the WAVE algorithm for colour preference was based on the Aalto Interface Metrics platform [33]². Task-relevant regions were automatically detected from the rendered chart in SVG format. For the FE and RV tasks, one task-related region was identified. In contrast, two or more target regions were defined for the CDV and CP tasks. To align these regions with annotated questions or answers, we matched the "aria-label" attribute in the SVG with the corresponding elements. We utilised the *boundingbox()* function from the Python *svg.path* package to extract the bounding boxes. Task-driven saliency maps were generated using the VisSalFormer model [62]. Regions with zero saliency were excluded from the analysis by discarding pixels within bounding boxes that had a saliency value of 0. For text legibility assessments, we used Pytesseract³ for OCR on a three-level image pyramid (at 1/8, 1/4, and 1/2 of the original image size).

Parameter Boundaries. The bounds for each parameter were carefully selected to define the limits of the hypercube. We set the aspect ratio between 0.33 and 3, varying the chart width from 200 to 1,800 pixels. Font sizes were restricted to 10-36 pixels, bar width to 20-180 pixels, and label rotation to $\{0, -45^\circ, -90^\circ\}$. We permitted the full range of the HSV colour space for bar colours.

Training Details. Weights of the objective function were set to $w_s = 4$, $w_c = 1$, $w_w = 3$, $w_t = 2$. The candidate list was constructed by sampling from the parameter hypercube using a Sobol sequence. We sampled 50 candidates with ChartOptimiser for every chart-task pair, which took about 5-7 seconds per iteration. While more candidates provide better search resolution, we considered 50 candidates sufficient to demonstrate the strength of ChartOptimiser. All experiments were conducted on a Desktop PC with an AMD Ryzen 7 3700K 8-Core Processor and NVIDIA GeForce RTX 2060 Super GPU with 8GB VRAM.

4 EVALUATION

To gain further insights, we conducted a user study to let participants qualitatively rate chart designs generated from our method against human-designed charts and three strong baseline approaches. Then, we further analysed the optimised parameters from ChartOptimiser.

¹<https://vega.github.io/vega-lite>

²<https://github.com/aalto-ui/aim>

³<https://pypi.org/project/pytesseract>

4.1 Study Design

Participants. We recruited 60 participants (31 males, 29 females) aged from 20 years ($M = 33.75$, $SD = 10.94$) via the Prolific platform. Only participants with normal or corrected-to-normal vision were involved. 57 of the participants confirmed they understood how to read bar charts, and 45 had experience designing bar charts before. The study took an average of 34 minutes ($SD = 19$ minutes) to complete. Participants received 5 pounds as compensation. Upon completing all trials, we asked participants to provide qualitative feedback on the most important characteristics they used in their subjective evaluation.

Experimental Protocol. We randomly sampled 12 charts from the ChartQA dataset, corresponding to three tasks from each of the four task types introduced in Section 3: Find Extremum (FE), Retrieve Value (RV), Compute Derived Value (CDV), and Compare (CP). RV and FE were considered simple tasks, as they require observing only a single data point. In contrast, CP and CDV were considered more complex, necessitating observing multiple data points and performing calculations [14]. In the study, participants were introduced to the tasks before starting. We presented participants with five chart designs in each of the 12 study tasks (see Figure 4). Study participants were asked to evaluate the five chart designs from three aspects: 1) chart aesthetics, 2) chart clarity, 3) and task-solving ease. Each aspect was evaluated on a 7-point Likert scale, where 1 is the strongest negative, and 7 is the strongest positive. After completing ratings for each task, participants are asked to leave comments to briefly explain their ratings.

Design Comparison. We compared the chart designs from ChartOptimiser against human-designed charts and three baseline approaches. Several examples of chart designs are shown in Figure 4.

- *Human-designed charts (Human).* These are human-designed bar charts from the original ChartQA dataset [27]. We cropped the additional information in the image to preserve only the data regions for a fairer comparison.
- *Vega-Lite default designs (VegaLite).* These are the recreated charts from ChartQA data tables, using the Vega-Lite library [41] with fixed chart design parameters (see Section 4.2).
- *GPT-4o optimised charts (GPT-4o).* These are the responses from GPT-4o⁴ [1] with the prompt “{ $\$VEGA_JSON$ }”, “optimise the above Vega-lite JSON with the task: { $\$TASK$ }”. The { $\$VEGA_JSON$ } is the JSON file of the VegaLite baseline, while the { $\$TASK$ } is either FE, RV, CP, or CDV task from the ChartQA dataset. We noticed that GPT-4o filters data in some CP and CDV tasks, so we added the prompt “please add the filtered data back” to prevent editing the data source.
- *LQ2 optimised charts (LQ2).* The Layout Quality Quantifier (LQ2) [65] is a machine learning model that evaluates chart layouts from paired crowdsourcing data, yielding a preference score given the layout parameters as input. We used the LQ2 score as the objective function in our proposed Bayesian pipeline to optimise charts. It takes the number of bars, bar width, and aspect ratio (with height fixed) as input and yields a score ranging from 0 (worst) to 1 (best). Since the LQ2 score does not constrain colour, we fixed the design parameter of dimension 4) the bar colour and 5) the highlight bar colour for LQ2. The VegaLite baseline was used as the initial parameter of LQ2.

⁴<https://platform.openai.com/docs/models/gpt-4o>

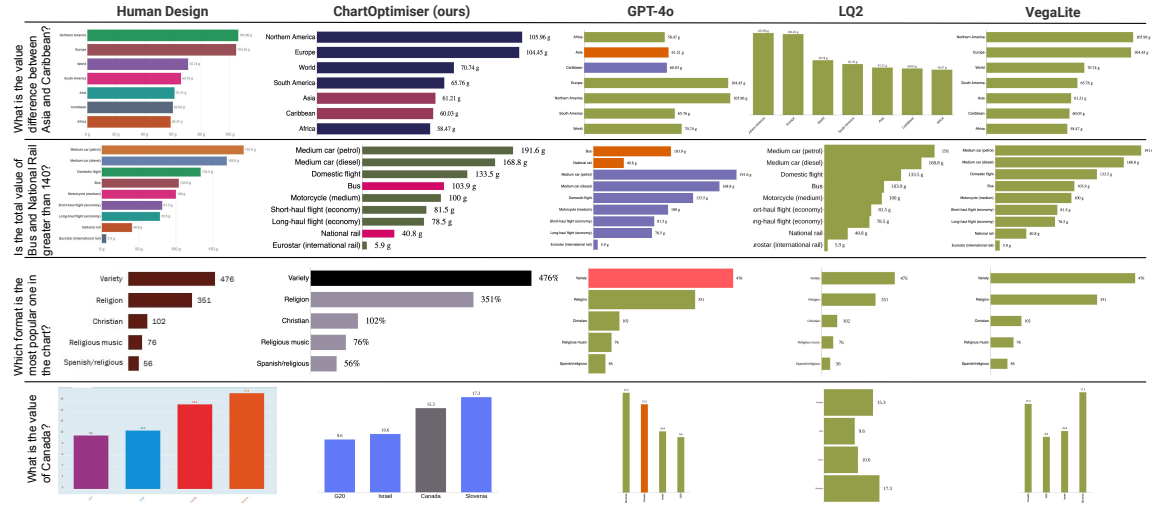


Fig. 4. From left to right: Sample bar charts from the ChartQA [27] dataset as well as corresponding bar charts optimised using ChartOptimiser, Vega-Lite default [41], LQ2 [65], and GPT-4o [1].

4.2 Study Results

Ratings. Figure 5 illustrates the participants' ratings for visual aesthetics, chart clarity, and task-solving ease for all chart designs. Overall, ChartOptimiser ranks first in clarity ($M = 5.6, SD = 1.4$) and task-solving ease ($M = 6.1, SD = 1.2$), with the GPT-4 design coming in second. The human-designed chart outperforms others in aesthetics ($M = 5.4, SD = 1.5$), with our ChartOptimiser ranking second ($M = 4.9, SD = 1.5$). The results indicate that human designers consider more details to ensure the charts are pleasing, while automatic approaches can improve chart clarity and task-solving ease. The normality of the ratings was confirmed via the Shapiro-Wilk Normality test. A one-way ANOVA revealed a statistically significant difference in ratings between these methods in aesthetic ($F(4, 1795) = 39.2, p < 0.01$) and clarity ($F(4, 1795) = 3.2, p < 0.01$). The task-solving ease was insignificant based on the one-way ANOVA analysis ($F(4, 1795) = 1.8, p = 0.13$). No significant differences were found in the post-hoc Tukey's HSD test between methods regarding task-solving ease ($p > 0.05$). However, in terms of aesthetics, human designs were significantly better than other methods ($p < 0.05$). Additionally, ChartOptimiser was significantly better than LQ2 ($p < 0.05$) and slightly better than GPT-4o and VegaLite ($p > 0.05$). In clarity, ChartOptimiser was significantly better than human designs and LQ2 ($p < 0.05$), but also slightly higher than GPT-4o and VegaLite ($p > 0.05$). This result indicates that the method has the potential to design charts suitable for tasks in terms of both aesthetics and clarity.

Next, we examined the ratings for each task (see Figure 6): 1) *CDV*: ChartOptimiser outperformed others in clarity and task-solving ease, ranked second in aesthetics, following human-designed charts. 2) *CP*: ChartOptimiser ranked first in aesthetics, surpassing human designs that ranked second. This is the only task for which human designs did not rank first. Our method ranked in the top two for clarity and task-solving, with no significance found against LQ2, which ranked first ($p > 0.05$). 3) *FE*: All designs received high task-solving ratings, suggesting this task's easiness. VegaLite ranked first in clarity, as the

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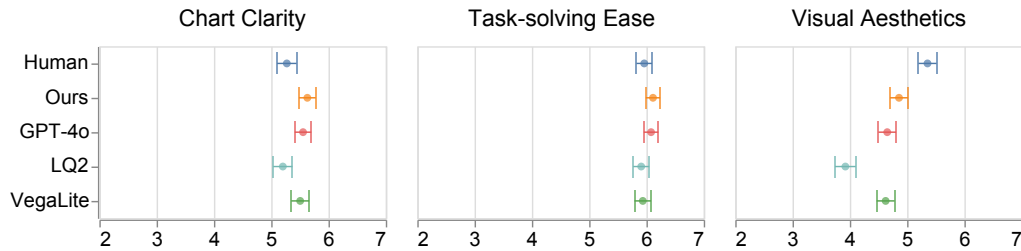


Fig. 5. Mean ratings and 95% confidence intervals for visual aesthetics, chart clarity, and task-solving ease for the different methods.

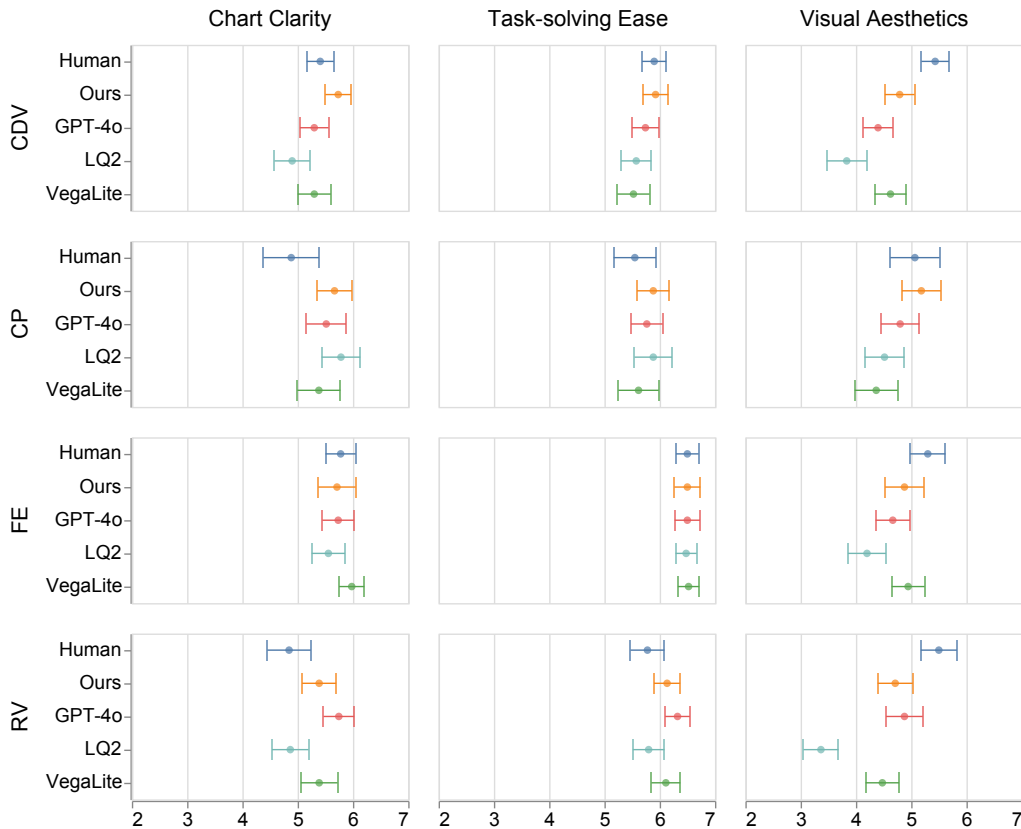


Fig. 6. Mean ratings and 95% confidence intervals for visual aesthetics, chart clarity, and task-solving ease for the different methods and four task types.

simplest design can show extreme values clearly. Human design ranked first in aesthetics. 4) *RV*: GPT-4o designs performed well in the simple retrieve value task, with ChartOptimiser in second place with no significance. Our proposed approach performed best in complex tasks (CDV and CP). It also demonstrated its superiority in simple tasks, although comparable to other approaches.

Comments. Participants’ comments indicated that our objective function’s design was effective by emphasising saliency, text legibility, colour preference, and white space ratio. Participants frequently mentioned the following factors that influenced their ratings: 1) *Highlighting key data points (mentioned 17 times)*. Using different colours to emphasise the highest value or relevant data points made it easier for users to quickly identify important information; 2) *Clear labelling (mentioned nine times)*. Easily visible labels and numbers next to each bar were essential for quickly understanding the data and making decisions based on it; 3) *Pleasing colour scheme (mentioned five times)*. Aesthetically pleasing colour combinations made charts more engaging, especially using contrast or harmonious colours. Charts with multiple colours were generally preferred over monochromatic designs; 4) *Well-spaced bars (mentioned four times)*. Well-spaced bars and well-proportioned bar sizes enhanced visual appeal and improved the overall aesthetic experience. Users preferred charts that had clear distinctions between different data segments; 5) *Legible font sizes (mentioned three times)*. Readable font sizes for labels and values were essential for making charts easily understandable. Smaller fonts were noted as a barrier to clarity.

4.3 Parameter Analysis

We further investigated the optimised parameters in the design space and compared our ChartOptimiser with both human-designed charts [27] and LQ2-optimised designs [65] on the 300 charts introduced in Sec. 4.1. We selected aspect ratio and bar width as the parameters for analysis, as they are the most general design factors when humans create a bar chart [65]. Figure 7 illustrates the relationship between bar widths and aspect ratios across the 300 charts. In the human-designed charts, the most preferred region is an aspect ratio of 1.6 and 2.0 when the bar width is between 140 and 160 pixels. Our ChartOptimiser closely aligned with these human-designed results, with the most frequent region having an aspect ratio of 1.6 and 2.0 when the bar width is between 120 and 140 pixels. However, the baseline approach LQ2 yielded substantially different results from those of humans, with an aspect ratio of 0.4 and 0.8 when the bar width is between 80 and 100 pixels. In addition, we find that ChartOptimiser covers the parameter space more comprehensively than human and LQ2. This shows that our design can be adapted to diverse design combinations.

5 DISCUSSION

5.1 On ChartOptimiser

The core innovation of ChartOptimiser is the proposed objective function, including four essential perceptual metrics in the Bayesian optimisation pipeline: white space ratio, colour preference, visual saliency in the highlight region, and text legibility. This combination enables the generation of optimised bar charts highly attuned to users’ analytical tasks. The empirical results demonstrate that, by leveraging these perceptual metrics, ChartOptimiser generates charts that are competitive with human-designed charts regarding clarity and task-solving ease. This is particularly notable in complex tasks like computing derived values or comparing multiple data points.

Furthermore, the design space of ChartOptimiser allows for a wide range of design possibilities, where font sizes, aspect ratio, bar width, and bar colour allow continuous choices. In stark contrast, previous chart optimisation works all limited their design space to discrete values [29, 65]. Despite the expanded design space in ChartOptimiser, Figure 7 shows that the parameter selections closely align with human-generated

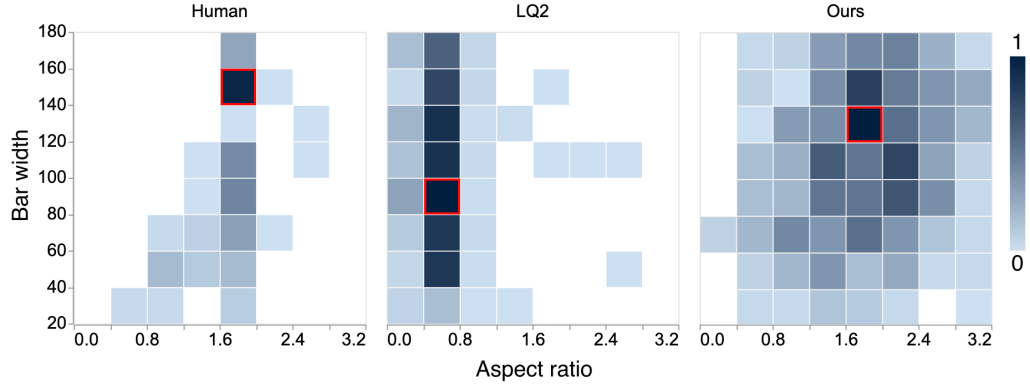


Fig. 7. Heatmaps of the normalised distribution of human-selected parameters and parameters optimised using LQ2 and ChartOptimiser across 300 charts. The figure shows the distribution for the only two design parameters LQ2 can optimise: aspect ratio and bar width. The most commonly used parameter combinations are highlighted in red. ChartOptimiser picks parameters that closely align with those the human experts select. In contrast, LQ2 deviates notably from the human parameters.

designs. By efficiently exploring this space through Bayesian Optimisation, ChartOptimiser consistently achieves highly effective chart designs. This adaptability makes it a robust tool for specific applications, such as chart designing for accessibility or content localisation.

5.2 On the User Study Results

The user study revealed essential insights into the performance of ChartOptimiser. Participants consistently rated ChartOptimiser highest in clarity and task-solving ease across all task conditions, demonstrating the value of incorporating perceptual metrics like saliency and text legibility in optimising chart designs (see Figure 5). The four most frequently mentioned factors – highlighted key data points, clear labelling, a pleasing colour scheme, well-spaced bars, and legible font sizes – strongly aligned with our objective function, confirming ChartOptimiser’s effectiveness in enhancing visual clarity and usability.

Notably, ChartOptimiser demonstrated strong performance in complex tasks (CP and CDV), likely due to the method’s effective layout design and colour usage to emphasise task-related data points (see Figure 6). In contrast, for simple tasks like RV and FE, ChartOptimiser did not achieve the first place. This finding is consistent with prior work suggesting that perceiving extremum values requires minimal cognitive effort [14]. The insignificant differences were observed in the FE tasks, indicating those simple tasks do not necessarily require an optimised design for the observation condition.

Moreover, human-designed charts significantly outperformed all automatic methods in terms of aesthetics, which indicates that while automation can greatly assist with functional aspects, human designers can still better capture the subtle visual elements that enhance the overall appeal of a chart. Nevertheless, ChartOptimiser ranked second in aesthetics, promising to balance functionality and visual appeal.

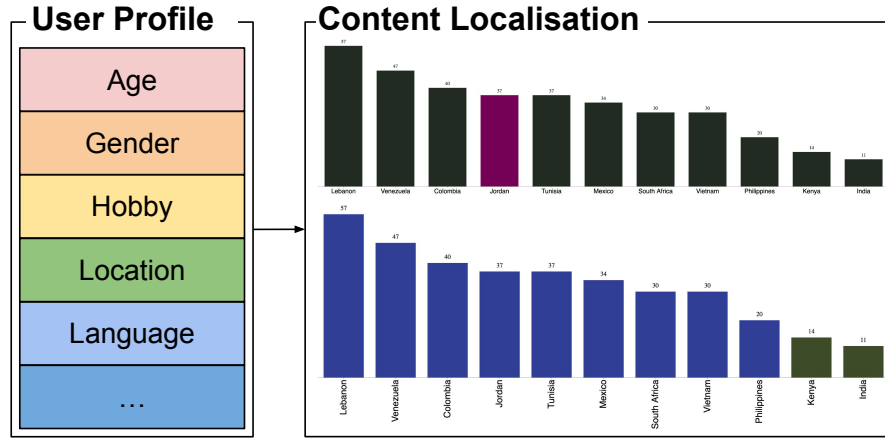


Fig. 8. Sample content-localised charts generated by our method based on a user profile. The chart at the top was optimised for a user in Jordan, while the lower one was for a user interested in Kenya and India.

5.3 On Applications

Accessibility. Data Visualisation Literacy is the ability to interpret visual patterns in the visual domain as properties in the data domain [7]. Users with low Data Visualisation Literacy might need help with complex data interpretation tasks, like comparison or computing derived values. ChartOptimiser has strong competence in optimising charts for those complex tasks, making the charts more engaging. For users with low visual literacy, complex visualisations can be overwhelming. To mitigate this, ChartOptimiser could prioritise lower information density by increasing the white space ratio, thus avoiding clutter and presenting only essential information. This would help users focus on the most critical aspects of the data. The colour design space of ChartOptimiser could be simplified to ensure accessibility. Prioritising contrasting and accessible colour schemes would facilitate quicker comprehension for users with low visual literacy [6]. Moreover, ensuring that charts adhere to colour guidelines for colour blindness, like avoiding red-green contrasts, makes visualisations more inclusive and comprehensible to a broader audience.

Content Localisation. Journalists and media outlets frequently use visualisations to convey data to the public. Using ChartOptimiser can enhance these visualisations by adaptively emphasising different data points for different audiences, a process known as content localisation [21]. Figure 8 visualises the percentage of people accessing a personal computer in different countries. For instance, the top figure fits the user located in Jordan, as Jordan is highlighted in the chart. The bottom figure fits the user with interest (e.g. travel plans) in Kenya and India. ChartOptimiser ensures that the charts are visually appealing and optimises them for relevance to specific audiences based on their demographic information (user profile), making it easier for readers to extract key insights and increase engagement with localised stories. Nevertheless, more engineering work is needed given localisation differences, such as reversing the order of axis labels given a language reading from right to left, and choosing culturally plausible colour schemes.

5.4 Limitations and Future Work

Currently, ChartOptimiser focuses on bar charts, which do not cover the full spectrum of chart types used in practice. Expanding the design space to include other chart types, such as line or scatter plots, could increase the versatility of ChartOptimiser. Another avenue for future work is incorporating dynamic, multi-task visualisations, where charts are optimised to simultaneously support multiple user tasks. In future work, as data storytelling continues to play a pivotal role in data visualisation [46, 48], integrating narrative-driven elements into the automatic chart design process presents a promising direction [12]. Extending ChartOptimiser to incorporate storytelling could support a wider range of applications, particularly in dashboard design and data communication, where contextualised narratives are essential. Furthermore, ChartOptimiser holds the potential to be integrated into a “ChartGPT” system [57], where optimised charts are dynamically generated as responses to user queries, offering tailored data insights on demand. This direction would enhance interactive data exploration and make data insights more accessible through conversational interfaces.

6 CONCLUSION

In this work, we introduced ChartOptimiser— the first method for task-driven optimisation of information visualisations. At its core is a Bayesian approach that optimises chart designs with respect to a novel objective function integrating four perceptual metrics – visual saliency, text legibility, colour preference, and white space ratio. Through empirical evaluation for common analytical tasks, we showed that our method can effectively optimise bar chart designs to enhance chart clarity, aesthetics, and task-solving ease. ChartOptimiser demonstrated significant performance improvements over human-designed and baseline charts, especially in more complex tasks such as comparing or computing derived values.

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