How Dimensional and Semantic Attributes of Visual Sign Influence Relative Value Estimation

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High-quality decision making requires accurate estimation of relative values. The perceptual bias when estimating relative values displayed by a visual sign may weaken the accuracy and cause misjudgment. This research explores the heuristic estimation of relative values using visual cues, namely linear, areal, and volumetric information. We conduct experiments to empirically test the influences of dimensional information on perceptual biases. First, we investigate the conspicuity of areal information. Our experiments indicate that the responses of participants instructed to estimate rates defined by either linear or volumetric information are biased by the corresponding rates determined by areal information. Second, visual cues implying three-dimensional information (e.g., depth) can lead to overestimation. Third, we probe the influence of vividness as the boundary condition on relative value estimation. Empirical evidence on perceptual bias sheds light on the pragmatics of visual signs, helps suggest guidelines for visual persuasions, and improves decision-making quality.

CCS Concepts: • **Human-centered computing → HCI design and evaluation methods**; **Laboratory experiments**; **Empirical studies in visualization**

Additional Key Words and Phrases: Information visualization, relative value estimation, perceptual bias, dimensional information, visual cue

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1. INTRODUCTION

Quantity information is often visualized by mapping values to various attributes of icons. Whether viewers can access the value through these icons is unknown. A simple example is used to investigate

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Fig. 1. Icons of the 360 Safeguard software showing difference in the percentage by volume and number.

this issue. As reported by https://www.360totalsecurity.com, nearly 500 million active users, mostly located in mainland China, have installed an antivirus software called the 360 Safeguard on their computers. This software sets an icon on the users' desktop and reports the rate of internal memory usage in real time. Users can manually release memory and speed up their computers. The icon is similar to a green glass sphere that contains liquid (Figure 1). The rate of memory usage equals the height of the liquid level divided by the diameter of the sphere. A numeric percentage is also provided. Figure 1 shows icon images captured before and after a user manually released memory. Prior to the user's operation, the percentage of memory usage is 70%. Liquid occupies more than 80% of the space in the glass sphere, thereby suggesting high urgency for memory release. By contrast, after the memory release, the percentage drops to 35%. Very little liquid (approximately 26% of the volume) is left in the glass sphere, thereby implying excellent function of the software. Given that the rates by height are nonlinearly correlated to the rates by volume, the disparity between the estimated percentage by volume and the marked numeric percentage exaggerates the necessity to release memory and the effect of release. The icon may be misleading, but the designer can deny their intention to deceive, because the numerical value clearly and precisely demonstrates the information. This tricky design manipulates visual cues. Users may not be aware of the persuasive intention of the icon, regard such a visual expression as a convention, and perceive high utility of the software. Manipulation of visual cues (i.e., linear, areal, and volumetric information) appears in many other cases of data visualization, thereby suggesting the bias in relative value estimation.

Data visualization is created as a coding system to represent quantity information [Cleveland and McGill 1987]. Practitioners often claim that visual signs can convey information quickly and result in efficient decision making; however, considerable evidence in the psychological literature has indicated the risk caused by perceptual bias [Ozimec et al. 2010]. Although the significance of human-centered design methodology [Tory and Möller 2004] is highlighted in data visualization, the scientific foundation of decision-making quality has not been studied systematically. To our knowledge, research on the influence of different types of dimensional information on relative value estimation is limited. Consequently, understanding the perceptual bias in decision making and properly using dimensional information are difficult. Our research explores the heuristic estimation of relative values using linear, areal, and volumetric information. The contributions of our research are as follows:

- We distinguish the linear, areal, and volumetric information of a visual sign as a target or interfering information, clarify the different roles of dimensional information in rate estimation, and provide insights into the semantic influence of visual attributes.
- We analyze the influence of dimensional information on relative value estimation. Our empirical evidence sheds light on the perceptual bias in visual information decoding and suggests implications for designers and users.
- We test the impacts of representative and nonrepresentative signs on relative value estimation and confirm that vividness facilitates understanding on concepts and enhances the accuracy of estimation.
- This research indicates the prevalence of perceptual bias in relative value estimations. Current mainstream research assumes that visual deception is caused by a deliberate design. By contrast,

our research illustrates the limited attainability of accurate estimations and depicts the heuristic deployment of dimensional information in relative value estimation.

2. RELATED WORK

2.1 Relative Value Estimations

Relative value estimation refers to the calculation of percentage, time, rate, or ratio. This estimation is a complex cognitive task in information decoding and starts from magnitude estimation. Magnitude estimation requires interpreting the meaning of a benchmark and evaluating the richness of a stimulus [Hsee et al. 2005]. Quality difference (i.e., Which one is larger?) is determined first and then quantity differences (i.e., One is larger than the other by exactly how much exactly?) are estimated. Accurate relative value estimation requires precisely evaluating and comparing the quantities of two items. The effort on relative value estimation can be rewarding, because a certain rate is often used as a threshold or a standard of judgment. For example, the Engel coefficient [Holmberg 1975] in economics refers to the proportion of income spent on food and indicates the living standard of a country. A low proportion indicates a high living standard. A proportion below 0.2 signifies an affluent society. Knowledge of the Engle coefficient [Houthakker 1957] may drive users to compare visual signs indicating food expenses and other expenses, calculate the rate, and infer the living standard of a country. The accuracy of relative value estimation influences the quality of judgment and decision making [Hsee et al. 2005, Hsee and Zhang 2004]. Inaccurate estimations may lead to a large deviation in the judgment of a situation, particularly when the judgments are sensitive to the relative values.

2.2 Perceptual Bias

Human's perceptual bias, such as "size effect" in reading visual scales, has been well documented in the psychological literature [Pearson 1964]. Size effect refers to the phenomenon that users are inclined to underestimate the magnitude of the difference between the sizes of circles when using areas rather than radii to illustrate quantities [Teghtsoonian 1965; Been 1964]. The reason is that areal information contaminates the estimation of rates defined by linear information. Further research indicates that magnitude is judged holistically and intuitively by relying mainly on one dimension (e.g., height or width) rather than all three dimensions. The most salient dimension will be weighted heavily [Folkes and Matta 2004; Krider et al. 2001], such that a large height-width ratio of containers leads to a large estimated volume [Baddeley and Andrade 2000; Holmberg 1975; Pearson 1964]. Tall or elongated containers are perceived to accommodate more products than short containers of the same volume [Raghubir and Krishna 1999]. Product changes in size appear larger when packages and portions change in only one dimension than when they change in all three spatial dimensions [Chandon and Ordabayeva 2009]. Excessive influences of certain dimensional information over others are identified on the basis of psychological experiments on either two-dimensional (2D) graphs or 3D objects (e.g., real containers or packages). Scarce research has explored the different influences of dimensional information when a 2D visual sign represents a 3D object [Li et al. 2016].

The literature in geography provides insightful knowledge on the proportional relationships represented by visual sign [Brewer and Campbell 1998; MacEachern 1995]. Flannery [1971] discovered that users underestimate 29.5% of the size differences when cycles are used to display quantity. The topic of apparent value scaling facilitates discussion on the possibility and boundary conditions of accurate estimations in the geography community [Brewer and Campbell 1998; Cox 1976].

As early as in 1954, statisticians in the domain of information visualization have warned about the possibility of visual deception caused by perceptual bias in the famous book entitled "How to Lie with Statistics" [Huff 1954]. Huff claimed that "if visualizations are able to make messages more accessible, comprehensible, and persuasive, it can also be easily misused and misunderstood even by their creators" [Huff 1954]. Recent studies analyze four types of distortion techniques, namely truncated axis, area as quantity, aspect ratio, and inverted axis. These works also empirically testify to the deceiving influences of the above-mentioned techniques on message exaggeration, understatement, and message reversal [Pandey et al. 2015]. However, the way in which different types of dimensional information engenders perceptual bias and leads to inaccurate estimation in various scenarios remains unknown.

2.3 Pragmatics of Visual Signs

Visual communication involves encoding and decoding [9] based on visual grammars [Bertin 1983]. Quantity information is encoded into linear, areal, or volumetric information by creating a set of analogies. The encoding rules are usually regarded as visual conventions, which are assumed to guarantee clear and complete interpretation of semantic meanings. However, corruption in visual presentations violates such an assumption [Tufte 2006; Tufte 1985]. Users' perceptual bias can still occur even if visual signs are clearly displayed and defined. Extant research has indicated that the figuration of components, Euclidean width, and clutter can influence numerosity perceptions [Dixon 1978; Gebuis and Reynvoet 2012; Krishna and Raghubir 1997]. For example, when a dotted line is arranged with high Euclidean length, the perceived numerosity of dots is also high [Krishna and Raghubir 1997]. People may be influenced by the heuristic space and intuitively use undefined visual attributes. Our research adopts a perspective of coding and decoding to empirically study the influence of visual attributes on visual sign interpretation.

3. RESEARCH HYPOTHESES

In this research, we focus mainly on the visual signs defined by width and height in 2D space. Height and width are potentially assigned meanings or are set as defaults. For example, bars in a typical bar chart are assigned different heights but the same width. Meanwhile, bubbles in a bubble chart are assigned the same value of width and height. Apart from simple geometric shapes, representative signs are also adopted in data visualization. Figure 2 shows an example in which human silhouettes (Figure 2) indicate job positions in a company, and the height of each figure shows the average annual income (one unit equals one thousand dollars). In Figure 2(a), the height and width of a sign are scaled simultaneously. By contrast, in Figure 2(b), the signs are elongated but maintain the same width. In Figure 2(a) and (b), the height of each sign is the *target information* and is supposed to be processed for judgments. The width of the sign is defined irrelevant to the income amount and is the *redundant information*. Obviously, the signs in Figure 2(a) conform to our visual experiences and are thus legible. The width is linearly correlated to the height but redundant. The width also causes quadric changes in the area and cubical changes in the space in which a person can occupy. When viewers are asked to compare the factors related to income (e.g., ability and social influences) between people at different positions, the redundant information may be intuitively used and make a difference.

In the following paragraphs, we will discuss the influence of redundant dimensional information on the estimation of relative values. For a given icon, we use R_n ($n = 1, 2, 3$) as an abbreviation of the rate defined by linear, areal, or volumetric information. A visual sign inherently has R_1 and R_2. Certain visual signs may activate the concept involving volumetric information (e.g., containers), suggesting R_3. Only one among R_1, R_2, and R_3 will usually be selected to indicate rates, leaving the two other as redundant but possibly influential data. Our research focuses on the influence of R_2 and R_3 as redundant information (Table I). Hypotheses 1–4 are discussed below.

The theory of perceptual bias clearly indicates the inevitable risks caused by redundant information in reading visual scales [Krider et al. 2001]. Information is not equally processed [Hsee et al. 2005], and conspicuous dimensions can cause systematic biases in the value estimation [Dixon 1978; Gebuis and

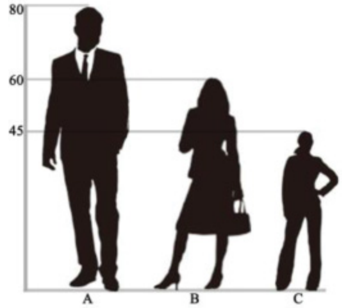


Fig. 2a. Scaled visual signs.

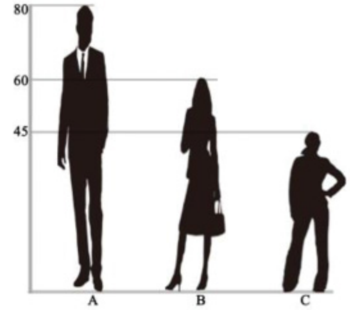


Fig. 2b. Elongated visual signs.

Table I. Combinations of Target and Redundant Dimensional Information

RATE	Target Dimensional Information Defining the Rate	Redundant Dimensional Information Eliciting Bias
R_1	Height-Width	Area (H_1), Volume (H_3 and H_4)
R_2	Area	Volume (H_3 and H_4)
R_3	Volume	Area (H_2)

Reynvoet 2012; Krishna and Raghubir; 1997]. Given that real size is the most conspicuous attribute of 2D visual signs, viewers may subconsciously adopt areal information. We infer that when users are instructed to estimate R_1, R_2 may influence their estimation accuracy when R_1 and R_2 are nonlinearly correlated. Specifically, if R_2 is higher than R_1, then R_1 will be overestimated. Otherwise, if R_2 is lower than R_1, then R_1 will be underestimated. In summary, we hypothesize that

H_1: A small R_2 leads to an underestimation of R_1.

The validity of H_1 will lead to a parallel inference. In other words, when viewers are asked to estimate a rate defined by volumetric information, R_2 may similarly influence R_3. In particular, when R_2 and R_3 are nonlinearly correlated and if R_2 is higher than R_3, then R_3 will be overestimated. Otherwise, if R_2 is lower than R_3, then R_3 will be underestimated. Hence, we propose that

H_2: A small R_2 leads to an underestimation of R_3.

The quantities displayed by volumetric information are not immediately apparent, because such information involves a cubic equation. Prior research used evaluability to measure the ease with which information can be assessed and compared [Hsee 1996]. A low evaluability of visual information may hinder users' acquisition and processing [Ozimec et al. 2010]. When encountering difficulties in direct absorption of volumetric information, users can adopt a substitute way for convenience. Considering that $y = x^3$ is steeper than $y = x^2$ when $x > 1$, the imagery of a sharp increment may lead to perceptual contamination. Users may simply use 3D information as a sign to estimate a high rate. Hence, we assume that

H_3: 3D information elicits overestimation of relative values.

Volumetric information influences only if the concept of 3D space is evoked. First, this concept originates from the knowledge of the visual sign's denotation. For example, once the users recognize a visual sign referring to a cup, the concept of spatial occupancy is activated even when the cup is shown in a front view as a rectangular shape. Second, a certain arrangement of visual cues (e.g., dark shading around a visual object) can convey cubic information and enhance the illusion of depth. We propose that

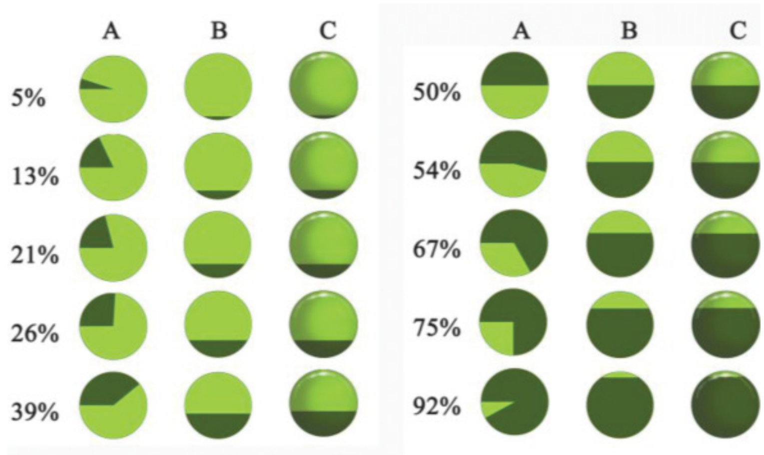


Fig. 3. Visual stimuli for Study 1. Specifically, Stimulus Group A is composed of typical pie charts containing central angle linearly correlated with the percentage of the area. By contrast, in Stimulus Groups B and C, the rate defined by height differs from that defined by area for most of the cases. The stimuli in Stimulus Group C are shaded to highlight the volumetric information.

H_4: A visual cue implying 3D information elicits overestimation.

Visual signs in information visualization can be geometric shapes or vivid images [Taylor and Thompson 1982]. Vividness is an objective characteristic of visual stimuli and refers to the richness of representation. A vivid sign provides much detail to mimic the visual feature of the object in reality, and this sign allow users access to the meanings effortlessly. A vivid sign is imagery provoking [Nisbett and Ross 1980] and can simultaneously evoke a range of relevant information to facilitate viewers' thought generation [Burns et al. 1993], event prediction, action planning [Baddeley and Andrade 2000; Baddeley 1998; Blondé and Girandola 2016], and judgment making [Keller and Block 1997]. A vivid sign may lower the viewers' mental process in absorbing areal information, thereby directing users to capture less-biased semantic meanings. Therefore, we further hypothesize that

H_5: High vividness enhances the accuracy of rate estimation.

4. EMPIRICAL RESEARCH

We conduct four studies to test the above-mentioned five hypotheses. In particular, Studies 1, 2, and 3 verify Hypotheses 1–4. Study 4 proves Hypothesis 5 and explores the boundary condition of the influences of dimensional information.

4.1 Study 1

4.1.1 *Stimulus Design.* We design three groups of stimuli (Stimulus Groups A, B, and C) to test the influences of areal information on the estimation of rates defined by height.

Figure 3 shows Stimulus Group A, which is composed of typical pie charts containing a central angle linearly correlated with the percentage of the area. The rate in Stimulus Group A is defined as the area of the dark green sector divided by the area of the entire cycle. For Stimulus Groups B and C, the rates are defined by the height (h) of the dark green portion divided by $2r$, which is the diameter of the cycle (Figure 4). The stimuli in Stimulus Group C are rendered with shade to simulate the sense of volume. The differences in the estimated rates of Stimulus Groups A and B can provide evidence

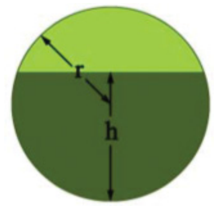


Fig. 4. Rate in Group B defined by height (i.e., rate = $h/2r$).

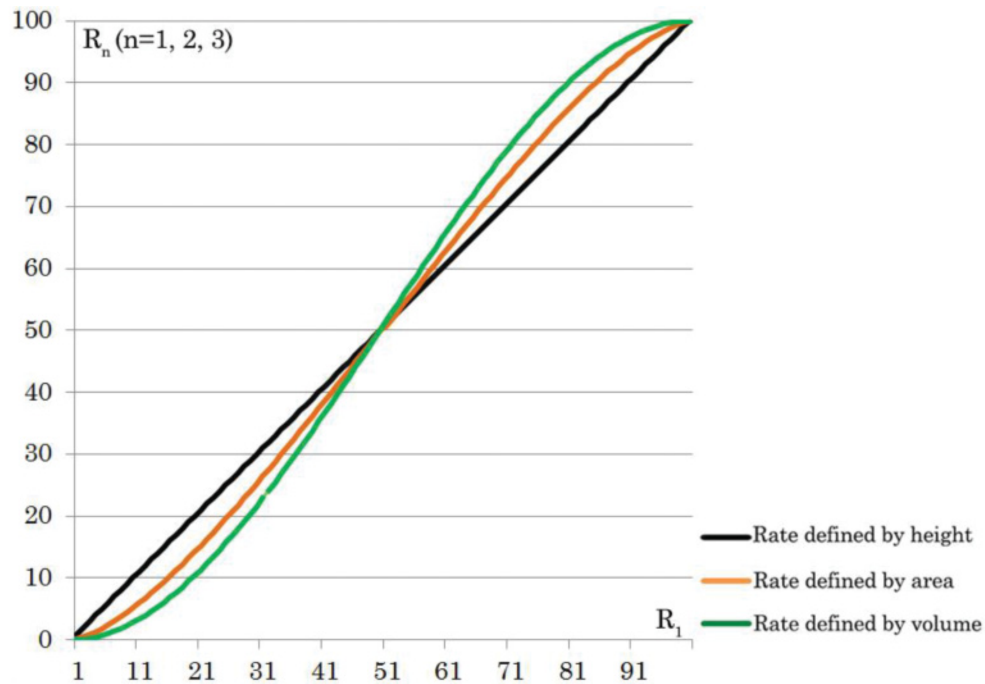


Fig. 5. Rates defined by height, area, and volume for icons shown as stimuli in Stimulus Group B. R_1, R_2, and R_3 are curvilinearly correlated.

on the influences of R_2 on R_1 (H_1). The comparison between the estimated rates of Stimulus Groups B and C can prove the influences of R_3 on R_1 (H_3 and H_4).

A total of 10 rates between 1% and 100% are selected for the tests. Among the selected rates, 50% and 75% are the anchor points of the pie chart and are featured by a semi-cycle and a right angle, respectively. The eight other rates are selected randomly. For convenient estimation of participants, the stimuli in each group are presented in an ascending order of the rates.

The R_1 (black line) values of the icons in Stimulus Group B are curvilinearly correlated with their R_2 (orange line) and R_3 (green line) values. In Figure 5, the horizontal axis refers to R_1, and the vertical axis refers to the rate defined by height, area, or volume. Obviously, when $R_1 < 50\%$, $R_3 < R_2 < R_1$. When $R_1 > 50\%$, $R_3 > R_2 > R_1$. When $R_1 = 50\%$, $R_3 = R_2 = R_1$. This pattern provides a baseline to compare the actual rates with the estimated rates.

In our experiment, we adopt a pie chart as the benchmark to eliminate the influence of redundant dimensional information. The reason is that the central angle of a pie chart increases linearly with the increase in area (the same pattern as the black line in Figure 5).

Table II. Means of the Estimated Rates of Each Group

Actual rate (%)	Estimated Rate of Group A	Estimated Rate of Group B	Estimated Rate of Group C
5.00	7.63*	5.57	6.25*
13.00	18.76*	14.37	13.59
21.00	23.42*	19.92*	22.18
26.00	31.87*	26.53	28.75*
39.00	39.39	37.10*	39.14
50.00	50.68	50.25	53.00*
54.00	57.67*	58.88*	60.00*
67.00	67.71	69.65*	72.05*
75.00	75.13	79.16*	80.48*
92.00	88.58*	91.43	91.39

*Signifies that the estimated value statistically differ from the actual values.

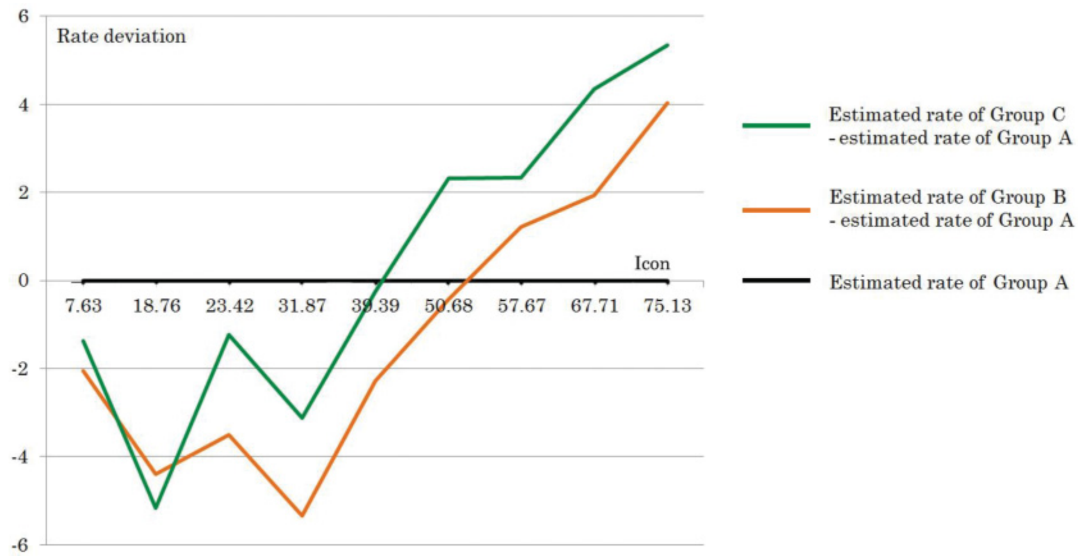


Fig. 6. Estimated rates of the three groups with the estimated rates of Group A as the baseline. The intersecting of Lines A and B suggests underestimation first and then overestimation due to the influences of the areal information on the rate estimation bias. Line C is above Line B, and this condition indicates overestimation because of the influences of the volumetric information.

4.1.2 *Main Study.* We invite 135 participants and divide them into three groups (39 in Group A, 51 in Group B, and 45 in Group C). We ask the participants to play a game called "Guess Rates." The experiment is conducted on the questionnaire platform www.sojump.com. The participants in Groups A, B, and C are presented with Stimulus Groups A, B, and C, respectively. The participants in Group A are advised that the area of the dark green sector in a sign represents the amount of a particular product. The participants in Groups B and C are informed that the *height* of the dark green portion of a sign represents the amount of a particular product. All participants are asked to estimate the rate of a certain product among all the products.

4.1.3 *Results and Analysis.* Table II displays the average estimated rates of each group depicted in Figure 6.

First, we use repeated measurements of the general linear model in SPSS to compare the estimated rates of the three groups. The result shows the significant differences among the three groups ($p < 0.001$). We conduct one sample t-test to compare the estimation accuracy of the participants in each group. Overall, the participants in Group A overestimate the rates, except for 26%, 50%, 67%, and 75% represented by approximately 1/4, 1/2, 2/3, and 3/4, respectively, of the pie chart. The estimations of 26% and 75% correspond roughly to the right angle, that of 50% can be identified by the diameter, and that of 67% can be considered 1/3 of a cycle. These conspicuous features are easy to process and can be used as references during the absence of interfering information. The data show that the rates displayed by the pie charts are estimated with bias when below 40%, and the rates can be estimated accurately when above 40%. This phenomenon can be attributed to the conspicuous features of the pie chart. However, this inference can be misleading because of the lack of further evidence.

Second, we compare the estimated rates of Groups A and B. We divide the rates into two sets: one above 50% and the other under 50%. We conduct repeated measurements for each set. The result shows that, for the sets above 50%, the estimated rates of Group A are significantly lower than those of Group B. On the contrary, for the sets below 50%, the estimated rates of Group A are significantly higher than those of Group B. The intersection of the black and orange lines in Figure 6 is similar to that of the same color scheme in Figure 5. Thus, the areal information contaminates the estimation of the rate defined by height. In other words, H_1 is supported.

Third, we conduct repeated measurements of the general linear model to calculate the difference between Groups B and C. The result shows that the estimated rates of Group B are statistically significantly lower than those of Group C ($p < 0.001$). In Figure 6, the green line is above the orange line for most of the cases. This trend differs from the intersection of the green and orange lines in Figure 5. Thus, volumetric and areal information influence relative rate estimations in different ways. Volumetric information can cause overestimation, while areal information can bias the estimated rates toward the rate by area and result in either overestimation or underestimation. Therefore, the sense of depth elicits overestimation (H_3 and H_4).

4.2 Study 2

Study 1 explores the influence of areal and volumetric information on the estimation of rates defined by height. If volumetric information is extremely challenging to use for estimation, then the users may use areal information as a substitute reference (H_2). Therefore, the curve of their estimation may not be as steep as a cubic curve.

4.2.1 *Stimuli and Main Study.* We adopt the visual stimuli for Group C and advise the participants to estimate the rate by the volume of water filled in the transparent sphere. A total of 42 participants are invited online (also on www.sojump.com) to estimate the rate. The participants who may have participated in previous studies are excluded by their IP addresses. All procedures are conducted exactly the same as in Study 1.

4.2.2 *Results and Analysis.* Table III shows the actual rates by volume in Column 1, the average estimated rates of Study 2 in Column 2, and the estimated rates of Group C in Study 1 in Column 3. The overall results of Study 2 are plotted in Figure 7. In the figure, the vertical axis denotes the estimated rates, and the horizontal axis marks 10 icons.

In general, the curve of the estimated rates in Study 2 is less steep than that of the actual rates. We infer that the estimations of the rates defined by volume are influenced by the areal information. In other words, H_2 is supported. The dotted blue line does not intersect the gray line at 50% but does at nearly 70%. This trend implies that shading generates higher estimated rates than the stimuli without shading (H_4).

Table III. Estimated Rates of Study 2 and Group C in Study 1

Actual Rates by Volume (%) (Gray solid line in Fig. 7)	Estimated Rates in Study 2 (%) (Blue dotted line in Fig. 7)	Estimated Rates of Group C in Study 1 (%) (Green dotted line in Fig. 7)
0.73	5.45	6.25
4.63	12.43	13.59
11.38	20.32	22.18
16.76	27.34	28.75
33.77	38.36	39.14
50.00	51.82	53.00
55.98	58.80	60.00
74.51	71.61	72.05
84.38	79.95	80.48
98.18	91.61	91.39

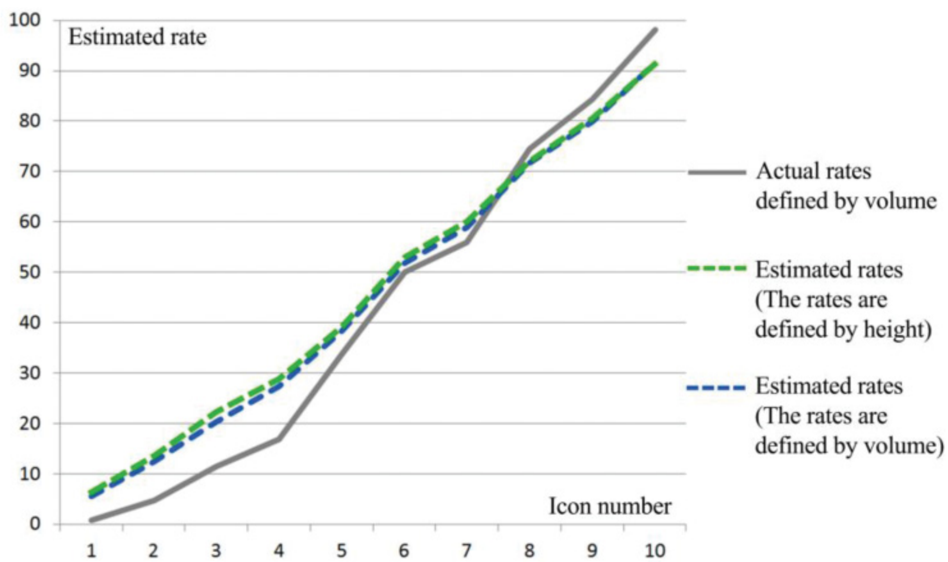


Fig. 7. Results of Study 2. The pattern of the blue and gray lines indicates the effect of shading on overestimation. The nearly overlapping blue and green lines suggest that the estimated rates are the same, although the participants are instructed to adopt different types of dimensional information.

We compare the data collected in Study 2 and those of Group C in Study 1. Surprisingly, the different instructions on the dimensional information for estimation do not generate differences in the estimated rates. The participants who are clearly instructed to estimate the rate relying on volumetric information make no difference from those who are advised to estimate the rate using areal information ($p > 0.1$). The same visual stimuli generate the same estimation, thereby suggesting that the participants fail to compute the volume but rely on the similar method in Study 1.

4.2.3 *Discussion.* Study 1 identifies the effect of areal and volumetric information on the estimation of rates defined by height. Meanwhile, Study 2 provides evidence on the influence of areal and volumetric information on the estimation of rates defined by volume. The two studies confirm that areal information is processed as the baseline for estimations, and visual cue implying 3D information

(a) Volumetrically shaded signs. (b) Flat-shaded signs.

Fig. 8. Visual stimuli for Study 3.

causes ancillary overestimation over such a baseline. The dominant role played by areal information in rate estimation may be attributed to the conspicuous planar nature of visual signs.

4.3 Study 3

Study 3 is conducted for three reasons. First, representative figures can convey information straightforwardly, decrease users' cognitive load to remember the meaning of each visual attribute, [Li et al. 2015], and enhance persuasion. These figures are pervasively used in information visualization [Pandey et al. 2014] but are scarcely studied. Study 3 adopts the signs of wine bottles, unlike the geometric shapes in Studies 1 and 2. A wine bottle is represented by a visual sign as a combination of two rectangles and a trapezoid. Once the visual sign is successfully recognized, the concept of a container is evoked and the estimation is affected.

Second, in Studies 1 and 2, the participants are asked to estimate the rates based on the dimensional information of one sign. In Study 3, the estimation tasks require processing the information of two items.

Third, we manipulate the evaluability of signs by assigning two types of dimensional information to two different meanings. The participants may perform differently in processing the information at different levels of evaluabilities, thereby providing the boundary condition of estimation bias.

4.3.1 *Stimulus Design.* We design a cover story to introduce the meanings of visual attributes. The instructions to the participants are as follows.

John is a young and aggressive businessman. He has to attend business banquets very often. The graphic shows the amount of wine he had in the past two years. The height of each wine bottle indicates the amount of wine he had in a day on average in 2014. Since January 2015, he attended fewer banquets due to a crisis in his industry. The level in dark red in each bottle shows the amount of wine he had in a day on average in 2015.

All participants read the same cover story, and then they are randomly assigned volumetrically shaded signs or flat-shaded signs (Figure 8). The volumetrically shaded signs (Figure 8(a)) highlight the sense of depth, while the flat-shaded signs are the silhouettes of wine bottles (Figure 8(b)). The complex shape of the wine bottle makes the rational calculation more challenging than simple geometric shapes. The amounts of wine in 2014 and 2015 are mapped to different visual attributes, such that the evaluability of dimensional information varies.

4.3.2 *Main Study.* We invite 208 participants (95 are assigned volumetrically shaded signs and 113 with flat-shaded signs) to complete the surveys on www.sojump.com. We ask the participants to observe one of the graphs illustrated in Figure 8 as long as they wish and then answer the following five questions.

Table IV. Estimated Rates of Study 3 and p-Values

	Estimated Rates of the volumetrically shaded signs	Estimated Rates of the flat shaded signs	p-value
Q1	1.97	1.80	0.151
Q2	2.84	2.74	0.534
Q3	2.20	1.93	0.023
Q4	1.59	1.37	0.005
Q5	2.85	2.34	0.025

Q1: How many times did John have the amount of wine on Friday in 2014 as that on Monday in 2014?
Q2: How many times did John have the amount of wine on Saturday in 2014 as that on Friday in 2014?
Q3: How many times did John have the amount of wine on Saturday in 2015 as that on Friday in 2015?
Q4: How many times did John have the amount of wine on Tuesday in 2015 as that on Thursday in 2015?
Q5: How many times did John have the amount of wine on Sunday in 2015 as that on Monday in 2014?

Q1 and Q2 relate exclusively to the heights of the bottles. Q3 and Q4 require extra effort of the participants in estimating the levels of wine. To simplify the estimation, we set the levels of Tuesday and Thursday at the same height (referred in Q4), and the levels of Friday and Saturday at the same height (referred in Q3). If the participants estimate by relying only on the height of the wine levels, then they will report one. Otherwise, the participants will intuitively adopt areal or volumetric information for estimation. Q5 requires the participants to compare the amounts of wine in 2014 and 2015. This challenging task can result in failures of exact volume calculation and forces the participants to use a simple heuristic method to estimate. The participants can assume height as the measurement of rates or as the visual cue implying area or volume, which ultimately determines the rate. We detect what dimensional information does the participants used in their estimation. For this purpose, immediately after answering Q5, the participants are asked to choose a factor (from the three options below) that they used to determine the amounts of wine intake in 2015:

A. The height of the wine level;
B. The area of the wine on the sign;
C. The volume of the wine indicated by the sign.

4.3.3 *Results and Analysis.* The average estimated rates are shown in Table IV. Apparently, the participants who are assigned volumetrically shaded signs report higher rates than those who are assigned flat-shaded signs. Therefore, H_3 is supported. The differences between the estimated rates are significant for Q3–Q5 but not significant for Q1 and Q2. For Q1 and Q2, the height of the bottle measures the rate and is easy to process. However, for Q3–Q5, the visual cues indicating quantities are challenging to process. High evaluability as a boundary condition may help the participants to focus on the target information, avoid the interference from irrelevant information, and attenuate the influences of shading. In particular, for Q3–Q4, the estimated rates of both groups are statistically higher than 1. Thus, the influence of interfering dimensional information is confirmed.

The efforts in solving Q5 involve processing the bottle heights and the wine levels. The participants report their usage of the dimensional information for estimating the amount of wine in 2015; specifically, 30.6% of the participants select "the height of the wine level," 19.9% select "the area of the wine on the sign," and 49.5% select "the volume of wine indicated by the sign." Q5 can be regarded as a (linear, areal, volumetric) $\times$ (volumetrically shaded signs, flat-shaded signs) between-subjects

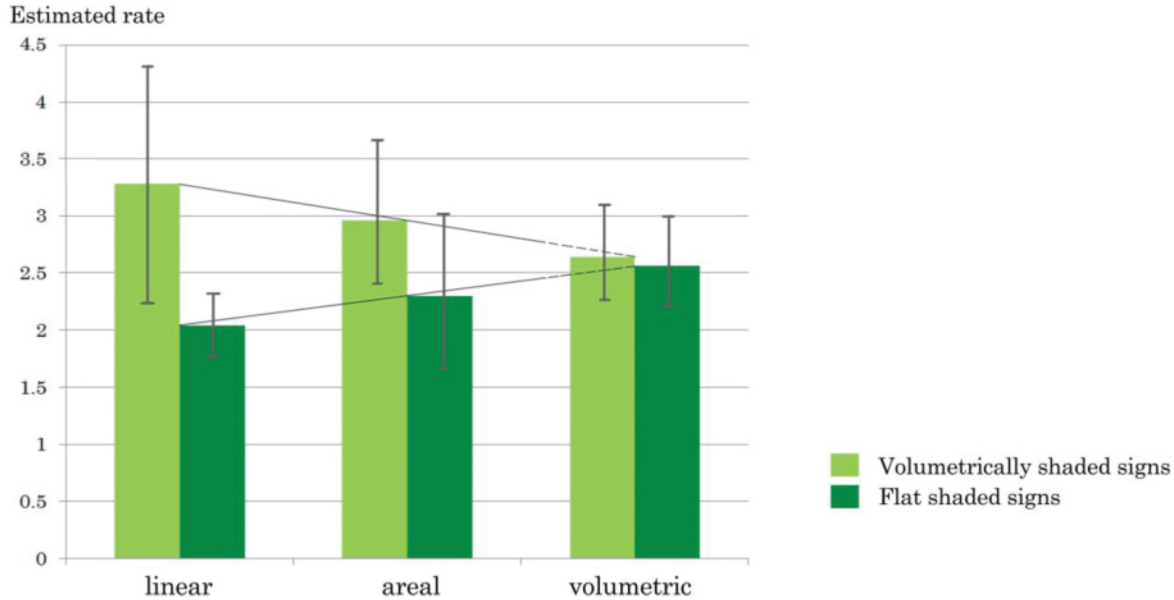


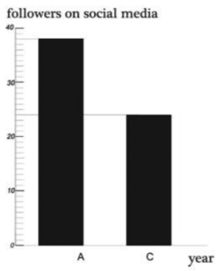
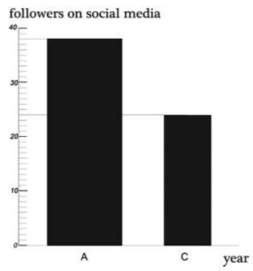
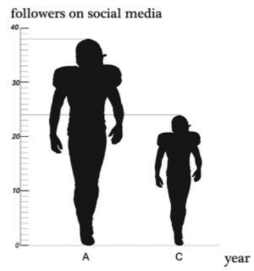
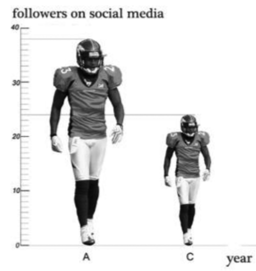
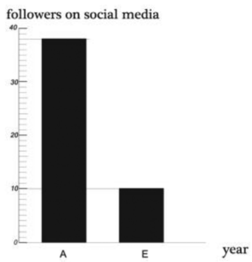
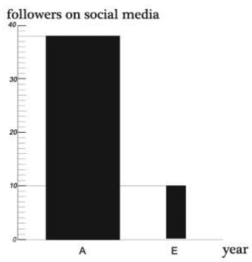
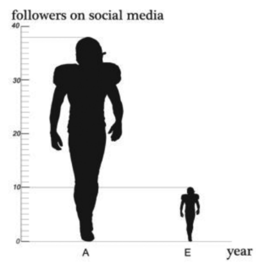
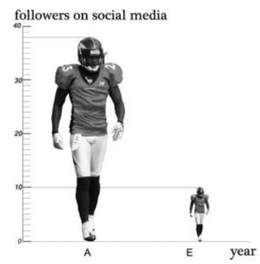
Fig. 9. Average estimated rates of the volumetrically shaded signs (light green bars) and the flat-shaded signs (dark green bars) for Q5. The pattern of Figure 9 implies the interaction effect of shading and adopts the dimensional information for estimation. The participants who adopt low-dimensional information to determine the amount of wine intake in 2015 report high average values for 3D signs and low average values for silhouette signs. When the participants adopt 3D information for estimation, the two groups show no statistically significant difference.

experiment. We compute the average estimated values of six groups as depicted in Figure 9. Furthermore, we use MODPROBE in SPSS to explore the influences of the adopted dimensional information on the estimated rates [Hayes and Matthes 2009]. The result confirms a significant positive main effect of shading on the estimated rates ($b = 0.63$, SE $= 0.23$) with a 95% confidence interval of 0.17 to 1.08. The interaction of shading and adopted dimensional information has a significant effect on the estimated rates ($b = -0.59$, SE $= 0.26$, $\Delta R^2 = 0.02$, $F(1, 205) = 5.19$, $p = 0.02$), with a 95% confidence interval of -1.09 to -0.08 [Hayes 2013]. Moreover, high-dimensional information has a negative effect on the estimated rates of the volumetrically shaded signs, whereas a positive effect on the estimated rates of the flat-shaded signs.

We use the Johnson-Neyman technique to explore the difference between the two groups when different types of dimensional information are adopted to estimate the rates. The Johnson–Neyman technique calculates the focal point, the transition point between the significant and non-significant effects of an independent variable on the dependent variable, and provides the regions of insignificance associated to the test of the difference between the two treatments [Johnson and Fay 1950]. The results show that the estimated rates of signs in the two treatments significantly differ when adopting linear and areal information but do not significantly differ when using volumetric information.

For Q5, the estimated rate should be less than 1.003, regardless of the dimensional information used to calculate. The participants in both groups overestimate, and the shading causes great overestimations. Basically, estimations using low-dimensional information are likely to be influenced by shading. Specifically, when high-dimensional information is adopted, overestimations on volumetrically shaded signs are attenuated, but overestimations on flat-shaded signs are exaggerated.

Table V. Stimuli for Study 4

Stimuli for Group 1	Stimuli for Group 2	Stimuli for Group 3	Stimuli for Group 4
			
Q1: How many times of followers does Dennis have in year A over those in year C??			
			
Q2: Dennis was paid 100,000 US dollars in Year E as an endorser for a certain brand. Given that the number of followers on social media is an important indicator of the endorsement amount, how much endorsement will Dennis be paid in Year A?			

4.3.4 *Discussion.* The results of Study 3 provide evidence on the influence of shading as the visual cue of 3D information on estimation (H_3 and H_4). Meanwhile, this study conducted the following tasks:

- tests using the representative signs to extend the scenario;
- indicates the role of evaluability in the influences of dimensional information; and
- explores the different effects of shading on rate estimation using height, area, or volume information.

4.4 Study 4

In Study 4, we extend the estimation scenario by clearly marking the numerical values. We also evaluate the robustness of the previous conclusions, compare the influences of representative and non-representative signs on the estimation bias, and discuss the moderation effect of vividness of representative signs.

4.4.1 *Stimulus Design.* Study 4 tests the influence of vividness on the relative value estimations. We design four types of stimuli for the participants in Group 1–4 (Table V). These types are (1) typical bar charts, (2) modified bar charts in which all bars have a constant height/width ratio, (3) modified bar charts in which each bar is replaced by the black silhouette of a football player, and (4) modified bar charts similar to those in (3) but using a black-and-white image of a football player with much detail.

The visual signs for Group 1 still have a constant width, while those for Groups 2–4 have a constant height-width ratio. Stimuli 1 and 2 are nonrepresentative signs, while Stimuli 3 and 4 are

Table VI. Results for Each Group of Study 4

		Group 1	Group 2	Group 3	Group 4
Q1	Mean	2.91	3.52	3.73	3.58
	p	.138	.550	.715	
Q2	Mean	55.69	67.07	76.89	62.14
	p	.094	.088	.002	

representative signs. The latter are supposed to easily activate the imagery of a real person, thereby implying 3D information. We select the image of an American football player as a representative sign, given that the Chinese participants are unfamiliar with American football. They must exert a little effort to understand the visual signs, such that the manipulation of vividness can be facilitated by arranging details. Stimuli for Group 4 are more vivid than those for Group 3. Rich details of the vivid signs may strengthen the concept of a player, rebuild the scenario of height comparison between persons (usually adults and kids), and avoid the abuse of 3D information.

In addition, we clearly mark the numerical value of each sign on a scale to explore the estimation bias when numerical values are given. Such a boundary condition has not been tested in Study 1–3, in which the estimations are exclusively based on visual features. Furthermore, we arrange different levels of information sufficiency for each question. With sufficient information for problem solving, Q1 can be answered by simply performing division using the given numbers in the diagram. Visual signs play the role of redundant dimensional information to induce the relinquishment of mathematical calculations. By contrast, sufficient information is unavailable to solve Q2. In particular, the participants are required to estimate using visual stimuli for inferences.

4.4.2 *Main Study.* A total of 271 participants completed the online survey (45, 83, 80, and 58 participants in Groups 1–4) after being informed of the following cover story:

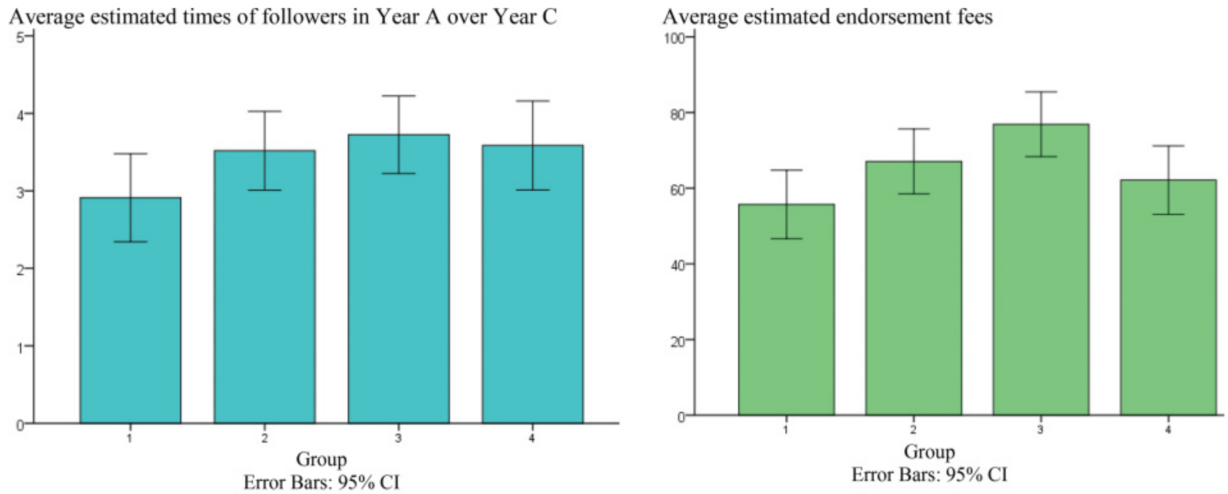
Dennis is a football player in Country Z. He has become famous in recent years for his excellent performance. To launch new products in the foreign market of Country Z, your company is planning a sponsorship deal with Dennis. You are appointed to execute relevant businesses. A third-party consulting company provides you a diagram of Dennis' performance on social media in the past 5 years (marked as A–E). The vertical axis indicates the number of Dennis' followers on social media (the unit is ten thousand). The horizontal axis indicates the year.

The participants are asked to answer two simple questions. The questions and visual stimuli for each group are shown in Table V.

4.4.3 *Results and Analysis.* Table VI shows the results for four groups. Figures 11 and 12 visualize the averages of the estimated relative values.

For Q1, if the participants estimate logically (i.e., exclusively using the given numerical values in the diagram), then the answer is 1.85. We conduct one sample t-test for each group. Consequently, the estimated values of the four groups for Q1 are significantly higher than 1.85 ($p = 0.000$). For Q2, if the number of followers on social media is considered the only indicator of the endorsement amount, then the answer to Q2 is 38. As a result, the estimated values of the four groups for Q2 are significantly higher than 38 ($p = 0.000$). Therefore, the participants overestimate possibly because of visual attributes.

The answers of the four groups to the two questions show similar patterns. However, the differences in the estimated values between the groups for Q1 are insignificant ($p = 0.25$), whereas those for $Q2$



(a) Results for Question 1 (b) Results for Question 2

Fig. 10. Results of Study 4.

are significant ($p = 0.012$). This finding indicates the influences of visual attributes when numerical information is insufficient.

For Q2, the p-value in Table VI shows (marginal) the differences in estimated values among the groups. We explain the following three results.

- The average estimated values of Group 1 are lower than those of Group 2 ($p = 0.012$), indicating that the areal information as the redundant information influences the estimation of the rate defined by height (H_1).
- The average estimated values of Group 2 are marginally lower than those of Group 3 ($p = 0.088$), indicating that the player silhouette can enhance the influence of 3D information on overestimation by activating the concept of a person.
- The average estimated values of Group 3 are higher than those of Group 4 ($p = 0.002$), indicating that high vividness depresses the overestimation that resulted from redundant 3D information.

Furthermore, we conduct a crosstabs chi-square test to explore the moderation effect of vividness in the influence of dimensional information on relative value estimations ($p = 0.000, T = 9.8 > 5$). The results support the moderation effect of vividness. In particular, using the representative signs can increase overestimation, but high vividness of representative signs depresses overestimation.

4.4.4 *Discussion.* The results show that, when numerical information is insufficient, the participants are likely to estimate using somehow relevant visual features. The comparison of the estimated values based on nonrepresentative and representative signs (stimuli for Groups 2 and 3) confirms the influences of visual representativeness. An abstract sign (e.g., a bar) gains meaning through assigning, while a representative sign carries its meaning inherently. Having intuitively understood the meaning of a representative sign, the participants easily access to the imagery of a 3D entity, with little effort to elaborate the attached text. Therefore, 3D information activated by the meaning of a visual sign enhances overestimation (H_3). Furthermore, this effect of representative signs may be moderated by vividness. The stimuli for Groups 3 and 4 are both representative but differ in vividness. The rich details of the visual signs for Group 4 activate the imagery of a player on a sports field and the experiences of height comparison in daily life. Accordingly, understanding of the mapping between the height and the number of followers on social media is facilitated. Therefore, the comprehensive knowledge activated by high vividness of representative signs attenuates overestimation.

5. GENERAL DISCUSSION

We empirically provide evidence to support our hypotheses across all four experiments. Specifically, we use two types of icons in Studies 1–3 to explore the dominant role of areal information in the estimation of rates defined by height or volume (H_1 and H_2) and to prove that 3D information can elicit overestimation of rates defined by height or areal information (H_3 and H_4). Study 4 discusses the influences of representability and vividness on rate estimation (H_5) and provides further evidence of the robustness of our conclusions. This research contributes to the literature of numerosity by exploring the use of visual dimensional information.

Prior literature has documented the ambiguous meaning of a visual sign [Messaris 1996]. Perceptual bias cannot be eliminated, even when the mapping between visual attributes and meanings are well known. In other words, grammatical correctness of a visual sign cannot guarantee high accuracy in communication. However, extant literature has failed to explicitly explain the way in which redundant dimensional information produces perceptual bias in relative value estimation. To contribute to existing literature, the first three studies explore the limited accuracy of relative value estimations and indicate diversified influences of areal and volumetric information. Specifically, people are inclined to adopt areal information to estimate a rate defined by height-width and volume, and overestimate as the response to 3D information or its visual cues. We identify the target dimensional information from the redundant ones, discern over- or underestimation, unveil the causalities between visual attributes and their cognitive consequences, and provide empirical evidence on visual information processing to the mechanism of perceptual bias.

Our research also indicates the boundary conditions of perceptual bias in relative value estimation. The results show that information sufficiency may enhance estimation accuracy. Furthermore, the influence of 3D information is enhanced when low-dimensional information is adopted for estimation. These findings enrich the literature on heuristic visual information processing and improve understanding of visual languages.

Study 4 provides insights into the influences of representative visual signs. Hsee et al. [2005] tested the donation amount to endangered pandas while presenting the pandas as dots or pictures. The respondents donate significantly more when shown pictures of adorable pandas than when shown dots. However, when the number of pandas and dots equally increase, the amount of donations does not proportionally increase. They indicated that pictures evoke emotion but the participants are insensitive to numbers. Apart from emotional influences, our research investigates the impacts of vivid representative signs on concept activation and imagery provoking and then on relative value estimation.

In business communication, reading visualized information has become an indispensable skill. Human beings are usually assumed "born to read images." However, biased estimation due to the lack of training and ignorance of visual perception science may lead to undesired consequences. The understanding of perceptual bias and heuristic information processing provide implications to human–machine interactivity in information visualization and enhance the prudence in decision making. On the one hand, designers can apply the conclusions of our research to manipulate dimensional information and strengthen the power of persuasion. On the other hand, users should bear the potential of perceptual bias in their mind, be cautious when estimating relative values, and avoid misjudgment.

Visual deception in information visualization may be assumed as the consequences of deliberate manipulation. Moral advocators allow zero tolerance for any deceptions. However, in reality, the priority of the design objectives and the tradeoffs among multiple visual attributes challenge the proposition of zero deception. For example, in a design displaying multiple variables, the intention to accurately convey one variable possibly induces perceptual bias for other variables. In other cases, designers may intentionally bias certain attributes to emphasize certain features [House et al. 2006]. Apart from objective reasons, viewers' comprehensive ability may also influence the accuracy of information interpretation. As a result, the absolute accuracy of visual communication is cherished but unachievable. Awareness of the unattainable absolute accuracy may help designers in adjusting their goal of designs.

6. FUTURE RESEARCH

The prevalence of perceptual bias has been indicated in this research; thus, future research may provide auto- or semi-automated software solutions to arrange visual attributes, avoid the consequences of perceptual bias, and support accurate estimations. Highly empirical evidence of the perceptual bias on processing various visual signs is needed for potential automated solutions.

We discuss the evaluability of visual signs, information sufficiency for problem solving, and transparency of semantic meanings in Studies 3 and 4. Low evaluability, information insufficiency, and low transparency of semantic meanings imply fewer cognitive resources available for information processing. Further studies can explore the influences of cognitive resources on the perceptual bias of relative value estimation.

In Study 4, we ask participants to estimate the relative values of two given signs. In practice, designers may use many representative signs in one graph. The relative value estimation between two signs may be influenced by the position and other surrounding signs. This influence requires further investigation.

Persuasion is one of the most important goals of visual communication. Future research may explore whether users will notice their high possibility of perceptual bias and the way in which users will evaluate their own judgments and decision makings before and after they realize the inevitable inaccuracy. The influences of other visual features on persuasion, fluency of information processing, and trust on the conveyed information can be further explored.

Future research may focus on a special phenomenon relevant to value estimation based on dimensional information, that is, perceptual bias caused by cartographic information. In the time of globalization, an increasing amount of decision making involves worldwide geographic information. Cartographers have developed multiple methods to project the surface of Earth onto a two-dimensional space, thereby leading to inevitable distortions. For example, on a map of cylindrical projection, the high-latitude area is perceived much bigger than the low-latitude area. The size of Greenland (high latitude, near the Arctic Ocean) is perceived to be the same as that of Australia. In fact, Greenland is approximately one-third of Australia in size. For another example, an airline route from Beijing, China, to Chicago, USA, is usually drawn on an America-centered map by connecting the two cities across the North Atlantic Ocean rather than the Arctic Ocean [Zhang et al. 2016]. A 2D display space provides a default framework for problem solving, thereby impeding the imagery of a sphere, which demonstrates geographical information in a 3D space. The distortion as a result of the projection from a sphere to a 2D surface has been well documented; however, the consequences of decision making based on cartographic information are scarcely discussed. People have realized the possibility of lies by words. Nevertheless, the over-confident belief that "seeing is believing" may underestimate the importance of in-depth investigation on visual deceivability. Research on this topic can extend the understanding on the "framing effect" caused by visual attributes.

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