MediVizor: Visual Mediation Analysis of Nominal Variables

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Abstract—Mediation analysis is crucial for diagnosing indirect causal relations in many scientific fields. However, mediation analysis of nominal variables requires examining and comparing multiple total effects and their corresponding direct/indirect causal effects derived from mediation models. This process is tedious and challenging to achieve with classical analysis tools such as Excel tables. In this study, we worked closely with experts from two scientific domains to design MediVizor, a visualization system that enables experts to conduct visual mediation analysis of nominal variables. The visualization design allows users to browse and compare multiple total effects together with the direct/indirect effects that compose them. The design also allows users to examine to what extent the positive and negative direct/indirect effects contribute to and reduce the total effects, respectively. We conducted two case studies separately with the experts from the two domains, sports and communication science, and a user study with common users to evaluate the system and design. The positive feedback from experts and common users demonstrates the effectiveness and generalizability of the system.

Index Terms—Information Visualization, Visual Analytics, Exploratory Causal Analysis, Mediation Analysis

1 Introduction

Mediation analysis is necessary for scientific researchers to identify direct and indirect causal effects underlying a wide range of phenomena [1], [2], [3]. When an independent variable (IV) is observed to have a causal effect on a dependent variable (DV), it is often considered a direct effect. However, it is also possible that the IV affects a mediating variable (MV), which in turn influences the DV. This indirect effect is what mediation analysis aims to identify, along with whether it is stronger than the direct effect and the main cause of the total observed effect [4]. Analysts usually employ a model (linear or nonlinear) to estimate the total and direct/indirect effects among three variables and then explore the effects to derive insights.

However, mediation analysis of nominal variables requires examining and comparing complex total, direct, and indirect effects, which are difficult to achieve by domain analysis tools such as Excel tables. When the IV, DV, and MV are nominal variables, each of them is decomposed into multiple dummy variables for mediation analysis. For instance, we assume the IV is *family composition* (Its values include a single parent with a child, two grandparents with a child, and so on), the DV is *when the family watches TV* (Its values include morning, afternoon, and evening), and the MV is *the type of the TV channel the family watches* (Its values include news, entertainment, sports and so on). In this case, the IV, DV, and MV are nominal variables and each needs to be decomposed into many dummy variables. For instance, the IV *family composition* needs to be decomposed into whether the family composition is *a single parent with a child or not*, *two grandparents with a child or not*, and so on. In this way, the original IV, DV, and MV are decomposed into multiple derived IVs, DVs, and MVs. Each pair of IV and DV has a direct effect and multiple indirect effects through different MVs, which compose the total effect. It is required to browse and compare the many total and direct/indirect effects among the multiple IVs, DVs, and MVs no matter which model is used to estimate the effects[1]. Experts in scientific fields employ multiple tables to present these effects [5] or simply list all effects in a table regardless of whether particular effects share the same IV/DV/MV [6], [7], leading to tedious and error-prone analysis processes.

Interactive visualization designs have provided new possibilities for exploratory and comparative data analysis in many domains [8], [9], [10], [11], [12], [13], [14]. Besides, visualization systems have contributed to a causal analysis by helping users preprocess the data [15], adjust the causal structure [16], and present the complex causal effects [17]. However, these systems cannot support the analysis of mediation effects among nominal variables, which presents two major challenges. (1) The first one is how to browse and compare the total and direct/indirect effects among multiple IVs, DVs, and MVs efficiently. There are total effects among multiple IVs and DVs and each total effect is composed of a direct effect and multiple indirect effects through multiple MVs. It is required to examine and compare how different total effects are composed of direct/indirect effects while preserving their context information (e.g., the IVs and DVs that the total effects are between), which is difficult. (2) The second one is how to present the ratio of each direct/indirect effect versus its corresponding total effect. Positive and negative direct/indirect effects offset each other when they are added up to a total effect. The size of the total effect can be smaller than the size of an

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1. It should be noted that we need to analyze multiple IVs, DVs, MVs, and effects because nominal variables are decomposed into multiple dummy variables for mediation analysis. No chains of MVs are considered in this study

indirect effect it contains. It is hence difficult to present the part-to-whole ratios.

In this study, we seek to fill the gap in the visual mediation analysis of nominal variables. We interview experts in two scientific domains with mediation analysis experiences and summarize their requirements. We then propose a visualization design, the effect view (Fig. 3A), to solve the challenges. To solve the first challenge, we present the total effects between many IVs and DVs in a matrix view. We then use leader lines with a particular layout to link each total effect with the multiple indirect effects that compose it and the corresponding MVs in a bar chart. To solve the second challenge, we propose a heuristic design, a paired pie chart, to present the part-to-whole ratios when there are positive and negative parts. Moreover, we propose MediVizor (Fig. 3), a visualization system that allows users to explore and validate the mediation effects among nominal variables interactively. We invite experts from two scientific domains to evaluate the system and report two case studies. The main contributions of this study are as follows:

- Requirements synthesized from interviews with four experts from sports and communication science for analyzing the mediation effects of nominal variables;
- A visualization system, MediVizor, for exploring the total and direct/indirect effects among nominal variables in a systematic way;
- Two case studies with experts that demonstrate the augmented capacity of mediation analysis of nominal variables using the system.

2 Related Work

In this section, we review and discuss relevant literature on mediation analysis and visualizations of causal relations.

2.1 Mediation Analysis

Mediation analysis assesses whether a direct relationship between two variables, A and B, is spurious because A influences a third variable, C, that in turn affects B. It has both methodology significance (e.g., how to calculate the mediation effects) and theoretical significance (e.g., how to frame the causal relations in a phenomenon) [4]. Mediation analysis with a continuous MV and DV is easier to model, understand, and present compared to that with a nominal MV and DV. It is because a continuous MV/DV can only vary in one direction while a nominal MV/DV can vary among multiple categories. Nevertheless, statistical methods and tools for the mediation analysis of a nominal MV and DV are increasingly available [18], [19].

However, presenting and analyzing the effects output by a model remains a challenge. Each nominal IV, DV, and MV is decomposed into multiple dummy IVs, DVs, and MVs. It is then required to examine the total and direct/indirect effects among the many variables, and how the positive and negative direct/indirect effects compose the total effect. Previous studies in scientific fields have used multiple tables to display the mediation effects among nominal variables [5], which can be inefficient. This study aims to address this issue by developing a visualization system.

2.2 Visualization of Causal Relations

Theoretical studies explore the empirical problems of whether visualization could enhance the perception of causality and causal semantics [20], [21], [22], [23], [24], [25]. Yen et al. [20] and Kale et al. [21] investigated whether a visualization view (e.g., a bar chart or scatterplot) could enhance the perception of causality. Xiong et al. [22] explored to what extent users perceive causality or correlation from different visualizations. Besides, Kadaba et al. [23], [24] tested whether animation can enhance the representation of causality. Elmqvist and Tsigas [25] tested whether a new design, i.e., animated growing polygons, can enhance the perception of the transmission of causal effects in a causal structure compared to causal diagrams.

Visual causal analysis has also been investigated in application studies. Two visualization studies investigate how to integrate visualization techniques into the preprocessing, such as feature subset selection, before causal analysis [15], [26]. Some other studies examine the visualization and interactive adjustment of automatically generated causal diagrams [27], [28], [29]. Additionally, some studies [16], [30], [31], [32] aim to visualize the complex causal structure among multiple variables in a comprehensible and navigable manner. Wang and Mueller propose a set of designs that are specially intended for visualizing the time delay in causal relations [33]. Further studies investigate visual analytics of causal effects in diverse contexts, such as social media, urban analysis, games, air quality, and online learning [17], [34], [35], [36], [37], [38], [39].

However, previous studies on visualization applications inadequately address visual mediation analysis, which is a crucial elaboration of causal analysis. Two visualization systems, Outcome-Explorer [32] and Causality Explorer [16] support visual analytics of multi-step effects among multiple variables. A mediation effect is also a kind of multi-step effect. But mediation analysis focuses on how the total effect of an IV on a DV is composed of different direct and indirect effects. The two systems only present each direct/indirect effect individually, without indicating which group of effects should be regarded as a total effect and which effects should be compared as they consist of the same total effect. New challenges of visual mediation analysis include enabling the examination and comparison of multiple total effects together with the direct/indirect effects that compose them.

3 Informing The Design

This study is the result of a long-term collaboration between four experts in sports and communication science and us. These experts employ mediation analysis as an essential analysis method for investigating causal relations behind phenomena in their fields. Two sports science experts, including an authority in analyzing table tennis techniques and tactics (E1), and a postdoctoral researcher and senior analyst of table tennis data (E2), employ the mediation model to analyze players' techniques and scoring behaviors. The other two experts, both experienced in using mediation models to analyze communication phenomena, are from communication science, including a Ph.D. (E3) and a senior Ph.D. student (E4).

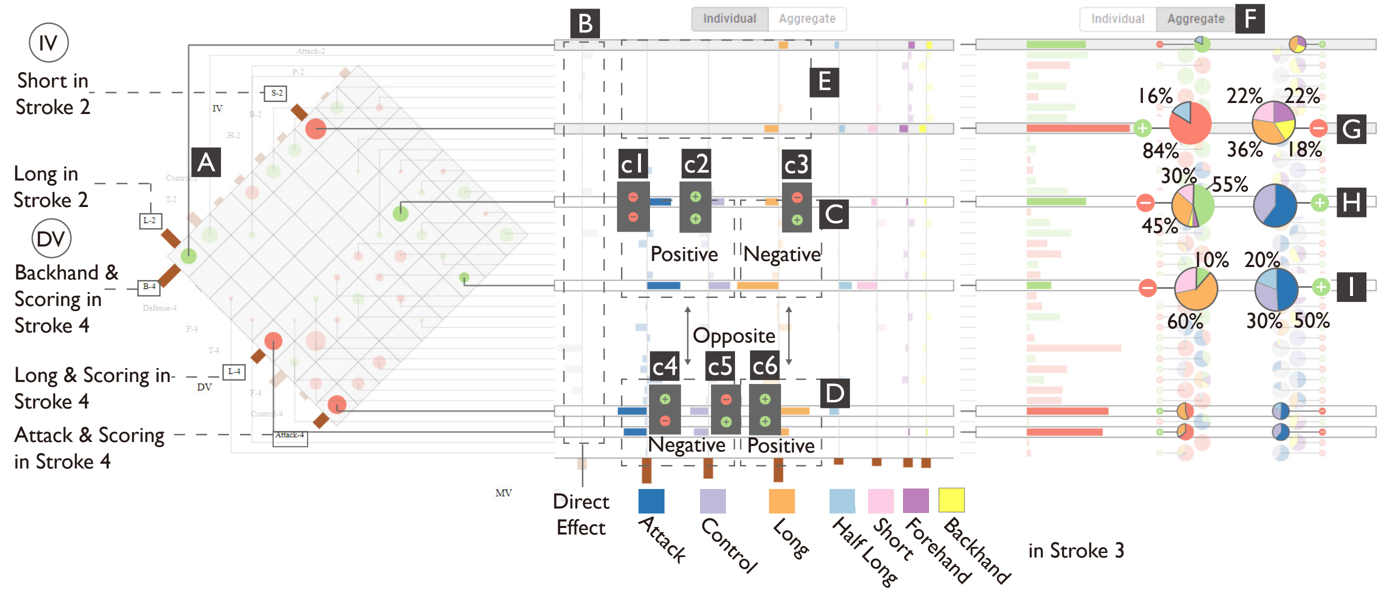

Fig. 1. (A–E) illustrate the analysis process in the case study in Section 6.1.1. (A) illustrates that the experts selected the total effects of *Short* and *Long* in Stroke 2 on *Backhand & Scoring*, *Long & Scoring*, and *Attack & Scoring* in Stroke 4. (B) illustrates there are no direct effects in these total effects. For the effects on *Long & Scoring* and *Attack & Scoring* in Stroke 4, (C) and (D) illustrate that the polarity of the indirect effects of *Short* and *Long* in Stroke 2 are opposite. For the effects on *Backhand & Scoring* in Stroke 4, (E) illustrates that the opposite indirect effects are mainly through *Long* in Stroke 3. (F–I) illustrate the analysis process in the case study in Section 6.2.1. (F) illustrates that the expert switched the button to examine the paired pie chart. (G), (H), and (I) illustrate how total effects of *Short* in Stroke 2 are composed of positive and negative indirect effects through different variables in Stroke 3.

We conducted two semi-structured interviews with the sports and communication science experts, respectively, asking the experts about their experiences and difficulties with conducting mediation analysis of nominal variables. Additionally, we observed their approach to conducting such analysis in their respective fields.

The sports experts analyze players' strokes using mediation analysis, which involves nominal variables such as stroke techniques and ball positions. To conduct this analysis, each variable is decomposed into multiple dummy variables. For instance, the stroke technique is decomposed into whether the technique is *attack or not*, *control or not*, and *defense or not*. The analysis results are typically presented using tables, which allow for analyses of one MV and one DV at a time. However, when there are multiple MVs and DVs, multiple tables are used, which can lead to oversights and make it difficult to find valuable effects and compare them among different variables. The communication experts often face similar challenges when analyzing nominal DVs and MVs with multiple values, such as nationality, race, and media type. To analyze the mediation effects, they must review numerous tables. Typically, they first analyze total effects before examining direct and indirect effects.

To identify the requirements better, we also conducted a meeting and let one communication expert discuss the requirements with the two sports experts. A designated note-taker documented the interviews and discussions. We synthesize the requirements of the mediation analysis of nominal variables proposed by at least one expert from each field as follows.

R1 ***Compare total effects between one or more IVs and DVs and their corresponding direct/indirect effects and MVs.*** The experts require an overview that enables them to **examine and compare the total effects between all IVs and DVs at a glance (N1)**. In the overview, they can quickly find the strong total effects and locate the effects between particular IVs and DVs. The experts also need to **examine and compare the indirect effects and MVs in the total effects (N2)**.

R2 ***Compare direct and indirect effects that compose a total effect and examine the ratios of them versus the total effect.*** The experts require to **compare the direct/indirect effects in a total effect (N3)** to find out the strongest indirect effect and its corresponding MV. Experts also need to **examine the part-to-whole ratios of the positive and negative direct/indirect effects versus the total effect (N4)** to understand their contributions to the total effect.

R3 ***Compare indirect effects mediated by one or more MVs and examine the IVs and DVs that the MVs mediate.*** Different total effects might contain indirect effects mediated by the same MV. The experts need to **compare indirect effects through the same MV (N5)** and **examine the IVs and DVs involved (N6)**. This information helps experts understand how an MV mediates the effects between various IVs and DVs.

R4 ***Analysis order and validation.*** The experts require that **the mediation analysis should be conducted in a specific order (N7)**. The total effects should be examined first. The direct and indirect effects within the same total effect are then investigated. The indirect effects mediated by the same MV are compared finally. As the mediation effects are calculated by the statistical model and are not intuitive, experts hope to **validate the identified interesting indirect effects**

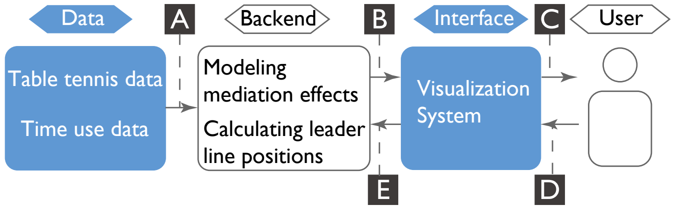

Fig. 2. The workflow of the system. The raw data is sent to the backend (A). The total and direct/indirect effects output from the mediation model are presented in the visualization system (B) and a user can analyze and compare the effects visually (C). The user can also adjust the number of displayed effects (D) and the backend calculates the layout of the visualization accordingly (E).

through the conditional frequency distributions of relevant variables (N8).

4 Modeling Mediation Effects

In this section, we introduce how to model the mediation effects among nominal variables in the raw data.

Estimation of Total and Direct/Indirect Effects. Three nominal variables, IV, MV, and DV, are decomposed into three sets of dummy variables $\{IV_1, IV_2, ...IV_m\}$, $\{MV_1, MV_2, ...MV_n\}$, $\{DV_1, DV_2, ...DV_l\}$ before analysis. We estimate the mediation effects among the dummy variables using a general approach proposed by Imai et al. [18], which has been implemented in R [19] and Python. We calculate the direct and indirect effects among each triad $\{IV_i, MV_j, DV_k\}$, where i ranges from 1 to m, j ranges from 1 to n, and k ranges from 1 to l. When estimating the effects of a specific triad $\{IV_i, MV_j, DV_k\}$, we use other IVs and MVs as control variables. The approach outputs the estimated coefficients for the direct and indirect effects and their significance. We use the general linear model as the outcome and mediator models and the logit function as the link function because the DVs are dummy variables.

An estimated effect is an odds ratio (OR, which is the ratio between the odds that a DV is one when the IV is one and the odds when the IV is zero. As the interpretation of an odds ratio is not straightforward, we transform the odds ratio into the changed probability ($P_{changed}$) of DV being one when the IV is one compared to that the IV is zero.

$$O_B = OR * O_A = OR * P_A/(1 - P_A)$$

$$P_{changed} = P_B - P_A = O_B/(O_B + 1) - P_A$$

where the P_A and O_A represent the original probability and odds that a DV is one. We use the variable's frequency in the data as the original probability. The P_B and O_B represent the probability and odds the DV is one after the direct/indirect effect of the IV varying from zero to one. We use the calculated changed probability of the DV being one to measure the direct/indirect effect on the DV, and the sum of direct and indirect effects as the total effect.

Are the Effects Comparable? A question to ask is whether the effects are comparable. If multiple continuous IVs, DVs, and MVs are involved, their effects cannot be compared due to the different variable units. In the analysis of nominal variables, however, the effects are among dummy variables. The effect size represents the pure changed probability that a dummy variable equals one if another dummy variable is yes versus no. The unit of any IV is yes or no and the unit of any DV is the changed probability, and the unit of every effect is hence the same. Therefore, all effects are comparable practically.

Are the Effects Additive? The effects from different IV_i and through different MV_j are additive and can be interpreted as the total effects of multiple IVs on the DV. The indirect effects from an IV_i on a DV_k through different MVs can be added up to obtain the total effect of IV_i on DV_k. The effects on different DV_k are not additive because their sum is meaningless.

5 System Design

The workflow of this system is shown in Fig. 2. A user first selects a dataset with nominal variables for analysis (Fig. 3a-1) and sends it to the backend (Fig. 2A). The backend model processes the variables into dummy variables and calculates the direct and indirect effects (as introduced in Section 4). The derived effects are then presented in the visualization system for analysis (Figs. 2B and 2C). The user can examine the raw data in the variable view (Fig. 3B) for anomalies. In the effect view, the user can browse and compare different total effects in the matrix (Fig. 3a4). Besides, the direct/indirect effects that compose the total effects are presented in the bar chart (Fig. 3a5) and are directly linked with the total effects with leader lines to support comparison of total effects together with their direct/indirect effects. The user can filter small total effects (Fig. 2D) in the system (Fig. 3a2) and the backend calculates leader line positions accordingly (Fig. 2E). The user can also switch (Fig. 3a3) the bar chart to the paired pie chart (Fig. 3a6) to examine how the positive and negative direct/indirect effects contribute to the total effects. Finally, the user can validate each indirect effect by clicking it and examining the conditional frequency distributions in the validation view (Fig. 3C). The workflow of the system is specially designed for the required analysis order of mediation effects, i.e., from total effects to indirect effects (N7). Users can explore the total effects in the matrix view first, and then explore their indirect effects in the bar and paired pie charts conveniently using the system. The system is implemented through React.js. Positive and negative effects are color-coded in green and red, respectively.

5.1 Effect View

We divide the effect view design into two parts, linking total effects to their corresponding direct/indirect effects and presenting the ratios of positive and negative direct/indirect effects versus a total effect. We present the design for each part, followed by a discussion of the design process.

5.1.1 *Linking Total Effects to Direct/Indirect Effects*

Designs. The designs aim to support the examination and comparison of the total and direct/indirect effects among multiple IVs, DVs, and MVs (R1, R3). We present the total effects of multiple IVs on multiple DVs (N1) using a matrix view (Fig. 3a4) on the left of the effect view. The row and column titles of the matrix represent different IVs and DVs.

Fig. 3. The user interface of MediVizor. (A) is the effect view that supports the analysis and comparison of the total and direct/indirect effects. (B) is the variable view that supports the examination of the distributions of the variables analyzed in the system. (C) is the validation view that supports the validation of an interesting indirect effect identified in the effect view using the conditional frequency distributions of relevant variables.

Each entry in the matrix presents the total effect between the corresponding IV and DV. The area of the circle in an entry encodes the size of the total effect and the color hue encodes whether the effect is positive or negative. Users can browse the matrix to detect strong total effects or find a total effect through its IV and DV. Additionally, a bar is provided for each IV or DV, encoding the average size of the total effects associated with that variable, to aid users in navigating into interesting total effects.

For each total effect represented by a circle, we link it to its direct and indirect effects represented by bars in a bar chart using leader lines(Fig. 3a5). The bar chart is placed on the right of the effect view and each row corresponds to a total effect. The first column presents the direct effects, while the subsequent columns display the indirect effects mediated by MVs. In each column, we use a bidirectional bar chart to represent the positive and negative effects. The positive effect is on the right side and the negative effect is on the left side. The direct effect and indirect effects mediated by different MVs are distinguished by color hues, which are different from those representing polarity. We assign color hues based on a qualitative color scheme (as shown in the legend in Fig. 1), which is initially generated by a color tool [2] and further improved by the experts and us. There are ten color hues in the effect view in total. If more MVs need to be displayed, we repeat the colors or use similar colors for the MVs with similar meanings. A bar is provided for each MV, encoding the average size of the indirect effects associated with the MV, to help users navigate into interesting indirect effects. A bar is also provided for the direct effects. Users can compare direct and indirect effects within a total effect row (N3) and compare indirect effects mediated by the same MV within a column (N5).

Leader lines are employed to link each total effect in a matrix entry to a row in the bar chart that presents the direct and indirect effects in the total effect. To minimize their lengths and prevent them from crossing, we use one-sided boundary labeling algorithms [40] to calculate the leader line layout. The algorithm constructs a complete weighted bipartite graph between all matrix entries and rows, where the weight of each edge represents the length of the leader line. It then calculates an optimal bipartite matching to minimize the total leader line length, links the entries and rows accordingly, and eliminates all crossings while maintaining the total leader line length.

We opt for "L-shaped" leader lines because they perform better in relevant tasks and are preferred by users compared to other shapes [41]. The vertical parts of the leader lines output by the algorithms might overlap. Nonetheless, there is the freedom to move the circles within the entry in the matrix. We use a quadratic program to adjust the positions of the circles to remove the overlap.

The main interactions between the matrix and the bar charts are as follows.

- When users select multiple total effects in the matrix view for comparison, the corresponding leader lines and linked direct and indirect effects are highlighted (Fig. 1). This allows users to quickly identify which MVs mediate these total effects and compare the

2. https://colorbrewer2.org/

sizes of the indirect effects (N2).
- When users select an MV in the bar chart, the corresponding column of indirect effects is highlighted (Fig. 5B). The matrix entries linked with these indirect effects are also highlighted and the encodings in these entries are updated to reflect the indirect effects. This enables users to easily browse the IVs and DVs mediated by the MV (Fig. 5A) and the polarity and sizes of the effects (N6).

Design Process. The visualization problem here is two-fold. (1) There is a need to visualize many total and direct effects of multiple IVs on multiple DVs and to visualize many indirect effects of multiple IVs on multiple DVs and through multiple MVs. Visualizing these effects involve presenting relations from many entities to many entities (many-to-many relations). (2) There are two levels of analysis units. The level-one analysis unit is the total effect and the level-two analysis unit is the direct and indirect effect. Two analysis units need to be analyzed together. That is, when users compare total effects, they also examine and compare corresponding direct/indirect effects and vice versa.

For the first problem, there are mainly two approaches to visualize the many-to-many relations, a node-link diagram and a matrix view. We propose a node-link design to visualize the effects among IVs, DVs, and MVs. (The detailed discussion of the design can be referred to in the supplementary materials.) The design is intuitive for illustrating mediation relations among variables but has two limitations. First, it lacks a systematic layout to quickly identify which combinations of IVs, DVs, and MVs do not have effects among them. Second, it is limited in scalability due to overlapping links. We hence employ a matrix layout to present the total effects and direct/indirect effects for its conciseness and scalability.

For the second problem, we have tried two approaches. (1) Overview and detail of demand. A classical multi-level visualization approach is to present an overview of the total effects and a detail view to display the direct/indirect effects when users click a total effect. However, this approach does not allow users to compare multiple total effects' direct/indirect effects while preserving the information on total effects. For instance, when users select many total effects of two IVs, they cannot distinguish which direct/indirect effects displayed in the detail view are of the same IV. (2) Embed details in the overview. Another approach is to embed the information on direct/indirect effects in the overview. For instance, a glyph can be placed in each entry of the matrix to present the information corresponding to the total effect. However, the glyph is too small to recognize when there are many entries in the matrix (Fig. 3a4). Besides, it is not easy to compare the indirect effects mediated by the same MV when they are presented in different glyphs.

We hence choose to employ two views to present the total effects and direct/indirect effects separately and use leader lines to link them for navigation. When users highlight the total effects of an IV, corresponding direct/indirect effects are highlighted. When users highlight all indirect effects mediated by an MV (Fig. 5B), corresponding matrix entries and the IVs and DVs are then highlighted (Fig. 5A). There are two ways to place the matrix (Fig. 4a1 and a2). In Fig. 4a1, the leader lines are confusing, as they are arrayed in the same direction as the DVs. We hence choose the way in Fig. 4a2, where the leader lines are arrayed in the diagonal direction of the matrix.

TABLE 1
Definition of Key Terminology about Paired Pie Chart

Term	Definition
Total positive effect (TPE)	The sum of all positive effects.
Total negative effect (TNE)	The sum of all negative effects.
Total effect	The sum of all effects.
Effect size A is a part of effect size B	We define that effect size A is a part of effect size B as that (1) effect size A is smaller than effect size B and (2) effect size A plus other meaningful effects' sizes equals effect size B.

5.1.2 *Presenting Part-to-whole Ratios of Positive and Negative Effects*

Designs. To support examining the ratios of direct and indirect effects versus a total effect (N4) and comparing the sizes of different total effects (N1). We propose a paired pie chart design. Users can switch between bar charts (Fig. 3a5) to paired pie charts (Fig. 3a6) by clicking a button (Fig. 3a3).

Key terminology. To ease reading, we present the key terminology in the design of the paired pie chart in Table. 1. Direct/indirect effects can be positive or negative. The total positive and negative effects (TPE and TNE) combine to form the total effect, whose size is smaller than the larger TPE and TNE sizes because they offset each other (as shown in Fig. 4B). It is counterintuitive to understand the ratio of an effect's size versus the total effect's size when the effect's size is larger than the total effect's size. We aim to find a new effect size so that each effect's size is a part of it (The definition of that effect size A is a part of effect size B is presented in Table. 1). The larger one of the TPE and TNE sizes is the effect size we need. We assume the TPE' size is larger than the TNE's size for the convenience of discussion in the following paragraphs of this section. If the TNE's size is larger than the TPE's, the discussions are similar.

Why is each effect size a part of the TPE's size? We have three straightforward points. (1) The size of each positive direct/indirect effect is part of the TPE's size. (2) The size of each negative direct/indirect effect is part of the TNE's size. (3) The sizes of the TNE and total effect are both parts of the TPE's size (as shown in Fig. 4C). We contend that every effect's size, regardless of whether it's positive or negative, is a part of the TPE's size. A positive effect's size is a part of the TPE's size according to (1). A negative effect's size is a part of the TNE's size according to (2) and the TNE's size is a part of the TPE's size according to (3), making a negative effect's size a part of the TPE's size. The total effect's size is a part of the TPE's size according to (3).

How to interpret the ratio of each effect size versus the TPE's size? That every effect's size is a part of the TPE's size allows us to interpret the ratio of each effect's size versus the TPE's size as follows. (1) The ratio of a positive effect's size

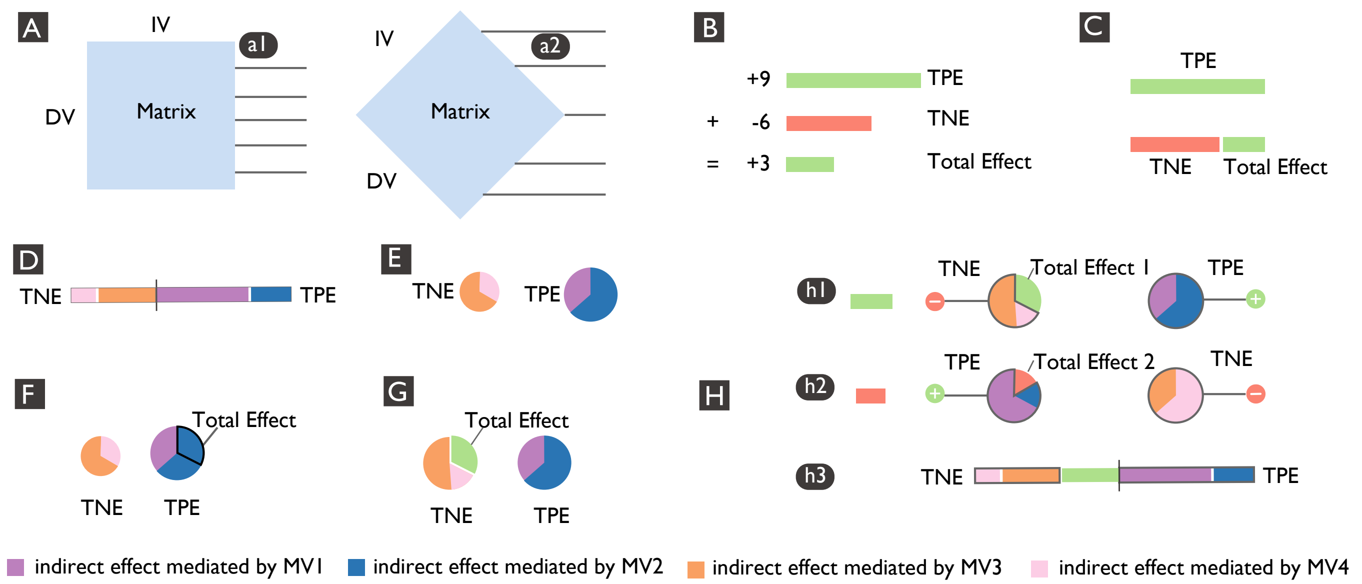

Fig. 4. The design process of the paired pie chart in the effect view. (A) presents two ways to place the matrix in the effect view. (B) illustrates that the TPE plus TNE equals the total effect. (C) illustrates that the TPE's size equals the TNE's size plus the total effect's size. (D) illustrates a bidirectional stacked bar chart, which is an alternative to the two pie charts (E). (F) and (G) illustrate two ways to present the total effect together with the TPE and TNE. (H) illustrates the final design of the paired pie chart. (h1) illustrates the case that the TPE's size is larger than the TNE's size and (h2) illustrates the opposite case. (h3) illustrates an alternative design to the paired pie chart, which is analyzed in the user study.

versus the TPE's size indicates how much the positive effect contributes to the TPE. (2) The ratio of a negative effect's size versus the TPE's size indicates how much the TNE offsets the TPE. (3) The ratio of the total effect's size versus the TPE's size reflects the extent to which the TPE remains after the TNE has offset it.

We discussed with the domain experts and decided to display each effect's size ratio versus the one of the TPE and TNE with a larger size using a paired pie chart. The chart consists of two parts. The right part represents the one of the TPE and TNE with a larger size. The left part represents the total effect and the one of the TPE and TNE with a smaller size. For instance, the TPE's size is larger than the TNE's size in Fig 4h1. Then the TPE is on the right side, and the total effect (positive) and TNE are placed on the left side. In this manner, each side's pie size equals the TPE's size, enabling easy examination of each effect's size ratio versus the TPE. When the TNE's size is larger than the TPE's size (Fig 4h2), the TNE is placed on the right side, and the total effect (negative) and TPE are placed on the left side, enabling easy examination of each effect's size ratio versus the TNE. Users can view each effect's ratio by hovering over the fan representing the effect.

Design Process. Pie charts (Fig. 4E) and stacked bar charts (Fig. 4D) are commonly used designs to present part-to-whole ratios. Some studies find that a pie chart is more accurate than a stacked bar for estimating the part-to-whole ratios [42], [43], [44]. Although there are studies proposing that a stacked bar is better than a pie chart for comparing different parts [45], the requirement in this study focuses on examining the ratio of each effect, and therefore, we choose a pie chart.

Direct/indirect effects can be grouped into positive and negative effects. It is straightforward to use two pie charts to represent the TPE and TNE (Fig. 4E), respectively. Then there are mainly two designs to represent the total effect. The first design (Fig. 4F) reuses a part of the TPE to represent the total effect, but this may cause confusion and mislead users into thinking that these particular effects are the total effects. It is also difficult to examine the ratio of each negative effect versus the TPE. The second design (Fig. 4G) compensates the TNE and uses the added fan to represent the total effect as the TNE's size plus the total effect's size equals the TPE's size. In this design, both pie charts represent the TPE's size, making it easy to examine the ratio of each effect versus the TPE's size. Therefore, we choose the second design.

We place the pie chart representing the TPE on the right and the pie chart representing the TNE plus the total effect on the left (Fig. 4h1). We highlight the TPE and TNE in the two pie charts and link them with positive and negative signs, respectively. If the TNE's size is larger than the TPE's size, we reverse their positions, placing the pie chart representing the TNE on the right and the pie chart representing the TPE plus the total effect on the left (Fig. 4h2). Additionally, we include a bar representing the total effect on the left of the paired pie chart to facilitate the comparison of multiple total effects (Fig. 4h1 and h2).

5.2 Variable and Validation Views

The variable view (Fig. 3B) aims to help users examine the distributions of IVs, DVs, and MVs in the raw data and confirm that there are no anomalies.

The validation view (Fig. 3C) supports visual verification of an indirect effect identified in the effect view through frequency distributions (N8). When the analyst selects an indirect effect in the effect view (Fig. 6D), the encodings in the two bar charts (Fig. 7) vary accordingly.

An indirect effect involves an IV, DV, and MV, and requires verification of two conditions. (1) The IV has an effect on the MV. We verify this by comparing MV values of cases that have different IV values. A bar chart is appropriate for this value comparison task. In particular, We divide cases into two groups by the IV value and compared their ratios of cases where the MV is one (represented by the two bars in Fig. 7A). If users find an explicit difference between the two bars, the IV has an effect on the MV. (2) The MV has an effect on the DV. We verify this by comparing the DV values of cases that have different MV values but the same IV value. A grouped bar chart is appropriate for this value comparison task. In particular, We divide cases into two groups by the IV value and each group was divided into two subgroups by the MV value. We compare the ratios of cases where the DV is one in two subgroups in each group (represented by two bars in each bar group Fig. 7B). If users find an explicit difference between the two bars within either bar group, the MV has an effect on the DV when the IV is controlled.

6 Case Studies

We invited two new experts, a master's student in sports science (E5) and an assistant professor in communication science (E6), to evaluate our system, in addition to the four experts who developed the requirements (introduced in Section 3). The evaluation process consisted of five steps: (1) introducing the requirements to the new experts, (2) introducing the visualization design and demonstrating how to use the system, (3) letting the experts use the system and answering their questions, (4) asking the experts to conduct a mediation analysis of their domain data for an hour using the system, and (5) interviewing the experts about the system's usefulness and usability. The three experts in communication science analyzed the time use data of 6,697 people from 2014 to 2015 in the UK [46], while the three experts in sports science analyzed the table tennis data of 100 matches among the top 25 female and male table tennis players from 2018 to 2020. The experts in both domains detected interesting patterns, and we recorded their analysis processes and selected parts of them (conducted by E2, E3, E5, and E6) as two case studies. The case studies were conducted on Google Chrome on a PC equipped with a 1920×1080 display.

6.1 Case Study I: Comparing Total and Direct/Indirect Effects among Table Tennis Strokes

In this case study, we demonstrate how MediVizor can help an expert browse and compare the total effects and corresponding direct/indirect effects among technical variables of Stroke 2, 3, and 4 in table tennis rallies (R1). Besides, we demonstrate how the system helps an expert compare the indirect effects mediated by a variable of Stroke 3 and browse the relevant variables in Stroke 2 and Stroke 4 (R3).

6.1.1 Opposite Indirect Effects of Short and Long in Stroke 2

Table Tennis Dataset. E1 and E2 in sports science provided a dataset of 100 matches among top table tennis players and explored whether the variables of Stroke 2 affect those of Stroke 4 in table tennis rallies and how the effects are mediated through the variables of Stroke 3. The dataset includes three nominal variables for each stroke, stroke position, stroke technique, and ball position. The IVs, DVs, and MVs in this dataset are listed in Table 2.

TABLE 2
Variables in Case Study I

	Nominal Variable	Dummy Variable
IV (Stroke 2)	Stroke position	Forehand, Backhand, Backhand Turn, Pivot
	Stroke technique	Attack, Defense, Control
	Ball position	Long, Half Long, Short
DV (Stroke 4)	Stroke position	Forehand & Scoring, Backhand & Scoring, Backhand Turn & Scoring, Pivot & Scoring
	Stroke technique	Attack & Scoring, Defense & Scoring, Control & Scoring
	Ball position	Long & Scoring, Half Long & Scoring, Short & Scoring
MV (Stroke 3)	Stroke position	Forehand, Backhand, Backhand Turn, Pivot
	Stroke technique	Attack, Defense, Control
	Ball position	Long, Half Long, Short

Analysis Process. After loading the table tennis dataset, E2 browsed the distributions of the IVs, DVs, and MVs (Fig. 3B) and confirmed that there are no unusual patterns. E2 then focused on the effects of *Short* and *Long* in Stroke 2 to different DVs in Stroke 4 (Fig. 1A) because these two IVs are deemed essential based on previous experiences and their average effect sizes are large. He then clicked the effects on *Backhand & Scoring*, *Long & Scoring*, and *Attack & Scoring* in Stroke 4 because they have relatively large effect sizes. He found that these total effects are composed entirely of indirect effects and do not contain direct effects (Fig. 1B). A new conclusion was drawn that *Short* and *Long* in Stroke 2 cannot influence these DVs in Stroke 4 directly.

He examined the indirect effects on *Long & Scoring* and *Attack & Scoring* in Stroke 4. He found that among the indirect effects of *Short* in Stroke 2, those through *Attack* and *Control* in Stroke 3 are positive while those through *Long* in Stroke 3 are negative (Fig. 1C). Interestingly, the opposite pattern was observed for the indirect effects of *Long* in Stroke 2 (Fig. 1D).

E2 explained *Short* in Stroke 2 usually indicates good performance according to his knowledge. It influences *Long & Scoring* and *Attack & Scoring* in Stroke 4 (hereafter referred to as "Scoring in Stroke 4") mainly in three ways according to the pattern in the bar charts. In the first way, it reduces the chance that *Attack* happens in Stroke 3, *Attack* in Stroke 3 commonly reduces the chance of Scoring in Stroke 4, and overall, it increases the chance of Scoring in Stroke 4 (Fig. 1c1). In the second way, it increases the chance that *Control* happens in Stroke 3, which further increases the chance of Scoring in Stroke 4 (Fig. 1c2). In the third way, it reduces the chance that *Long* happens in Stroke 3, which is a side effect and further reduces the chance of Scoring in Stroke 4 (Fig. 1c3). The detailed views of these indirect effects confirmed E2's ideas.

Long in Stroke 2 usually indicates bad performance according to E2's knowledge. It also influences *Long & Scoring*

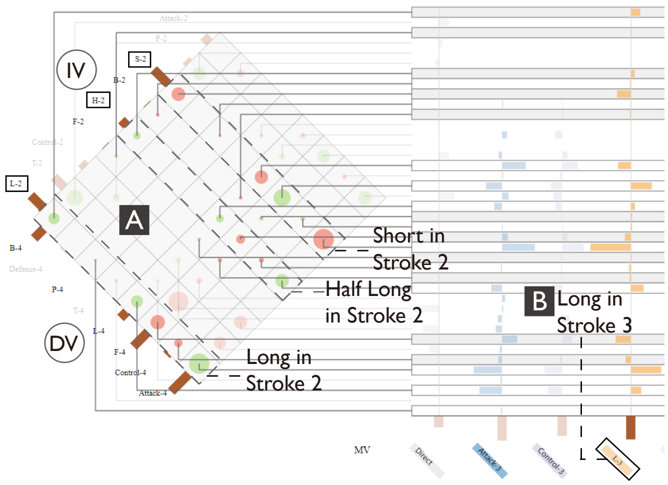

Fig. 5. Analysis process in the case study illustrated in Section 6.1.1. (B) illustrates that E2 hovered on the *Long* in Stroke 3 and all indirect effects mediated by this MV are then displayed in the matrix. (A) illustrates that the indirect effects' sizes from *Short* and *Long* in Stroke 2 are larger than those from *Half Long* in Stroke 2.

and *Attack & Scoring* in Stroke 4 in these three ways but with opposite effects. In the first two ways, it exerts a negative effect by increasing the chance that *Attack* happens in Stroke 3 (Fig. 1c4) and decreasing the chance that *Control* happens in Stroke 3 (Fig. 1c5). In the third way, it exerts an unexpected positive effect by reducing the chance that *Long* happens in Stroke 3 (Fig. 1c6). The polarity of their two causal edges in the detailed views confirmed E2's ideas.

The indirect effects on *Backhand & Scoring* are not through *Attack* and *Control* in Stroke 3 (Fig. 1E), but mainly through *Long* in Stroke 3. Similarly, the indirect effect of *Short* is negative and that of *Long* is positive (Fig. 1E).

E2 also examined how *Long* in Stroke 3 mediates the effects of variables in Stroke 2 on those in Stroke 4 as *Long* in Stroke 3 is a key technical behavior and the average size of the indirect effects it mediates is large. He clicked *Long* in Stroke 3 (Fig. 5B) and the matrix switched to encode the indirect effects mediated by *Long* in Stroke 3 (Fig. 5A).

He found that the sizes of indirect effects of *Short* and *Long* in Stroke 2 are larger than those from *Half Long* in Stroke 2 (Fig. 5A), which is a new and interesting pattern. To better understand this pattern, E2 examined the frequency distributions of several indirect effects in the validation view. E2 then commented that *Short* and *Long* in Stroke 2 exert negative and positive strong indirect effects through *Long* in Stroke 3, respectively. It is because *Short* and *Long* in Stroke 2 certainly reduce and increase the chance that *Long* happens in Stroke 3, respectively. *Half Long* in Stroke 2, however, does not have a strong effect on whether *Long* happens in Stroke 3.

In this case study, E2 discovers new insights including that *Short* and *Long* in Stroke 2 cannot influence several DVs in Stroke 4 directly and they influence these DVs indirectly through different MVs in Stroke 3 differently. Also, E2 finds a new insight that sizes of indirect effects of *Short* and *Long* in Stroke 2 are larger than those of *Half Long* in Stroke 2. E2 exerted his knowledge to the selection of effects to compare and the interpretation of the polarity

TABLE 3
Variables in Case Study II

	Nominal Variable	Dummy Variable
IV	Time	Weekend, Vacation, Workday, Schoolday, Vacation leave, Morning, Afternoon, Evening
DV	Media Use	Computer, TV, Reading, Telephone, Radio
MV	Location	Shop, Travel, Hotel, Home, Work/School, Other

patterns. These insights cannot be detected by using domain tools (tables) or previous visualization systems because they don't support interactive comparisons of multiple total and direct/indirect effects while preserving their connections.

6.2 Case Study II: Examining the Ratios of Total, Direct, and Indirect Effects versus the TPE or TNE

This case study showcases how MediVizor assists experts in analyzing the ratios of the total, direct, and indirect effects versus the TPE/TNE among nominal variables in the table tennis and media use datasets (R2). The study also demonstrates that the system supports validating an interesting indirect effect (R4).

6.2.1 A Large-size TPE and TNE but A Small-size Total Effect on Attack in Stroke 4

Analysis Process. E5 decided to examine the ratios of different indirect effects versus the total effects of *Short* in Stroke 2 on *Backhand & Scoring*, *Long & Scoring*, and *Attack & Scoring* in Stroke 4 (Fig. 1) according to his experiences. He switched the bidirectional bar chart to paired pie chart (Fig. 1F) and examined the corresponding paired pies (Fig. 1G, H, and I).

He quickly found that the indirect effects on *Attack & Scoring* in Stroke 4 are interesting (Fig. 1I) as the ratio of the total effect's size versus the TPE's size is small. He found that the positive indirect effects through *Half Long*, *Control*, and *Attack* in Stroke 3 contribute around 20%, 30%, and 50% of the TPE. At the same time, the negative indirect effects through *Long* and *Short* in Stroke 3 offset around 60% and 30% of the TPE. Only around 10% positive effect is left as the total effect. In the effects on *Long & Scoring* in Stroke 4 (Fig. 1H), the TNE only offsets around 55% of the TPE and the total effect, which equals 45% of the TPE, is hence larger than the total effect in Fig 1I.

As explained in Section 6.1.1, the TNE is the side effect of *Short* in Stroke 2 on *Attack & Scoring* and *Long & Scoring* in Stroke 4. E5 interpreted the pattern as that the side effect on *Attack & Scoring* in Stroke 4 offsets a greater percentage of the TPE compared to the side effect on *Long & Scoring*.

For the effects on *Backhand & Scoring* in Stroke 4 (Fig. 1G), the total effect is negative. E5 hovered on each indirect effect and found that the indirect effects through *Short*, *Long*, *Backhand*, *Forehand* in Stroke 3 contribute 22%, 22%, 18%, and 36% of the TNE, respectively, while the indirect effect through *Half-Long* offsets 16% of the TNE. Around 84% of the TNE is left as the total effect.

6.2.2 Opposite Total Effects on Computer Use and TV Use due to Various Indirect Effects with Different Ratios

Media Use Dataset. E3 and E4 in the communication science field provided a dataset of the daily time use of 6,697 individuals in the UK [46], from which we extracted a random sample. E3 and E6 investigated the effect of time points (e.g., morning and afternoon) on people's media use (e.g., use of TV and computer), and how this effect is mediated through location (e.g., home and workplace). Each of the three nominal variables, time point, location, and media use, has multiple values as shown in Table 3.

Analysis Process. After loading the media use dataset, E3 and E6 found that the significant and strong effects are mainly on computer and TV usage. She filtered out small effects and focused on the effects of *Workday* because this IV has a strong effect on both *Computer* and *TV* (Fig. 6A). She clicked the effects of *Workday* on *Computer* and *TV* and examined the ratios of direct/indirect effects versus total effects using paired pies.

The total effect of *Workday* on *Computer* is positive (Fig. 6B). The direct effect contributes to 75% of the TPE and the indirect effect through *Work Place or School* contributes around 25%. E3 explained that people are very likely to use a computer on workdays, excluding the effects of locations. Besides, people are more likely to be in the workplace on workdays, which further increases the chance of using a computer. However, the indirect effects through *Home* and *Travel* offset 12% of the TPE in total. E3 explained that people are at home less on workdays, which decreases the chance of using a computer at home. Besides, people commute more on workdays, which also decreases the chance of using a computer. Around 88% of the TPE is left as the total effect. To verify whether *Home* mediates the indirect effect, E6 clicked the indirect effect (Fig. 6D) and examined the validation view (Fig. 7). She found that people are at home less on workdays (Fig. 7A), which indicates that *Workday* has an effect on *Home*. Besides, people use a computer more at home when it is not a workday and use a computer less at home when it is a workday (Fig. 7B), indicating that *Home* has an effect on *Computer* when *Workday* is controlled.

In comparison, the total effect of *Workday* on *TV* is negative (Fig. 6C). Both the direct and indirect effects through *Home* are negative and there is no positive direct/indirect effect. The direct effect contributes to around 64% of the TNE and the indirect effect contributes to around 36% of the TNE. E6 explained that people watch TV less on workdays, regardless of their location, and are less likely at home on workdays, further decreasing the chance of TV watching.

In this case study, E5, E3, and E6 discovered new insights, such as the larger percentage of the TPE offset by the side effect on *Attack & Scoring* in Stroke 4 compared to that offset by the side effect on *Long & Scoring* in Stroke 4. They also found that the effects of *Workday* on *Computer* and *TV* use are mainly direct effects, and that locations such as *Home* and *Workplace* mediate a part of effects between time and media use. Experts applied their knowledge to select and interpret the part-to-whole ratios in the process. These insights cannot be detected by previous visualization tools as they do not facilitate the examination of the part-to-whole ratios of positive and negative effects.

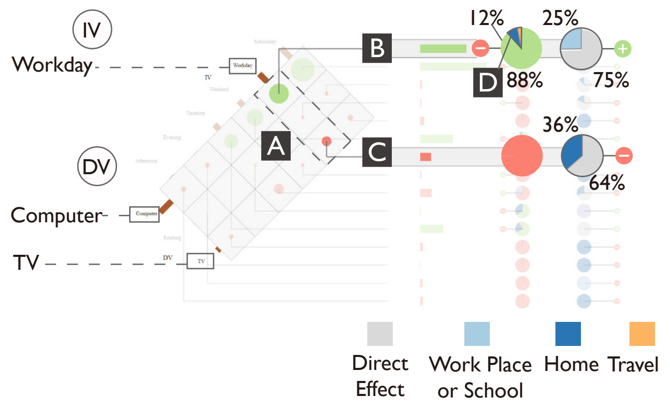

Fig. 6. Analysis process in the case study illustrated in Section 6.2.2. (A) illustrates that the expert focused on two total effects of *Workday* on *Computer* and *TV*. (B) illustrates that in the effects on *Computer*. The direct and indirect effects through *Work Place or School* contribute 75% and 25% of the TPE. The negative indirect effects through *Home* and *Travel* together offset 12% of the TPE and 88% of the TPE is left as the total effect. (C) illustrates that in effects on *TV*. The direct and indirect effects through *Home* contribute 64% and 36% of the TNE and there is no positive indirect effect. (D) illustrates that the expert clicked the indirect effect through *Home*.

6.3 Expert Feedback

Usefulness. Experts in sports science and communication science agreed that the system is useful for conducting mediation analysis among nominal variables and meets the requirements proposed in Section 3. E3 and E6 commented: "We often use multiple tables to present the mediation effects when the variables are nominal. In that case, we have to browse different tables and compare the effects. The visualization system provides a new way to present the effects and enables us to browse all effects at a glance." E2 commented: "The visualization system is useful for displaying the total and direct/indirect effects among consecutive three strokes in table tennis. We can obtain insights into indirect effects using the system and conduct a follow-up investigation. Without the system, we need to spend a lot of time analyzing the effects one by one. This visualization system improves our analysis process." E5 commented: "The system has high generalizability and can be used to present mediation effects from different projects."

Usability. Experts agreed that the system is easy to learn and use and understood the system's design after the introduction. E4 commented: "The system is easy to understand and use. I can teach my colleagues how to use it." E2 commented: "The interactions in the system are straightforward and easy to learn. Besides, the system allows us to validate interesting indirect effects by examining the frequency distributions, which makes the effects easier to understand." The two new experts (E5 and E6) quickly grasped the visual encoding and interactions of the system. E6 had difficulty understanding the encoding of the paired pie chart at first, but learned it after the explanation and found it useful for examining effect ratios efficiently.

Suggestion. E2 suggested improving the effect view to present two-step mediation effects, as the current design only supports one-step mediation. We will discuss this limitation part in Section7. E6 suggested integrating more mediation models and allowing users to switch between

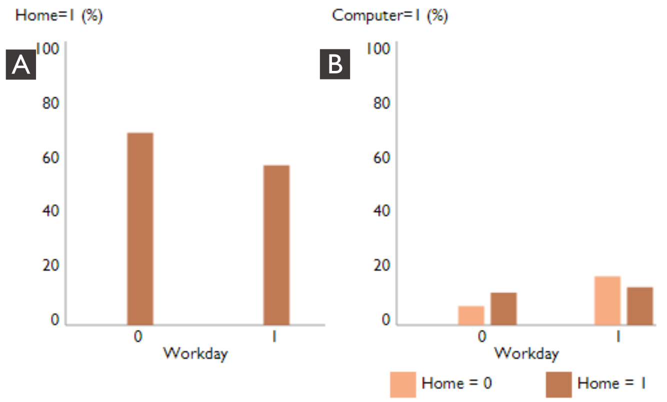

Fig. 7. Analysis process in the case study illustrated in Section 6.2.2. (A) People are less likely to be at home on workdays than non-workdays, suggesting that *Workday* has an effect on *Home*. (B) The probability of people using a computer at home and away from home differs, whether it is a workday or not being fixed.

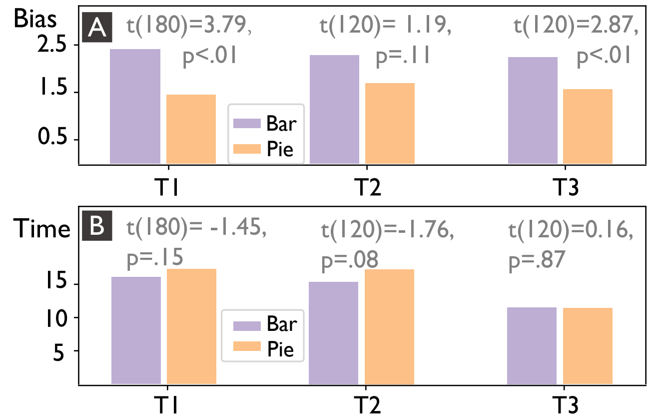

Fig. 8. Analysis of the bias (A) and time (B) when participants use the paired pie and bar charts to accomplish T1, T2, and T3.

them. Other experts thought the system meets all requirements comprehensively.

6.4 User Study

The paired pie chart contains relatively complex information which might increase the possibility of not understanding and misunderstanding. Therefore, we conducted a task-based user study to evaluate its effectiveness in satisfying N4. The study has two objectives: to determine whether common users can easily understand the design and accurately examine the ratios, and to compare the paired pie chart with an alternative design, the paired stacked bar chart (Fig. 4h3), to determine whether the paired pie chart is significantly better than the paired stacked bar chart. We choose horizontal bars for the paired stacked bar chart so that it can be displayed in a row.

6.4.1 Task and Hypotheses

Three tasks approximate how well the paired pie chart helps users examine the part-to-whole ratios of positive and negative effects. T1. Examine the ratio of a positive (negative) effect versus the TPE (TNE) when the TPE (TNE) is larger than the TNE (TPE). T2. Examine the ratio of a negative (positive) effect versus the TPE (TNE) when the TPE (TNE) is larger than the TNE (TPE). T3. Examine the ratio of the total effect versus the larger one of the TPE and TNE. Based on the tasks, we formulated three hypotheses as follows. H1–3. Using the paired pie chart to accomplish T1–3 is more accurate (a) and efficient (b) than using the paired stacked bar chart.

6.4.2 Variables, Participants, and Processes

Variables. The treatment variable is the type of design used, either a paired pie chart or paired stacked bar chart. The dependent variables are the efficiency and accuracy of completing different tasks. To avoid testing the treatment variable's effects on the dependent variables under specific conditions, we include cases where (1) the TPE is larger or smaller than the TNE, (2) the ratio to estimate is large (around 50%) or small (around 20%), (3) the beginning position of the effect to estimate is 0% or 40%, and (4) the number of divisions is four or two. These conditions are derived from the effect data in case studies, such as the most frequent beginning positions of effects being 0% and 40%. We used a within-subject design, where each participant uses both designs to complete tasks under all conditions. In theory, there are 96 questions (3 tasks * 2 designs * 2 TPE/TNE conditions * 2 ratio conditions * 2 beginning positions * 2 division conditions). However, particular combinations are impossible, such as when the division number is two and the ratio to estimate is 50%, the beginning position of the effect cannot be 40%. Besides, the beginning position of the total effect is always 0%. After removing the impossible combinations, there are 56 questions remaining (24, 16, and 16 questions are for T1, T2, and T3, respectively). The data were generated automatically based on the design and we randomly adjusted the target effect ratio to avoid repeatedly estimating the same ratio. For instance, if the experiment design specified a target effect ratio of 20%, we randomly adjusted it to a value between 10% and 30%.

Participants. We recruited 15 volunteers (five females and ten males) who were Ph.D. and Master's students with basic knowledge of data analysis. Their ages ranged from 20 to 30 (M = 25, SD = 2.3). The user study was conducted on a screen with 1920×1080 resolution.

Process. We collected informed information from the participants and provided a tutorial to help them understand the encoding of the designs. They were then asked to answer the 56 questions, using either the paired pie chart or paired stacked bar chart to examine the ratios and input estimated ratios. The system recorded the time and accuracy of the estimation. Besides, we asked the participants to think aloud while inputting the ratios to determine whether they used the design correctly. To minimize the practice effect [47], seven participants used the paired pie chart first, while eight participants used the paired stacked bar chart first. Afterward, we collected each participant's feedback on the ease of learning and using the design.

6.4.3 Results

Performance of the Paired Pie Chart in T1, T2, and T3. As

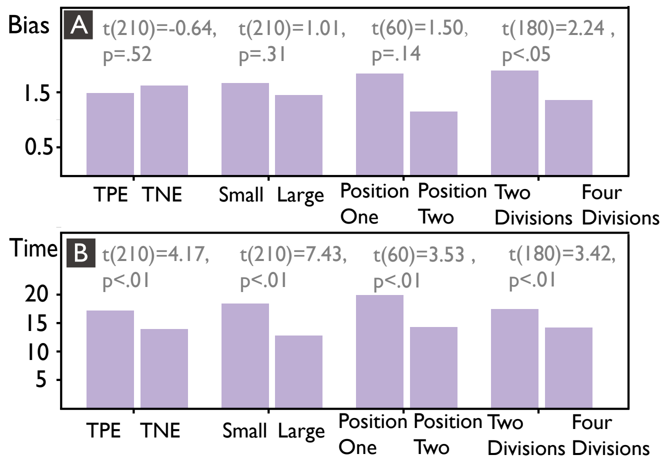

Fig. 9. Analysis of the bias (A) and time (B) when participants use the paired pie chart under different conditions.

mentioned above, participants thought aloud while using the design and we recorded their usage accuracy. Results show high accuracy rates for T1 (100%), T2 (93%), and T3 (93%), with only one participant misinterpreting the overall areas of the two pie charts as the TPE and TNE, respectively. The average bias of the paired pie chart is only 2%, indicating that most users can accurately estimate the ratios for all tasks using the paired pie chart.

Comparison of the Paired Pie Chart and Paired Stacked Bar Chart. We conducted a paired t-test to compare the bias and efficiency of using the paired pie and stacked bar charts. The bias of the paired pie chart is significantly less than that of the paired stacked bar chart in T1 (t (180) = 3.79, $p<.01$) and T3 (t (120) = 2.87, $p<.01$) as shown in Fig. 8A (H1a and H3a are supported). Although there is no significant difference in the bias of the paired pie and stacked bar charts for T2 (H2a is not supported), the average bias of using the paired pie chart is less than that of using the paired stacked bar chart (Fig. 8A). There are no significant differences in the paired pie and stacked bar charts' efficiency in accomplishing T1, T2, and T3 (Fig. 8B, H1b, H2b, and H3b are not supported).

Confounding Variables. To understand the influence of confounding variables on task performance, we conducted a paired t-test for each confounding variable. As shown in Fig. 9B, all confounding variables have effects on the time, whereas only the division number affects the bias (Fig. 9A). The main conclusions are as follows. (1) A negative total effect leads to quicker ratio estimation than a positive total effect. (2) A smaller ratio requires more time to estimate, as expected. (3) The estimated effect beginning at 0% prolongs usage time, possibly due to the greater distance between the encodings and the legend compared to beginning at 40%. (4) Estimating ratios takes longer and results in more errors when there are more divisions, as expected.

User Feedback. Participants were asked to rate the ease of learning and usefulness of the paired pie chart for completing T1, T2, and T3 on a 7-point Likert scale. Overall, participants found the paired pie chart easy to learn (M = 5.7) and effective for accomplishing T1 (M = 6.2), T2 (M = 6.1), and T3 (M = 6.1). Many participants noted that the paired pie chart simplifies the task of estimating ratios of positive and negative effects by presenting them in pie chart form. While some participants mentioned a learning curve for understanding the design, they successfully used the design to accomplish the tasks once they grasped it. Many participants preferred the paired pie chart over the paired stacked bar chart, citing its greater efficiency in estimating particular percentages like 25% and 75%.

7 Discussion

Simultaneous Displays of Visual Levels. An important design decision in creating a multi-level interface is to present different levels simultaneously or one at a time. Lam and Munzner [48] find that displaying simultaneous levels is suited for tasks that require multi-level information and tasks that require multi-level clues. In this study, our task, comparing multiple total effects and their direct/indirect effects, requires both high-level information (e.g., the IVs, DVs, sizes, and polarity of the total effects) and low-level information (e.g., the sizes and polarity of the direct/indirect effects). We hence choose to display simultaneous levels. Besides, the benefits of integrating multi-level information results are along with the costs of the display. In the effect view, we link the two visual levels and assure there are no crossings in the leader lines, which results in the cost that the bar chart on the right cannot be sorted by size.

Learning Curve of Paired Pie Chart. The paired pie chart design may present some challenges for users to learn. As discussed in the user study, users need some time to understand and become familiar with the design. The user rates 5.7 on a 7-point Likert scale for the design's ease of use. The complexity of the encoded information, i.e., positive/negative direct/indirect/total effects, might explain the moderate ease of use of the design. Nevertheless, the system is designed for domain experts who conduct mediation analysis repeatedly in daily work. The experts are willing to pay some time learning the design once and then keep using the design to do the mediation analysis afterward. The user study demonstrates that the paired pie chart produces significantly less bias than the alternative design after users have learned the design. Therefore, users are not likely to make mistakes using the design.

Limitation. A limitation of this study is that the current design does not support two-step mediation. The mediation in our cases is all one-step mediation. Two-step mediation indicates the one-step indirect effect is further mediated by another set of mediators. In that case, two-step indirect effects are required to be examined. One design approach is to replace the bar chart in the effect view with two columns of nodes representing mediators in two steps and then use leader lines to link them with corresponding effects in the matrix. But this design is limited in scalability and breaks the systematic structure. We plan to address this problem in our follow-up study.

Scalability. MediVizor can analyze at most 20 IVs and DVs according to the scalability of the matrix view in the effect view (Fig. 3a4). The number of rows in the bar chart (Fig. 3a5) will not restrict the scalability because only large total effects in the matrix will be displayed in the bar chart. MediVizor can analyze at most ten MVs as the width of each column in the bar chart cannot be too small and the effect view should not contain too many colors.

Generalizability. As demonstrated by the two case studies, MediVizor can be used to display and analyze mediation effects among nominal variables in datasets from different domains. More generally, it can be integrated into a statistical tool, such as SPSS or an R package, to visualize the derived mediation effects among nominal variables.

8 Conclusion

This study focuses on the visual mediation analysis of nominal variables, with input from experts in communication and sports science to synthesize the requirements. Our resulting visualization system enables experts to efficiently compare the total and direct/indirect effects across multiple IVs, DVs, and MVs, as well as examine the ratio of each direct/indirect effect versus the total effect. We conducted two case studies with the experts to demonstrate the system's usefulness and usability. The effect view proposes a heuristic design for displaying two levels of information and part-to-whole ratios with positive and negative parts. The design successfully helps experts in communication and sports science find insightful patterns in mediation effects among nominal variables. In the future, we will improve the system to integrate more mediation models and the paired pie chart for greater intuitiveness.

Acknowledgments

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