# AdaptLIL: A Real-Time Adaptive Linked Indented List Visualization for Ontology Mapping

Bo Fu(✉) and Nicholas Chow

California State University Long Beach, Long Beach, CA 90840, USA
Bo.Fu@csulb.edu, Nick.Chow01@student.csulb.edu

**Abstract.** Visual support designed to facilitate human interaction with ontological data has largely focused on one-size-fits-all solutions, where less attention has been paid to providing personalized visual cues to assist the user in the process of comprehending complex datasets and relationships. To address this research gap, this paper presents an adaptive visualization designed to tailor visual cues to an individual user during ontology mapping activities. The adaptative visualization utilizes physiological signals such as eye gaze to predict one's success in a given task, and in the event of a predicted failure, real-time visual interventions in the form of highlighting and deemphasis are deployed to direct user attention and assist with task completion. The proposed adaptive visualization is compared to a non-adaptive baseline in a user study involving 76 participants. The experimental results show statistically significant increases in user success with similarly perceived workload and time on task compared to those of the baseline, indicating that the proposed adaptive visualization is effective at improving user performance without tradeoff in workload or task speed. Furthermore, we report on the impact of highlighting and deemphasis on user success and provide recommendations in the development of future adaptive visualizations in human-machine teaming scenarios.

**Keywords:** Adaptive Linked Indented List · Gaze-adaptive Visualization · Eye Tracking

## 1 Introduction

Notable advances in user adaptive systems and interfaces across a wide range of human computer interaction scenarios such as recommender systems, intelligent emails, smart menus, search engines, as well as tutoring and learning environments [1] have demonstrated the benefits of tailoring to individual user needs, abilities, and preferences, whereby improved user performance and satisfaction are often observed [2–6]. Notable research in the Information Visualization (InfoVis) community has successfully demonstrated positive results such as increased task success and enhanced user experience in the presence of adaptive visualization [7, 8], where cohorts of research have focused


G. Demartini et al. (Eds.): ISWC 2024, LNCS 15232, pp. 3–22, 2025.
https://doi.org/10.1007/978-3-031-77850-6_1

on further investigating the impact of user traits in adaptation such as one's personality factors (e.g., locus of control, extraversion, neuroticism [3]), cognitive abilities (e.g., perceptual speed, verbal and visual working memory [5]), user expertise (e.g., self-reported knowledge in a given topic [5, 9]), as well as cognitive styles (e.g., field dependent vs. field independent [10]). In contrast, the Semantic Web community has largely focused on developing visualizations that offer one-size-fits-all solutions typically ignoring varied user characteristics and visual needs. While existing interactive visualizations are undoubtedly providing the much-needed visual support for human users in various knowledge engineering, discovery, sharing and reuse activities across the Semantic Web, there is an opportunity to advance the state of the art in semantic data visualization by means of adaptive visualization.

To this end, this paper presents a physiologically adaptive visualization for ontology mapping, namely *AdaptLIL* (*Adapt*ive *L*inked *I*ndented *L*ist) that tailors its visual cues dynamically in real time to an individual user depending on this person's predicted performance in a given task. We employ a Long Short-Term Memory (LSTM) network to continuously predict task success and failure based on eye tracking data collected from the user as the person interacts with visualizations of ontology mappings to assess their correctness and completeness. When a potential failure is predicted, AdaptLIL would then deploy graphical overlays to either highlight or deemphasize mappings shown to the user using a rule-based system. Within the context of this paper, we make distinctions between visual recommendations and visual adaptations, whereby a recommender system typically requires switching to entirely different visualization techniques or layouts, and an adaptive system typically alters the visual properties (e.g., color) displayed. Instead of changing to a completely different visualization mid-task, we believe adaptive visualizations are less disruptive for users who have already invested in a given task and acquainted with the visual cues on display.

In order to realize adaptive visualizations, there are three key decision points as noted in [6]: knowing *what* to adapt to, *when* to adapt, and *how* to adapt. The AdaptLIL is designed to adapt to an individual's task performance (the *what*), to intervene upon predicted task failure (the *when*), and to display personalized visual overlays (the *how*). The main contribution of this paper is the advancement beyond the traditional one-size-fits-all visualizations for ontology mapping. More specifically, we present a physiologically adaptive linked indented list that provides personalized visual cues to a user in real time upon inferred task failure. Advancing beyond mainly using eye tracking as an evaluation tool in the Semantic Web community [11, 12], this paper explores gaze as a source of input to achieve personalized visualization.

The significance of this work lies in its novel solution and novel techniques to adaptive visualization, whereby one particular instance of an implemented system (AdaptLIL) is presented to enable empirical evaluation of the proposed approach. A secondary contribution of this paper is that the proposed process to adaptation is transferable to other scenarios, such as various types of ontology and mapping visualizations, e.g., node-link diagrams, matrices, and treemaps to name just a few (in all stages of *what*, *when*, and *how* to adapt). Lastly, this work adds to the existing body of knowledge in visualizing ontological relations (e.g., mappings between separate ontologies as well as relations among entities within the same ontology) and presents findings that may spur new designs of future adaptive interfaces for the Semantic Web, as we empirically demonstrate the feasibility of a real-time gaze-based adaptive visualization and its effectiveness in achieving higher user success in ontology mapping activities without demanding additional workload or slowing task speed compared to a non-adaptive baseline.

## 2 Related Work

A number of tools and systems developed for ontology mapping have visual elements incorporated in them at varying capacity to assist the human user. A few notable tools with integrated visualizations are outlined in this section, and readers may refer to [13, 14] for more detailed surveys and [15] for recommendations on system requirements. Note that though visualizations of ontologies (e.g., classes, *is-a* relations etc.) are often inevitable when visualizing mappings between them, the focus of this paper is the visual illustration of mappings (e.g., equivalences, disjoints, broad and narrow matches, etc.) established between otherwise independent ontologies.

### 2.1 Visualizations for Ontology Mapping

One example of visual assistance for the human user during the ontology mapping process is the AgreementMaker [15], which provides an interface visualizing source and target ontologies as side-by-side indented lists, and mappings between them as color coded lines each associated with a confidence level. An extended user interface in the AgreementMakerLight [17] emphasizes on graphical support for large-scale ontology mapping, whereby regional neighborhoods associated with a specific mapping are visualized as node-link diagrams in an effort to better support the human in the loop during mapping validation. Another example such as AlViz [18] displays source and target ontologies as indented lists as well as clustered node-link diagrams, where mappings are illustrated as colored nodes that denote different types of mapping relations (e.g., equivalent, broad, or narrow matches).

In the CogZ interface [19], source and target ontologies are visualized as indented lists with connecting edges illustrating mapping relations between them. In the COMA [20] matching environment, a graphical interface is integrated to visualize mappings as connecting edges between two schemas or ontologies shown as indented lists. A similar technique to visualize structured datasets as indented lists and relations across them as connecting edges can be found in the RBA tool [21] designed to support mappings between ontologies and relational databases. Given that the number of mappings can grow exponentially between large-scale ontologies, other research efforts have also examined ways to reduce visual clutter by means of edge bundling when visualizing mappings as connecting edges across ontologies illustrated as indented lists [22].

Recognizing potential differences in user preferences and viewpoints, tools such as VOAR [23], AlignmentVis [24], and BioMixer [25] have provided an array of visualization techniques as well as collaborative visual support. In addition to commonly used techniques such as linked indented lists and node-link diagrams, other examples of mapping visualization have utilized matrices [26] and block metaphors [27]. A key observation of the aforementioned visualizations is the emphasis on the development of various layouts and techniques, and there are a few dominant approaches to visualize ontology mappings (such as linked indented lists), though all of which provide one-size-fits-all solutions, and none can adapt to an individual user at run time.

Given the limited research in user-adaptive solutions, there is an opportunity to advance the state of the art in personalized ontology mapping visualizations. One example of such effort is presented in the SemaVis framework [28] with adaptive semantic visualizations applied in digital libraries, web searches, and policy modelling, whereby the proposed framework presents user adaptations at each step (e.g., content, layout, visual variable generation) along the entire pipeline of turning data into visualization. At the visualization layer, different layouts are selected by the system and displayed to the user depending on user models and user input. Though various visualization styles can be adapted to a specific user, adaptations based on user models and user inputs require the availability of such modules that may not always be readily available (e.g., if the user is simply gazing at a visualization). Furthermore, the framework does not provide further adaptation to the user during task completion beyond the initial personalized visual display.

To overcome these limitations, this paper presents the AdaptLIL that can dynamically tailor visualizations of ontology mappings to an individual user during task completion (such as mapping generation, validation, and creation) in real time based on user gaze. Given that physiological signals such as eye gaze is relatively unique to an individual much like fingerprints, it therefore provides inherently unbiased information upon which adaptations may be built. To this end, we demonstrate the feasibility of gaze-based visual adaptations and showcase the effectiveness of the proposed approach in an implementation of the adaptive linked indented list.

## 2.2 Adaptive Visualizations

A brief overview of notable advances in adaptive visualizations stemmed from a number of related areas including InfoVis, intelligent systems, adaptation and personalization is outlined henceforth in an effort to differentiate this work from prior research and to outline the novelty and contribution of this work. Readers may refer to [28–30] for more detailed surveys.

Within the context of user-adaptive research addressing the question of *what* to adapt to, existing strategies typically seek to identify various attributes that may impact on user performance, such as the type of tasks being performed [2, 6], one's personality [3, 31], cognitive abilities [6], and combined factors such as user models and tasks [32]. Different from existing approaches, the proposed solution shown in this paper adapts to user performance based on predicted task failures utilizing user gaze. As such, the proposed approach does not require computational overhead such as prior knowledge of users' personality type or testing cognitive abilities in order to provide visual adaptation. Eye tracking has thus far been mostly applied as a mechanism to evaluate visualizations of semantic data [11, 12], to infer users' cognitive styles [10] and learning curves [33], to detect information relevance [34] and user intent [35], as well as guiding user attention in narrative visualization [36] and providing gaze-adaptive legends [37], but none have explored adapting visual needs to an individual upon this person's predicted task failure.

Addressing the question of *when* to adapt, prior work [7, 32] has observed user behaviors and signs of confusion to recognize those moments where intervention may be introduced. There has also been research tackling the *when to adapt* problem by utilizing gaze among other behavior data to predict users' performance during interactions with ontological class visualizations [38–42], where simulated experiments were conducted to demonstrate the feasibility of predictive gaze analytics in view of supporting future adaptive ontology visualizations. In contrast, this paper presents a comprehensive solution (addressing not only *when*, but also *what* and *how* to adapt) that recognizes timely interventions in real time and subsequently leverages upon this knowledge in dynamic visual adaptations before task completion.

Finally, to answer the question of *how* to adapt, prior work has investigated the use of notifications [43], hints [44], and alternative visualization recommendations [7, 45]. Inspired by the success of visual overlays demonstrated in [6, 46–48], we investigate highlighting and deemphasis in this paper when adapting to the user upon inferred task failure. We opted for these two specific visual interventions as we rationalize that informed individuals are likely to be confident and decisive in their visual needs, consequently, highlighting relevant visual cues is likely to reduce errors for them. In contrast, individuals who may be at a loss are likely to lack assertiveness or purpose in their visual searches, whereby deemphasizing and reducing irrelevant information is likely to be helpful. Different from prior work that incorporates visual overlays into bar graphs, pie charts, and line graphs highlighting or deemphasizing a visual datapoint in the visualization, this paper focuses on a distinctively different visualization type, namely linked indented lists, whereby the visual overlays are concerned with relationships connecting two separate ontological graphs.

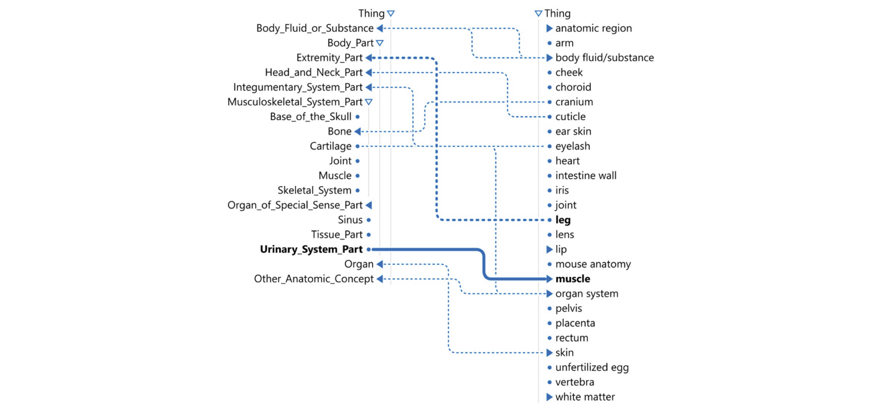
## 3 Adaptive Linked Indented List

Given the frequent use of linked indented lists (LIL) when visualizing ontology mappings amongst existing tools and systems as noted in Sect. 2.1, this paper uses a non-adaptive LIL as the baseline visualization (shown in Fig. 1a), whereby the AdaptLIL (shown in Fig. 1b and Fig. 1c) aims to improve upon by providing personalized visual cues to a user at run time depending on this person's predicted task success or failure informed by their gaze.

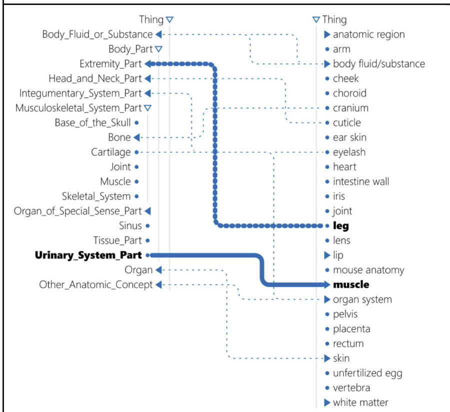
### 3.1 System Design

Two types of adaptation are integrated in the AdaptLIL including highlighting (shown in Fig. 1b) and deemphasis (shown in Fig. 1c), where the former amplifies relevant visual information, and the latter decreases the prominence of irrelevant visual attributes. Both methods adjust visual adaptations in 25% increments of strength in the range of 0–100%. Examples of highlighting and deemphasis in various adaptation strengths are shown in Fig. 2 and Fig. 3 respectively.

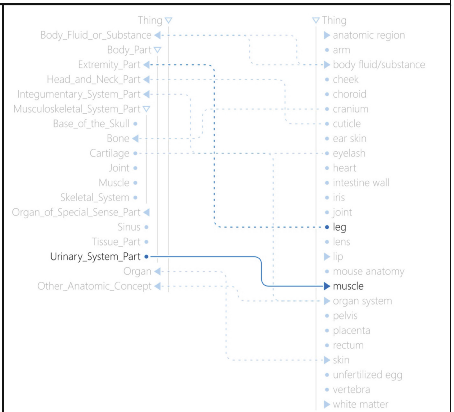
Toggling a node will expand or collapse a class, where solid triangles indicate child nodes, hollow triangles indicate fully expanded nodes, and dotted nodes indicate childless classes. Solid connecting edges, i.e., links, indicate mappings between classes that are fully visible (e.g., *Urinary_System_Part* is mapped to *muscle* in the example shown in Fig. 1), and dotted links indicate mappings between subclasses where at least one class is not yet visible in the visualization (e.g., *leg* is mapped to a subclass of *Extremity_Part* in the example shown in Fig. 1). A user can scroll both horizontally and vertically as the visualizations grow in length and width with toggled nodes. Finally, we recognize there are other possible implementations of a LIL, the visualizations shown in this paper aim to give one example implementation capturing the essence of LIL, whereby classes are visualized as lists of nodes, *is-a* relations are illustrated via indentations, and mappings are visualized as connecting edges between nodes. Given that the goal is to evaluate visual adaptation in an instance of LIL, the implementations shown in this paper are therefore sufficient for the purpose of the experiment.




a. Non-Adaptive Baseline LIL



b. AdaptLIL with Highlighting at 100% Strength



c. AdaptLIL with Deemphasis at 50% Opacity

**Fig. 1.** Non-adaptive Baseline LIL vs. AdaptLIL, implemented using D3.js [49]. (a) shows a non-adaptive LIL, (b) & (c) show two types of visual adaptations – highlighting and deemphasis respectively – by the AdaptLIL upon predicted user failure.

### 3.2 Implementation

Figure 4 illustrates the architecture of the AdaptLIL. As a user interacts with a given visualization, this person's gaze is collected continuously using a GazePoint GP3 HD eye tracker [50]. The Adaptation Mediator component reads gaze data from the eye tracker and places it in a window buffer. Once the buffer is full (i.e., two one-second segments of gaze data have been collected), the mediator sends a request to classify the gaze data. After 10 s of gaze data have been classified (i.e., five consecutive classifications have been performed), a rule-based system either selects a new adaptation, adjusts the adaptation strength, or performs no action. This allows AdaptLIL to continuously observe the effects of a new adaptation type, alter the current adaptation if unsuccessful, or try an entirely different adaptation.

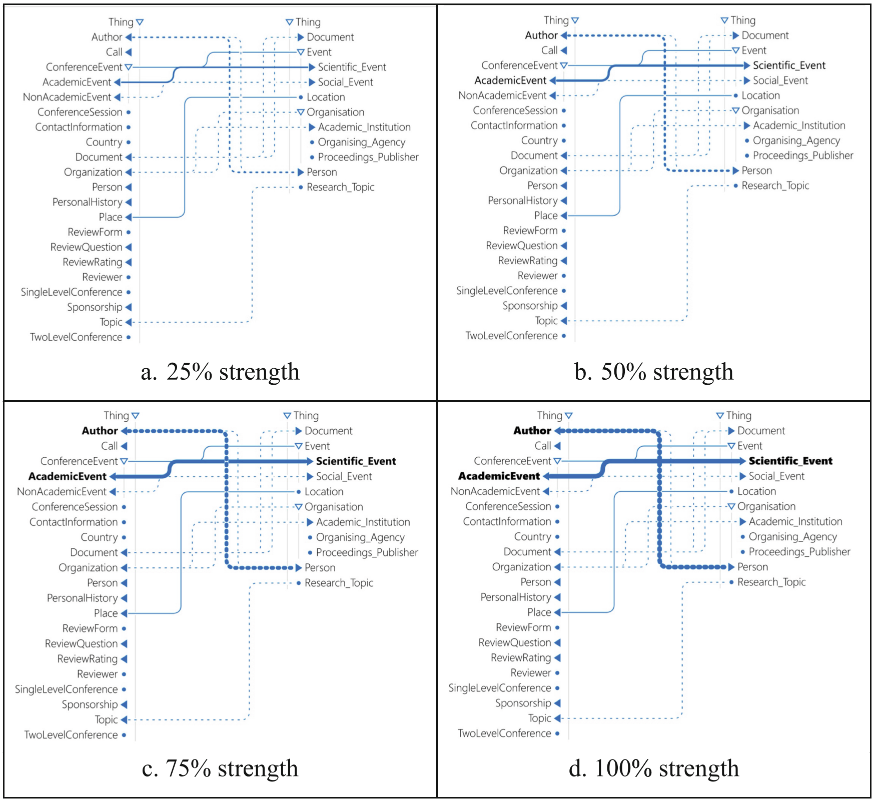



**Fig. 2.** Examples of highlighting at various adaptation strengths, where relevant visual cues are amplified.

A user's points of gaze are collected via the Gazepoint API [51] as a series of vectors $(x, y)$ indicating the x- and y-coordinates of this person's fixation locations as fractions of the screen size. Linear interpolation is applied in the event of invalid entries (as determined by the eye tracker, where binary validity is reported for each raw data

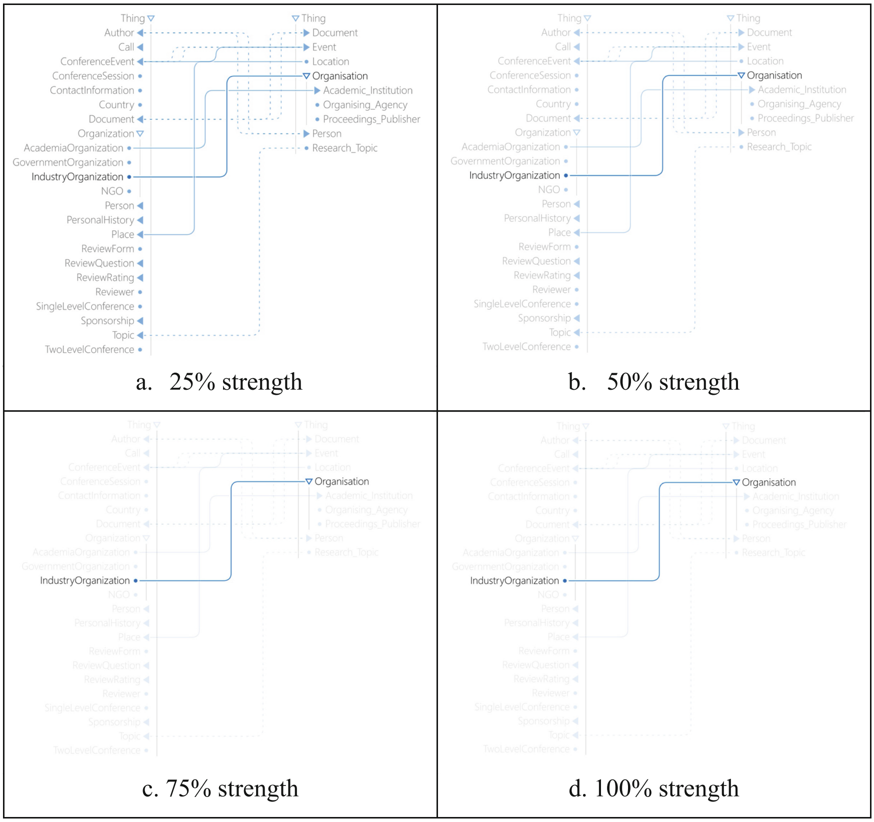



**Fig. 3.** Examples of deemphasis at various adaptation strengths, where irrelevant visual cues are reduced in their prominence.

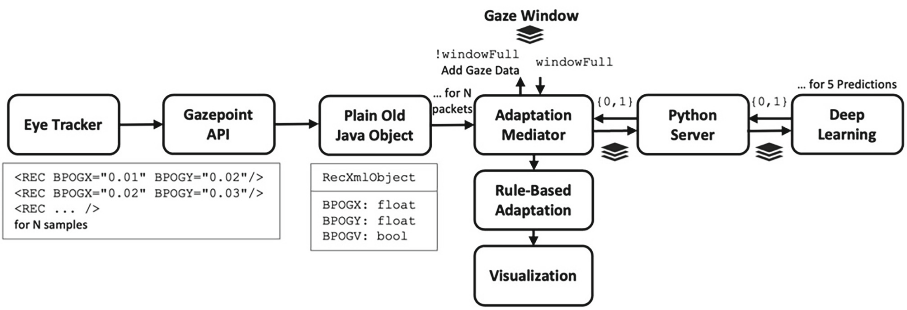



**Fig. 4.** AdaptLIL Architecture

entry), to ensure that subsequent predictions on user performance can be generated without disruption. Motivated by successful applications of spatiotemporal gaze data processing in predictive modeling and binary classifications of task performance [52, 53], we employed a deep learning model Convolutional LSTM and a Transformer Encoder [54] for time series data to predict if a user will succeed or fail at the current task. The transformer encoder captures relationships that could arise from the input sequence for tasks that occur later than what could be captured by the LSTM. In essence, the self-attention mechanism for time series data will use the context of the spatiotemporal input to better classify tasks much farther into the experiment.

The point-of-gaze $(x, y)$ coordinates are first translated into spatial-temporal space. The Convolutional LSTM network then transforms each time sequence $(x_0, y_0, \ldots, x_n, y_n)$ into a smaller input space and reduces the number of attributes for the predictive model, which outputs a binary classification in the end (i.e., either success or failure). For model evaluation, we used K-fold cross validation with 14 folds on gaze data from participants who interacted with the non-adaptive LIL, where the predictive model was trained to a specific task (such as those shown in Table 1). Each training dataset contains a two-dimensional array, corresponding to the number of point-of-gaze coordinates and time sequences. The Convolution layer receives a set of spatiotemporal gaze data as a 2D tensor containing two consecutive gaze frames, arranged as two non-overlapping one-second windows to make predictions on users' performance. This process is iterated five times over 10 s (determined through trial and error), where a rule-based system (illustrated in Fig. 5) then determines if a new adaptation is needed, whether to adjust the strength of an existing adaptation, or perform no action. Since interventions are only meaningful prior to task completion (given that personalized visual cues will no longer be relevant after the user finishes that task), we implemented the aforementioned intervals (i.e., observing and processing spatiotemporal gaze for 10 s) that were empirically determined based on the training dataset (given that time on task is approximately 30 s per task).

```
if (numFailurePredictions == 5 || numFailurePredictions == 4)
    if(!adaptationExists || gracePeriodExpired)
            selectNewAdaptationType()
    else
        increaseAdaptationStrength()

if (numFailurePredictions == 3 || numFailurePredictions == 2)
    if(adaptationExists)
        increaseAdaptationStrength()
     else
            selectNewAdaptationType()

if (numFailurePredictions == 1 || numFailurePredictions == 0)
    continue()
```

**Fig. 5.** Rule-Based Adaptation Selection Pseudocode. Depending on the number of predicted failures out of five classifications (where 4 or 5 predicted failures indicate a high level of confidence, 2 or 3 predicted failures indicate a moderate level of confidence, 0 or 1 predicted failure indicate a low level of confidence to intervene), the AdaptLIL would invoke a new adaptation, adjust the strength of an existing adaptation, or perform no action.

In an effort to prevent drastic changes to users who may be deeply engaged in a visual scene with a recently adapted interface, a 120-s grace period (approximate time needed to complete 3–4 tasks) is implemented in AdaptLIL, whereby the current type of adaptation cannot switch to a different type. The purpose of this grace period is to prevent rapid visual changes that may interrupt the user if new adaptations are frequently invoked, i.e., a user who has just become familiarized with the given visual cues would need to inspect a new visual scene if a different adaptation is put in place too soon, which may lead to setbacks in task progress.

## 4 Evaluation

To evaluate the proposed adaptive visualization, we carried out a between-subject controlled user study, with two different groups of participants each completing the same set of tasks using one visualization system - either the AdaptLIL or the non-adaptive baseline LIL. We opted for a between-subject approach as opposed to a within-subject approach in this particular experiment to remove order effects of the visualizations, which are inevitable if taking the latter approach. With the adaptation component being the only differing condition presented across the two user groups, this evaluation design aims to quantify differences (if any) that can be attributed to the visual adaptation itself, in terms of user success, task speed, and perceived workload. In addition, we investigate the effects of highlighting and deemphasis on user performance, report on the type of adaptation that may be superior and provide recommendations in the development of future adaptive visualizations.

### 4.1 User Task

The participants were assigned to a visualization system with no particular order, where overall, we aimed to have comparable sizes in each user group. Each user group was asked to evaluate a set of mappings between a given pair of ontologies, where the participants must interact with the given visualizations to determine if the mappings are correct and complete. The ontologies were taken from the Ontology Alignment Evaluation Initiative (OAEI) [55], where one domain focuses on the human anatomy (biomedical track) and the other on the organization of conferences (conference track).

A participant completed 30 questions with 15 in each domain (outlined in Table 1), and we counterbalanced the ordering of the domains shown to the participants. The given tasks have correct answers to them (based on the OAEI gold standards), where a success score can then be calculated for each participant in the range of 0 (complete failure) to 1 (complete success). The mapping visualizations contain a mixture of correct, incorrect, and missing mappings between each ontology pair, simulating an environment where a user needs to establish the correctness and the completeness of a set of existing mappings. All mappings in the study are equivalent relations and established between classes. The anatomy domain has 115 classes in the source ontology and 97 classes in the target ontology. The conference domain has 97 classes in the source ontology and 93 classes in the target ontology. A total of 10 mappings are visualized in each domain, 5 of them correct, 5 of them incorrect. In addition, 5 mappings are missing from the visualizations. This design ensures a comparable evaluation scenario across the two domains, where a user's time on task is not a result of having to evaluate a greater number of mappings in a particular domain. Finally, the tasks used in this study are not meant to be exhaustive, they are example tasks designed to provide the necessary conditions to evaluate user interactions with the baseline and the AdaptLIL.

**Table 1.** Mapping Tasks Used in the Study.

| | |
|---|---|
| Anatomy Domain | How many mappings are shown in the visualization in total?<br>How many classes is *Skin* (in the source ontology) mapped to?<br>What is *Viscera* (in the source ontology) mapped to?<br>Can *Joint* (in the source ontology) be mapped to another class (in the target ontology)?<br>What is *Skull* (in the source ontology) mapped to (in the target ontology)?<br>Can *Arm* (in the source ontology) be mapped to another class (in the target ontology)?<br>Is there a mapping between *Blood* (in the source ontology) and *blood* (in the target ontology)?<br>Is *Cartilage* (in the source ontology) correctly mapped?<br>*Urinary_System_Part* (in the source ontology) is mapped to *muscle* (in the target ontology). Is this correct?<br>*Cheek* (in the source ontology) is mapped to *cuticle* (in the target ontology). Is this correct?<br>*Skin* (in the source ontology) is mapped to *skin* (in the target ontology). Is this correct?<br>*Mucus* (in the source ontology) is mapped to *nasal mucus* (in the target ontology). Is this correct?<br>Which class could *Heart* (in the source ontology) be mapped to (in the target ontology)?<br>Which class could *Lip* (in the source ontology) be mapped to (in the target ontology)?<br>Is there any other mapping(s) that should be created between the ontologies but is currently absent from the visualization? |
| Conference Domain | How many mappings are shown in the visualization in total?<br>How many classes is *Author* (in the source ontology) mapped to?<br>What is *SlideSet* (in the source ontology) mapped to?<br>Can *Person* (in the source ontology) be mapped to another class (in the target ontology)?<br>What is *ConferenceDinner* (in the source ontology) mapped to (in the target ontology)?<br>Can *Workshop* (in the source ontology) be mapped to another class (in the target ontology)?<br>Is there a mapping between *AcademicEvent* (in the source ontology) and *Scientific_Event* (in the target ontology)?<br>Is *AcademiaOrganization* (in the source ontology) correctly mapped?<br>*SecurityTopic* (in the source ontology) is mapped to *Research_Topic* (in the target ontology). Is this correct?<br>*Place* (in the source ontology) is mapped to *Location* (in the target ontology). Is this correct?<br>*RejectedPaper* (in the source ontology) is mapped to *Assigned_Paper* (in the target ontology). Is this correct?<br>*IndustryOrganization* (in the source ontology) is mapped to *Organisation* (in the right ontology). Is this correct?<br>Which class could *Attendee* (in the source ontology) be mapped to (in the target ontology)?<br>Which class could *ConferenceDinner* (in the left ontology) mapped to (in the right ontology)?<br>Is there any other mapping(s) that should be created between the ontologies but is currently absent from the visualization? |

### 4.2 Study Configuration

The participants were seated in front of a desktop computer with a Gen 13 Intel Core i9 NVIDIA 16 GB graphics card and 64GB of DDR5 RAM (configured with mouse and keyboard) and a 24” Full HD monitor (1920 × 1080p) at 165Hz and 1ms response time. The GazePoint GP3 HD eye tracker (with a 150Hz sample rate) was positioned below the monitor on a tripod and has a movement tolerance range of 35 cm (horizontal) × 22 cm (vertical) × ± 15 cm (depth). Each participant completed a 9-point calibration before starting the tasks to maximize gaze validity. Participants were also seated on office chairs without wheels or swivels to minimize gaze loss. A short tutorial on ontology mapping and their visualizations were presented to the participants during pre-task briefing. The participants were instructed to do their best while being as fast as possible when completing the given tasks. We collected success scores, time on task, and perceived workload using the NASA task load index (TLX) [56] from the participants upon task completion.

### 4.3 Participants

We recruited a total of 76 participants in the study, where 41 participants interacted with the non-adaptive baseline LIL, and 35 participants interacted with the AdaptLIL to answer the questions outlined in Table 1. Due to various issues encountered during some experiment sessions (such as loss of gaze), invalid data from some participants were discarded. The results shown in this paper are aggregated from a total of 35 and 30 individuals belonging to the baseline group and the AdaptLIL group respectively. The participants are undergraduate and graduate students with a mixture of backgrounds in Computer Science, Computer Engineering, and Math, where some individuals have taken graduate level courses on the Semantic Web. However, such individuals shall not be considered as experts, given the many criteria (such as visualization literacy, expertise in ontology mapping, knowledge of the given domains) that one must satisfy in this experiment in order to qualify as a true expert. As such, the participant sample in this paper shall be considered as novices in all aspects of the study. Given that adaptive intervention is likely most helpful for novice users rather than expert users, the participant groups are sufficient in this study for the purpose of evaluating the adaptation component. This controlled experiment aims to limit the number of variables (such as expertise) that could have an effect on user success, to ensure that the findings (e.g., if a user performed well in the given tasks) can be attributed to the visual adaptations (as opposed to one’s prior knowledge).

## 5 Results and Findings

Figure 6a shows the average task success scores for the two groups of participants. Success scores are calculated as the proportion of correct answers across all 15 questions in the given domain (shown in Table 1). On average, the group who used the AdaptLIL achieved equal (in the conference domain) or higher success (in the anatomy domain) compared to those who used the non-adaptive baseline. Particularly in the anatomy domain, the improvement on user success (0.70 when using AdaptLIL vs. 0.64 when using the baseline) is also statistically significant ($p < 0.05$) when visual adaptations were deployed. Figure 6b shows the average task speed across the two domains for each user group. The differences between the users who used the baseline and the AdaptLIL are marginal, and we did not find statistically significant differences ($p > 0.05$). These results indicate that visual adaptations have likely attributed to increased user success without adding extra time for users to complete the given tasks.

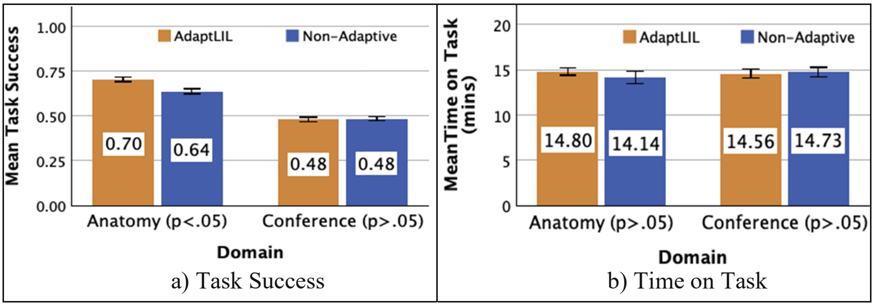



**Fig. 6.** Task Success and Task on Time by Domain. Error Bars: 95% Confidence Interval.

Figure 7 presents the users' perceived workload in each group. The NASA TLX aims to measure workload through six dimensions, including mental, physical, temporal demand, as well as effort, performance, and frustration using the visualization. We collected raw TLX (without assigned weights) using 7-point Likert scales after a user has completed all tasks in both domains using a given visualization. The overall TLX scores (accounting all six dimensions) for the AdaptLIL and the non-adaptive baseline are comparable, with a perceived overall workload rating at 62.10 for the former and 62.22 for the latter (out of 100). A notable difference is that the AdaptLIL was rated to be less demanding in effort, but more frustrating to use compared to the baseline, as some participants mentioned switching between highlighting and deemphasis was somewhat distracting. This finding suggests that visual adaptations may be helpful in reducing effort but can present usability challenges to the user at the same time, since small changes in the visual attributes (such as changing between highlighting and deemphasis in this case) can negatively impact the user experience. Nonetheless, it is worthy to note that higher user success in the given tasks did not lead to increased workload when using the AdaptLIL.

We performed Pearson correlation coefficient tests to investigate the relationships (if any) between the adaptation strength and user success. Figure 8 presents the correlation coefficient found in each domain by adaptation type. In the Anatomy domain (Fig. 8a), a statistically significant correlation was found when using the highlighting adaptation, where a moderate relationship ($r = 0.36$, $p < 0.05$) was found between user success and adaptation strength. This result indicates that for this particular domain, using highlighting as a mean to provide visual intervention becomes more and more effective as the adaptation increases in strength. In the conference domain (Fig. 8b) however, the opposite was found in our testing, whereby task success shows a negative relationship

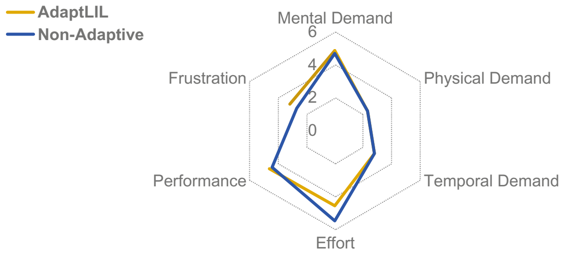
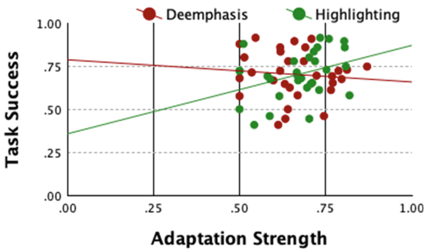
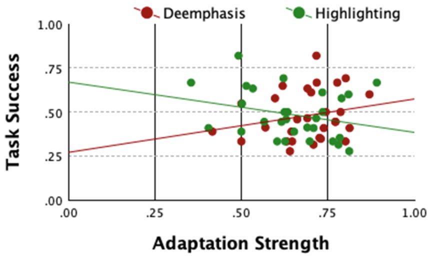



**Fig. 7.** Perceived Workload when using the AdaptLIL vs. the Non-adaptive Baseline.

($r = -0.27$, $p < 0.05$) with the strength of highlighting. In other words, the weaker the highlighting, the more successful the user in that domain. Similarly, we observed opposite effects when using the deemphasis adaptation across the two domains. In particular, a weak negative correlation ($r = -0.09$, $p > 0.05$) was found in the anatomy domain (Fig. 8a), indicating negligible associations between user success and adaptation strength. Whereas in the conference domain (Fig. 8b), a moderate positive correlation ($r = 0.23$, $p > 0.05$) was found when using the deemphasis adaptation, indicating increased user success with stronger deemphasis. Moreover, based on the feedback from the participants, in both domains, most participants preferred highlighting over deemphasis as the more helpful form of visual aid. Furthermore, a number of participants have noted that switching between highlighting and deemphasis were somewhat unhelpful, concurring with our rationale to provide less disruptive visual interventions mid-task as discussed in Sect. 1.




a) Anatomy Domain: Task success vs. adaptation strength, r = 0.36 (p < .05) for highlighting, r = -0.09 (p > .05) for deemphasis




b) Conference Domain: Task success vs. adaptation strength, r = -0.27 (p > .05) for highlighting; r = 0.23 (p > .05) for deemphasis

**Fig. 8.** Correlations of Task Success and Adaptation Strength by Domain

While some correlations did not show statistically significant differences, the contrasting effects of the adaptation strength on user success may be grounded in the nature of these visual cues. More specifically, in the case of highlighting, as the selected visual cues are made more visible, the rest of the elements in the visualization becomes less prominent as a result. In the case of deemphasis, as irrelevant visual elements become less emphasized, the relevant visual cues become amplified as if they are being highlighted. As such, highlighting and deemphasis may be perceived as two different methods that arrive to a similar visual outcome using contrary forces, leading to positive correlations in one and negative correlations in the other (evidentially in both domains). Another notable observation is the differing correlations in the two domains, whereby in the anatomy domain, a positive correlation was found for the highlighting technique and a negative correlation was found for the deemphasis technique. In the conference domain, the opposite was shown, i.e., a negative correlation was found for the highlighting technique and a positive correlation was found for the deemphasis technique. In other words, adaptation strength (regardless of highlighting or deemphasis) had comparable impact on user performance in the conference domain, but the stronger the highlighting, the higher the user success in the anatomy domain. This finding suggests that the effectiveness of an adaptation may likely be domain dependent, though additional experiments are needed to investigate further.

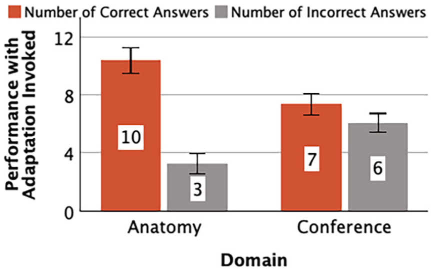



**Fig. 9.** User performance while adaptation is in effect. Error Bars: 95% Confidence Interval.

Within the AdaptLIL user group, on average, 324 number of failures were predicted in the anatomy domain and 310 number of failures predicted in the conference domain for an individual participant. While adaptation is in place (either highlighting or deemphasis), participants answered a greater number of questions correctly, particularly in the anatomy domain, as shown in Fig. 9. We further grouped participants using a median split as those who were more successful (i.e., task success above the median score) versus those who were less successful (i.e., task success below the median score) in the given tasks while assisted by the AdaptLIL. We observed that those who scored higher generally had longer periods of adaptation deployed while they completed the given tasks, particularly in the anatomy domain, as shown in Fig. 10.

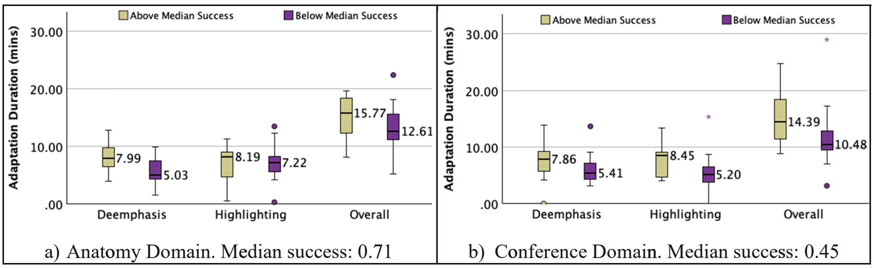



**Fig. 10.** Adaptation Duration Across Domains

## 6 Conclusions and Future Work

This paper presents a gaze-adaptive linked indented list visualization for ontology mapping that adapts to an individual user in its visual displays in real time. The AdaptLIL applies the Convolutional LSTM to predict a person's task success or failure based on this individual's gaze, upon an inferred failure, dynamic visual adaptations are invoked in an effort to provide interventions to assist the user during task completion. Two approaches to adaptations are investigated in this paper, including highlighting relevant visual cues and deemphasizing irrelevant visual information. Through an evaluation involving 76 participants in a between-subject ontology mapping experiment across two domains, we demonstrate the effectiveness of the AdaptLIL empirically with statistically significant increases in user success without additional workload perceived by the user or delay in task completion. Moreover, we found differing effects on user performance depending on the type of adaptation and the strength applied. In particular, stronger highlighting may be more effective than greater deemphasis in some domains, suggesting a need for further experiments to identify relevant domain specific parameters when applying a particular visual intervention.

While we have shown a motivating example of adaptive visualization for ontology mapping that moves beyond the traditional one-size-fits-all solutions, there are a number of future research directions in the advancement of gaze-adaptive visualizations for ontologies and mappings. Firstly, other forms of adaptations such as zooming in and out on regional structures and relationships may provide useful cognitive support in scenarios where large-scale datasets are visualized. The effects beyond highlighting and deemphasis may be investigated in future adaptative mapping visualizations, such as changing the color palette, background or text theme, size of the visual elements as noted in [29]. Secondly, depending on the task itself, there may be scenarios where changing the type of visualization can bring benefits outweighing the penalties. Such drastic interventions may not be appropriate for smaller tasks that do not require prolonged engagement such as those presented in this paper but may be suitable for longer tasks where a change of this nature will greatly benefit the user. Future research could investigate and determine the type of task where a change of the visualization type would be helpful. Moreover, instead of the system switching to another visualization style or layout, it is possible to provide suggestions of alternative visual aids (such as [57]), where the decision to switch or not is left to the user as opposed to defaulting to the system, in an effort to minimize disruption while maximizing flexibility. Thirdly, given the recent advances to infer personal traits using eye gaze [58, 59], it is possible to adapt to, e.g., cognitive styles and abilities, personality, language abilities, emotion, fatigue level, beyond user performance shown in this paper. Furthermore, while an adaptive LIL is presented in this paper, there are many other types of mapping visualizations such as node-link diagrams, matrices, treemaps, block metaphors that are not yet explored in the context of enriching them with adaptive features. Future research could identify other adaptations that may be most appropriate for a given mapping scenario and a specific visualization technique. Last but not least, in an effort to further refine the development of adaptive visualizations for ontological data, future research could investigate additional scenarios (e.g., mappings between instances, properties), types of mapping (e.g., broad-narrow matches, disjoints, part-of relations), tasks and domains (e.g., large-scale mappings, one-to-many mappings), user groups (e.g., evaluate the impact of different types of adaptation in the presence of distinct user backgrounds and prior knowledge), as well as exploring the use of readily available equipment such as webcams (e.g., as proposed in [60]) when realizing physiologically adaptive visualizations for everyday users at scale in day-to-day usage (i.e., without specialized eye tracking equipment).

*Supplemental Material Statement: Source code of the AdaptLIL and the ontologies used in the evaluation can be found at* https://github.com/TheD2Lab/AdaptLIL *The user data generated from the evaluation is available upon request.*

## References


1. Jameson, A.: Adaptive interfaces and agents. In: Jacko, J.A. and Sears, A. (eds.) Human-Computer Interface Handbook, pp. 305–330 (2003)
2. Conati, C., Maclaren, H.: Exploring the Role of Individual Differences in Information Visualization. In: Proceedings of the Working Conference on Advanced Visualization Interfaces, pp. 199–206 (2008)
3. Green, T. M., Fisher, B.: Towards the personal equation of interaction: the impact of personality factors on visual analytics interface interaction. In: Proceedings of the IEEE Symposium on Visual Analytics Science and Technology (VAST '10), pp. 203–210 (2010)
4. Flatla, D.R., Gutwin, C.: SSMRecolor: improving recoloring tools with situation-specific models of color differentiation. In: Proceedings of the ACM SIGCHI Human Factors in Computing Systems (CHI '12), pp. 2297–2306 (2012)
5. Toker, D., Conati, C., Carenini, G., Haraty, M.: Towards adaptive information visualization: on the influence of user characteristics. In: Proceedings of the 20th Conference on User Modeling, Adaptation, and Personalization (UMAP '12), pp. 274–285 (2012)
6. Carenini, G., Conati, C., Hoque, E., Steichen, B., Toker, D., Enns, J.T.: Highlighting interventions and user differences: informing adaptive information visualization support. In: Proceedings of the ACM SIGCHI Conference on Human Factors in Computing Systems (CHI '14), pp. 1835–1844 (2014)
7. Gotz, D., Wen, Z.: Behavior-driven visualization recommendation. In: Proceeding of the 14th International Conference on Intelligent User Interfaces (IUI '09), pp. 315–324. ACM, New York (2009)
8. Ahn, J., Brusilovsky, P.: Adaptive visualization for exploratory information retrieval. Inf. Process. Manage. **49**(5), 1139–1164 (2013)
9. Lee, S., Kim, S.H., Hung, Y.H., Lam, H., Kang, Y.A., Yi, J.S.: How do people make sense of unfamiliar visualizations? a grounded model of novice's information visualization sensemaking. IEEE Trans. Visual Comput. Graphics **22**(1), 499–508 (2016)
10. Steichen, B., Fu, B., Nguyen, T.: Inferring cognitive style from eye gaze behavior during information visualization usage. In Proceedings of the 28th ACM conference on user modeling, adaptation and personalization (UMAP '20), pp. 348–352. ACM, NY (2020)
11. Fu, B., Noy, N. F., Storey, M.-A.: Eye Tracking the User Experience - An Evaluation of Ontology Visualization Techniques. Semantic Web Journal – Interoperability, Usability, Applicability, IOS Press, 8(1), pp. 23–41 (2017)
12. Fu, B., Austin, A., Garcia, M.: Visualizing mappings between pairwise ontologies - an empirical study of matrix and linked indented list in their user support during class mapping creation and evaluation. In: Proceedings of the 22nd International Semantic Web Conference (ISWC '23) Part I, LNCS 14265, pp. 579–598, (2023)

13. Granitzer, M., Sabol, V., Onn, K.W., Lukose, D., Tochtermann, K.: Ontology alignment—a survey with focus on visually supported semi-automatic techniques. Future Internet. **2**(3), 238–258 (2010)
14. Dragisic, Z., Ivanova, V., Lambrix, P., Faria, D., Jiménez-Ruiz, E., Pesquita, C.: User Validation in Ontology Alignment. In: Proceedings of the 15th International Semantic Web Conference (ISWC '16). LNCS 9981, pp. 200–217, Springer, Cham (2016)
15. Ivanova, V., Lambrix, P., Åberg, J.: Requirements for and evaluation of user support for large-scale ontology alignment. In: The Semantic Web. Latest Advances and New Domains, ESWC '15, LNCS, vol. 9088, pp. 3–20 (2015)
16. Cruz, I., Antonelli, F., Stroe, C.: Agreementmaker: efficient matching for large real-world schemas and ontologies. In Proceedings of the VLDB Endowment **2**(2), 1586–1589 (2009)
17. Pesquita, C., Faria, D., Santos, E., Neefs, J., Couto, F.M.: Towards visualizing the alignment of large biomedical ontologies. In: Proceedings of the International Conference on Data Integration in the Life Sciences, vol. 8574, pp. 104–111. Springer, Cham (2014)
18. Lanzenberger, M., Sampson, J., Rester, M., Naudet, Y., Latour, T.: Visual ontology alignment for knowledge sharing and reuse. Knowl. Manag. **12**(6), 102–120 (2008)
19. Falconer, S., Storey, M.-A.: A Cognitive Support Framework for Ontology Mapping. In: Proceedings of the 6th International Semantic Web Conference, 2nd Asian Semantic Web Conference (ISWC '07 + ASWC '07), LNCS 4825, pp. 114–127. Springer, Heidelberg (2007)
20. Maßmann, S., Raunich, S., Aumüller, D., Arnold, P., Rahm, E.: Evolution of the COMA match system. In: Proceedings of 6th International Workshop on Ontology Matching (OM), CEUR-WS Vol-814 (2011)
21. Neto, L.E.T., Vidal, V.M.P., Casanova, M.A., Monteiro, J.M.: R2RML by assertion: a semi-automatic tool for generating customised R2RML mappings. ESWC 2013 Satellite Events. LNCS, vol. 7955, pp. 248–252, Springer, Heidelberg (2013)
22. Nasir, M., Hoeber, O., Evermann, J.: Supporting ontology alignment tasks with edge bundling. In: Proceedings of the 13th International Conference on Knowledge Management and Knowledge Technologies, Article 11, pp. 1–8, ACM (2013)
23. Severo, B., Trojahn, C., Vieira, R.: VOAR 3.0: a configurable environment for manipulating multiple ontology alignments. In: Proceedings of the ISWC 2017 Posters & Demonstrations and Industry Tracks, CEUR-WS Vol-1963 (2017)
24. Aurisano, J., Nanavaty, A., Cruz, I.: Visual analytics for ontology matching using multi-linked views. In: Proceedings of the International Workshop on Visualizations and User Interfaces for Ontologies and Linked Data, co-located with ISWC '15, CEUR-WS Vol-1456, pp. 25–36 (2015)
25. Fu, B., Grammel, L., Storey, M.-A.: BioMixer: a web-based collaborative ontology visualization tool. In: Proceedings of the 3rd International Conference on Biomedical Ontology, CEUR-WS Vol-897 (2012)
26. Dang, T., Franz, N., Ludäscher B., Forbes, A.G.: ProvenanceMatrix: a visualization tool for multi-taxonomy alignments. In: Proceedings of the International Workshop on Visualizations and User Interfaces for Ontologies and Linked Data, co-located with ISWC 2015, CEUR-WS Vol-1456, pp. 13–24 (2015)
27. Junior, A.C., Debruyne, C., O'Sullivan, D.: An editor that uses a block metaphor for representing semantic mappings in linked data. ESWC 2018 Satellite Events. LNCS, vol. 11155 (2018)
28. Nazemi, K.: Adaptive Semantics Visualization. Springer, Cham (2016)
29. Andreou, P., Amyrotos, C., Germanakos, P., Polycarpou, I.: Human-centered information visualization adaptation engine. In: Proceedings of the 31st ACM Conference on User Modeling, Adaptation and Personalization (UMAP '23), pp. 25–33. ACM, New York (2023)
30. Liu, Z., Crouser, R.J., Ottley, A.: Survey on individual differences in visualization. Comput. Graph. Forum **39**, 693–771 (2020)

31. Ziemkiewicz, C., Crouser, R.J., Yauilla, A.R., Su, S.L., Ribarsky, W., Chang, R.: How Locus of Control Influences Compatibility with Visualization Style. In: Proceedings of the IEEE Conference on Visual Analytics Science and Technology (VAST '11), pp. 81–90 (2011)
32. Conati, C., Hoque, E., Toker, D., Steichen, B.: When to adapt: detecting user's confusion during visualization processing. In: Proceedings of the 1st International Workshop on User-Adaptive Information Visualization (WUAV '13), in Conjunction with UMAP (2013)
33. Lallé, S., Toker, D., Conati, C., Carenini, G.: Prediction of users' learning curves for adaptation while using an information visualization. In: Proceedings of the 20th International Conference on Intelligent User Interfaces (IUI '15), pp. 357–368. ACM, New York (2015)
34. Feit, A.M., Vordemann, L., Park, S., Berube, C., Hilliges, O.: Detecting relevance during decision-making from eye movements for UI adaptation. In: ACM Symposium on Eye Tracking Research and Applications (ETRA '20), Article 10, pp. 1–11. ACM, New York (2020)
35. Karaman, C.C., Sezgin, T.M.: Gaze-based predictive user interfaces: visualizing user intentions in the presence of uncertainty. Int. J. Hum. Comput. Stud. **111**, 78–91 (2018)
36. Barral, O., Lallé, S., Conati, C.: Understanding the effectiveness of adaptive guidance for narrative visualization: a gaze-based analysis. In: Proceedings of the 25th International Conference on Intelligent User Interfaces (IUI '20). Association for Computing Machinery, New York, NY, USA, pp. 1–9 (2020)
37. Göbel, F., Kiefer, P., Giannopoulos, I., Duchowski, A.T., Raubal, M.: Improving map reading with gaze-adaptive legends. In: Proceedings of the 2018 ACM Symposium on Eye Tracking Research & Applications (ETRA '18), Article 29, pp. 1–9. ACM, New York (2018)
38. Fu, B., Steichen, B.: using behavior data to predict user success in ontology class mapping – an application of machine learning in interaction analysis. In: Proceedings of the IEEE 13$^{th}$ International Conference on Semantic Computing (ICSC '19), pp. 216–223 (2019)
39. Fu, B., Steichen, B., Zhang, W.: Towards adaptive ontology visualization - predicting user success from behavioral data. Int. J. Semantic Comput. **13**(4), 431–452 (2019)
40. Fu, B., Steichen, B., McBride, A.: Tumbling to succeed: a predictive analysis of user success in interactive ontology visualization. In: Proceedings of the 10th International Conference on Web Intelligence, Mining and Semantics (WIMS '20), pp. 78–87. ACM (2020)
41. Fu, B., Steichen, B.: Supporting user-centered ontology visualization: predictive analytics using eye gaze to enhance human-ontology interaction. Int. J. Intell. Inf. Database Syst. **15**(1), 28–56 (2021)
42. Fu, B., Steichen, B.: Impending success or failure? an investigation of gaze-based user predictions during interaction with ontology visualizations. In: Proceedings of the International Conference on Advanced Visual Interfaces (AVI '22), Article No.7, pp. 1–9. ACM (2022)
43. Bartram, L., Ware, C., Calvert, T.: Moticons: detection, distraction and task. Int. J. Hum. Comput. Stud. **58**(5), 515–545 (2003)
44. Muir, M., Conati, C.: An analysis of attention to student – adaptive hints in an educational game. In: Proceedings of the 11th International Conference on Intelligent Tutoring Systems, pp. 112–122 (2012)
45. Grawemeyer, B.: Evaluation of ERST – an external representation selection tutor. In: Proceedings of the 4$^{th}$ International Conference on Diagrammatic Representation and Inference, pp. 154–167 (2006)
46. Kong, N., Agrawala, M.: Graphical Overlays: Using Layered Elements to Aid Chart Reading. Visualization and Computer Graphics, pp. 2631–2638 (2012)
47. Steichen, B., Fu, B.: Towards Adaptive Information Visualization - A Study of Information Visualization Aids and the Role of User Cognitive Style. Frontiers in Artificial Intelligence, section AI for Human Learning and Behavior Change 2 (22) (2019)

48. Satkowski, M., Kessler, F., Narciss, S., Dachselt, R.: Who benefits from visualization adaptations? towards a better understanding of the influence of visualization literacy. In: Proceedings of the IEEE Visualization and Visual Analytics (VIS '22), Oklahoma City, OK, USA, pp. 90–94 (2022)
49. D3 Homepage. https://d3js.org. Accessed 31 June 2024
50. GazePoint eye tracker. https://www.gazept.com/product/gp3hd/?v=7516fd43adaa. Accessed 31 June 2024
51. Open Gaze API by GazePoint, version 2.0. https://www.gazept.com/dl/Gazepoint_API_v2.0.pdf. Accessed 31 June 2024
52. Sodoké, K., Nkambou, R., Dufresne, A., Tanoubi, I.: Toward a deep convolutional LSTM for eye gaze spatiotemporal data sequence classification. In: Proceedings of the 13th International Conference on Educational Data Mining (2020)
53. Spiller, M., Liu, Y.H., Hossain, M.Z., Gedeon, T., Geissler, J., Nürnberger, A.: Predicting visual search task success from eye gaze data as a basis for user-adaptive information visualization systems. ACM Trans. Interact. Intell. Syst. **2**(11), 1–25 (2021)
54. Vaswani, A., et al.: Attention is All you Need. In: Advances in Neural Information Processing Systems (2017)
55. Ontology Alignment Evaluation Initiative hompage. http://oaei.ontologymatching.org. Accessed 31 June 2024
56. Hart, S.G., Staveland, L.E.: Development of NASA-TLX (Task Load Index): Results of Empirical and Theoretical Research. North Holland Press, Human Mental Workload. Amsterdam (1988)
57. Mutlu, B., Veas, E., Trattner, C., VizRec: recommending personalized visualizations. ACM Trans. Interactive Intell. Syst. **6**, 4, Article 31 (2016)
58. Steichen, B.: Computational Methods to Infer Human Factors for Adaptation and Personalization Using Eye Tracking. In: Ferwerda, B., Graus, M., Germanakos, P., Tkalčič, M. (eds.) A Human-Centered Perspective of Intelligent Personalized Environments and Systems, pp. 183–204. Springer, Cham (2024)
59. Steichen, B., Fu, B.: Cognitive style and information visualization - modeling users through eye gaze data. Front. Comput. Sci. **2**, 562290 (2020)
60. Papoutsaki, A., Sangkloy, P., Laskey, J., Daskalova, N., Huang, J., Hays, J.: Webgazer: scalable webcam eye tracking using user interactions. In: Proceedings of the 25th International Joint Conference on Artificial Intelligence, pp. 3839–3845 (2016)