Designing the user experience of a co-adaptive data analytics interface in response to user trait

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ABSTRACT

When humans collaborate, the environment, task, and interactions with team members shape the way information is gained and responded to over time. Many applications people interact with today contain some form of customization, such as movie and television recommendations from Netflix, product suggestions from Amazon, or intelligent word suggestion in text messages and within many search engines such as Google. In this paper, we surmise that personalizing more effectively beyond recommendation engines requires a deeper understanding of each audience member for particular applications. A design process is described for developing adaptations to a data analytics interface based on a single user trait: Need for Cognition.

CCS CONCEPTS

• **Human-centered computing** → Human computer interaction (HCI) → HCI design and evaluation methods → Usability testing

KEYWORDS

User experience, design, evaluation, paper prototyping, adaptive software, personalization, information retrieval, data analysis

1 INTRODUCTION AND RELATED WORK

Humans adapt easily when working with each other; the environment, task, and interactions with team members shape the way information is gained and responded to over time. Increasingly, human-human interaction is replaced or augmented with human-machine interaction. A common human-machine system is a user interfacing with a software application to complete a task. Research in the Human-Computer Interaction field has shown that personalizing user interfaces can increase satisfaction, reduce cognitive overload, and increase performance [14, 17, 18, 19]. Many applications people interact with today contain some form of customization, such as content recommendations from Netflix, product suggestions from Amazon, or intelligent word suggestion in text messages and within many search engines such as Google. In this paper, we surmise that personalizing more effectively beyond recommendation-engines requires a deeper understanding of each audience member for particular applications, so that adjustments provide tailored value add while reducing distraction and decreasing cognitive load [2, 9].

Studies in psychology have shown that personality traits modulate how people understand the world and engage in specialized tasks**.** Personality traits are largely invariant (or slowly variant) observable human characteristics [13, 15]. One widely known trait is *Need for Cognition* (NFC), defined as the "individual's tendency to engage in and enjoy effortful cognitive tasks" [4]. We chose to focus on Need for Cognition for this study, since there are clear behavioral differences among people with varying NFC scores, particularly in how they approach problems and make decisions [7, 10, 11]. Individuals with higher NFC scores tend to prefer engaging with details to build up a picture of the world or problem [4, 5, 8]. Conversely, those with low NFC tend to want to quickly understand the high-level overview and avoid exploring the details [3, 4, 5]. This research into how High and Low NFC individuals interact with the world can be extended to how they interact with software applications

Information retrieval tasks are part of daily life; however, the number and type of interfaces we interact with to accomplish these tasks has increased dramatically. Along with more devices, there are more modalities to present information - visual, auditory, haptic - and more variance in the timing of when messages are presented. Often, information is presented instantaneously across multiple channels. As a result, information overload is an increasingly common experience [1, 12]. Our supposition is that users could benefit from personalized interfaces. By "understanding" a user and using that knowledge to inform information presentation and interface design, cognitive overload could be mitigated and natural processing capabilities can be supplemented. For our use case, we decided to explore the Analyst role, since the occupation is grounded in information retrieval, both in processing a high quantity of information and in needing to process it quickly.

We proposed a solution to address user needs in increasingly overwhelming information retrieval environments: a co-adaptive (human-machine) relationship. A co-adaptive relationship is defined as: both the human and software agent adjusting behavior and information presentation (graphics and content) based on context, state, trait, and task. In earlier work, we have shown that implementing this co-adaptive relationship, based on personality traits, increases user performance in accomplishing specific tasks and usability and satisfaction within the overall system [7, 10, 11].

To study how a machine could adapt to individuals, we chose an open-ended intelligence analysis task; users need to identify key information among data for decision-making within a restricted

Table 1: Methods Summary

Population	Characteristics	Round 1 Features Tested	Round 1 Feedback	Revised Design	Round 2 Test?	Round 2 Feedback
High NFC *n = 4*	• Likes detail • Deeply investigates areas of interest	• Notes • Tags • Pins • Pin & String "Connectors"	• Notes/tags used interchangeably • Name "Connector" confusing • Prefer limited visual clutter	• Notes • Pin & String (with labels)	No	N/A
Low NFC *n = 3*	• Likes "big picture" • Focus on areas specific to task	• Summary Stats Table • Tips	• Ignored Stats Table • Drawn to visual cues • Overwhelmed by data volume • Tips read, did not prompt exploration	• Data definitions and highlights • Suggested filters • Applied filters	Yes	• Much more helpful • Suggested filters prompt in depth data exploration

timeframe. We chose to use Next Century Corporation's open-source data visualization application, Neon, to test out our hypothesis [16]. The next section will discuss the methods and initial results we gathered from our qualitative pilot using paper prototypes.

2 METHODS

Our primary goal in adaptation design for a data analysis task was to support a more organized, efficient analysis process based on user trait (i.e., Low or High NFC). The goal of our design and evaluation process was to gain first-hand insight into expectations, approach, user experience and workflow for both High and Low NFC. This feedback informed designs completed for the Neon interface.

2.1 Testing Approach

Seven participants (4 High NFC, 3 Low NFC) were given ten minutes to engage in an open-ended data analysis task with NFC-specific interface adaptations (see Section 2.2 for more detail on designs). The participants were employees at Draper, an engineering research and development company. Participants were asked to use the dashboard to determine an answer to the following question using the available data and interface: *If you had 100 million dollars to build a production facility in any country in the world, what country would you choose?*

This research involved a User Experience (UX) approach using paper prototypes and a think-aloud protocol to test our hypothesis. We utilized the NFC 10-item testing instrument [4, 5] in order to assess individual NFC scores, and this research considered a score above 70 to be High NFC and below 50 as Low NFC.

A paper prototyping approach provided direct feedback from participants without spending development effort on creating prototype software. This approach involved presenting users with a paper version of the original Neon interface, and additional paper features designed for their specific trait (i.e., Low NFC or High NFC). Prior to beginning the task, participants were given a short training on how to use Neon. They also reviewed descriptive definitions of the available data sets for the given task (i.e. GDP Growth, Unemployment Rate, Foreign Domestic Investment, World Risk Index, Population Growth, and Earthquake Incidence for various countries over 20 years). During the task, participants explored the interface, using their index finger to move through the dashboard as they would a mouse on a screen, and verbalized any action or change they would like to perform (e.g. "click," "select data"). A research assistant made the necessary changes. The nature of the task was open-ended and participants were not expected to arrive at a specific "correct" answer to assess task performance. Instead, effectiveness in the task was observed qualitatively, primarily through user willingness to explore the data in an in-depth way without behaviors associated with cognitive overload.

2.2 Design Approach

2.2.1 High NFC Users. Since High NFC users like to dive into details, initial adaptations were designed to enhance exploration, while keeping them anchored to the goal and allowing them to save any insights gained. In this way, as High NFC users were drawn toward exploring deeper into specific data sets or areas, they may draw conclusions by maintaining awareness of previous observations. Initial High NFC design (Figure 1) included a pop-up menu from which users could select to add a note, tag, pin, or connector. Notes were text boxes written by the user while tags were single lines of text that the user could place on the dashboard. Pins were visual cues used to mark widgets, and connectors were lines that could be drawn between widgets to symbolize an observed link between the data. The rationale behind text boxes and tags was to let users refer back to insights gained. Similarly, pins could denote connections users found between data sets.

2.2.2 Low NFC Users. Since Low NFC users need to understand the big picture before they can synthesize details, adaptations were developed to enable quick orientation to the interface and data. Specifically, initial adaptations were designed to improve dashboard exploration and enable data trend identification. The initial Low NFC designs included providing tips and a summary table at the top of the page (Figure 2). The tips provided suggestions on interactions the user had not yet found. The summary table included information on each data set across all countries. The rationale behind tips and summaries was to provide quick hooks into the interface. However, after testing, these designs were drastically changed (Figure 3) and the revised designs were tested with the same participants (Table 1).

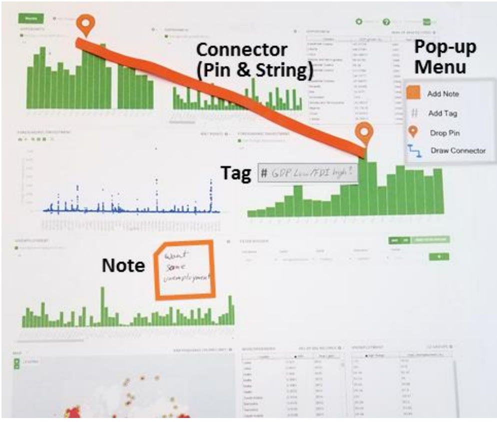

Figure 1: High NFC initial adaptation design paper prototype

Figure 2: Low NFC, Round 1 adaptation design paper prototype

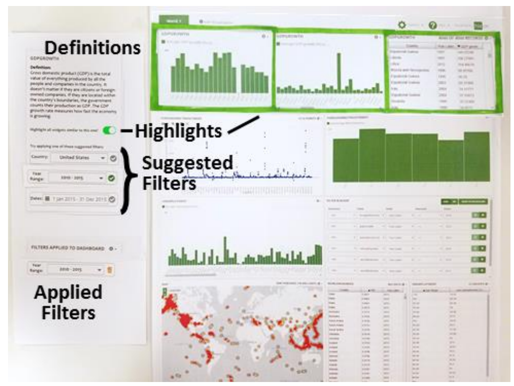

Figure 3: Low NFC, Round 2 adaptation design paper prototype

2.3 Results, Re-testing, and Design Updates

2.3.1 High NFC Users. Three of the four High NFC users were responsive to the presented options in the pop-up menu. Participant 3, who scored the highest NFC of all those screened, rejected additional tools, preferring "a clean interface… nothing covering the data." Among other High NFC participants, notes and tags became conflated, with participants using them to make quick notations in the same way. The visual design of the pins confused participants, who used them as place-holders for a tag or to mark the ends of a connector (Figure 1). Though two of the four participants found the connector option useful, three of the four found the word choice confusing, believing it implied some integration of the data sets rather than a visual notation.

Each High NFC participant followed a similar task flow, first reviewing each widget briefly from top-left to bottom-right. After exploring several widgets, participants often noticed a trend in the data they found interesting and proceeded to explore it. Those who engaged with the pop-up menu often added a tag, note, or other annotation before searching the dashboard again. After exploring all widgets, participants typically returned to annotated widgets to begin deeper investigation. Participant 4 exclusively returned for a second session, performing the same task at length using Neon without any adaptations. This informed our understanding of a typical High NFC user workflow. Primarily, the participant expressed difficulty remembering previously noticed data trends: *"I wish I could take notes and then do this [filter the data] all at once."*

Based on this feedback, the High NFC adaptation designs were adjusted to combine elements frequently used together and prevent visual clutter on the interface itself**.** All adaptation cues were moved from the pop-up menu to a panel on the side of the page. Connectors were re-named "Pin and String" to avoid confusion, with a "pin" marking the start- and end-points for any "string" drawn between two widgets. A list of drawn pin-and-string connections was added to the panel with options to label and hide/show each connection on the dashboard. The tags were removed, and a single notes section placed on the panel.

2.3.2 Low NFC Users. In the first test, Low NFC participants consistently expressed feeling overwhelmed when viewing the dashboard. Each spent more time reading the background information than the High NFC participants, carefully reviewing the dataset definitions. Two of the three participants experienced an initial period of feeling "frozen" in which they hovered over various parts of the interface without intent or direction. Once they started exploring the widgets available, they began a workflow similar to that observed for High NFC, quickly reviewing each widget from the top-left to bottom-right. However, the Low NFC participants were more methodical in reviewing each widget at a high level from beginning to end in this first pass. They tended to be drawn toward items that were visually interesting while avoiding any elements they felt they did not understand. Participants either avoided the summary tables outright or stated they "forgot it was there." Each had difficulty determining which data visualizations related to which data set. Although all three participants said they found the tips helpful and read any suggestions that came up, they never actively selected the icon for a new tip, and did not investigate the data across more than one parameter at a time. Two participants relied primarily on external knowledge for decision making, rather than exploring the data further.

Following initial Low NFC testing, the Low NFC adaptations were re-designed in entirety to better meet Low NFC individuals' needs. As in the final High NFC adaptations, all Low NFC adaptations were moved to a panel on the side of the page.

Descriptive definitions of the datasets were included in the panel, with the relevant definition appearing at the top of the panel for a given widget selected with the mouse. Optional highlights would appear around all widgets related to the same dataset as the one selected, leveraging Low NFC users' attention to visual changes. Replacing the tips adaptation, suggested data filtering options was added, including shortcuts for commonly requested filters. When a filter was applied, by any means, that filter was indicated in a list on the panel with a delete-option to simplify filter removal.

The redesigned adaptations were tested with the same Low NFC participants. Each expressed that the panel was more helpful than the previous adaptations, and all were more engaged with exploring the dashboard. The two participants that used the highlights stated that they aided in initially processing the dashboard, avoiding "overwhelmed" feelings. All three used at least one suggested filter. Two participants, upon applying a suggested filter, were immediately drawn to the *filter builder* tool included in the baseline interface – which they had previously ignored – and began narrowing the data based on multiple parameters.

3 LIMITATIONS AND IMPLICATIONS

The early results from the UX approach provided interesting implications for the future of co-adaptive interface design. We have integrated psychological theory and graphical user interface design together in our approach. Preliminary results indicate that High and Low NFC participants exhibit behavioral differences, even in exploring low fidelity paper prototypes. Our major takeaways were: High NFC participants relied on adaptations (note-taking and connectors) for organizing thoughts, planning, and execution; Low NFC participants immediately registered feeling overwhelmed with the large quantity of information presented and wanted an easy way to break up the space.

Due to constraints, this research does have some limitations. First, we were not able to gain direct access to our ideal user base – analysts – for these early paper prototype tests. As a result, we used participants from within our organization. Second, we had a smaller number of participants than ideal and would suggest a larger test population for more robust studies. However, we were able to obtain a mix of participants in skill set, occupation, age, and gender. For future studies, we suggest caution in use case selection in order to make sure testing can be done with the ideal end-user if possible. Third, the UX approach differs from quantitative user-study designs, and participants were not cross-tested on opposing adaptations. However, each participant began testing with the same dashboard and introduction prior to any adaptation engagement. During this start-of-task period, observed initial responses to the basic interface were drastically different between the two NFC groups. Finally, we controlled for certain variables within the approach (environment, task, interface, designs presented, timing, NFC score), but were unable to account for many others - additional personality traits, emotional state, expertise, experience, and other contextual factors. As a result, it is difficult to assert that NFC was the main factor which influenced behaviors seen during the prototyping; an assumption we knowingly undertook.

In this paper, we described a design process for evaluating adaptation designs for a data visualization platform based on a single user trait (NFC). In future work, we will explore the intersection of multiple factors within an interface in order to account for the interaction effects among different variables. More work needs to be done to account for these multiple factors and multiple domains. However, we recommend initially isolating one main variable at a time, such as a trait, especially if the approach is going to primarily rely on UX research methods as employed and described in this paper. In the future, we hope to incorporate multiple traits, along with user state and task, into a more comprehensive co-adaptive system.

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