Neuro-Adaptive Interface System to Evaluate Product Recommendations in the Context of E-Commerce

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Abstract. Personalized product recommendations are widely used by online retailers to combat choice overload, a phenomenon where excessive product information adversely increases the cognitive workload of the consumer, thereby degrading their decision quality and shopping experience. However, scientific evidence on the benefits of personalized recommendations remains inconsistent, giving rise to the idea that their effects may be muted unless the consumer is actually experiencing choice overload. The ability to test this idea is thus an important goal for marketing researchers, but challenging to achieve using conventional approaches. To overcome this challenge, the present study followed a design science approach while leveraging cognitive neuroscience to develop a real-time neuro-adaptive interface for e-commerce tasks. The function of the neuro-adaptive interface was to induce choice overload and permit comparisons of cognitive load and decision quality associated with personalized recommendations, which were presented according to the following three conditions: (a) not presented (control), (b) perpetually presented, or (c) presented only when a real-time neurophysiological index indicated that cognitive workload was high. Formative testing cycles produced a neuro-adaptive system in which the personalization of recommendations and neuro-adaptivity function as intended. The artifact is now ready for use in summative testing regarding the effects of personalized recommendations on cognitive workload and decision quality.

Keywords: Neuro-adaptive interface · digital technologies · e-commerce · choice overload · cognitive load · decision-making · design science

1 Introduction

Personalized product recommendation systems are being increasingly used in e-commerce. A 2019 Forrester report approximated that 67% of large-scale online retailers employed recommendation systems [1] to aid users in decision-making and combat choice overload, a phenomenon where consumers are unable to analyze and compare

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excessive quantities of products and product information [2–4]. Choice overload has been recognized to adversely increase cognitive workload [5–8], and thereby degrade purchase decision quality [9–12], or lead consumers to delay [13] or abandon their purchase [2, 4, 14]. However, e-commerce interfaces that offer personalized recommendations generally do so without considering whether a consumer is experiencing choice overload. Coincidentally, empirical research based on such interfaces has yielded inconsistent results regarding the benefits of personalized recommendations against choice overload [15–19]. This has given rise to the idea that the effects of personalized recommendations may be muted or counterproductive unless the consumer is in fact experiencing choice overload. Correspondingly, there has a been a call from e-commerce researchers for the development of a more robust system to evaluate the effects of personalized product recommendations [15, 18].

Answering this call to research requires the development of a system that detects the occurrence of choice overload in real-time and provides personalized product recommendations accordingly. However, to our knowledge, no such system exists, and commonly-used retrospective self-reported measures [15–17, 20–22] are not appropriate. To develop the needed system, we applied the design science research (DSR) approach, as it has demonstrated effectiveness for e-commerce interface design for both industrial and academic purposes [23–26]. We classified our development as a Type 4 research problem, which is characterized by an absence of relevant data available for manipulation, combined with yet unknown operations and methods to address the research problem [27, 28]. One viable approach to measure choice overload in real-time is to target cognitive workload using neurophysiology such as Electroencephalography (EEG). With its high temporal resolution, EEG provides the capability to measure brain activity continuously, and is also an established tool to measure cognitive workload [29–33]. Moreover, recent advances in cognitive neuroscience technology have now made it possible to analyze EEG-derived brain activity in real-time, thereby permitting the development of interfaces that adapt according to changes in a brain activity index (i.e. neuro-adaptive interface) [34–38].

Thus, we asked the following research question: *How can we address the aforementioned call to research by following a DSR approach while leveraging cognitive neuroscience to develop a real-time neuro-adaptive interface for e-commerce evaluation?* Specifically, we sought to design a system with a neuro-adaptive interface that could induce choice overload and permit neuropsychophysiological comparisons of cognitive load to assess the effects associated with personalized recommendations on choice overload and decision quality. The system presented recommendations according to the following three conditions: (a) not presented (control), (b) perpetually presented, or (c) presented only when a real-time neurophysiological index indicated that cognitive workload was high. This study demonstrates the applicability of DSR to neuro-adaptive system design and contributes a novel artifact to the field of e-commerce which answers the call to design a more rigorous means of evaluating the effects of personalized product recommendations against choice overload.

2 Foundations and Related Work

2.1 Choice Overload and Decision-Making

Choice overload is a form of information overload that occurs when a user is confronted with excessive quantities of information used to support decision-making [5–8]. Consequently, choice overload degrades decision quality, defined as the extent to which a purchase decision is objectively or subjectively optimal in relation to other product options [39]. The relationship between choice overload and decision quality is non-linear. As illustrated in Fig. 1, decision quality (accuracy) is thought to improve with information quantity up to a certain point, but then deteriorates thereafter with the onset of choice overload (information overload) [11]. As decision quality decreases, negative emotions and impulsive behaviour increase [7, 40, 41]. Consequently, users express less satisfaction with their shopping experience [42], and less confidence in their selections compared with those who did not experience choice overload [12, 17, 42]. Thus, assessing the decision-making process through the lens of decision quality, decision-making behaviour, and psychological measures of satisfaction and confidence are crucial to understanding choice overload and the effectiveness of strategies against it.

Many researchers attempted to predict the exact quantity of information required to induce choice overload [41, 43, 44]. Recently, a few studies have demonstrated that presenting as few as 24 products [2, 45] and 9 attributes [45] at a time is sufficient for inducing choice overload. However, it is also recognized that the threshold for choice overload differs between individuals as a function of level of expertise and cognitive workload capacity [7, 10, 42–44]. In other words, there is no universal threshold of information quantity which will induce choice overload. Therein likely lies a predominant reason why strategies against choice overload such as personalized product recommendations have yielded inconsistent results regarding their effects [15–19], as it is not clear when precisely a given user might be overloaded and thus needs the recommendations. For this reason, studies on choice overload might benefit from targeting measures of cognitive workload.

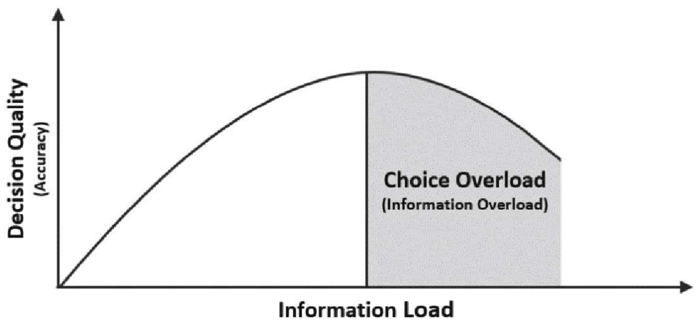

Fig. 1. Relationship between choice overload and decision quality. Based on [11].

2.2 EEG and Neuro-Adaptive Systems

EEG is a well-established neurophysiological modality which has been used to index cognitive workload [29–33]. A notable recent study used an EEG and event-related potentials to identify cognitive overload and link it with poor decision quality [46]. However, if using personalized product recommendations to counteract choice overload, it is important to not merely know whether choice overload occurred, but also to identify when it is happening in real-time to present recommendations to users at the appropriate time, both achievable using an EEG-based solution.

Recent advances in data processing technology have now made it possible to process neurophysiological data such as EEG in real-time [47–49]. This has given rise to a new technology known as neuro-adaptive systems [34–36]. A neuro-adaptive system is one that continuously evaluates the neurophysiological activity of its user, processing an index of cognitive or affective state in real time. Then, when changes in the cognitive or affective state index are detected, the system adapts, often via visual changes on the interface [34–36]. Due to its high temporal fidelity, portability, and customizability, EEG remains a predominant modality for neuro-adaptive applications [50].

Having originated in the field of biomedical engineering, neuro-adaptive systems have recently broadened their application into other fields. For example, some research teams attempted to establish remote communication and control systems between a user and a device [51–53]. Other instances vary from applying neuro-adaptive systems to support learning [37] and reading [34] in education, to maintaining vigilance and attention for air traffic control [38]. While some neuro-adaptive systems have relied upon cognitive indices of user attention and engagement [46, 54], others have targeted cognitive load [34, 37]. However, the application of such systems in the field of e-commerce, albeit relevant and of high potential, remains scant. Consequently, we sought to leverage this neuro-adaptive technology to capture consumers' state of choice overload in real-time via a neurophysiological index of high cognitive workload, which when detected, would cause an e-commerce interface to adapt and display personalized product recommendations.

2.3 Personalized Product Recommendations

The personalization of product recommendations is a strategy widely employed across the e-commerce industry. Most global e-commerce sites, including market leaders like Amazon [55], use an algorithm called collaborative filtering [56–58]. Though many variations of it exist, the most common ones are user-based, where individual product preferences are compared to those of other similar users to predict potential purchases, or product-based, where recommended items are similar to those previously liked or visited by a user [57, 59]. Another emerging trend has recently been to add a social component to the computation, such as social tags prediction, based on blogs and online communities [60] or social network graph algorithms, centered on recommendations from friends and other peers [61].

While sophisticated and effective, the algorithmic computational approaches employed by the industry to create personalized product recommendations are not practical for e-commerce research. This is because the historical product viewing or purchasing behaviour required to use industrial algorithms is nearly impossible to acquire for experimental participants within a typical data collection timescale. Instead, a simpler, more expedient method is required which nevertheless yields effective personalization. One commonly employed method is the Multi-Attribute Decision-Making (MADM) method [62], particularly the Simple Additive Weighting (SAW) approach. MADM-SAW permits comparison between large groups of products, taking into consideration the importance an individual places on each product attribute simultaneously [63]. MADM-SAW has been shown to facilitate optimal decision-making in the contexts of education [64, 65] and internships [66], media consumption [67], and e-commerce [68].

2.4 Application to Design Science Research

The multi-component and multidisciplinary complexity of a neuro-adaptive system artifact calls for a structured definition of requirements, as well as flexible iteration cycles of subcomponents of the solution, making the DSR framework the optimal approach. More specifically, given that current neuro-adaptive systems based on users' cognitive load exist in other fields, our research to extend and refine its application into the realm of e-commerce thereby constituted an exaptation solution, according to the knowledge contribution framework [28]. The envisioned contribution was thus twofold. First, creating an artifact to support the problem in e-commerce research regarding the lack of a rigorous means of evaluating the effect of product recommendations on consumers' choice overload. Secondly, contributing to the body of knowledge in IS through our proof-of-concept, which can serve as a prescriptive theory [69, 70] to successfully implement such an artifact.

3 Methodology and Research Design

To provide a logical framework for constructing the neuro-adaptive e-commerce system, we followed the DSR framework by Peffers et al. [71]. Following this approach was deemed appropriate given its widely-acknowledged application among DSR models [26, 28], and its cyclic nature that provides for various entry points into the process [26, 71]. Figure 2 illustrates said DSR approach, adapted to our study.

In Step 1, a literature review was performed regarding the problem at hand: the lack of a robust system to evaluate the effect of personalized product recommendations on choice overload and identify the state of currently deployed solutions. In Step 2, we derived and refined objectives of a system to solve the problem using a Rigor Cycle [72] grounded in the current body of knowledge and methods regarding e-commerce interfaces and recommendation systems. We also performed a Relevance Cycle [72], building upon neuro-adaptive interface artifacts from different fields and drawing upon exploratory testing formerly conducted at our lab. Step 3 comprised internal Design Cycles [72] over 8-months, cycling between design-related decisions, their implementation, evaluation, and refinement, until the objectives of the solution were fulfilled [73]. This and the following steps of the study were integrated in a research certificate ID 5071 approved by the institution's ethics review board (Comité d'éthique de la recherche de HÉC Montréal - CÉR). In Step 4 we demonstrated that the artifact adapts according to cognitive load classifications via real-time testing with a sample of 42 voluntary participants recruited through convenience sampling. All participants were adults aged 18 years old or older, fluent in English, right-handed, neurotypical and not taking any medication for neurological or behavioural disorders. Their consent and confidentiality were ensured through CÉR's protocols. Then in Step 5, the artifact was evaluated based on validity and quality criteria [28]. The "proof-of-concept" demonstrated through simulations revealed that all design requirements (discussed in the following section) were fulfilled, and interface adaptations occurred as intended. The artifact is now ready for the second evaluation phase, in which we intend to execute summative experimental testing [28]. Approximately 50 new participants are expected to be recruited through random sampling and the same inclusion criteria for this phase. In Step 6, the communication of our designed system will be achieved through two phases: 1) publication of the present manuscript, and 2) via implementation of the system throughout usability testing by practicing professionals, potentially with various customizations of on-screen adaptation elements and conditions.

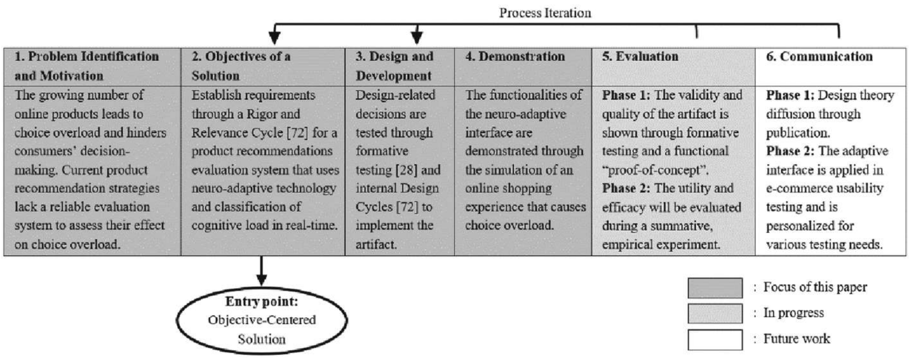

Fig. 2. DS Research methodology by Peffers et al. [71], adapted for this study.

4 Objectives of a Solution

Our overarching objective was to rigorously evaluate the effect of product recommendations on choice overload using neuro-adaptive technology. This technology permitted recommendations to be presented according to real-time EEG measurements of cognitive load. The components of this system were dissected based on Rigor and Relevance Cycles [72], translated into design requirements, and then prioritized according to resource availability and cost-benefit analyses.

First, the system had to comprise an assortment of selectable products and remain complex enough to potentially elicit choice overload (Table 1, DR 1). We used laptop computers as products due to their numerous attributes which complexify decision-making [9, 74]. Based on e-commerce research and formative testing, products and their attributes were displayed in a series of product comparison matrices, each with

24 products [2, 45], and 8 attributes per product [45], thereby permitting a trial-based approach for subsequent summative testing.

Next, product recommendations needed to be easily identifiable, yet not obstruct non-recommended products (DR 2). Iterative Relevance Cycles [72, 75] achieved this by highlighting a product row as an indicator of recommendation. The system was furthermore designed to be capable of highlighting (recommending) three product rows out of the 24 on each product matrix trial, with 3 products considered a small enough assortment size [9].

With an interest in comparing the effectiveness of our system to historical all-or-nothing approaches to investigating responses to product recommendations, we addressed the research problem (DR 3) by designing the system to present recommendations according to three conditions: (a) control (i.e. an interface which provides only the list of products and their attributes without any decisional aid in the form of recommendations), (b) static, perpetually presented from the onset of each product selection trial, and (c) neuro-adaptive, presented only when a real-time neurophysiological index has indicated that cognitive workload is high. To maximize the number of trials per participant, a within-subject experimental design was applied to the system, with three product selection trials, each two minutes long, in each evaluation condition to avoid experimental fatigue.

The next requirement was to personalize the recommendations to ensure their trustworthiness and pertinence (DR 4) [20, 21]. This was planned to be achieved by implementing a questionnaire to identify a user's preferences regarding the laptop product device attributes (DR 4.1). Then, the three highest-ranked products to recommend were to be determined using the MADM-SAW calculation method (DR 4.2) [62]. Lastly, the system needed to allow for a manual, but rapid insertion of this information regarding which product recommendations to display, when applicable, on a per user and per trial basis (DR 5).

To achieve the neuro-adaptive recommendations condition (c), the system needed to be capable of recording raw EEG signals (DR 6), which could also serve post-experiment analyses. Then, the system needed to calculate a cognitive load index in real-time based on raw EEG signals (DR 7), and transmit a classifier based on the index to the product recommendation interface (DR 8). Classifier transmission required both a send and receive component which ensured the classifier transmission was properly synchronized. Additionally, the interface required a set of rules on when to present recommendations, i.e. when to trigger the recommendations (DR 9). Given that display conditions required potential adjustment through formative testing, the system design needed to enable a modifiable field to input adaptation triggering rules. Finally, the system needed to support collection of self-reported measures and extraction of behavioural quantitative data for use in post-hoc analyses (DR 10). Self-reported questionnaires were to target choice overload, choice confidence and satisfaction (DR 10.1). Behavioural data would include decision time and product selections and recommendations (when applicable) for each trial (DR 10.2).

Table 1. Overview of design requirements (DR)

Design requirement	Description
User interface	
DR 1: Interactive user interface that displays a matrix of products and attributes to choose from, capable of inducing choice overload	A difficult-to-process product comparison matrix with 24 laptops [2, 45] (rows) and 8 attributes for each [45] (columns). Images and brand names are removed to avoid bias. To select a product, users may click on the chosen product and click the "Submit" button to confirm their selection
DR 2: A small number of product recommendations appear clearly, yet without interfering with the decision-making process	Recommendations appear in form of a highlight of three rows of products. Users are still free to select any product, i.e. to follow the recommendation or not. Three products of 24 are recommended to simplify decision making and reduce choice overload [9]
Experimental design	
DR 3: System permits isolation of recommendation effects for rigorous summative testing	The artifact presents recommendations according to three conditions: (a) no recommendations (control), product matrix only, (b) static, with recommendations always displayed, and (c) neuro-adaptive, with recommendations being triggered by a real-time EEG index of high cognitive load (signaling choice overload) The system uses a within-subject experimental design, with three product selection trials in each experimental condition
Personalized recommendations	
DR 4: Personalize product recommendations for each user	**DR 4.1 –** Gather personal user preferences: determine the relative importance each user allocates to different product attributes through a self-reported questionnaire **DR 4.2 –** Determine the three highest-ranked products to recommend per trial, when applicable, according to the MADM-SAW method [62]
DR 5: Inform the system of what personalized recommendations to display	Create a manual input field to inform the system of which products to recommend (obtained in DR 4), when applicable, for each trial and for each user

(*continued*)

Table 1. (*continued*)

Design requirement	Description
Real-time classification of neurophysiological data	
DR 6: Measure raw neurophysiological data throughout the experiment	Measure and record EEG data for cognitive load classification (DR 7) and post-experimental analyses
DR 7: Classify raw neurophysiological data as low or high cognitive load	Calculate an EEG cognitive load index and classify it in real-time in a format readable by the interface
Neuro-adaptation of the interface	
DR 8: Continuously transmit cognitive load classifiers to the user interface	Ensure synchronized and continuous transmission and receipt of cognitive load classifiers by the system throughout all trials
DR 9: Conditions to initiate the presentation of product recommendations	Enable a modifiable input field for recommendation display rules, based on the continuously received cognitive load classifiers
Self-reported evaluations/Trial performance data	
DR 10: Enable capture and extraction of trial performance data and self-reported measures for post-hoc analyses	**DR 10.1 –** Behavioural quantitative data: ensure capture and extractability of trial data regarding the classifiers received, products and (when applicable) recommendations displayed, product selected, and decision time **DR 10.2 –** Perceptual quantitative data: enable a pause after each trial to present post-trial questionnaires on choice overload, choice confidence and satisfaction

5 Design and Development

5.1 Classification and Transmission of Cognitive Load to the Interface

Real-time processing of neurophysiological activity (DR 6 from Table 1 above) and classification of cognitive load (DR 7) were designed using Simulink in MATLAB (version R2021b, IBM). The Simulink model was built to sample neurophysiological activity at 250 Hz from a g.tec Research: a 32-channel wireless, gel-based active electrode electroencephalographic (EEG) hardware, installed according to the 32-channel standard montage by g.tec. Real-time processing blocks for channel selection and band-power extraction were incorporated, in addition to Butterworth low-pass and high-pass filtering and a notch filter. A block was added to classify cognitive load as low (0), medium (1), or high (2), based on mean alpha-band power output over six-second intervals. Low and high cognitive workload band power thresholds were calibrated for each individual participant using EEG signals sampled during a 0-Back and a 2-Back task, respectively. The N-Back working memory paradigm is a well-established task for differentiating cognitive workload [76–78]. The raw and processed EEG data, and derived classifications, were set up to be recorded in parallel to permit post-hoc analysis and investigation of our phase 2 evaluation step (Fig. 2). Cognitive load classifications (0, 1, 2) were continuously transmitted to the interface (DR 8), as they were derived (every six seconds) over the local network via Lab Streaming Layer (LSL). The classification was then communicated to the web interface through a Python-based LSL receiver and a WebSocket client on a web server at the same rate of one classifier every six seconds.

5.2 Neuro-Adaptation Logic

Neuro-adaptation was designed such that the interface presented recommendations to users according to primary and secondary cognitive load classification logic. The primary logic consisted of the aforementioned classification of cognitive load sent from Simulink via LSL (transmitted values being 0, 1, or 2). The secondary logic, applied downstream from this using a Python script, converted the output value into a "3" if it satisfied a best out of three condition. In other words, if at least two 2's were received within the last three classifiers, the script would transform the next value that it would relay to the interface into a "3". The interface adaptation rules and conditions were implemented through a web application (see Sect. 5.4 below).

5.3 Product Recommendations

To enable users to attribute personal importance to each of the 8 laptop product criteria (DR 4.1), a 5-point Likert scale (with 1 being "Not important at all" and 5 being "Very important") was utilized in an online Qualtrics questionnaire. These attribute ratings were then input into an Excel file, which was designed to determine the three highest-ranked products per trial for each user (DR 4.2), according to the MADM-SAW method [62]. The calculation takes into account the total database of 360 fictitious, but plausible laptop products and their attributes which we included in the system, objectively assessing them in accordance with the subjective importance of the attributes reported by each user.

5.4 User Testing Interfaces

The front-end (DR 1, DR 2, and DR 3) of the system was developed in HTML and enhanced with CSS formatting, executed on a web browser with a computer operating on Windows 11. A front-end web application was developed in Google's AngularJS MVC framework, internally called Metamorph, to launch a separate interface for each recommendation presentation condition (control, static and neuro-adaptive) through a link generated on a per participant basis.

For the static and neuro-adaptive condition interfaces, the Metamorph application included a field to integrate the product ID's of the top-three laptops for each user and each trial – identified in the previous step – to inform the interface of which products to recommend, when applicable (DR 5).

For the neuro-adaptive condition interface, the application also comprised a rule engine library, that is, a functionality that permitted upload of a set of conditions into the database in form of a JSON file, meant to dictate the rules to display product recommendations (DR 9). These rules use Javascript objects to control the presentation of product recommendations. They were designed such that no recommendations would display the first and last 12 s of each trial, to give users the chance to read the entire matrix and react to recommendations if they were presented. Outside of these two time windows, the display of recommendations was triggered when the value received through the WebSocket client was "3" (see Sect. 5.2).

Meanwhile, the interface was designed such that users could select only one product with a left mouse click, and then submit their selection by pressing a "Submit" button on the bottom of the screen. After a selection was submitted, the interface presented a transition screen thanking the user and then paused. This pause permitted to present the post-trial questionnaires on choice overload, choice confidence and satisfaction via Qualtrics (DR 10.1). After the questionnaires were completed, the transition screen of the interface was redisplayed and the user was instructed to press a "Continue" button, which initiated the subsequent trial. The transition screen on the last trial displayed a message requesting users to await further instructions and had no "Continue" button.

Lastly, in provision of the second phase of our evaluation (Fig. 2) (DR 10), a feature was integrated in the application to enable capture and extraction of per-trial post-study behavioural quantitative data. The generatable output is in form of a JSON file, which compiles: a) the different values of classifiers received every six seconds throughout the trial, b) the time users took to complete their product selection, c) the products included in the trial, d) the three products that were recommended (for the static and the neuro-adaptive conditions, when applicable), and e) the product that the user selected.

6 Demonstration and Preliminary Evaluations

Daily to weekly iterations were executed over a period of 8 months and included 42 formative testing participants. These formative testing cycles were concluded with proof-of-concept simulations to establish the validity and quality [28] of the system we built, thereby completing the first phase of our evaluation defined in Fig. 2. A simplified mock-up of the resulting product comparison matrix of the user interface is shown in Fig. 3, with an example of what a product recommendation looked like. From a technical standpoint, the system now operates consistently and dependably to satisfy sought goals and design requirements defined in previous steps. This development and implementation serve as the main result of our paper. The proof-of-concept demonstration of the artifact working as intended is illustrated in Fig. 4.

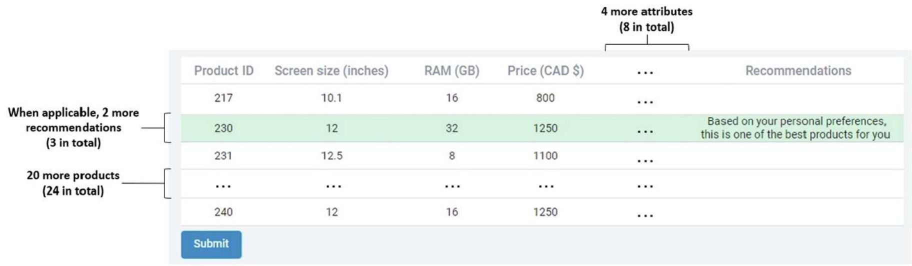

Fig. 3. Simplified illustration of the product comparison matrix of the user interface. When applicable, recommendations take the form of a green highlight across the entire product row.

The results of our research carried out during the Rigor Cycle [72] (step 3 in Fig. 2) suggest a high level of potential utility of the constructed artifact. Given the limited availability of evaluation tools to assess the effectiveness of product recommendations, the value our system can bring outside of the development environment [28, 71] is highly promising. However, the system's utility and efficacy are yet to be evaluated in a second evaluation phase (Fig. 2) to assess its practical application in summative and empirical research.

7 Discussion

7.1 Implications for Design Science

The present study followed a DSR methodology to build a neuro-adaptive system which would permit more rigorous assessment for e-commerce research regarding the effects of personalized product recommendations on choice overload. Formative testing through live simulations revealed that the design requirements of the system [28] functioned as intended. This effectively demonstrated the success of our approach to answer our research question and the call for solutions from e-commerce researchers. The novel application of neuro-adaptive technology in the development of an e-commerce evaluation artifact can now be formalized into a dependable prescriptive (Type V) design theory [69, 70] to guide the choice of functionalities and construction of similar tools. Table 2 outlines our acquired design knowledge using the Jones and Gregor framework [79].

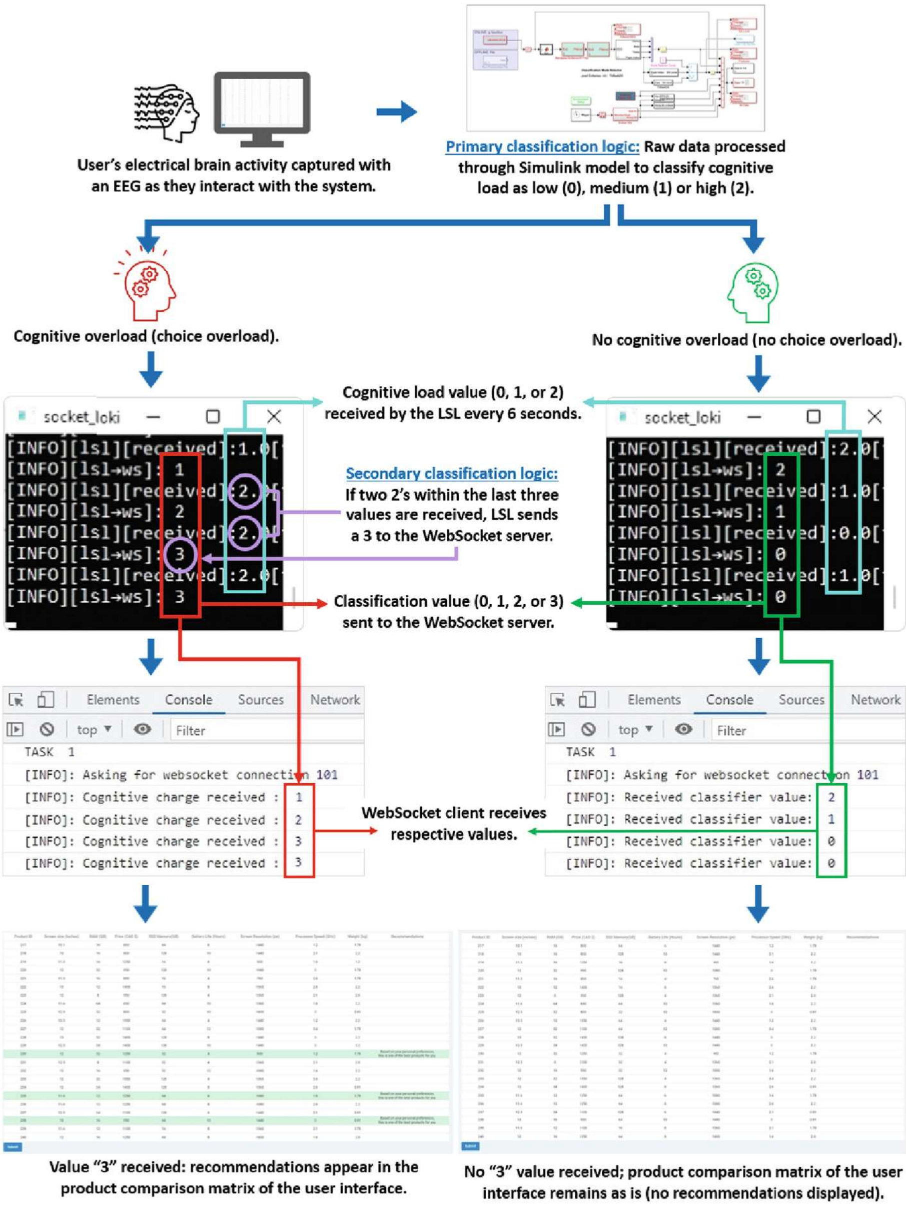

Fig. 4. Demonstration of neuro-adaptivity through simulation.

Table 2. Components of a design theory for the evaluation of personalized recommendations in the context of e-commerce, adapted from Jones and Gregor [79].

Type	Component
Purpose and scope	Development of a more robust and reliable evaluation system to assess the effects of personalized product recommendations in an e-commerce context. To efficiently isolate the effect of recommendations, the system includes three recommendations conditions: (a) no recommendations (control), (b) recommendations displayed perpetually, or (c) recommendations triggered by a real-time neurophysiological classification of cognitive workload as high, captured through an EEG
Constructs	Choice overload, cognitive load, decision quality, decision confidence, satisfaction
Principles of form and function	A difficult-to-process product comparison matrix with 24 products (rows) and 8 attributes for each (columns). Recommendations appear in form of a highlight of the rows with recommended products
Artifact mutability	The system is an exaptation of a neuro-adaptive artifact based on cognitive load to apply it to the field of e-commerce evaluation, which constitutes a novel solution that has not yet been explored
Testable propositions	1. The interface presents a number of products and product attributes that are sufficiently high to induce choice overload 2. Provided recommendations are personalized 3. When applicable, personalized recommendations are provided according to a neurophysiological cognitive load index measured in real-time through an EEG
Justificatory knowledge	The artifact builds on current knowledge from e-commerce user experience, choice overload theory, decision-making theory, cognitive workload theory, real-time neurophysiological processing theory (current neuro-adaptive technology), product recommendations strategies
Principles of implementation	The tool is intended for use by researchers, as well as industry practitioners in marketing, IS, user experience, etc. to better assess e-commerce strategies to cope with choice overload, in controlled experimental settings, where the users (participants) must be healthy and autonomous adults

7.2 Implications for Stakeholders

There are three main advantages of the system. One, whereas past approaches predominantly have relied upon retrospective self-reports of choice overload, the present system permits continuous, real-time assessment of choice overload via an EEG cognitive workload index. Two, the continuous assessment of choice overload via EEG-based cognitive workload permits delivery of personalized recommendations only when choice overload is being experienced by the user, rather than an all or nothing approach. And three, the use of three recommendation conditions and recording of raw EEG along with behavioural and self-reported data permits rigorous evaluation of the hypothesis that personalized product recommendations are most effective against choice overload when it is indeed being experienced at the time of recommendation delivery.

The implications of the present system for stakeholders, particularly marketing and user experience researchers, are manifold. The flexibility of the system permits manipulation of adaptivity elements, conditions, and overall interface design. Not only can the content of the matrices in the e-commerce interface be modified to match different e-commerce contexts, but the HTML-based graphics could be redesigned to model real-world websites while still retaining the neuro-adaptive functionality. Moreover, the brain activity index used for classification can easily be changed, thereby permitting researchers to study responses based on cognitive factors other than cognitive load, such as fatigue or attention. Thus, the present system could potentially be used to investigate behavioural responses to recommendations driven by a multitude of cognitive factors, which could then be leveraged in the industrial domain. Correspondingly, studies using the present system could potentially derive insights about context-dependent information display preferences. The present system could potentially even be used to accurately identify behavioural indices of choice overload, which could then be employed industrially. Ultimately, the present system could drive a change in personalized recommendation strategies, improving their effectiveness along with the experience for consumers.

7.3 Limitations and Directions for Future Research

Though overarching objectives have been achieved, there are some limitations to the current iteration of the designed system. First, recommendation conditions were not centralized within the rules agent of the Metamorph application, necessitating the more cumbersome approach of two-step adaptation logic discussed in the Design and Development section (see Sect. 5.2). Additionally, the identification and input of personalized recommendation criteria for each user (DR 4 and DR 5 from Table 1) must currently be performed manually using an online Qualtrics questionnaire, Excel spreadsheet, and an input field in the Metamorph application. However, these limitations do not fundamentally impede system function and can thus be addressed in future development cycles. Indeed, the present system functioned smoothly and appropriately, as was demonstrated through formative testing and proof-of-concept simulations.

8 Conclusion

This study demonstrates the applicability of DSR to neuro-adaptive interface design to solve Type 4 research problems, and contributes a novel, functional artifact to the field of e-commerce which answers the call to design a more rigorous means of evaluating the effects of personalized product recommendations against choice overload. The system is now ready for summative testing, which should further cement its contribution to the fields of e-commerce and DSR. The present publication marks an important milestone in dissemination of the DSR knowledge gained. Going forward, the system's inherent flexibility should permit improvement of operational efficiency, and context-independent evolution of visual design and adaption based on other cognitive constructs.

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