5-15-2019

NUDGED TO UNLOAD: APPLYING CHOICE ARCHITECTURE TO PREVENT COGNITIVE OVERLOAD OF PARTICIPANTS IN OPEN IDEA EVALUATION

Carina Benz
Karlsruhe Institute of Technology, carina.benz@kit.edu

Carola Stryja
Karlsruhe Institute of Technology, carola.stryja@kit.edu

NUDGED TO UNLOAD: APPLYING CHOICE ARCHITECTURE TO PREVENT COGNITIVE OVERLOAD OF PARTICIPANTS IN OPEN IDEA EVALUATION

Research in Progress

Benz, Carina, Karlsruhe Institute of Technology, Karlsruhe, Germany, carina.benz@kit.edu

Stryja, Carola, Karlsruhe Institute of Technology, Karlsruhe, Germany, carola.stryja@kit.edu

Abstract

Open idea evaluation is based on the vision of leveraging the crowd's wisdom for screening and evaluation of early stage innovations. However, when being confronted with the task to evaluate a large number of idea proposals, cognitive capacity of participants in open idea evaluation is challenged. Given the diminishing effect of cognitive load on the ability to make elaborate decisions, this paper aims to answer the question of how to lower cognitive load of participants in open idea evaluation. Therefore, we leverage knowledge from research in choice architecture, a concept incorporating tools to influence decisions by the design of decision situations. We derive two design variations–partitioning of options and decision staging–and propose an experimental design for their evaluation in a laboratory experiment. With the proposed study, we aim to contribute to theory by combining knowledge from choice architecture with the design of crowdsourcing platforms. Consequently, we aim to provide novel insights into decision support for crowdsourced decision tasks.

Keywords: Open Idea Evaluation, Choice Architecture, Nudging, Cognitive Load.

1 Introduction

With growing popularity of open innovation approaches such as online idea contests, which aim to foster the generation and availability of innovative ideas, organizations need to find ways to effectively manage the evaluation and selection of an increasing number of idea proposals (Schulze et al., 2012). While traditional expert-based approaches are subject to enormous time- and knowledge restrictions (Blohm et al., 2011), thus, limiting absorptive capacity of organizations (Cohen and Levinthal, 1990), crowd-based approaches constitute an attractive alternative for the evaluation of early stage ideas. This approach that is often referred to as open idea evaluation represents a collective evaluation task (Corney et al., 2009): Building on the wisdom of crowds–the notion that under the right circumstances large groups of individuals can perform as well (or even better) than small groups of experts (Surowiecki, 2004)–a number of individuals are tasked with assessing the attractiveness of a pool of ideas.

Since it is associated with a vast cultural and organizational upheaval for companies to mainly rely on the assessment of a crowd of non-experts when selecting potential future fields of activity, evaluation and choice behavior of crowds need to be clearly understood. In this context, research in the field of open idea evaluation has been centering around the question how crowds decide compared to experts (Feldmann et al., 2014; Görzen and Kundisch, 2016; Magnusson et al., 2016). In this regard, cognitive load can be identified as fundamental theoretical lens of several studies addressing the effect of idea evaluation mechanism selection on choice behavior of crowds (Blohm et al., 2011; Fu et al., 2017; Wagenknecht et al., 2017). Cognitive load hereby refers to "the ease with which information may be processed in working memory" (Sweller et al., 1998, p. 266). Consequently, when the information provided exceeds an individual's limited working memory, cognitive load occurs (Fu et al., 2017). Being confronted with the evaluation of a large amount of idea proposals (e.g. 34 idea proposals on IBM's internal crowdfunding platform (Muller et al., 2013)), the borders of individuals' cognitive ability are pushed and cognitive load is manifested (Fu et al., 2017). Blohm et al. (2011), furthermore, find cognitive load to be a moderator of the relationship between idea evaluation mechanism and evaluation quality as well as user's satisfaction with their decision.

Given the diminishing effect of cognitive load on a crowd's ability to accurately evaluate ideas' quality, the question how idea evaluation platform design can be altered to improve the ease of information processing arises. The present paper, consequently, aims to elaborate on the following question:

RQ: *How should an open idea evaluation platform be designed to lower evaluator's cognitive load?*

To answer this question, we refer to knowledge from the research field of choice architecture (CA). Choice architecture, a concept coined by Thaler and Sunstein (2008), refers to the design of decision situations to overcome irrational decision biases or to promote certain behaviors while ensuring freedom of choice. Research in the notion of choice architecture proposes a number of elaborate strategies and tools to design decision situations. Nudges–the use of defaults, incentives, feedback or the structuring of complex tasks, etc.–constitute a set of promising strategies available for choice architects. Under the term "digital nudging" these strategies are extended to "the use of user-interface design elements to guide people's behavior in digital choice environments" (Weinmann et al., 2016).

Drawing upon this knowledge, we derive two design variations–partitioning of options and decision staging–with the overarching goal to reduce cognitive load of participants in open idea evaluation. We propose to assess the effect of these design variations on cognitive load in a laboratory experiment. The controlled setting of laboratory experiments allows us to reliably control decision-making while excluding possible alternative impacts on cognitive load.

With the proposed study, we leverage knowledge from choice architecture for the design of crowdsourcing platforms. Specifically, we want to demonstrate how the design of open idea evaluation platforms can be improved to lower participants' cognitive load beyond the choice of idea evaluation mechanisms. Consequently, our scope is to provide novel insights into decision support for crowdsourced decision tasks.

2 Theoretical Background

In the following chapter, we provide theoretical background on open idea evaluation and the according decision-making process. Additionally, we elaborate on bounded rationality and cognitive load that can occur in situations such as the evaluation of idea proposals. Finally, we present choice architecture and digital nudging as means to re-design the evaluation situation in such a way, that cognitive load is lowered.

2.1 Open Idea Evaluation and Decision-Making

Open idea evaluation refers to the selection, filtering or relative quality assessment of idea or innovation proposals based on the opinion of a large group of participants, which is often facilitated by IT-based platforms. Hence, open idea evaluation constitutes a special form of crowdsourcing which's fundamental idea is that a company, an institution, or a non-profit organization performs an open call to a group of potential contributors to voluntarily execute a given task (Blohm et al., 2011). By aggregating knowledge from a diverse and independent group of contributors, crowdsourcing is building upon the principle of the crowd wisdom or collective intelligence (Afuah and Tucci, 2012; Bonabeau, 2009; Surowiecki, 2004). In the case of open idea evaluation, the crowd may consist of employees only (e.g. in enterprise crowdfunding (Feldmann et al., 2014)), customers (e.g. in innovation contests (Velamuri et al., 2017)) or the public (e.g. in participatory budgeting (Niemeyer et al., 2016)). Successful implementations of open idea evaluation have been reported by Allianz UK or the IBM corporation, which both have drawn towards their employee base to evaluate idea proposals submitted by their colleagues (Benbya and Leidner, 2016; Muller et al., 2013).

Decision-making on open idea evaluation platforms is steered through idea evaluation mechanisms. These can be divided into mechanisms implying sequential or simultaneous evaluation tasks: using *rating scales*, participants need to assign a numerical score to each idea, which is equal to online product references (Riedl et al., 2010). Hence, rating scales are idea evaluation mechanisms that imply a sequential evaluation task, which does not require to make trade-offs between competing options (Lipusch et al., 2017). Simultaneous evaluation tasks (also called 'choice task' (Lipusch et al., 2017)), require evaluators to concurrently weight ideas and their characteristics against each other. *Ranking*, *voting*, *preference* or *idea markets*, as well as *enterprise crowdfunding* are idea evaluation mechanism that fall under this category. The *ranking* idea evaluation mechanism tasks participants with the formation of a full or partial order to a given set of idea proposals (Cui et al., 2018). *Preference* or *idea markets* mimic a stock market where users can buy and sell stocks representing the value of an idea (Blohm et al., 2011). Using *voting* or *enterprise crowdfunding* participants receive a share of votes or funds, which they can freely allocate to different ideas (Bao et al., 2011; Feldmann et al., 2014). The choice of the idea evaluation mechanism, as well as other design decisions (e.g. whether to display peer evaluations (Wagenknecht et al., 2017)) become crucial, since they determine the way the evaluation situation is perceived and the participants' decisions are performed (Blohm et al., 2011).

2.2 Cognitive Load in Evaluating Idea Proposals

Cognitive load is a theoretical construct grounded in research on education and learning psychology. Cognitive load theory assumes that the capacity of humans' working memory is restricted (Sweller, 1988). It is generally considered as representing "the load that performing a particular task imposes on [an individual's] cognitive system" (Sweller et al., 1998, p. 266). Hence, when performing a certain task, task solvers are confronted with mental effort, which is the load imposed by the task. Consequently, they need to put mental effort in form of cognitive capacity and resources in to accommodate the task's demands (Sweller et al., 1998). High levels of cognitive load are provoked in situations in which individuals are confronted with high information volumes that need to be processed, or when they experience time or cost constraints (Milkman et al., 2008). When information processing requirements of a task to be fulfilled by an individual in a certain situation exceed the processing capacity of her cognitive system, it is referred to as cognitive *over*load (Mayer and Moreno, 2017). Cognitive overload results in individuals acting in bounded rational ways (Simon, 1955), which in the light of dual process theory (Petty and Cacioppo, 1986; Tversky and Kahneman, 1974) refers to acting in a mode of intuitive, unconscious information-processing and decision making. This "peripheral route" (Petty and Cacioppo, 1986) of information processing or "system 1 thinking", as labeled by Tversky and Kahneman (1974), is associated with the prevalence of biases and the application of heuristics or rules of thumbs (e.g. relying on defaults) to lower the ease of cognitive load in making judgements. Hence, cognitive load affects the thorough evaluation of alternatives, often leading to suboptimal decisions (Weinmann et al., 2016). In addition, it is found that high levels of cognitive load negatively influence individuals' perception of the decision in so far as retrospective satisfaction with decision is lowered (Blohm et al. 2016; Bechwati & Xia 2003).

Indicators for cognitive load and consequential system 1 thinking can be identified in several studies in the context of open idea evaluation: Feldmann and Gimpel (2016) demonstrate that users often overlook criteria such as novelty, feasibility and relevance. In contrast, they are rather driven by the degree of idea elaboration and the use of media. Hence, rather mainstream than radical ideas are preferred by crowds, which could be an indicator of status quo bias and the usage of heuristics (e.g. deciding upon the media usage, rather than distinct characteristics of idea quality (Feldmann and Gimpel, 2016)). Lauto and Valentin (2016) found that crowds penalize lengthy and complicated proposals. This is in accordance with Blair and Mumford (2007), who show that people prefer ideas that are easy to understand and provide short-term benefit to many others.

2.3 Choice Architecture and Digital Nudging to Reduce Cognitive Load

Choice architecture (also popularized under the term "nudging") is a concept grounded in the domain of behavioral economics that is based upon the knowledge that the configuration of a decision situation is affecting individuals' decisions (Johnson et al., 2012). Hence, choice architecture aims to shape decision behavior by consciously designing decision situations (Thaler et al., 2012). The original toolset for choice architects proposed by Thaler et al. (2012) comprises six methods efficient in shaping human decision making: *Understanding of mapping*, i.e. reflects the organization of information in an accessible form such decision makers can map them to familiar problems and, hence, process them more easily. The preselection of certain options as *default* or *giving feedback* by providing information on the decision maker's performance are further mechanisms. *Expecting error* is a technique that an-

ticipates potential mistakes in human behavior and provides measures to prevent potential misbehavior. The mechanism *structuring complex choices* aims to provide additional information, thus, to make tradeoffs easier. Last, *incentives* shall further motivate humans to decide in a specific way. Further approaches to design choice situations have been proposed by Johnson et al. (2012), who divide their techniques into tools to structure the choice task and tools to describe choice options. Münscher et al. (2015) suggest a taxonomy with nine techniques covering the three areas of decision information, decision structure and decision assistance. Dolan et al. (2012) introduce their MINDSPACE framework, which comprises the most prevalent automatic effects that influence human behavior.
When applied to the design of digital user interface, the implementation of choice architecture techniques is referred to as “digital nudging” (Mirsch et al., 2017; Weinmann et al., 2016). Digital nudging is defined as the “use of user-interface design elements to guide people’s behavior in digital choice environments” (Weinmann et al., 2016). Digital nudging is being applied to various context, i.e. in the promotion of health-beneficial decisions (Purpura et al., 2011), for nudging towards more environmentally-friendly behavior (Iveroth and Bengtsson, 2014) or for assisting consumers, i.e. when making financial decisions (Jung et al., 2018). The foremost purpose of applying (digital) nudges in choice situations is the attempt to either counter or to encourage the use of heuristics and biases (Weinmann et al., 2016). Since heuristics are more likely being applied when individuals perceive high levels of cognitive load (Tversky and Kahneman, 1974), digital nudging reflects a promising approach to reduce cognitive load. However, research studying this effect is rare: Basu and Savani (2017) compare individuals’ optimality of choices in sequential and simultaneous choice situations under cognitive load. Their findings are in accordance to Carroll et al. (2018), who find unhealthy food options to be chosen more likely when individuals perceive cognitive load or when these options are bundled and price reduced.

To sum up, a strategically designed choice architecture has the potential to help participants to make more elaborate decisions in open idea evaluation. In our case, this would be to reduce the cognitive load associated with evaluating and deciding upon the quality of ideas in a set of idea proposals. For that purpose, we propose two choice architecture techniques to implement in open idea evaluation platforms in the following.

3 Research Model

We aim to design a choice situation which supports un-biased and reasoned decision-making by lowering the cognitive load associated to the evaluation of idea proposals. As for the selection of choice architecture techniques we are restricted by several design requirements: First, we aim to apply only such techniques that are non-persuasive. Since there is no *correct* decision when evaluating idea proposals (compared to e.g. choosing the healthier food option), we only consider choice architecture techniques that do not nudge participants towards a certain option (i.e. defaults are no appropriate nudge for our setting). Second, we will not implement any choice architecture technique that provides social cues, since those can diminish the crowd’s wisdom. According to Surowiecki’s (2004) definition of the wisdom of crowds, a crowd’s smartness depends on independence of opinion and decentralization of opinion collection. Third, since we do not intend to create a long-term behavior change, choice architecture techniques such as *reminders* or *commitments* will not be suitable. Fourth, we don’t want to favor techniques which require the modification idea proposals themselves, as the presentation of an idea should remain within the scope of responsibility of the respective proposer. Last, we do not aim to provide any financial incentives or consequences with respect to the evaluation. This is to ensure external validity of findings, since firms or public organizations might not be able to legally justify financial awards.
As for the identification of relevant choice architecture techniques, we scan the four previously introduced choice architecture frameworks by Thaler et al. (2012), Münscher et al. (2015), Johnson et al. (2012) and Dolan et al. (2012) based on our five constraints. Since the filtered choice architecture techniques are not free of overlaps, they can be grouped in three categories: category one (C1) subsumes techniques relying on the change of option composition. The second category contains techniques aiming to provide better structure to the task at hand. Other techniques are mentioned only once and are consequently aggregate under category three. An overview of this process and its result is de-

picted in Figure 1. For the application in our study, we build upon the two first categories proposing the modification of option and process structures. Techniques within those categories not only demonstrate high relevance due to their overlapping occurrence, but also promise high external validity (e.g. priming participants as highly cognitively able persons does not seem to be practical on idea evaluation platforms).

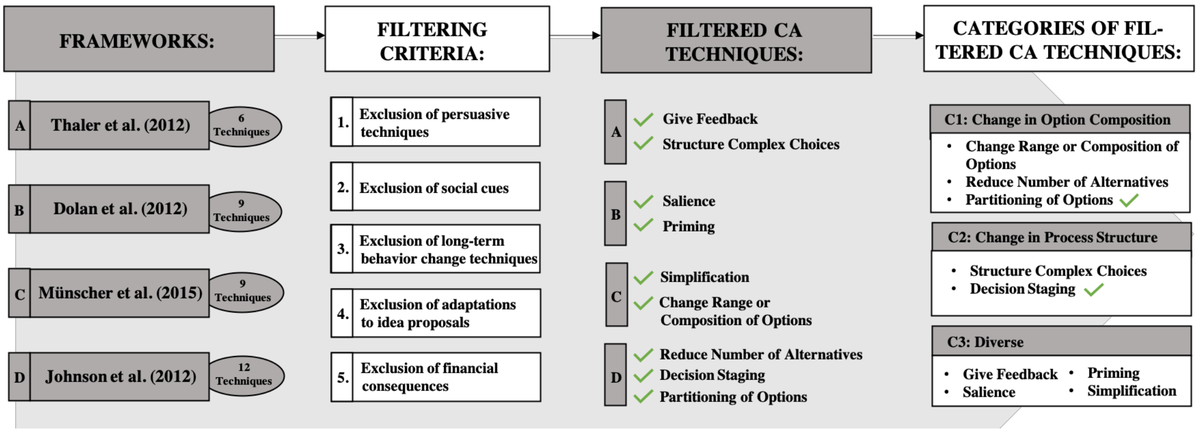

Figure 1: Process of selecting choice architecture techniques

First, we propose the *partitioning of options* to reduce the number of alternatives that have to be considered simultaneously. When facing a small number of well-understood alternatives, people tend to examine all attributes of the total of available alternatives and make trade-offs when required (Thaler et al., 2012). Consequently, people are more likely to adopt simplifying strategies when choices become more numerous or complex (Thaler et al., 2012). Additionally, Iyengar and Lepper (2000) report on the phenomenon of choice overload and provide evidence for greater subsequent satisfaction of individuals when their original set of options is limited. In contrast, Johnson et al. (2012) remark that there is a tradeoff between too many and too few alternative options and conclude that a set of four to five non-dominant alternatives can be considered as directive for choice architects. Hence, we propose the partition of the idea pool into subsets of four idea proposals that are displayed and evaluated simultaneously. Since option partitioning results in a split of the idea sets, sequential idea evaluation mechanisms offer themselves as ideas evaluation mechanism to avoid a distortion of the evaluation results. Consequently, we hypothesize:

> ***H1:*** *When using a sequential idea evaluation mechanism, partitioning of options will decrease idea evaluator's cognitive overload.*

Second, we pick up on Thaler et al.'s (2012) nudge of structuring complex choices and Johnson et al.'s (2012) choice architecture technique of decision staging. When people make complex decisions, they tend to successively explore and narrow down their alternatives to a subset of favored options which is more easily comparable (Johnson et al., 2012). Häubl and Trifts (2000) describe this phenomenon as two-stage process of decision making. At first, individuals screen a large set of available options and identify a subset of most promising alternatives. Next, the latter are evaluated in more depth and relative comparisons across important attributes are performed (Häubl and Trifts, 2000). Assisting this mental process by breaking down a complex decision into multiple stages can facilitate the choice process. Previous research by Schnabel et al. (2016) has applied the concept of staging decisions for decreasing cognitive load while choosing movies on a streaming platform. They propose the implementation of a shortlist–a temporary list of favored options. With the help of a shortlist participants in open idea evaluation could unload their working memory, since they can partition their decision process into a pre- and final selection phase while preserving preferred options in the shortlist rather than their working memory. This choice architecture technique especially supports idea evaluation with simultaneous idea evaluation mechanisms, such as voting, idea markets or enterprise crowdfunding. Following this argumentation, we hypothesize:

H2: *When using a simultaneous idea evaluation mechanism, decision staging will decrease idea evaluator's cognitive overload.*

The according research model is depicted in Figure 2. Our dependent variable is the cognitive load (Sweller, 1988) of evaluators. Control variables are duration of task completion and general cognitive ability.

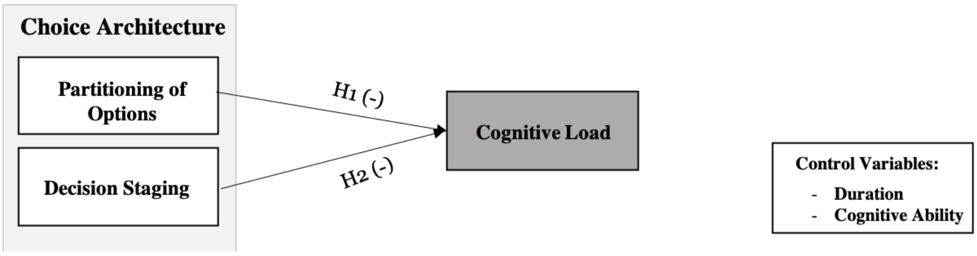

Figure 2. Research Model

4 Empirical Study Design

To understand cognitive load in open idea evaluation and to test our research model, we perform a laboratory experiment. The controlled environment of a laboratory allows us to largely control alternative stimuli influencing the dependent variable. In addition, experiments permit the formulation of generalizable statements about causation (Kantowitz et al., 2005).

4.1 Sample

The experiment is planned to be conducted in a behavioral research lab of an academic research institution. Participants are being recruited from a pool of students. As we aim to study general decision-making processes in open idea evaluation, using students as sample will not lower the external validity of our research (Falk et al., 2013). However, we are aware of the limitations evoked by the above-average level of education. As a-priori approach to determine the required sample size, we refer to data reported by (Blohm et al., 2016) on cognitive load in open idea evaluation for the estimation of the effect size (Cohen's d) to be expected. Given a low effect size (d= 0.084) as well as the desired significance level (α=0.05) and statistical power (β=0.8), 696 participants will be required.
For our idea sample, we refer to a pool of 29 ideas submitted to a national innovation contest with the topical focus on electric mobility. This domain restriction allows us to partially control for personal preferences. For the experiment, idea descriptions are anonymized and standardized to only contain textual descriptions to prevent biases related to the exposure of images.

4.2 Procedure and Treatment Design

We test our research model applying a 4x1 between-subject research design. Treatment variables are *partitioning of options* and *decision staging,* which both represent choice architecture techniques to be incorporated in platforms for open idea evaluation. The baseline platform, which serves as comparative basis for measuring the effectiveness of treatments, resembles a standard platform design for open idea evaluation, consisting of two main components: a summary page containing an overview of projects and separate project pages providing a detailed description of each idea. Since both treatments require the application of two different idea evaluation mechanisms (sequential vs. simultaneous), we rely on two different baseline platforms. Baseline platform one (B1) applies multi-criteria rating scales as idea evaluation mechanism. The multi-criteria rating scale consists of four 5-point rating scales, which reflect the key dimensions of idea quality: novelty, value and feasibility and elaboration (Dean et al., 2006). Baseline platform two (B2) is supposed to reflect a simultaneous evaluation task to compare to the *decision staging* treatment. Therefore, we rely on voting as idea mechanisms which requires participants to simultaneously consider all ideas and to make trade-offs when distributing a fixed budget of votes. We prefer voting over other simultaneous idea evaluation mechanisms, since it does not incorporate further complexity through money as distribution object (as in enterprise crowdfunding) or trading options (as in preference markets). Nevertheless, we allow votes to be cumulated and to be distributed to any desired number of idea proposals.

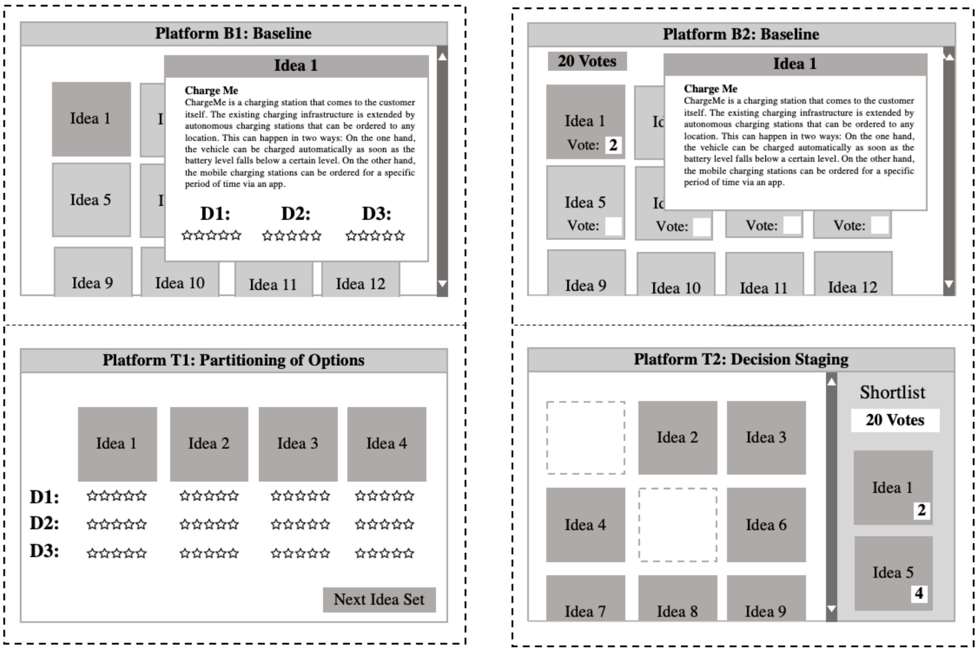

Figure 3. Schematic representation of the design of the baseline (B1, B2) and treatment (T1, T2) platforms

The first treatment (T1), *partitioning of options,* is implemented by redesigning the summary page in so far that only four ideas are concurrently displayed. After having done the evaluation using the 5-point multi-criteria rating scales, participants can trigger to get a new set of ideas. The second treatment (T2), *decision staging*, is realized via as shortlisting feature in a sidebar. Idea proposals can be drag-and-dropped into the sidebar, when participants decide to mark them as currently favored ideas. In a second step, participants can distribute votes among these idea proposals in the same manner as on baseline platform two (B2). Figure 3 schematically depicts the four different instances of the open idea evaluation platform. The two different viewing modes (summary page and detailed project pages), as illustrated for the baseline platforms, also apply for the treatment platforms. However, these are not illustrated in Figure 2 to enhance clarity of visualization.
Participants are randomly assigned to one of the four treatment or baseline conditions. Prior to the experiment, a clear explanation of the task at hand is given to the participants. To ensure participants' comprehension of the task, a short, repeatable quiz containing three questions has to be completed before starting the task. After the idea evaluation task, participants are guided to a questionnaire which collects data on demographics, perceived cognitive load and general cognitive ability.

4.3 Measurement of Variables

We aim to measure the dependent variable of our research model–cognitive load–in a combined way, including retrospective and situational measures. Retrospective measurement is instantiated combining two renowned self-reporting scales: the 7-item scale proposed by Cooper-Martin (1994) and the Paas' unidimensional mental effort scale (Paas et al., 1994). Although it appears questionable whether individuals are able to intro- and retrospect on their cognitive load, the successful applicability of measuring perceived cognitive load using Likert-scales has been previously demonstrated and is widely acknowledged (Paas et al., 2003). To situationally measure cognitive load, we refer to the secondary task methodology, which is based on the understanding that an individual's performance in a relatively simple secondary task reflects the level of cognitive load imposed by the primary task (Paas et al., 2003). Following Brunken et al. (2014), we implement a continuous visual observation task as secondary task: A black-colored letter is being displayed in a corner of the idea evaluation platform and participants' reaction time of pressing the space bar in response to a color change in the letter is assessed in multiple random intervals. Since all experimental groups are confronted with this situational measure, potentially higher levels of cognitive load due to the exposure to a second task will be balanced out. General higher order cognitive ability is measured using a short version of Raven's Advanced Progressive Matrices (Arthur and Day, 1994). Raven's Advanced Progressive Matrices are a popular non-verbal measure for higher order general cognitive ability. This test in particular assesses two main components of intelligence important for our scenario: the ability to think clearly and structured, and the ability to store and recall information (Arthur and Day, 1994).

5 Conclusion and Expected Contribution

In this study, we propose the design of idea evaluation platforms which assist participants in lowering their cognitive effort associated with the evaluation of idea proposals. We apply knowledge from choice architecture to the case of non-persuasive decision support for crowdsourced evaluation tasks. Specifically, we derive and propose two choice architecture techniques: (1) the partitioning of options into reduced sets of four simultaneously displayed options and (2) a shortlisting feature which assists participants in open idea evaluation in lowering their cognitive load by splitting the evaluation task into two decisions stages.

In doing so, we follow the call of research by Weinmann et al. (2016) demanding contributions to generate a comprehensive understanding of mechanisms underlying nudging. With this study we aim to provide empirically grounded evidence on the impact of choice architecture on cognitive load–a relationship that is often implied, but still lacks empirical validation. Additionally, we expand application areas of digital nudging: Currently, the application of choice architecture has been mainly studied in consumer or user decision making (e.g. in the setup of online retail stores (Lamberton and Diehl, 2013), the promotion of health-related behavior (Vallgårda, 2012), or for nudging towards more environmentally-friendly behavior (Bothos et al., 2014; Stryja et al., 2017)). Applying strategies proposed by choice architecture to decision situations in business contexts and for decisions whose outcome do not necessarily have direct, palpable effects on the decision maker herself (the successful selection and implementation of ideas evaluated in open idea evaluation will in most cases not have a direct noticeable or tangible impact on participants), represents a novel perspective for research in this field.

References

Afuah, A., Tucci, C.L., 2012. Crowdsourcing as a solution to distant search. Acad. Manag. Rev. 37, 355–375.

Arthur, W., Day, D. V., 1994. Development of a Short From of the Raven Advanced Progressive Matrices Test. Educ. Psychol. Meas. 54, 394–403.

Bao, J., Sakamoto, Y., Nickerson, J. V., 2011. Evaluating Design Solutions Using Crowds. In: Proceedings of the 17th Americas Conference on Information Systems (AMCIS), Detroit, Michigan, USA.

Basu, S.;, Savani, K., 2017. Choosing one at a time? Presenting options simultaneously helps people make more optimal decisions than presenting options sequentially. Organ. Behav. Hum. Decis. Process. 139, 76–91.

Bechwati, N.N., Xia, L., 2003. Do Computers Sweat? The Impact of Perceived Effort of Online Decision Aids on Consumers' Satisfaction With the Decision Process. J. Consum. Psychol. 13, 139–148.

Benbya, H., Leidner, D., 2016. Harnessing Employee Innovation in Internal Crowdsourcing Platforms: Lessons from Allianz UK. In: Proceedings of the 37th International Conference on Information Systems (ICIS). Dublin, Ireland.

Blair, C.S., Mumford, M.D., 2007. Errors in idea evaluation: Preference for the unoriginal? J. Creat. Behav. 41, 197–222.

Blohm, I., Riedl, C., Füller, J., Leimeister, J.M., 2016. Rate or trade? Identifying winning ideas in open idea sourcing. Inf. Syst. Res. 27, 27–48.

Blohm, I., Riedl, C., Leimeister, J.M., Krcmar, H., 2011. Idea Evaluation Mechanisms for Collective

Intelligence in Open Innovation Communities: Do Traders Outperform Raters? In: Proceedings of the 32nd International Conference on Information Systems (ICIS), Shanghai, China.
Bonabeau, E., 2009. Decisions 2.0: The Power of Collective Intelligence. MIT Sloan Manag. Rev. 50, 45–52.
Bothos, E., Prost, S., Schrammel, J., Röderer, K., Mentzas, G., 2014. Watch your emissions: Persuasive strategies and choice architecture for sustainable decisions in urban mobility. PsychNology J. 12, 107–126.
Brunken, R., Plass, J.L., Leutner, D., 2014. Assessment of Cognitive Load in Multimedia Learning with Dual-Task Methodology : Auditory Load and Modality Effects. Instr. Sci. 32, 115–132.
Carroll, K.A., Samek, A., Zepeda, L., 2018. Food bundling as a health nudge: Investigating consumer fruit and vegetable selection using behavioral economics. Appetite 121, 237–248.
Cohen, W.M., Levinthal, D.A., 1990. Absorptive Capacity: A New Perspective on Learning and Innovation. Adm. Sci. Q. 35, 128–152.
Cooper-Martin, E., 1994. Measures of Cognitive Effort. Mark. Lett. 5, 43–56.
Corney, J.R., Torres-Sánchez, C., Jagadeesan, P.P., Lynn, A., Regli, W.C., 2009. Outsourcing labour to the cloud, International Journal of Innovation and Sustainable Development.
Cui, Z., Kumar Pm, S., Gonçalves, D., 2018. Scoring vs. Ranking: An Experimental Study of Idea Evaluation Processes. Prod. Oper. Manag. (forthcomi.
Dean, D.L., Hender, J.M., Rodgers, T.L., Santanen, E.L., 2006. Identifying Good Ideas : Constructs and Scales for Idea Evaluation. J. Assoc. Inf. Syst. 7, 646–699.
Dolan, P., Hallsworth, M., Halpern, D., King, D., Metcalfe, R., Vlaev, I., 2012. Influencing behaviour: The mindspace way. J. Econ. Psychol. 33, 264–277.
Falk, A., Meier, S., Zehnder, C., 2013. Do lab experiments misrepresent social preferences? The case of self-selected student samples. J. Eur. Econ. Assoc. 11, 839–852.
Feldmann, N., Gimpel, H., 2016. Financing Projects through Enterprise Crowdfunding: Understanding the Impact of Proposal Characteristics on Funding Success. In: Proceedings of the 24th Conference on Information Systems (ECIS). Istanbul, Turkey.
Feldmann, N., Gimpel, H., Muller, M., Geyer, W., 2014. Idea Assessment via Enterprise Crowdfunding: An empirical analysis of decision-making styles. In: Proceedings of the 22nd European Conference on Information Systems (ECIS). Tel Aviv, Israel.
Fu, S., de Vreede, G.-J., Cheng, X., Seeber, I., Maier, R., Weber, B., 2017. Convergence of Crowdsourcing Ideas : A Cognitive Load Perspective. In: Proceedings of the 38th International Conference on Information Systems (ICIS). Seoul, South-Korea.
Görzen, T., Kundisch, D., 2016. Can the Crowd Substitute Experts in Evaluating Creative Jobs? An Experimental Study Using Business Models. In: Proceedings of the 24th European Conference on Information Systems (ECIS). Istanbul, Turkey,.
Häubl, G., Trifts, V., 2000. Consumer Decision Making in Online Shopping Environments: The Effects of Interactive Decision Aids. Mark. Sci. 19, 4–21.
Iveroth, E., Bengtsson, F., 2014. Changing behavior towards sustainable practices using Information Technology. J. Environ. Manage. 139, 59–68.
Iyengar, S.S., Lepper, M.R., 2000. When Choice is Demotivating : Can One Desire Too Much of a Good Thing ?. J. Pers. Soc. Psychol. 79, 995–1006.
Johnson, E.J., Shu, S.B., Dellaert, B.G.C., Fox, C., Goldstein, D.G., Häubl, G., Larrick, R.P., Payne, J.W., Peters, E., Schkade, D., Wansink, B., Weber, E.U., 2012. Beyond nudges: Tools of a choice architecture. Mark. Lett. 23, 487–504.
Jung, D., Erdfelder, E., Glaser, F., 2018. Nudged to win: Designing robo-advisory to overcome decision inertia Research in Progress. In: Proceedings of the 26th European Conference on Information Systems (ECIS). Portsmouth, UK.
Kantowitz, B.H., Roediger, H.L., Elmes, D.G., 2005. Experimental Psychology - Understanding Psychological Research, 8th editio. ed., Wadsworth Thomson Learning, Stanford, USA.
Lamberton, C.P., Diehl, K., 2013. Retail Choice Architecture: The Effects of Benefit-and Attribute-Based Assortment Organization on Consumer Perceptions and Choice. J. Consum. Res. 40, 393-411.
Lauto, G., Valentin, F., 2016. How preference markets assist new product idea screening. Ind. Manag. Data Syst. 116, 603–619.

Lipusch, N., Dellermann, D., Philipp, E., 2017. Using Crowdfunding for Start-Up Evaluation: How Task Representation Influences Prediction of the Crowd. In: Proceedings of the 25th European Conference on Information Systems (ECIS). Guimarães, Portugal.
Magnusson, P.R., Wästlund, E., Netz, J., 2016. Exploring Users' Appropriateness as a Proxy for Experts When Screening New Product/Service Ideas. J. Prod. Innov. Manag. 33, 4–18.
Mayer, R.E., Moreno, R., 2017. Nine Ways to Reduce Cognitive Load in Multimedia Learning. Educ. Psychol. 38, 42–52.
Milkman, K.L., Chugh, D., Bazerman, M., 2008. How can decision making be improved? Working Paper, Harvard Business School.
Mirsch, T., Lehrer, C., Jung, R., 2017. Digital Nudging: Altering User Behavior in Digital Environments, Proceedings der 13. Internationale Tagung Wirtschaftsinformatik (WI). St. Gallen, Switzerland.
Muller, M., Geyer, W., Soule, T., Daniels, S., Cheng, L.-T., 2013. Crowdfunding inside the Enterprise: Employee-Initiatives for Innovation and Collaboration. In: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems. Montreal, Canada.
Münscher, R., Vetter, M., Scheuerle, T., 2015. A Review and Taxonomy of Choice Architecture Techniques. J. of Behav. Dec. Making. 29, 511–524.
Niemeyer, C., Wagenknecht, T., Teubner, T., Weinhardt, C., 2016. Participatory crowdfunding: An approach towards engaging employees and citizens in institutional budgeting decisions. Proc. Annu. Hawaii Int. Conf. Syst. Sci. Koloa, HI, USA.
Paas, F., Tuovinen, J.E., Tabbers, H., Van Gerven, P.W.M., 2003. Cognitive Load Measurement as a Means to Advance Cognitive Load Theory. Educ. Psychol. 38, 63–71.
Paas, F., Van Merrienboer, J.J.G., Adam, J.J., 1994. Measurement of Cognitive Load in Instructional Research. Percept. Mot. Skills 79, 419–430.
Petty, R.E., Cacioppo, J.T., 1986. The Elaboration Likelihood Model of Persuasion. In: Advances in Experimental Social Psychology, 19, 123–205.
Purpura, S., Schwanda, V., Williams, K., Stubler, W., Sengers, P., 2011. Fit4Life : The Design of a Persuasive Technology Promoting Healthy Behavior and Ideal Weight. CHI 2011. Vancouver, Canada.
Riedl, C., Blohm, I., Leimeister, J.M., Krcmar, H., 2010. Rating scales for collective intelligence in innovation communities: Why quick and easy decision making does not get it right. In: Proceedings of the 31st International Conference on Information Systems (ICIS). St. Louis, MO, USA.
Schnabel, T., Bennett, P.N., Dumais, S.T., Joachims, T., 2016. Using Shortlists to Support Decision Making and Improve Recommender System Performance. In: International World Wide Web Conference Committee (IW3C2). Montreal, Canada.
Schulze, T., Indulska, M., Geiger, D., Korthaus, A., 2012. Idea assessment in open innovation: A state of practice. In: Proceedings of the 20th European Conference on Information Systems (ECIS). Barcelona, Spain.
Simon, H.A., 1955. A Behavioral Model of Rational Choice. Q. J. Econ. 69, 99-118.
Stryja, C., Satzger, G., Dorner, V., 2017. A Decision Support System Design to Overcome Resistance towards Sustainable Innovations. In: Proceedings of the 25th European Conference on Information Systems (ECIS). Waikoloa, Hawai.
Surowiecki, J., 2004. The wisdom of crowds: why the many are smarter than the few and how collective wisdom shapes business, economies, societies and nations, XXI. ed. Anchor Books, New York.
Sweller, J., 1988. Cognitive Load During Problem Solving: Effects on Learning, Cognitive Science.
Sweller, J., Van Merrienboer, J.J.G., Paas, F., 1998. Cognitive Architecture and Instructional Design. Educ. Psychol. Rev. 10, 251–296.
Thaler, R.H., Sunstein, C.R., 2008. Nudge: Improving Decisions about Health, Wealth, and Happiness. Yales University Press, New Haven, Connecticut.
Thaler, R.H., Sunstein, C.R., Balz, J.P., 2012. Choice Architecture. In: Shafir, E. (Ed.), The Behavioral Foundations of Public Policy. Princeton University Press, New Jersey, pp. 428–439.
Tversky, A., Kahneman, D., 1974. Judgment under Uncertainty: Heuristics and Biases. Science, 185., 1124–1131.

Vallgårda, S., 2012. Nudge-A new and better way to improve health? Health Policy (New. York). 104, 200–203.

Velamuri, V.K., Schneckenberg, D., Haller, J.B.A., Moeslein, K.M., 2017. Open evaluation of new product concepts at the front end of innovation: objectives and contingency factors. R D Manag. 47, 501–521.

Wagenknecht, T., Crommelinck, J., Teubner, T., Weinhardt, C., 2017. When Life Gives You Lemons: How rating scales affect user activity and frustration in collaborative evaluation processes. In: Proceedings der 13. Internationale Tagung Wirtschaftsinformatik (WI). St. Gallen, Switzerland.

Weinmann, M., Schneider, C., vom Brocke, J., 2016. Digital Nudging. Bus. Inf. Syst. Eng. 58, 433–436.