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Designing a Digital Nudge for Convergence: The Role of Decomposition of Information Load for Decision Making and Choice Accuracy

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Abstract:

Innovation contests offer organizations the opportunity to source innovative ideas to achieve competitive advantage. However, raters cannot easily converge on the most promising ideas because they can easily feel overwhelmed by the high number of generated ideas. Further, information overload will likely impair raters' decision-making processes and how well they can accurately distinguish good from bad ideas. Digital nudging may counteract this convergence challenge via user interface elements to change how information is presented to users. To design a digital nudge in a convergence platform to effectively nudge raters towards improved choice accuracy, one needs to understand the decision-making processes associated with the convergence task. Considering this goal, we conducted an online experiment in which 190 participants eliminated the least promising ideas in presentation modes with either a high (two ideas/screen) or low (30 ideas/screen) decomposition of information load. Our findings suggest that convergence platforms with a high decomposition of information load help raters make more accurate choices. The extent of elimination and revision decisions raters make partially explained this effect. However, these paradoxical mediation effects depended on whether raters showed a high or low tendency to follow the crowd's opinion. Our findings add to the growing academic knowledge base on idea-selection processes and how one can design convergence platforms with digital nudges to help raters deal with their cognitive constraints and ensure successful convergence.

Keywords: Digital Nudging, Decision Making, Choice Accuracy, Judgment, Innovation Contests.

Torkil Clemmensen was the accepting senior editor for this paper.

1 Introduction

As society moves towards a more digital collaborative environment due to the digitization of organizational processes, organizations have shown an increasing tendency to draw on crowds to generate innovative solutions using online innovation contests (Armisen & Majchrzak, 2015). Such contests usually encompass a generation and a subsequent selection phase (Nagar, Boer, & Garcia, 2016). During generation, crowd members use online ideation platforms to generate ideas, comment on, or rate ideas. In the selection phase, raters have to narrow the number of submissions from hundreds or even thousands down to the few most promising ones, which constitutes a convergence process (Fu et al., 2017; de Vreede, Massey, & Briggs, 2009). Convergence constitutes a complex, difficult decision-making process that requires raters to read ideas descriptions, process additional idea attributes such as ratings or likes, compare ideas, and, ultimately, choose good ideas for later implementation. Organizations need to have effective convergence processes in place given that the innovative solutions they select may provide a competitive advantage (Rass, Dumbach, Danzinger, Bullinger, & Moeslein, 2013).

Contest organizers use convergence platforms to distribute the large number of generated ideas among (crowd) raters so that they can independently evaluate ideas (Benbasat, 2010; Germonprez, Hess, Kacmar, & Lee, 2008; Zhang et al., 2002). Related work on platform design for idea convergence provides relevant insights into effective rating systems for idea evaluation (Blohm, Riedl, Füller, & Leimeister, 2016; Klein & Garcia, 2015). However, convergence requires a high cognitive load required from raters (Kolfshoten & Brazier, 2013) when reading, evaluating, and choosing ideas. When a rater's cognitive load exceeds the rater's memory capacity in any of these dimensions (Paas, Renkl, & Sweller, 2004), cognitive overload sets in and the rater performs poorly in selecting ideas (Blohm, Riedl, Leimeister, & Krcmar, 2011; Fu et al., 2017) and, ultimately, cannot accurately choose good ones. As such, for platform design, we need to understand that technology interacts with users in a complex way and, thus, that positive outcomes can arise only when this interaction is effective (Lyytinen, 2010). Therefore, platform designers must consider not only a convergence platform's functional requirements but also raters' behavioral needs (e.g., cognitive load) when using them (Carey, Kim, & Wildemuth, 2004). In other words, we must understand how raters interact with the convergence platform interface when processing ideas in order to develop platforms that can effectively guide raters' decision making towards improved choice accuracy. To achieve this guidance, one can use digital nudging (Oinas-Kukkonen, 2013). Digital nudging refers to design elements in computerized environments that can steer human's cognitive processing towards a certain behavior (Meske & Potthoff, 2017). When it comes to idea presentation, the number of ideas presented simultaneously to evaluators can either ease or complicate choices (Johnson et al., 2012), which suggests that, while showing all ideas at once imposes a certain information load, presenting subsets of ideas in multiple rounds could decompose this information load and, thus, ease the convergence task. Moreover, researchers have also considered information presentation format one factor that affects how individuals cognitively process information and, consequently, their decision-making performance (Meske & Potthoff, 2017). Given the potential effects that decomposition of information load (DIL) may have on choice accuracy, it remains unclear *how* this digital nudge of the decomposition of information load affects how individuals process information when selecting the best ideas.

Past research has indicated that decision makers engage in decision-making processes that one can subdivide into information acquisition, evaluation, action, and feedback/learning processes (Einhorn & Hogarth, 1981) when choosing between alternatives (ideas). Hence, raters' decision-making subprocesses may explain the effects that an idea-presentation mode that focuses on decomposing information load has on decision making (e.g., how much effort they invested in information acquisition or action processes). However, it remains unexplored if raters' decision-making processes explain the relationship between DIL and choice accuracy.

Furthermore, we must also consider other idea attributes that might affect how decision-making processes interact with decomposition of information load. Many convergence platforms include the number of likes or ratings from the crowd during the idea-generation phase as a feedback attribute. These elements can nudge raters to follow the crowd's opinion rather than rely on their own decision making. Also, in this case, research has not yet established whether the raters' tendency to follow the crowd's opinion changes the effect that decomposition of information load has on decision making and choice accuracy. Therefore, we address the following research question (RQ) in this study:

RQ: How does idea presentation nudge raters' decision making to improve choice accuracy on an idea-convergence platform?

We fill this research gap by analyzing how two idea-presentation modes that differ in their decompositions of information load (DIL) affect choice accuracy, how raters' decision-making process mediates this effect, and how tendency to follow the crowd's opinion moderates the direct and mediation effects. We conducted an online experiment in which 190 participants eliminated ideas in presentation modes with either a high (15 subsets of two ideas at a time) or low (30 ideas displayed at once) decomposition of information load. We found that a high decomposition of information load was associated with increased choice accuracy, especially for raters who had a high tendency to follow the crowd's opinion. In addition, raters' decision-making processes in the convergence task mediated the effect that decomposition of information load had on choice accuracy. Moreover, mediation effects occurred depending on raters' tendency to follow the crowd's opinion. The findings confirm the relevance of a simple feature such as idea presentation as a potential nudge that can guide raters towards more accurate decision making in idea convergence.

This paper proceeds as follows: in Section 2, we provide the theoretical conceptualizations involving cognitive load, digital nudging, and decision making in innovation contests. In Section 3, we develop hypotheses. In Section 4, we describe the experiment and explain the variables we measured and the analyses we performed. In Section 5, we describe the results. In Section 6, we discuss the results, the study's contributions to theory and practice, and the study's limitations. Finally, in Section 7, we conclude the paper.

2 Background and Theory

2.1 Cognitive Load Theory

Because cognitive load poses a challenge to individuals when selecting ideas (Kolfshoten & Brazier, 2013), convergence platforms need to consider the cognitive load that a convergence task might impose on raters. According to cognitive load theory (Sweller, 1988), cognitive load represents the mental effort that individuals deploy in their working memory to process information and functionally divides it into *intrinsic*, *germane* and *extraneous* cognitive load (Paas et al., 2004). *Intrinsic* load refers to the cognitive load that a task itself imposes, and elements such as the total amount of information one needs to process represent it. The rater's familiarity with the task also influences intrinsic load (Sweller, Ayres, & Kalyuga, 2011). *Germane* load refers to how raters process available information from their short to long-term memory. In particular, designs that help people process information to construct schemas, which they can store in their long-term memory and use to process similar information in a more efficient way in the future, constitute germane load (Fu et al., 2017). Germane load includes instructional guidance such as prompts that remind raters of the task process and information regarding displayed attributes. *Extraneous* load refers to the way one presents information to raters. In a convergence task, for example, presenting a certain amount of ideas in one screen might impose a different extraneous load compared to when one divides the ideas among different screens. As Fu et al. (2017) state, extraneous load increases when convergence platforms present information in a poor or inadequate manner.

In situations with intrinsic load (total amount of ideas) in particular, one needs to reduce the extraneous load by modifying how one presents information (Sweller et al., 2011) in order to not surpass raters' working memory capacity. In idea-convergence settings, intrinsic load can quickly achieve high levels. In fact, past research has suggested that decision makers can already experience cognitive overload with 30 ideas (Misuraca & Teuscher, 2013). Therefore, one needs to consider how to present ideas when developing convergence platforms that help keep cognitive load at manageable levels and, thus, improve choice outcomes.

2.2 Digital Nudging

To successfully identify high-quality ideas, organizations use IT tools (Girotra, Terwiesch, & Ulrich, 2010). However, they often fail to exploit the crowd's true potential due to inadequately designing evaluation tasks (Riedl, Blohm, Leimeister, & Krcmar, 2010) and poorly understanding how and why IT-enabled interventions affect the quality of convergence outcomes (Seeber, de Vreede, Maier, & Weber, 2017).

When designing convergence platforms, one needs to consider the way users interact with a platform as this interaction will ultimately affect task outcomes (Lyytinen, 2010). Therefore, one needs to understand how design elements can influence raters' decision-making behavior (Schneider, Grupp, Lins, Benlian, & Sunyaev, 2017) to enhance their performance when rating ideas on convergence platforms.

Digital nudges describe user interface design elements that influence decision makers' information processing in predictable ways (Weinmann, Schneider, & vom Brocke, 2016). In the idea-convergence context, changes to the user interface should change extraneous load to ease decision making and, ultimately, increase the likelihood that raters will make more accurate choices. Based on nudging and persuasive systems research, Meske and Potthoff (2017) proposed a digital nudging process model (DINU) in which they divide the nudging process into phases and suggest activities for each phase that will help raters choose the right nudges that will work effectively in achieving its purpose. According to the model, the first phase includes defining possible reasons for undesired behavior and the nudging's goals. Based on these reasons and goals, one selects proper elements for the digital nudge design in the second phase. Finally, after implementing the nudge, one should critically assess the obtained behavior and adjust the nudge as required.

Applying this model to designing convergence platforms, we have cognitive limitations as reasons and choice accuracy as goal for the nudge. For the design, customized information, simplification and social influence in the form of crowd ratings might help raters coping with their cognitive limitations. When evaluating the implemented nudge, one should consider whether it increased choice accuracy and make modifications if the nudge fails. Furthermore, Schneiderman and Plaisant (2010) recommend that one presents information in a simple way to reduce (extraneous) short-term memory load.

When it comes to the technical aspects, defining how many alternatives to present at the same time to raters represents a key factor in determining how raters make decisions (Johnson et al., 2012; Tversky & Kahneman, 1986). Given the nudging principles, having a simpler design with high decomposition of information load seems to benefit the idea-selection process. However, it remains unclear how either a high or a low decomposition of information load nudges raters' decision making towards more in-depth processing and which choice outcomes each decomposition of information load yields.

2.3 Decision Making Processes in Choice Tasks

As a complex decision-making process in which one selects the most promising ideas, idea convergence demands judgment and risk (Oman, Tumer, Wood, & Seepersad, 2013). Einhorn and Hogarth (1981) divide the decision-making process into four subprocesses: information acquisition, evaluation, action, and feedback/learning. In information acquisition, raters search for and store information in their memory and in the external environment. During evaluation, raters use search strategies such as maximization of expected value, elimination-by-aspects or satisficing to process the acquired information. Action processes represents the final choice and typically involves more commitment than evaluation. Finally, feedback involves learning through the decision experience. Whereas decision makers' behavior explains information-acquisition and action processes, it does not explain evaluation and feedback learning processes due to their cognitive nature, which means one cannot easily observe or measure such processes. Hence, in this study, we focus on information acquisition and action processes to understand raters' decision making.

However, not every rater acquires information and judges information (action process) in the same way. Depending on the contest, raters apply either a more compensatory or a more non-compensatory heuristic-based decision-making strategy (Pilli & Mazzon, 2016).

Compensatory decision making describes raters that apply utility weights or values to the complete set of attributes and select the alternative with the best utility (Johnson & Payne, 1985). In this case, raters make a rational choice on the idea (alternative) based on systematically processing idea attributes such as idea description, ratings, likes, and comments (attributes). In contrast, non-compensatory decision making does not consider all available attribute information or trades off the benefit of one attribute against the deficit of another attribute (Payne, Bettman, & Johnson, 1993).

In summary, we might be able to understand how raters interact with a convergence platform on each case and, thus, how one could better judge them to achieve increased choice accuracy.

3 Hypotheses Development

As Tversky and Kahneman (1986) state, choice is a maximization process in which rational decisions lead to better decisions. When raters go through a convergence process, they choose what information to consider and what information to ignore in order to narrow down the number of (often high) alternatives (Johnson et al., 2012). Moreover, choices depend not only on how much information one presents but also

how one presents it (Schneider, Weinmann, & vom Brocke, 2018). According to Rosati (2013), Hickman's law affirms that having more options presented one time makes for quicker and less stressful decisions in comparison with breaking the choice down across screens. However, when one does not organize choices into categories, Hick's law does not apply anymore, and splitting the presented information becomes the preferable option (Rosati, 2013). By having a simpler design with less information displayed per screen, the convergence platform can decompose the amount of information load being that it presents to raters at once, which will decrease extraneous cognitive load and, thus, help them cope with the high intrinsic load by not having to deal with a lot of information at the same time. With that, raters can apply more effort in the rating task and use their cognitive resources to evaluate ideas more thoroughly and, thus, get closer to the maximization process. The higher amount of effort applied to examine ideas extensively will then enable raters to make more accurate choices (Johnson & Payne, 1985). Therefore, we hypothesize:

H1: Higher decomposition of information load leads to higher choice accuracy.

But why would applying more effort lead to increased choice accuracy? In the context of a pairwise idea presentation mode, where decomposition of information load is high, raters will be guided towards searching for more information that describes an idea (Johnson & Payne, 1985). As a result, they will get closer to the maximizing goal, which should yield higher accuracy when the number of alternatives does not become too excessive (Cui, Kumar Pm, & Gonçalves, 2019). In addition, decomposing the convergence task into smaller subtasks should help raters construct mental schemas as they will feel less cognitively overloaded and, thus, can evaluate the ideas presented to them more efficiently (Amir & Levav, 2008). Since acquiring more information allows raters to build more comprehensive mental schemas, they should feel less overloaded and more certain about their judgments, which will enable them to make more accurate choices. The same applies for raters' actions. Because presenting a few alternatives allows raters to make a more reasoned comparison that does not overwhelm them (Johnson & Payne, 1985), they will engage in more evaluation. Raters that take action based on their evaluation will make more judgments. As raters judge more, they become more certain about their decisions and, consequently, more likely to take action regarding the choice at hand (Lepora & Pezzulo, 2015). In turn, the increased effort applied in thoroughly processing ideas will make raters more accurate. Thus, we hypothesize:

H2: Information acquisition (H2a), eliminate actions (H2b), and keep actions (H2c) positively mediate the effect that DIL has on choice accuracy.

The information that raters consider when weighing ideas represents another important factor. When convergence platforms present fewer ideas at once and raters apply more compensatory decision processes to process this information, raters will acquire information on more attributes (Johnson & Payne, 1985; Wibmer, Wiedmann, Seeber, & Maier, 2019). Among these attributes considered, the number of loves that the crowd gives an idea might influence raters' decisions especially if they have uncertainty about an idea's quality. Nevertheless, raters can also use these ratings instead of relying on their judgment process as a way to decrease effort they apply in the rating process. As much as the number of likes can help raters make their choices, the crowd might have a limited ability to identify an idea's true quality (Klein & Garcia, 2015). Therefore, raters who have a higher tendency to follow the crowd might rely too much on the crowd's opinion and be misled, which can result in their making less accurate choices. However, such conscious acts of manipulating votes usually affect only a fraction of rated ideas. In fact, crowds can quite effectively eliminate ideas with poor quality (Görzen & Kundisch, 2017). Hence, the larger proportion of honestly rated ideas should indicate an idea's latent quality so that raters that follow the crowd's opinion should overall also end up with more accurate choices. Therefore, we hypothesize:

H3: The direct positive effect that decomposition of information load has on choice accuracy increases in magnitude when raters have a high tendency to follow the crowd's opinion.

Relying heavily on the crowd's opinion to rate ideas also affects the way raters make decisions. While a higher decomposition of information load might lead raters to consider more information about ideas, in a more adaptive decision making style, they might focus their attention on attributes such as how many loves an idea has in an attempt to make accurate decisions with less effort (Payne et al., 1993). Doing so will cause raters to acquire less information about certain attributes such as idea descriptions. They will also evaluate ideas less frequently given that they would not consider all available attributes when comparing ideas. Therefore, we hypothesize:

H4: A higher tendency to follow the crowd's opinion decreases the mediation effect that information acquisition (H4a), eliminate actions (H4b) and keep actions (H4c) have on the effect that decomposition of information load has on choice accuracy.

Altogether, our hypotheses focus on how a technical aspect such as decomposition of information load affects choice accuracy, how raters' decision making mediate this relationship, and how tendency to follow the crowd's opinion moderates the way decomposition of information load affects raters' decision making and convergence outcomes. By understanding these mechanisms better, we can derive suggestions about designing convergence platforms. We depict the hypotheses in Figure 1.

Figure 1. Research Model

4 Method

To test the proposed research model, we conducted a between-subject online experiment with 190 participants. The experiment comprised an idea-selection task in which participants reduced a set of 30 ideas by eliminating those ideas they did not consider worthy of further consideration. In this section, we describe the experimental design in more detail.

4.1 Treatment Variable: Decomposition of Information Load

Decomposition of information load (DIL) refers to how much information we displayed simultaneously to participants. We operationalized DIL with two different presentation modes that displayed a distinct number of ideas per screen. The low DIL treatment displayed all 30 ideas at once, while the high DIL treatment displayed two ideas per screen and moved through 15 screens. With the high DIL treatment, we focused on prompting them to process ideas in a more compensatory way. In both treatments, we presented the 30 ideas in random order to avoid a position bias (Blohm et al., 2011). Figure 2 and Figure 3 depict both treatments.

Figure 2. Low DIL Treatment (30 Ideas/Screen)

Figure 3. High DIL Treatment (Two Ideas/Screen x 15 Screens)

4.2 Subjects and Sampling

We invited business administration students enrolled in the course “Introduction to Information Systems” at a European University to participate in the experiment. From the 240 students enrolled, 190 voluntarily participated and received extra course credits as a reward if they answered the task-attention check correctly. The participants could access the online experiment for one week, and, as soon as they accessed the platform, we randomly assigned each participant to one of the two treatment groups. We deemed students as appropriate participants because real-world idea convergence teams often rely on team members that have little domain knowledge of the contest domain (Merz et al., 2016).

4.3 Procedure, Task, and Supporting Idea-selection Platform

When participants accessed the platform, we first redirected them to the survey platform SoSci Survey where they filled in an introductory survey containing the control variables. Subsequently, we introduced them to the platform and the task. In introducing them to the platform, we showed participants what an idea looked like and the available feedback information for every idea (see Figure 4). In addition, we informed participants that we collected all information including the indices from the original platform and that the

contest had closed. Participants had no option to comment or applaud an idea or any other option that would change the information on ideas. We then specified the task with the prompt:

You will see 30 ideas in total. In this phase, your task is to ELIMINATE ideas which do not seem promising for further consideration. How many ideas you eliminate is up to you. You can eliminate zero, one or multiple "bad" ideas from each set.

We also provided them with a page in which we outlined the contest goal through the prompt: “how might we inspire experiences and expressions of gratitude in the workplace?”. We did not specify other selection criteria besides the prompt. As the experiment began, participants went through the idea-selection task in one of the two treatments. As the prompt mentioned, participants could freely eliminate as many ideas as they wished. They could also change their minds and retain an idea they intended to select as long as they did not confirm the elimination through the option “finish”. On every screen, we positioned “about contest” and “about attributes” buttons, which provided additional information on the contest and the feedback attributes (loves, ideator score) if the participant clicked them. While each participant went through the task, the system saved an activity log in the database each time participants selected the “read more” or “eliminate” buttons. If participants deselected a previously eliminated idea, the system generated a keep log entry. In order to assess participants’ honest commitment, the task included a task-attention check in which participants had to select the option that described the task they just concluded. As soon as participants eliminated ideas and confirmed the elimination, they moved on to the end survey to answer the task attention check. After that, the task ended.

4.4 Idea Set

We drew a stratified sample of 30 ideas from a real innovation contest on “expressions of gratitude in the workplace” that the open innovation platform openIDEO hosted in 2017. We chose this contest topic because business administration students should be familiar with human resources issues and organizational workplace settings. Thus, the contest topic should increase the experiment’s ecological validity (Pomeroy & Adam, 2004). A small team of graduate and PhD students manually shortened each idea to about 120 words to control for idea length and reformulated the ideas to make sure that all ideas answered the questions 1) “what is the idea about?” and 2) “how does it work?”. The convergence platform presented each idea with its title, description, and two feedback attributes (i.e., the number of applauds/loves and the ideator score (ideator’s past success)). We took the values for both attributes from the original platform. We added these additional attributes to each idea’s description to keep the idea-selection setting as realistic as possible to convergence processes in practice.

4.5 Measures

4.5.1 Information Acquisition

Information acquisition encompasses the processes of searching and storing information (Einhorn & Hogarth, 1981). In the idea-selection context, people can acquire information by actively searching for more information on an idea. We measured this concept by counting how often a user clicked the “read more” button on each idea card. When the system presented participants with the ideas, they could only see a short introductory sentence about each idea with about 30 words and the number of “loves” and the “idea score”. In case participants wished to read the entire idea description and, hence, acquire more information, they could select the “read more” button to see the remaining text.

4.5.2 Action

Taking action describes the final choice after decision makers evaluate the alternatives (Einhorn & Hogarth, 1981). In the underlying case, an action occurs when a rater eliminates an idea or revises the decision to keep an idea. We measured eliminate with the number of clicks on the *eliminate* checkbox that the database stored. Once users decided to eliminate ideas because they found them not worthy of further consideration, the platform showed a garbage bin and the text eliminate occurred next to the checkbox. We measured keep as the number of clicks on the checkbox for re-including ideas into the consideration set that the participant had previously eliminated. In that case, the checkbox changed to its original look. Figure 4 depicts how we presented read more and eliminate.

Figure 4. Idea Card Template

4.5.3 Choice Accuracy

Choice accuracy refers to each participant's effectiveness in identifying the best ideas from the idea set (Riedl et al., 2010). One cannot easily assess idea quality. Therefore, researchers often compare raters' selection choices with experts' selection choices. When both types of raters select the same choices, choice accuracy is high, and, hence, one could deduce the quality of the selected idea set. Given the fact that we do not possess detailed knowledge as to how the original platform assessed idea quality, we established a quality benchmark or "gold standard" to operationalize this concept. Following previous research (Magnusson, Netz, & Wästlund, 2014; Riedl et al., 2010), we adopted the consensual assessment technique (Amabile, 1982) and asked four domain experts to rate the ideas. Each rater assessed each idea in terms of its novelty, feasibility, elaborateness, and relevance—well-established criteria to measure ideas' creativity (Dean, Hender, Rodgers, & Santanen, 2006). After evaluation, we used the aggregated ratings to create a ranking for idea quality. We considered the top 30 percent of ideas as "good ideas" (Blohm et al., 2011). After establishing the benchmark, we calculated choice accuracy by relying on the accuracy-performance measure that information-retrieval systems use (Baeza-Yates & Ribeiro-Neto, 2011). Hence, choice accuracy comprises the fraction of ideas correctly classified as good (true positives, TP) and bad (true negatives, TN) divided by all ideas (see Equation 1 in the set of eliminated ideas).

$$\text{Choice accuracy} = \frac{TP + TN}{\text{total number of ideas}} \quad (1)$$

4.5.4 Tendency to Follow the Crowd's Opinion (TFCO)

Tendency to follow the crowd's opinion checked whether the feedback attribute number of applaus of an idea influenced the raters' actions and outcomes. Hence, we calculated tendency to follow the crowd's opinion by summing the number of applaus from the ideas that remained in the idea set divided by the number of remaining ideas to consider different sizes of the remaining idea sets (see Equation 2). Thus, the higher this number, the better indication that participants considered the crowd's opinion when selecting ideas. The crowd's opinion concurred with the expert rating about 50 percent of the time, so the number of loves did not correlate to good ideas ($r = -0.149$, $p = 0.432$). As tendency to follow the crowd's opinion was a continuous variable, we created three groups based on a tercile split (0 = low, 1 = medium, 2 = high).

$$\text{Tendency to follow crowd opinion} = \frac{\Sigma \text{number of applaus from remaining idea set}}{\text{number of ideas in the remaining set}} \quad (2)$$

4.5.5 Other Variables

We used work experience to control for participants' familiarity with the topic, which could have influenced their cognitive load management and, consequently, their performance. We also controlled for age and gender.

4.6 Statistical Analyses

In total, 190 individuals participated in the online experiment. We removed 27 entries because the participants did not answer the task attention check correctly, which resulted in a sample with 163 cases. Before we tested the hypotheses in RStudio Version 1.1.456, we checked for outliers (Hair et al., 2010) and violations against statistical assumptions (Mertens, Pugliese, & Recker, 2016). From visually inspecting the scatterplots, quantile-quantile plots, and influential observations using Cook's distance, we found several extreme cases. To ensure that the identified outliers did not bias our results, we carefully assessed each one. We tested statistical assumptions and ran regression models with and without outliers. We observed no substantial differences in outcome. We excluded only one case since we identified it to include random responses (Zijlstra, van der Ark, & Sijsma, 2011). Therefore, we continued our analysis with 162 participants in the sample. As for the error terms' linearity, crPlots showed that this assumption had been met. The Durbin-Watson test showed that the values of residuals were independent since the obtained values were always close to 2. In addition, plots of standardized residuals versus standardized predicted values showed no obvious signs of funneling, which suggested that the assumption of homoscedasticity was satisfied. Finally, the assessment of studentized residuals suggested that the values of the residuals had a normal distribution with the exception of the models that involved the logs information acquisition and keep action, which indicated slight deviations from normality. Nevertheless, the large sample size makes the models more robust to this assumption's violation (Schmidt & Finan, 2018).

To test the hypotheses, we conducted different analyses. First, we ran two linear regression analyses to investigate the effect that decomposition of information load (DIL) had on choice accuracy (H1): one with the covariates and one without them. Then, to verify whether the information acquisition and eliminate and keep actions mediated the effect that decomposition of information load had on choice accuracy, we performed a causal mediation analysis (Imai, Keele, & Tingley, 2010a) with the R package mediation (Imai, Keele, Tingley, & Yamamoto, 2010b; Tingley, Yamamoto, Hirose, Keele, & Imai, 2014). As Tingley et al. (2014) state, researchers frequently use causal mediation analysis to assess potential causal mechanisms. We first fitted the mediation and outcome models and then used the outputs of the fitted models to run the causal mediation analyses with the function `mediate`, which estimated the causal mediation (ACME), direct (ADE) and total effects (Imai et al., 2010b; Tingley et al., 2014). We estimated confidence intervals via bootstrapping with 5,000 resamples. To assess the results' robustness, we used the output of the `mediate` function to run the sensitivity analyses with the `medsens` function (Imai et al., 2010a). Imai et al. (2010a) and Imai, Keele, and Yamamoto (2010c) describe the algorithms used in estimating the causal mediation in detail. Subsequently, we conducted a moderated mediation analysis to assess whether tendency to follow the crowd's opinion (TFCO) moderated the direct and mediation effects we observed (Tingley et al., 2014).

5 Results

In this section, we describe the sample and how we tested the hypotheses.

5.1 Sample

Table 1 overviews the sample, which comprised 162 participants (100 males and 62 females). Participants were rather young and had limited work experience. Participants in both treatment groups had a similar age, work experience, and gender. However, participants in the treatment groups differed with respect to their selection behavior as we hypothesized. Participants in the high decomposition of information load (DIL) treatment eliminated more ideas, took longer for their selection task, and engaged in more information acquisition, eliminate and keep actions. Finally, on average, participants in the low DIL treatment achieved a choice accuracy of 49 percent, whereas participants in the high DIL treatment achieved 53 percent.

Table 1. Sample Description

		Low DIL (30 ideas/screen) N = 85		High DIL (2 ideas/screen) N = 77		Total N = 162	
Gender	Male	53		47		100	
	Female	32		30		62	
		Mean	St. dev.	Mean	St. dev.	Mean	St. dev.
Age		21.64	1.84	21.71	1.98	21.67	1.90
Work experience (months)		15.44	18.67	16.97	19.03	16.17	18.80
Number of ideas eliminated		13.28	5.80	15.69	3.88	14.43	5.11
Time on platform		07:47	05:32	10:57	07:39	09:17	06:47
Information acquisition		7.79	9.88	11.47	11.92	9.54	11.02
Eliminate action		14.69	5.82	18.55	4.56	16.52	5.59
Keep action		1.41	1.39	2.84	1.90	2.09	1.80
Choice accuracy		.49	.09	.53	.08	.51	.09

5.2 Hypotheses Testing

To test our hypotheses, we structured the analyses as follows. First, we checked the direct effect that DIL had on choice accuracy with linear regression (H1). Then, we conducted causal mediation analyses to verify if information acquisition and eliminate and keep actions mediated the effect that DIL had on choice accuracy (H2). Finally, we conducted moderated mediation analyses to check whether tendency to follow the crowd's opinion (TFCO) moderated the direct and causal relationships (H3 and H4).

5.2.1 Effect of DIL on Accuracy

H1 posits that raters who complete a high DIL (two ideas per screen) achieve higher choice accuracy in comparison to raters who complete a low DIL (30 ideas per screen). We tested this hypothesis with multiple regression and results are provided in Model 1 in Table 2. We found a significant positive relationship between DIL and choice accuracy ($\beta = 0.035$, $p < .05$). Hence, we found support for H1 (see Table 2).

With respect to the model's fitness, Model 1 results indicated that decomposition of information load and work experience explained only 4.1 percent of the variation in choice accuracy ($R^2 = 0.041$, $F(2, 159) = 3.375$, $p < .05$). When we added information acquisition, eliminate action, and keep action processes and the moderator TFCO, we found a stark increase in model fit as reported in Model 2. The adjusted R^2 rose to 23.7 percent, and, hence, the model explained a good portion in the variance of choice accuracy ($R^2 = .270$, $F(7, 154) = 8.139$, $p < .01$). The treatment variable's previously strong effect vanished, which indicated mediation. Therefore, we followed up with a causal mediation analysis.

5.2.2 Causal Mediation Analyses

For each decision-making subprocess that we measured (information acquisition and eliminate and keep action processes), we performed causal mediation. As the processes influenced one another (Einhorn & Hogarth, 1981), we added the other two processes to each model as covariates so that the model could also consider their effect on the mediator and outcome variables. Table 3 shows the results from the three causal mediation analyses.

H2 posits that information acquisition, eliminate actions, and keep actions mediate the relationship between DIL and choice accuracy. For information acquisition, the average causal mediation effect (ACME) with a likelihood estimate of 0.001 was not significant ($p = .42$). This finding means that information acquisition did not mediate the relationship between DIL and choice accuracy. Hence, we did not find support for H2a. For the eliminate actions, the ACME with an estimate of 0.011 was significant ($p = .018$). Hence, we found support for H2b. Regarding *keep actions*, the ACME had a negative effect on choice accuracy (estimate - 0.017) and was strongly significant ($p < .001$). While the mediation effect was significant, we did not hypothesize the negative effect direction. Hence, we did not find support for H2c.

In all three models, the average direct effect was significant and positive, which suggests that DIL was significantly and positively associated with choice accuracy and that eliminate and keep actions partially

mediated this relationship. Therefore, our results suggest that information acquisition does not mediate the effect that DIL has on choice accuracy but that eliminate and keep actions partially mediate the effect that DIL has on choice accuracy. Whereas the mediating effect was positive for eliminate actions, it was negative for keep actions. Table 3 summarizes the causal mediation results and Figure 5 depicts the effect plots for each mediation analysis.

Table 2. Regression Models

	Dependent variable <i>Choice accuracy</i>	
	(1)	(2)
Decomposition of information load (DIL)	0.035** (0.014)	-0.007 (0.020)
Tendency to follow the crowd's opinion (TFCO)		-0.069*** (0.024)
Information acquisition		0.001 (0.001)
Eliminate actions		0.007*** (0.001)
Keep actions		-0.018*** (0.004)
Work experience	0.00005 (0.0004)	-0.0003 (0.0003)
DIL_P1:TFCO_P1		0.036** (0.015)
Constant	0.458*** (0.022)	0.451*** (0.031)
Observations	162	162
R ²	.041	.270
Adjusted R ²	.029	.237
Residual Std. error	0.086 (df = 159)	0.077 (df = 154)
F statistic	3.375** (df = 2; 159)	8.139*** (df = 7; 154)
Note: * p < .1; ** p < .5; *** p < .1		

Table 3. Causal Mediation Analyses Results

	Mediator											
	information acquisition (H2a)				Eliminate action (H2b)				Keep action (H2c)			
	Estimate	95%CI lower	95%CI upper	p-value	Estimate	95%CI lower	95%CI upper	p-value	Estimate	95%CI lower	95%CI upper	p-value
ACME	0.0012	-0.0015	0.01	.42	0.0115	0.0018	0.02	.018*	-0.0175	-0.0315	-0.01	<2e-16***
ADE	0.0326	0.0048	0.06	.027*	0.0326	0.0042	0.06	.024*	0.0326	0.0053	0.06	.02*
Average total effect	0.0338	0.0062	0.06	.020*	0.0441	0.0154	0.07	.002**	0.0151	-0.0118	0.04	.28
Note: Significance codes (p-value): p < .001 ***, p < .01 **, p < .05 *. Simulations: 5,000.

Figure 5. Effect Plots for Causal Mediation Analyses

5.2.3 Moderated Mediation Analyses

To test the potential moderating effect of a rater's tendency to follow the crowd's opinion (TFCO), we repeated the analyses and included two interaction terms: one to test the moderating effect of TFCO on the direct path between DIL and choice accuracy and one to test the moderating effect of TFCO on the indirect path between DIL and each of the three processes that represent raters' decision making. We compared raters with extreme TFCO values (low vs. high) in order to deduce if the ACME and ADE differed significantly between those groups. Table 4 shows the results and Figure 6 depicts the effect plots for the moderated mediation analyses.

5.2.4 Moderation of the Direct Path

H3 posits that tendency to follow the crowd's opinion moderates the direct effect that DIL has on choice accuracy. For mediation Models 1 to 3, DIL always had a significant and positive direct effect on choice accuracy when raters had a high TFCO. Hence, under the condition that raters tend to follow the crowd's opinion, a presentation mode that decomposes the information load will lead to more accurate choices. Hence, we found support for H3.

The ADE differed significantly between raters with low and high TFCO in all three causal mediation models. For instance, in Model 1, DIL did not help raters with low TFCO to achieve higher choice accuracy (ADE estimate = -0.0079, $p = .71$). However, we observed a significant effect for raters with high TFCO (ADE estimate = 0.0665, $p = .0012$). The difference between both levels of TFCO was significant ($ADE_{low\ TFCO} - ADE_{high\ TFCO} = -0.0746$, $p = .0096$). We found the same difference for Model 2 ($ADE_{low\ TFCO} - ADE_{high\ TFCO} = -0.0743$, $p = .0092$) and keep action ($ADE_{low\ TFCO} - ADE_{high\ TFCO} = -0.0636$, $p = .0404$). These results further support H3.

Finally, H4 posits that tendency to follow the crowd's opinion also moderates the indirect effect that decomposition of information load has on the three decision-making elements.

5.2.5 Moderation of the Indirect Path

Confirming the findings we obtained from the causal mediation analysis, information acquisition did not mediate the effect that decomposition of information load had on choice accuracy for raters with either a low tendency to follow the crowd's opinion (ACME estimate = 0.0016, $p = .56$) or a high tendency to follow the crowd's opinion (ACME estimate = 0.0003, $p = .73$). In addition, in testing the statistical significance of the difference in ACME between raters with low and high tendency to follow the crowd's opinion, we found no statistical difference between both conditions ($ADE_{low\ TFCO} - ADE_{high\ TFCO} = 0.0013$, $p = .7788$). Therefore, we did not find support for H4.

As we establish in Section 5.2.2, eliminate actions mediated the positive effect that DIL had on choice accuracy. The moderated mediation analysis showed that such mediation occurred among raters with low TFCO (ACME estimate = 0.03, $p = .0016$). In contrast, eliminate actions did not act as a mediator for raters with high TFCO (ACME estimate = -0.0008, $p = .89$). The moderated mediation test showed a significant difference in ACME between raters with low and high TFCO ($ACME_{low\ TFCO} - ACME_{high\ TFCO} = 0.031$, $p = .0336$). Therefore, we found support for H4b.

We previously found *keep actions* to negatively mediate the positive effect that DIL had on choice accuracy. When considering the mediating path's potential moderation, we found that TFCO strengthened the negative mediation effect among raters who had a high TFCO (ACME estimate = -0.023, $p = .0076$) but not among raters with low TFCO (ACME estimate = -0.010, $p = .24$). However, the magnitude of this moderation effect was minimal as the difference in the ACME between low and high TFCO groups was not significant

($ACME_{low\ TFCO} - ACME_{high\ TFCO} = 0.013$, $p = .3892$). Hence, we found support for H4, but one should interpret this finding with caution since the difference in the moderation effect was small.

Table 4. Moderated Mediation Analyses Results

	Mediation											
	(1) Information acquisition				(2) Eliminate action				(3) Keep action			
	Estimate	95%CI lower	95%CI upper	p-value	Estimate	95%CI lower	95%CI upper	p-value	Estimate	95%CI lower	95%CI upper	p-value
Low TFCO												
ACME	0.0016	-0.0037	0.01	.56	0.0302	0.0098	0.06	.0016**	-0.0100	-0.0312	0.01	.24
ADE	-0.0079	-0.05	0.03	.71	-0.0077	-0.0490	0.04	.7384	-0.0036	-0.0450	0.04	.82
Average total effect	-0.0063	-0.0473	0.04	.79	0.0226	-0.0192	0.07	.2912	-0.0136	-0.0573	0.03	.51
High TFCO												
ACME	0.0003	-0.0034	0.01	.73	-0.0008	-0.0178	0.01	.89	-0.0233	-0.0611	0.00	.0076**
ADE	0.0665	0.0263	0.11	.0012**	0.0665	0.0261	0.11	.0008***	0.0604	0.0170	0.11	.0056**
Average total effect	0.0669	0.0279	0.11	.001***	0.0658	0.0226	0.11	.0028**	0.0371	-0.0005	0.07	.0552
Test of statistical significance difference between ACME and ADE in the low TFCO and high TFCO groups												
ACME low TFCO — ACME high TFCO	0.0013175				0.030918				0.012743			
p-value	0.7788				0.0336				0.3892			
95% conf. int.	-0.0078 to 0.0121				0.0025 to 0.0637				-0.0177 to 0.0444			
ADE low TFCO — ADE high TFCO	-0.074603				-0.074307				-0.063622			
p-value	0.0096				0.0092				0.0404			
95% conf. int.	-0.1316 to -0.0183				-0.1338 to -0.0161				-0.1230 to -0.0034			
Note: Significance codes (p-value): p < .001 ***, p < .01 **, p < .05 *. Simulations: 5,000.

Figure 5. Effect Plots for Causal Mediation Analyses

As a robustness check, we performed a series of sensitivity analyses. The results with the sensitivity parameter ρ and the product coefficient $\tilde{R}_M^2 \tilde{R}_Y^2$ show that our mediation results were robust against uncontrolled confounding variables (see Appendix A for more details on the sensitivity analyses). We summarize the support we found for our hypotheses in Table 5.

Table 5. Summary of Hypotheses

Hypothesis		Result
H1	Higher decomposition of information load leads to higher choice accuracy.	Supported
H2a	<i>Information acquisition</i> positively mediates the effect that DIL has on choice accuracy.	Not supported
H2b	<i>Eliminate actions</i> positively mediates the effect that DIL has on choice accuracy.	Supported
H2c	<i>Keep actions</i> positively mediates the effect that DIL has on choice accuracy.	Not supported
H3	The direct positive effect that decomposition of information load has on choice accuracy increases in magnitude when raters have a high tendency to follow the crowd's opinion.	Supported
H4a	A higher tendency to follow the crowd's opinion decreases the mediation effect that <i>information acquisition</i> has on the effect that decomposition of information load has on choice accuracy.	Not supported
H4b	A higher tendency to follow the crowd's opinion decreases the mediation effect that <i>eliminate actions</i> have on the effect that decomposition of information load has on choice accuracy.	Supported
H4c	A higher tendency to follow the crowd's opinion decreases the mediation effect that <i>keep actions</i> have on the effect that decomposition of information load has on choice accuracy.	Supported

6 Discussion

In this paper, we address the research question: “How does idea presentation nudge raters’ decision making to improve choice accuracy on an idea-convergence platform?”. We found that a presentation mode with a high decomposition of information load (two ideas/15 screens) enabled raters to eliminate bad ideas and retain good ideas more accurately than a presentation mode with a low decomposition of information load (30 ideas/screen). We explain this effect by drawing on literature on cognitive load theory, which argues that raters will be less likely to experience cognitive overload or will experience it later in the process when they have fewer information items that they need to process at a time (Jacoby, Speller, & Kohn, 1974; Miller, 1956). Raters can then apply more effort in the idea-selection task, which increases their choice accuracy (Johnson & Payne, 1985). As such, our results suggest that the convergence platform feature decomposition of information load can facilitate raters’ performance on convergence platforms. In fact, the decomposition of information load led to a four percent increase in choice accuracy, which resulted in a choice accuracy of 53 percent—slightly better than random. Klein and Garcia (2015) found a similar average performance for idea-selection tasks. However, we found this positive effect of decomposition of information load on choice accuracy only for raters who showed a tendency to follow the crowd’s opinion, which indicates heuristic processing. Related research has found that raters pay more attention to feedback attributes when one decomposes the amount of information (Wibmer et al., 2019). Hence, the high DIL presentation mode might have especially supported raters that tended towards heuristic processing. By doing so, raters used the number of loves in order to cope with the total amount of information load imposed on them and used more adaptive decision-making strategies, which require less effort but still might be quite accurate (Johnson & Payne, 1985). Hence, convergence platforms with a high decomposition of information load helps raters (particularly for those raters that show a high tendency to follow the crowd’s opinion) make more accurate choices.

Second, we found eliminate actions to be a causal mechanism that can explain why decomposition of information load leads to increased choice accuracy. By analyzing raters’ clicking behavior on the convergence platform, we found that the judgment actions eliminate partially mediated the effect that decomposition of information load had on choice accuracy. We can consider the eliminate actions, which represented making the decision to remove an idea from further consideration, the mechanism that explains why raters from the high DIL treatment eliminated ideas more accurately. The higher engagement in judgment possibly led to a decrease in uncertainty, which made the elimination task easier and contributed to improved choice accuracy. Consequently, our findings suggest convergence platforms with a high decomposition of information load facilitate raters to make more accurate choices because they engage in more judgments. However, this positive mediation effect of eliminate only occurred when raters had a low tendency to follow the crowd’s opinion (moderated mediation effect). Given this finding, it seems reasonable to assume that decomposition of information load nudged people in more compensatory or more reasoning-based decision making. Hence, when raters with a low tendency to follow the crowd’s opinion were certain about an idea’s goodness, they also took action and eliminated an idea regardless of the number of loves that the crowd gave it.

Third, we found keep actions to be a causal mechanism that can explain why decomposition of information load leads to increased choice accuracy. Keep actions (i.e. reversing one's decision to eliminate an idea) partially mediated the effect that decomposition of information load had on choice accuracy but in a negative way. While we found empirical support for theorized mediation effect, we did not find support for the effect's direction. Lepora and Pezzulo's (2015) findings could provide a reasonable explanation for this outcome. They suggest that, although changes of mind usually lead to higher accuracy, waiting too long to review one's choice (i.e., revising after checking the whole set) might penalize choice accuracy. Hence, checking the keep process to keep alternatives open possibly indicated choice deferral in our study due to information overload (Pilli & Mazzon, 2016). Particularly, in the high DIL treatment, raters may have become uncertain about their choices and revised their decisions. Raters who went back and changed their minds might have considered the screens as interconnected choice sets and, hence, compared ideas across screens. Given that researchers consider evaluating a set of 30 ideas a cognitively demanding task (Iyengar & Lepper, 2000), they might have experienced cognitive overload after all and further deferred their choice, which researchers have found to diminish choice accuracy (Pilli & Mazzon, 2016). Consequently, on convergence platforms with a high decomposition of information load, overthinking elimination decisions that result in revisions harm convergence. Furthermore, the results we observed in the keep actions also provide interesting insights. While keep actions negatively mediated the effect that decomposition of information load had on choice accuracy, they did so only when raters had a high tendency to follow the crowd's opinion. This finding suggests that, when raters that tend to follow the crowd's opinion (heuristic processing) eliminate ideas on a convergence platform that nudges raters towards more compensatory decision making (reasoning-based processing), raters engage in more revisions in their judgments. However, these more frequent changes partially explained why they make less accurate choices.

Finally, we did not find empirical support for our mediation hypothesis that participants who saw fewer ideas per screen achieved improved choice accuracy because they engaged in more information acquisition. This process did not mediate the effect that decomposition of information load had on choice accuracy. Such a finding corroborates Jamieson and Hyland's (2006) argument that additional information does not necessarily inform better decisions and reduce uncertainty.

6.1 Implications for Theory and Practice

Our findings have implications for theory and practices and provide opportunities for further research. Our findings contribute to cognitive load theory since they confirm that individuals who see fewer ideas at a time (i.e., high decomposition of information load) make better decisions. Having to deal with fewer ideas at the same time decreases extraneous load (Fu et al., 2017, 2019), which helps raters better manage cognitive load. Hence, research on cognitive load involving idea selection (Blohm et al., 2011; Fu et al., 2019, 2017) should recognize that a convergence platform presents at the same time influences choice accuracy.

Our research also contributes to literature on digital nudging because the number of ideas presented simultaneously on a convergence platform constitutes a design interface element. Our findings confirm a dependency between design interface features and decision-making processes. This finding reinforces the importance of considering raters' needs when designing convergence platforms. Our research provides novel insights as we demonstrate that the judgment actions of eliminating and keeping ideas mediate the effect that number of ideas that a convergence platform presents has on choice accuracy in a contrasting manner. While we found that eliminate actions positively mediated the effect that decomposition of information load had on choice accuracy, keep actions mediated this relationship in the opposite direction. Hence, our findings imply that the decomposition of information load as a presentation mode has paradoxical effects: it facilitates choice accuracy because people engage in more judgments, but it reduces choice accuracy because people are more inclined to revise their decisions. By uncovering these causal mechanisms, we inch closer to understanding how idea presentation affects raters' decision making process in convergence platforms.

Our findings have also implications for dual processing theory (Kahneman, 2003). Our findings show that the feedback attribute number of loves affected raters who adopted more compensatory decision strategies and raters who tended toward heuristic processing in different ways. On the one hand, presenting fewer ideas at the same time nudges raters who have a low tendency to follow the crowd's opinion to apply more effort to the task by engaging them in more judgment processes (eliminate actions), which, in turn, results in more accurate choices. Moreover, our findings also provide insights about why going back on one's decision to eliminate an idea (keep actions) negatively mediates the effect that decomposition of information load has on choice accuracy. By showing that this negative effect only occurred among raters who had a

high tendency to follow the crowd's opinion, we demonstrate that presented fewer ideas on one screen in combination with allowing raters to reverse their decision might be somewhat detrimental to choice accuracy when raters have a tendency to follow the crowd (heuristic decision makers). This finding implies that the digital nudge of decomposition of information load combined with the digital nudge of the crowd's opinion affect decision makers and their outcomes in complex ways. Future research could investigate if such raters achieve better performance on adaptive convergence platforms in which they could choose if they want to see all ideas at once or in subsets and if they want to see crowd feedback (e.g., likes) or not. With these findings, we present a more holistic view of raters' interaction with convergence platforms in that we do not study the role of interface features in isolation but as integrated components of a complex interaction process.

Our findings also have implications for innovation contest hosts and choice architects with interest in the sociotechnical design of IT-enabled convergence mechanisms. Choice architects should recognize that they can nudge raters towards a more deliberate decision-making process by decomposing the information load (i.e., showing fewer ideas on a screen). We also show that having fewer ideas per screen consider more feedback attributes such as number of likes/loves, which can help raters to make accurate decisions. Designers can easily and inexpensively implement a feature that decomposes information load, which, however, could improve the quality of ideas that raters select. Since the convergence process demands a great deal of effort and resources, convergence platforms that help raters overcoming their cognitive constraints and, thus, more accurately select good ideas hold great potential for increasing efficiency in the convergence process.

6.2 Limitations and Avenues for Future Research

Although we better understand how idea presentation interacts with raters' decision-making process when selecting ideas in a convergence platform and how tendency to follow the crowd's opinion influences that role from this study, readers should consider some limitations. First, although we analyzed how number of loves affects the role of decomposition of information load in a convergence platform, we considered no other features. As Geiger, Rosemann, Fieft, and Schader (2012) recommend, one should also consider other features that might be affected by the feature one studies (i.e., decomposition of information load). Future studies could build on our findings and analyze how other features such as different rating systems interact with decomposition of information load and how such features will affect raters' decision making in convergence platforms. Further, future studies could also measure different choice outcomes such as satisfaction and perceived cognitive effort to better understand how decomposition of information load affects raters' wellbeing and cognitive constraints. Other performance measures such as false positive rate and false negative rate, which indicate the occurrence of type I and type II errors, might assess how well raters can eliminate bad ideas given different decomposition of information load modes. Such measures would enable deeper insights into the social aspects at play. In addition, even though researchers have often used the consensual assessment technique (Amabile, 1982) to develop a gold standard for idea quality, such standards vary greatly across domain experts and studies. Therefore, we need more research in this area to establish guidelines about how to consistently conduct idea-quality measurements.

Moreover, the reduced idea descriptions in the experiment might have distanced the choice task from a real-world convergence scenario. We needed such a measure to ensure an amount of information load that would not surely cause choice paralysis (Álvarez, Rey, & Sanchis, 2014), which would hinder choice accuracy. Future research could investigate whether present findings still hold in settings with more ideas, longer idea descriptions, or additional idea feedback attributes.

Furthermore, we did not measure the decision making elements evaluation and feedback/learning as we did not identify search strategies and participants did not receive outcome feedback during or at the end of the task. Hence, effects on choice accuracy might change when these elements are also considered in the analyses. Future studies could assess which decision strategies raters use and how they react when they a convergence platform presents them with feedback and, hence, learn from their outcomes, which could influence choice accuracy.

7 Conclusion

Selecting the best ideas from an innovation contest can help organizations succeed in the complex, fast-moving environment in which they operate today. Thus, idea convergence platforms need to efficiently nudge raters to perform this task in alignment with organizational goals. Overall, we shed light onto how to

design idea convergence platforms in terms of decomposition of information load to help raters to manage their cognitive load and, consequently, make more accurate decisions in the convergence process. Our findings add to the growing academic knowledge base on idea-selection processes and how one can design IT platforms to ensure a successful convergence process.

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Appendix A: Sensitivity Analyses

We ran sensitivity analyses to inspect possible violations against the sequential ignorability assumption (i.e., if mediation analyses results were robust against unidentified confounders) (Imai et al., 2010c; Seeber, 2019). We based the robustness check on the sensitivity parameter ρ (rho) and the product of coefficients of determination ($\tilde{R}_M^2 \tilde{R}_Y^2$).

The sensitivity parameter ρ is based on the correlation between the error for the mediation and outcome model. In the case an unobserved confounder exists, ρ no longer equals 0 and the sequential ignorability assumption is violated (Tingley et al., 2014). The plots of ACME against ρ depicted in Figures A1, A2 and A3 show how ACME varies as a function of ρ (Imai & Yamamoto, 2013). The dashed horizontal line indicates the estimated value of ACME when ρ equals 0, the solid line shows the values of ACME under distinct ρ values, and the gray area represents the 95 percent ACME confidence bands.

As previous research indicates that ρ is a difficult value to interpret (Imai & Yamamoto, 2013; Seeber, 2017), we also used the product of coefficients of determination from mediator and outcome models ($\tilde{R}_M^2 \tilde{R}_Y^2$). This product represents the proportion of original variance that an unobserved confounder explains (Imai, Keele, Tingley, & Yamamoto, 2009). In other words, the product constitutes the change in R^2 in the mediator and outcome when one omits confounding variables (Imai & Yamamoto, 2013; Seeber, 2019). The more relevant the effect of the confounding variable, the lower the R^2 will be in a model that includes this confounder in comparison to a model without it (Seeber, 2019). According to Keele, Tingley, Yamamoto, and Imai (2013), if a sensitivity analysis shows that an unobserved confounder would need to explain a big portion of the remaining variance in the mediator and outcome for the ACME to lose significance, one can consider the results robust against unmeasured confounders. When observing the graphical representation of $\tilde{R}_M^2 \tilde{R}_Y^2$ in Figure A3, the plotted contours represent ACME to the proportions of the variance in the mediator ($\tilde{R}_M^2$) and outcome ($\tilde{R}_Y^2$) that the unobserved confounding variable explains. The bolded contour shows ACME at 0, and, in the case $\tilde{R}_M^2 \tilde{R}_Y^2$ increases, ACME would change sign and become negative (Seeber 2019).

We describe the results from our sensitivity analyses in the following paragraphs.

Eliminate Action

We maintained the sequential ignorability assumption in the causal mediation analysis unless the ρ sensitivity parameter exceeded 0.35. The confidence interval covered the ACME value of 0 when ρ was between 0.30 and 0.40. In addition, the product of coefficients of determination representing the proportion of original variance explained by unobserved confounders ($\tilde{R}_M^2 \tilde{R}_Y^2$) was 0.0655, which shows that one would need to question the robustness of results of the causal mediation analysis having eliminate action as a mediator if an unobserved pretreatment confounder explained more than 53.5 percent of the variance in eliminate actions and 12.25 percent of variance in choice accuracy ($0.535 \times 0.1225 = \sim 0.0655$). Regarding the moderated mediation analyses, we can maintain the sequential ignorability assumption unless the ρ sensitivity parameter exceeded 0.4 (confidence interval between 0.35 and 0.45). The product of total variance of $\tilde{R}_M^2$ and $\tilde{R}_Y^2$ was 0.0747, which means that an unobserved pretreatment confounder would need to explain more than 46.7 percent of the variance in eliminate actions and 16 percent of the variance in choice accuracy for one to question the results' robustness ($0.4668 \times 0.16 = \sim 0.0747$).

Keep Action

One maintain the sequential ignorability assumption for keep actions unless the ρ sensitivity parameter exceeded than -0.3 (confidence interval between -0.35 and -0.25). The product of coefficients of determination $\tilde{R}_M^2 \tilde{R}_Y^2$ is 0.0519, which shows that as long as unobserved confounders did not explain more than 58 percent of the variance in keep actions and 16 percent of the variance in choice accuracy, one can consider the results robust.

Since the indirect effect (ACME) was not significant for information acquisition and the moderated mediation analysis of keep actions, we do not report the sensitivity analyses from these cases.

In conclusion, our results appear robust against unmeasured pre-treatment confounders.

Table A1. Results of the Sensitivity Analyses for Information Acquisition

Mediator: Information acquisition		ρ (Rho)	ACME	95% CI lower	95% CI upper
Causal mediation analysis					
	[1,]	0.05	0.0006	-0.0018	0.0029
	[2,]	0.10	-0.0001	-0.0022	0.0020
	[3,]	0.15	-0.0008	-0.0034	0.0018
	ρ at which ACME = 0: 0.1	Residual variance $R_M^2 * R_Y^2$ at which ACME = 0: 0.01		Total variance $R_M^2 \sim R_Y^2$ at which ACME = 0: 0.0067	
Moderated mediation analyses					
Low TFCO	[1,]	0.10	0.0004	-0.0026	0.0034
	[2,]	0.15	-0.0002	-0.0030	0.0026
	[3,]	0.20	-0.0008	-0.0047	0.0030
	ρ at which ACME = 0: 0.15	Residual variance $R_M^2 * R_Y^2$ at which ACME = 0: 0.0225		Total variance $R_M^2 \sim R_Y^2$ at which ACME = 0: 0.0142	
High TFCO	[1,]	0.10	0.0004	-0.0026	0.0034
	[2,]	0.15	-0.0002	-0.003	0.0026
	[3,]	0.20	-0.0008	-0.0047	0.003
	ρ at which ACME = 0: 0.15	Residual variance $R_M^2 * R_Y^2$ at which ACME = 0: 0.0225		Total variance $R_M^2 \sim R_Y^2$ at which ACME = 0: 0.0142	

Information acquisition**Causal Mediation Analysis****Moderated Mediation Analysis** **Figure A1. Sensitivity Analyses for Analyses with Information Acquisition as Moderator**

Table A2. Results of the Sensitivity Analyses for Eliminate Action

Mediator: Information acquisition		ρ (Rho)	ACME	95% CI lower	95% CI upper
Causal mediation analysis					
	[1,]	0.30	0.0020	-0.0030	0.0070
	[2,]	0.35	0.0002	-0.0045	0.0049
	[3,]	0.40	-0.0017	-0.0067	0.0032
	ρ at which ACME = 0: 0.35	Residual variance $R_M^2 * R_Y^{2*}$ at which ACME = 0: 0.1225		Total variance $R_M^2 \sim R_Y^2 \sim$ at which ACME = 0: 0.0655	
Moderated mediation analyses					
Low TFCO	[1,]	0.35	0.0052	-0.0100	0.0204
	[2,]	0.40	0.0010	-0.0139	0.0159
	[3,]	0.45	-0.0035	-0.0186	0.0115
	ρ at which ACME = 0: 0.4	Residual variance $R_M^2 * R_Y^{2*}$ at which ACME = 0: 0.16		Total variance $R_M^2 \sim R_Y^2 \sim$ at which ACME = 0: 0.0747	
High TFCO	[1,]	0.35	0.0052	-0.0100	0.0204
	[2,]	0.40	0.0010	-0.0139	0.0159
	[3,]	0.45	-0.0035	-0.0186	0.0115
	ρ at which ACME = 0: 0.4	Residual variance $R_M^2 * R_Y^{2*}$ at which ACME = 0: 0.16		Total variance $R_M^2 \sim R_Y^2 \sim$ at which ACME = 0: 0.0747	

Eliminate action

Causal Mediation Analysis

Moderated Mediation Analyses

Figure A2. Sensitivity Analyses for Analyses with Eliminate Action as Moderator

Table A3. Results of the Sensitivity Analyses for Keep Action

Mediator: Information acquisition		ρ (Rho)	ACME	95% CI lower	95% CI upper
Causal mediation analysis					
	[1,]	-0.35	0.0021	-0.0061	0.0102
	[2,]	-0.30	-0.0010	-0.0091	0.0071
	[3,]	-0.25	-0.0040	-0.0123	0.0044
	ρ at which ACME = 0: -0.3	Residual variance $R_M^2 * R_Y^2$ at which ACME = 0: 0.09		Total variance $R_M^2 \sim R_Y^2$ at which ACME = 0: 0.0519	
Moderated mediation analyses					
Low TFCO	[1,]	-0.45	0.0018	-0.0045	0.0081
	[2,]	-0.40	0.0002	-0.0053	0.0058
	[3,]	-0.35	-0.0012	-0.0072	0.0047
	ρ at which ACME = 0: -0.4	Residual variance $R_M^2 * R_Y^2$ at which ACME = 0: 0.16		Total variance $R_M^2 \sim R_Y^2$ at which ACME = 0: 0.085	
High TFCO	[1,]	-0.45	0.0018	-0.0045	0.0081
	[2,]	-0.40	0.0002	-0.0053	0.0058
	[3,]	-0.35	-0.0012	-0.0072	0.0047
	ρ at which ACME = 0: -0.4	Residual variance $R_M^2 * R_Y^2$ at which ACME = 0: 0.16		Total variance $R_M^2 \sim R_Y^2$ at which ACME = 0: 0.085	

Keep action**Causal Mediation Analysis** **Moderated Mediation Analyses** **Figure A3. Sensitivity Analyses for Analyses with Keep Action as Moderator**

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