Configurations of Digital Choice Environments: Shaping Awareness of the Impact of Context on Choices

Research Paper

Phillip Oliver Gottschewski-Meyer[1], Fabian Lang[2], Paul-Ferdinand Steuck[1], Marco DiMaria[1], Thorsten Schoormann[3], and Ralf Knackstedt[1]

[1] Universität Hildesheim, ISUM, Hildesheim, Germany
{gottschewskimeye,steuckp,maria,knacks}@uni-hildesheim.de
[2] Hochschule Hannover, Faculty IV - Business Informatics, Hannover, Germany
fabian.lang@hochschule-hannover.de
[3] Roskilde University, Department of People and Technology, Roskilde, Denmark
tschoormann@ruc.dk

Abstract. The impact of digital choice environments (DCEs) on the choice process remains unexplored. This paper seeks to investigate the influence of DCE components on choice and how they interact with interventions that nudge users towards specific choices. Employing a configurational perspective, we explore whether the presence, position, and perception of DCE components have an impact on both choice and intervention effectiveness. We conducted an online experiment with 421 participants in a fictional e-commerce store with six different configuration instances and particularly found that the presence and position of DCE components influence user choices. Our contribution creates awareness of the interplay of DCE components and highlights the subtle yet impactful role of DCE configurations on user choices.

Keywords: Digital choice environments, digital interventions, configuration.

1 Introduction

Digital Choice Environments (DCEs) are user interfaces (UIs) in which users make choices in the digital realm (Weinmann et al., 2016). They consist of various components to ensure functionality (Alnawas & Al Khateeb, 2022), differ in the presentation of the choices (Gottschewski-Meyer et al., 2024), and are used in many application contexts (Li et al., 2022). Designers, so-called choice architects, create DCEs to best possibly arrange and modify components and design elements to affect user outcomes (Bleier et al., 2019). Take, e.g., Amazon: Designers intentionally add distracting components such as up-selling or cross-selling initiatives (Schmitz et al., 2014), as well as use design elements such as prominent ‘Bestseller’ cues, which can influence choices (Beşer et al., 2022). Unconsciously or not, choice architects change behaviour by design (Sunstein, 2015) because presenting choices neutrally is challenging, and each design decision in a DCE is likely to influence user choices (Weinmann et al., 2016).

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Research on how individual components interact—both with each other and with digital interventions such as nudges—remains scarce, even though the configuration of DCE component characteristics can act synergistically and determine user outcomes (Gottschewski-Meyer et al., 2024). Modifying a single characteristic in a DCE can influence the effects of the entirety of the characteristics. For example, the holistic website design acts as a stimulus that affects consumers' visual, cognitive, and affective perception that, in turn, affects their choices (Boardman & McCormick, 2022).

DCEs become even more complex when understood as configurations. The prevailing paradigm is that DCE components only serve to ensure the functionality of a website, with deliberate or inadvertent interventions being employed to promote a particular behaviour. However, each change of a component or design element (i.e., colour, shape, position, etc.) within the DCE changes the configuration and their modes of action. The implementation of a digital intervention should be seen as an integral part of the DCE configuration rather than a standalone addition. We aim to highlight the role of systematic and intentional design of DCEs and their potential impact on the effectiveness of digital interventions. Thus, we ask the following research questions (RQ):

- **RQ1:** How do changes to components within DCEs affect the choice process?
- **RQ2:** How do DCE components interact with digital interventions?

We conducted an online experiment in a fictive e-commerce store, testing a digital intervention and its effectiveness in six different DCE configurations. We seek to advance our understanding of the interdependencies of DCE components, their design elements and their common effect on interventions. We apply the idea of the configurative nature of DCEs and shape awareness of the connections between individual components, their characteristics and interventions deliberately implemented. Our study highlights that adding DCE components or interventions always alters the entire configuration in which they are embedded, thereby affecting the configurational outcomes.

The remainder of the paper is as follows: After the Introduction, we place our research endeavour in the context of related work (Section 2), formulate hypotheses (Section 3), and describe our methods (Section 4). We then present the results (Section 5), as well as discuss limitations and potential for future research (Section 6).

2 Research Context and Related Work

2.1 Digital Choice Environments and their Configurations

DCEs are interfaces where users in domains, such as citizens in e-government or consumers in e-commerce, choose between options (Weinmann et al., 2016). They consist of individual components that not only ensure the functioning of the environment (Alnawas & Al Khateeb, 2022) but can also interact and influence each other (Gottschewski-Meyer et al., 2024). Such components are higher-order structures, each having several characteristics that together form a DCE configuration. Each characteristic may have several design elements that define the appearance and the way the characteristics affect users (Gottschewski-Meyer et al., 2024). From a conceptual view, DCEs can be regarded as configurations, unique combinations of interconnected system characteristics that can produce different results through their synergetic interaction (Park et al., 2020; El Sawy et al., 2010). DCE components are integral parts of the overarching UI and encompass all possible characteristics that are inherent within the DCE taxonomy as part of a DCE configuration (Gottschewski-Meyer et al., 2024).

In DCEs, various factors impact the choice of users. Empirical studies in e-commerce identified website quality, personal characteristics, attitudes and intentions, website features, and product and service offerings (among others) to be influential on consumption behaviour (Li & Zhang, 2002). Even aspects that are deemed to be irrelevant may influence user choices (Congiu, 2022). That may include colour (Zhang et al., 2025), the arrangement (Oulasvirta et al., 2020) or implementation of different types of components, such as unidirectional (e.g., testimonials) and bidirectional interaction components (e.g., chatbots), among others (Gottschewski-Meyer et al., 2024).

Choices in DCEs can be altered by the usage of digital interventions (Ixmeier & Kranz, 2024). They can serve to change behaviour towards overarching societal goals such as pro-environmental behaviour (Horneber et al., 2025) and more socially (Gottschewski-Meyer et al., 2023) and economically sustainable decisions (Haki et al, 2023). Digital interventions are distinct from modifications to the components of a DCE since digital interventions are always used deliberately by choice architects, as they are applied in an already existing DCE. There are several behavioural intervention techniques in the digital realm, such as boosts, technocognition and nudges, which aim to promote behavioural outcomes in favour of society or oneself (Kozyreva et al., 2020). However, some design strategies, such as ‘dark patterns’, are deliberately manipulative (Kollmer & Eckhardt, 2023). Accordingly, choice architects must be aware of the impact of their designs to ensure the ethical design of DCEs (Lembcke et al., 2019). In particular, digital nudges have been widely used in IS research to promote more sustainable practices in the digital domain. *Default* and *social nudges* are among the most frequently and effectively used concepts, but also with partly divergent results in terms of effectiveness within the same concepts (Berger et al., 2022; Mertens et al., 2022).

2.2 Research Gap and Objectives

Although nudge effectiveness is often linked to design or target group (Berger et al., 2022), the influence of the implementation context (i.e., DCE) has yet to be examined. This is problematic because the effectiveness of digital nudges is contingent upon the application context, such as e-commerce or e-government (Schneider et al., 2018; Berger et al., 2022; Gottschewski-Meyer et al., 2023). Also, empirical studies have shown that the interplay between interventions and DCE components can change behaviour. For example, the effect of *scarcity cues* (nudge intervention) in combination with *textual reviews* (interaction component) on purchase decisions (Wrabel et al., 2022).

We posit that digital interventions can be regarded as additional design elements that are intentionally or unintentionally implemented in existing DCEs. From a configuration standpoint, adding an intervention changes the collective whole of individual characteristics, potentially altering the results of the configuration (Ma et al., 2023). This is an aspect that has not yet received sufficient attention. For example, while several experimental studies from digital nudging have used DCEs, they did not explicitly report how they designed the DCE around the nudges to avoid interference (Costello et al., 2022; Michels et al., 2022). If the configurative character of DCEs is overlooked, we cannot be sure whether previous findings regarding the effectiveness of interventions have been controlled for a possible lack of isolating it from the effects of the DCE configuration. Thus, the paucity of studies that fully capture the holistic effects necessitates a deeper understanding of the inherent configurative nature of DCEs and their effect on digital interventions, which this study seeks to explore.

3 Hypotheses to Investigate the Impact of Context

To develop our hypotheses, we draw on a combination of configuration theory, findings from UI design and the concept of digital nudging (Weinmann et al., 2016).

Configurational theory describes systems or phenomena holistically in terms of their bidirectional, non-linear relationships between individual characteristics and attempts to identify complex forms of interaction (Fink, 2008). In this vein, DCEs constitute an ensemble of various components that interact with each other either synergistically or antagonistically (Gottschewski-Meyer et al., 2024). We assume that adding a component will have an impact on the user's choices as components serve as cues that work as visual stimuli (Sergeeva et al., 2023). The visual stimuli shift attention towards the spatial position of the added component. The rationale is that visual selection is object-based rather than location-based. (Posner, 1980). However, previous research indicates that spatial position and distinctiveness of objects can serve as effective predictors of initial attention engagement (Still, 2018). Also, attention is important in decision-making (Orquin et al., 2021). In comparison with a DCE without this additional component, a distraction from the choice options towards a certain spatial position of an added component within the DCE takes place and shifts the perception of the available choice options (Lavie, 2005). Perception is defined as the experience that results from environmental stimuli (Wade & Swanston, 2013). Accordingly: **H1 (component presence) –** *The addition of a component within a DCE alters the distribution of user choices across available options compared to a DCE without this additional component.*

If the spatial position of the component is shown to exert an influence on the product choices, it is imperative to establish how choices change if the additional component changes the spatial position. According to Faraday (2000), the position of visual elements on a webpage has a significant impact on how they are cognitively processed. While parts of his work have been refuted already, the position of elements was confirmed to be a salient entry point for starting to explore a new interface (Still, 2018). We argue that adding a component in one spatial position of the interface will exert different choices than one on the other side. Accordingly: **H2 (component position) –** *The actual position of a component within a DCE influences the choices of users.*

In our study, the intervention is implemented via a digital social norm nudge (i.e., a 'Bestseller' tag), as it is often used on e-commerce platforms (Beşer et al., 2022). When faced with a choice but in the absence of information, the indication of a socially accepted product via the nudge can lead to a decision for the target option of the intervention (Cialdini et al., 1991). Social norms are cognitively processed within the impulsive brain system that acts rather unconsciously and fast (Vlaev et al., 2016), as shown in extant research (Beşer et al., 2022). If an additional element is either consciously (voluntary attention) or unconsciously (involuntary attention) perceived and thus cognitively processed (Bettman et al., 1998), the element disrupts the users' decision process and requires more time for cognitive processing. This, in turn, leads to a reduction in the social norm nudge effect (Gottschewski et al., 2022). Furthermore, more salient information is perceived most frequently, and the nudged product is most likely acquired and prioritised (Jarvenpaa, 1990). The effectiveness of the bestseller nudge is contingent upon these two effects. If implemented in different configuration instances of the same DCE, this intervention might work differently. In detail, we assume that the addition of a component shifts the overall perception of the DCE (Boardman & Mccormick, 2022) and its components, characteristics and design elements, particularly of the salient bestseller tag, so that the user is distracted from the nudge by the additional element (Lavie, 2005). Accordingly: **H3 (component perception) –** *The addition of a component within a DCE configuration reduces the visual salience of a social norms nudge intervention, thereby weakening its effect on promoting targeted choices.*

4 Research Method

We conducted an online experiment with a between-subjects design in a fictive web store (i.e., DCE) using Hypertext Markup Language, JavaScript and Cascading Style Sheets. Following the DCE design taxonomy (Gottschewski-Meyer et al., 2024), we implemented *multiple choice options* (physical choice object: over-ear headphones) within a single category, using an *input-centred interface setup* (search bar) and a *bidirectional interaction element* (chatbot) in three of the six DCE instances. We chose a simple design with confined visual and textual information to avoid information overload (Phillips-Wren & Adya, 2020) and distracting users' attention from the choice.

To emulate the behaviour of a real database underlying the search interface, we deliberately introduced a latency period before presenting the search results. We add a bidirectional interaction component–a chatbot–to the DCE to compare it against an instance without. Chatbots interact with users through natural language, generating appropriate responses to human conversations (Janssen et al., 2020). Since interactive website components have already been shown to have a positive impact on behavioural intentions, especially in e-commerce (Roy Dholakia & Zhao, 2009), we disregarded the aspect of interactivity in this study and only installed a rule-based chatbot via JavaScript. When asked, the bot provided the same product information that was available in the product description in a neutral way. We deliberately did not embed an avatar of the DCE representative within the chatbot to avoid associated perceptions that might influence the user's decision (Khosrawi-Rad et al., 2024). Rules contained buying specific keywords such as "product", "buy", "choose". Non-purchase-related inquiries received a short message apologising and stating that contact would be available shortly.

Overall, six DCE instances were built. Within each DCE, the same six choice options were arranged in two rows. A total of three images were used for the selection options. One of each was mirrored (similar to Wrabel et al., 2022), resulting in six different images of a real existing product. Visual features by which the product could be recognised were retouched. Product characteristics were displayed in text and were the same for all products, but arranged in a different order to mimic a more realistic DCE.

To avoid any influence of brand-related product preferences or price effects, the available headphones were all non-branded and mid-range priced (€149). The top left and bottom right products were priced differently (€129 and €179, respectively) to appear more realistic, but sold out. We did this deliberately to ensure that no participant would run afoul of a status quo bias and chose the first option (Thaler & Sunstein, 2009) and to provoke an asymmetric arrangement of the choice options to avoid humans' tendency towards the middle choice option (Schneider et al., 2018). To investigate the effects of such avoidance, we measured all product choices to see whether the arrangement had an impact on the choices. Further, we implemented the bidirectional interaction element in the form of a chatbot once on the left and once on the right side of the choice options to control for a possible effect of the position of the chatbot in influencing choices or, respectively, the effectiveness of the intervention. The intervention was implemented using an orange-coloured bestseller tag (rationale cf. H3 in Section 3) on the last available product in the second row (*Centre Bottom*). Six instances were created for the experiment, that acted as the independent variable in our study (cf. Table 1, an overview of the designed DCE instance is depicted in Figure 1), while the dependent variable was the product choices of the participants (***H1*** & ***H2***) and the nudge success rate (i.e., whether the nudged product was selected; ***H3***).

Table 1. Overview of DCE instances

	DCE 1	**DCE 2**	**DCE 3**	**DCE 4**	**DCE 5**	**DCE 6**
Chatbot	No	No	Yes	Yes	Yes	Yes
Intervention	No	Yes	No	Yes	No	Yes
Chatbot Position	None	None	Right	Right	Left	Left

We performed an internal Pre-Test to validate the functionality of the experimental environment and iterated it until fully functional. We used the crowdsourcing service 'Clickworker' to recruit participants and perform an external validation of the survey and experimental environment. They also collected user information (e.g., age and gender), which we used as covariates. The use of crowdsourcing services has proven successful in behavioural science and IS research (Wrabel et al., 2022; Gupta et al., 2024). Additionally, 28 participants were recruited from a university course. The study was conducted in German, and only native speakers were invited from Germany, Switzerland, and Austria. Participants were randomly assigned to one of the DCE instances. On entering the test environment, a pop-up window with a description of the scenario was displayed, and participants were asked to choose one of the available options, as they would if they were buying it for themselves. To test user attention and exclude speeders, we added two buttons: one to confirm reading the scenario and the other to be excluded from the experiment. User interactions, including search queries and chatbot usage, were recorded in the browser's local storage and documented when the purchase button was clicked. This was done to control for possible interaction effects of these components and served as covariates, to be able to control whether the mere presence of the interactive component influenced choices or the interaction. Once the participants decided on an option, they were presented with a pop-up from which they had to copy a code to enter it into the survey tool to finalise the experiment. A message expressing gratitude concluded the survey.

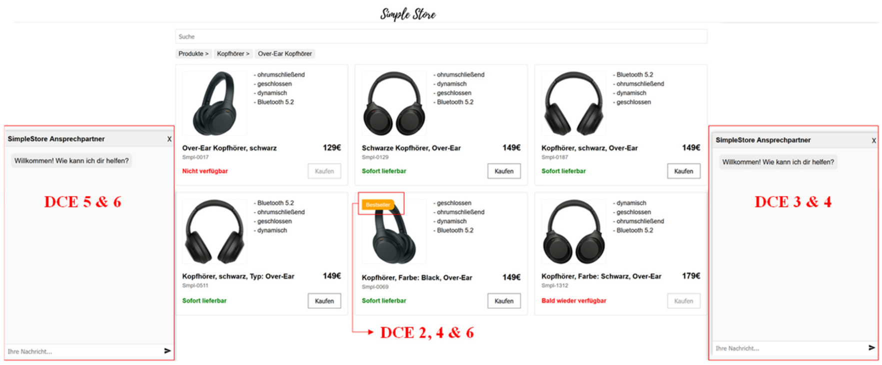
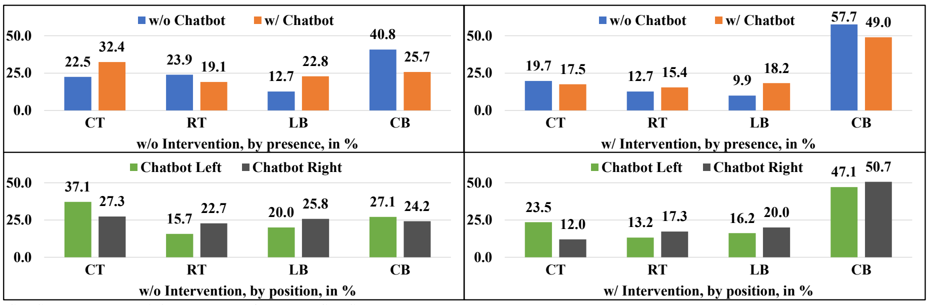


Figure 1. Experimental environment (changes made to DCE instances are marked in red)

5 Results

The experiment collected a total of 421 data points, with 66 to 75 participants assigned to each DCE instance. The mean age of the participants was 40.65 years (SD = 13.09), and 62.7% of them were male, so the participant sample of our study is characterised by a younger demographic and a higher proportion of males than is typical of the German population. The composition of the six DCE groups showed minimal variation in age and gender. Mean ages ranged from 38.2 to 42.4 years, with standard deviations between 11.5 and 14.9 years. The proportion of male participants across groups varied—except for group 6 with a slightly smaller 54,4 %—between 62,7 % and 66.2%. The data analysis was conducted using R version 4.2.

With 40.8%, the *Centre-Bottom* option was the most frequently selected choice in the baseline scenario (without an intervention or chatbot, DCE1; cf. Table 2). The intervention (the bestseller badge as a nudge) further increased the selection rate to 57.7% without a chatbot and 49.0% with a chatbot. Conversely, the *Left-Bottom* option was the least frequently chosen with 12.7%/9.9% (without/with intervention) in the baseline condition. However, the presence of a chatbot substantially increased the selection rate for this option, rising to 22.8%/18.2%. Regarding the chatbot position, the left-sided chatbot was associated with an increased selection of *Centre-Top*, rising from 22.5%/19.7% in the baseline scenario to 37.1%/23.5%. The right-sided chatbot showed the largest increase for *Left-Bottom*, increasing from 12.7%/9.9% to 25.8%/20.0%.



CT: Center-Top; RT: Right-Top; LB: Left-Bottom; CB: Center-Bottom.

Figure 2. Relative frequencies for product choice and chatbot positioning

The Chi-squared test for stochastic independence between the presence of a chatbot and product choice indicates that, although only with a minor effect, product selection is statistically dependent on chatbot presence (χ^2= 8.220, p = 0.042, Cramer's V = 0.140). This suggests that the distribution of product choices differs significantly at a p < 0.05 level between conditions with and without a chatbot, **confirming H1**.

To examine which specific product choices were influenced by the chatbot, we conducted a multinomial logistic regression, controlling for age and gender (cf. Table 2).

Table 2. Multinomial logistic regression for chatbot presence

Coefficient (p-Value)	**Centre-Top**	**Right-Top**	**Left-Bottom**
Intercept	-0.325 (0.516)	-0.570 (0.291)	-1.326* (0.021)
Age	-0.013 (0.197)	-0.007 (0.491)	-0.003 (0.751)
Gender	0.021 (0.937)	-0.164 (0.564)	-0.004 (0.989)
Chatbot	0.371 (0.180)	0.141 (0.637)	0.717* (0.032)
Chatbot Usage	0.189 (0.689)	0.311 (0.545)	0.839° (0.058)

*Reference category: Centre-Bottom. *** p < 0.001, ** p < 0.01, * p < 0.05, ° p < 0.1.*

As indicated by the contingency data, **the presence of a chatbot substantially increased the likelihood of selecting Left-Bottom (p = 0.032)**, resulting in an odds ratio (OR) of 2.048 (95% confidence interval (CI) = [1.064 – 3.942]) when converting the regression coefficients. This OR means that the **presence of a chatbot approximately doubled the odds of selecting Left-Bottom**. The chatbot use may have influenced this choice, but the effect is inconclusive (p = 0.058; OR = 2.314, 95 % CI = [0.973 – 5.502]). The regression model as a whole fails the likelihood ratio test (p = 0.272), indicating that they do not significantly outperform a null model in terms of predictive accuracy. However, when control variables (age and gender) are removed, the model's significance improves but remains marginal (p = 0.057), failing to reach the conventional 5% threshold. When considering only the presence of a chatbot (without chatbot usage), the model passes the likelihood ratio test (p = 0.037), suggesting that the additional variables may introduce noise rather than contribute to predictive power.

Table 3. Multinomial logistic regression for chatbot position

Coefficient (p-Value)	**Centre-Top**	**Right-Top**	**Left-Bottom**
Intercept	-0.847*** (<0.001)	-0.990*** (<0.001)	-1.476*** (<0.001)
Chatbot Right	0.136 (0.677)	0.297 (0.374)	0.816* (0.025)
Chatbot Left	0.635* (0.039)	0.018 (0.960)	0.625° (0.099)
Chatbot Use	0.150 (0.752)	0.281 (0.583)	0.829° (0.060)

*Reference category: Centre-Bottom. *** p < 0.001, ** p < 0.01, * p < 0.05, ° p < 0.1.*

Considering the chatbot's position, Table 3 presents the results of the multinomial logistic regression, excluding control variables due to their noise effect. The **right-sided chatbot significantly** increased the probability of selecting the **Left-Bottom option** (p = 0.025; OR = 2.260, 95 % CI = [1.106 – 4.622]). For the left-sided chatbot, the effect on *Left-Bottom* remains inconclusive (p = 0.099), showing a tendency toward rejection. However, the **left-sided chatbot significantly** increased the selection of **Centre-Top** (p = 0.039; OR = 1.887, 95 % CI = [1.033 – 3.446]). Thus, **we confirm H2**. Additionally, actual chatbot usage may also contribute to an increased selection of Left-Bottom (p = 0.060; OR = 2.290, 95 % CI = [0.966 – 5.431]), though this effect is only marginally significant. The model passes the likelihood ratio test (p = 0.038), confirming the overall fit. However, removing the usage variable further improves the model (p = 0.029), suggesting that the observed effect may be driven by noise rather than a true underlying relationship. All regression models pass the Hosmer–Lemeshow test, confirming goodness of fit, meaning that the predicted probabilities align well with the observed outcomes. The observed effects are consistent with the frequency analyses.

Table 4. Logistic regression and moderation analysis

Coefficient (p-Value)	**Model 1** (AIC: 555.51)	**Model 2** (AIC: 551.88)	**Model 3** (AIC: 550.64)
Intercept	-0.679 (0.121)	-0.370 (0.125)	-0.490* (0.015)
Age	0.006 (0.427)		
Gender	0.064 (0.762)		
Usage of Chatbot	-0.500 (0.189)		
Intervention (I)	0.683* (0.045)	0.683* (0.045)	0.921*** (<0.001)
Chatbot (B)	-0.641* (0.043)	-0.728*(0.020)	-0.530* (0.014)
I × B	0.377 (0.381)	0.374 (0.382)	

*Dependent variable: Choice = Centre-Bottom. *** p < 0.001, ** p < 0.01, * p < 0.05, ° p < 0.1.*

The *Centre-Bottom* option was the most frequently chosen in the baseline condition, before the reinforcement of the intervention. To analyse the effect of the intervention and its statistical interaction with the chatbot, we conducted a logistic regression analysis, using the choice of *Centre-Bottom* as the dependent variable and testing for moderation effects (see Table 5). When testing for the selection of the nudged option (*Centre-Bottom*), all models indicate a positive effect of the intervention and a negative effect of the chatbot. However, the interaction term indicating a moderating effect remains non-significant (p=0.381), even after removing control variables to reduce noise (p=0.382). Model comparison based on the Akaike Information Criterion (AIC) shows that Model 3 (without the moderation term) performs best, further suggesting that moderation does not improve explanatory power. In this model, **the intervention significantly increases the likelihood of choosing Centre-Bottom** ($p < 0.001$; OR = 2.513, 95 % CI = [1.684 – 3.776]), **while the chatbot significantly decreases this likelihood** ($p = 0.014$; OR = 0.589, 95 % CI = [0.386 – 0.895]). Both **effects occur concurrently but are not interdependent**, further confirming that the chatbot does not moderate the effect of the intervention. When considering only the data points where the intervention was present, the Chi-squared test indicates that the choice of the nudged option (Centre-Bottom) is statistically independent of chatbot presence ($\chi^2 = 3.209$, $p = 0.361$, Cramer's V = 0.122), i.e., the chatbot does not significantly alter the effect of the intervention. Thus, we have to **reject H3**.

6 Discussion, Contributions, and Conclusion

The study examines how DCE components impact choices and how they interact with interventions. We focused on three aspects: Presence, position and perception of DCE components. Based on an online experiment with 421 participants, we found concerning **RQ1** that the addition of a DCE component alters user choices. The distribution of choices is dependent on the mere *presence* of the additional component. Its spatial *presence* is perceived as a visual cue that stimulates attention, which is in line with previous literature (Lavie, 2005; Sergeeva et al., 2023; Still, 2018). Besides, our experimental condition was kept simple to avoid information overload and distraction. Research suggests that in conditions with low perceptual load, adding a component can intensify its role as a salient distractor (Lavie, 2005). The chatbot's size, especially compared to the available products, may attract further attention (Wolfe & Horowitz, 2004). This is important for the component *position*. For example, our analysis supports that left-sided components provoke different product choices than right-sided components. An explanation might be that a chatbot on the left is unexpected and attracts involuntary attention, and thus, is shifting choices in another direction (Bettman et al., 1998). Right-sided chatbots, instead, are expected and avoid such effects because users process choices sequentially from left to right, triggering the serial position effect where first and last options are selected more frequently (Bar-Hillel, 2015).

Concerning **RQ2**, we observe that the chatbot *presence* does not significantly modify the *perception* and the effectiveness of the intervention; rather, they function in a manner that is distinct from one another. Although the nudged option *Centre-Bottom* was selected less frequently when the chatbot was present, especially when implemented on the left, *Centre-Bottom* was also less frequently selected in scenarios with a chatbot but without intervention. As there were no moderation effects found, it may be concluded that the interaction of these two variables is either non-existent or only manifests in conjunction with other as yet unmeasured factors. If the former is true, one explanation could be that the participants distinguish relevant from irrelevant stimuli, which means that the salient bestseller badge that promises social acceptance of the nudged product is perceived as more relevant for the task of choosing a product than the presence of a DCE component (Orquin et al., 2021). This is because of the goal relevance that determines visual attention (Peschel et al., 2019). If the latter is true, a possible reason could be that the DCE instances still included factors we did not take into consideration, but might have a configurative impact. For example, recent research showed that changing visual attributes (size and saliency) of a design element influenced choice likelihood only through their combined interaction effect on visual attention (Peschel et al., 2019). This aligns with the feature integration theory, which posits that visuals are detected in parallel (i.e., holistic) and are perceptually grouped (Treisman & Gelade, 1980), indicating a non-linear relationship between the addition of a design element and the overarching effect on the user.

In addition, we found that even without intervention and a chatbot in a centred DCE with asymmetrically arranged available choices, the exact horizontal centre of the visual environment was primarily selected. This can be explained by the centre-stage effect (Kreplin et al., 2014). The horizontal centrality affects visual attention, which affects the selection (Atalay et al., 2012). Further, the intervention was found to be effective in all instances and confirms previous research (Mirbabaie et al., 2021; Stuber et al., 2022; Fei et al., 2021). Thus, we confirmed our assumption that more salient information is perceived most frequently and prioritised for acquisition (Jarvenpaa, 1990). Finally, our experiment showed that DCE design directly influences user decisions. Presence and spatial positioning (e.g., central placement of products) can bias selection, while interventions effectively steer choices predictably and intentionally.

6.1 Contributions to Theory

First, we show that the DCE configuration, in particular the mere *presence* of an additional component, can possibly influence the choice between options. While conceptual research has posited context-dependent decision-outcome relationships (Weinmann et al., 2016; Gottschewski-Meyer et al., 2024), this study offers one of the first empirical demonstrations within the configurative paradigm of DCEs. We offer initial insights into the role of DCE components in decision-making processes and encourage researchers to adopt a configurational approach when designing DCEs or digital interventions. *Second*, our results indicate that the component position in a DCE may affect the user's choice. This is important for researchers investigating digital interventions in experimental settings because attention must be paid to the details and settings, and appropriately tested for possible disturbance factors. *Third*, we contribute to the understanding of the configurative nature of DCEs with inputs from UI design, especially in the realm of visual environment and attention theory. Our results indicate that the configurational model of DCEs does not sufficiently account for the influence of perceptual attention on choice. While some factors within the dimension choice presentation (*extent of the visual and informational content*) were partly addressed, the potential effects of component *presence*, *position*, or *perception* on user outcomes remain underexplored, warranting further research.

6.2 Implications to Practice

First, our result raises awareness for choice architects and UI designers about the configurative nature and the role of DCE components and design elements. Practitioners can draw on our results to reflect on the current DCE designs to improve user outcomes and reinforce desired effects. *Second*, we provide UI designers with knowledge on how to consider aspects of the visual environment that interact with the holistic DCE design and its configurative nature, and may also have an impact on the implementation of digital interventions. Designers should ensure that they have internalised the role of the surrounding context, the DCE, to avoid making uninformed design changes. It should prompt caution when implementing additional components or interventions in existing DCEs. Thus, our results are important for understanding how websites adapt to user preferences and for promoting specific choices, as well as for adaptive user interfaces, since the position and perception of components can vary between devices. *Third*, our findings emphasise that the *presence*, *position*, and *perception* of DCE components are critical factors in shaping user choices. Practitioners should carefully evaluate how different elements interact within the overall environment of the DCE. Poorly placed or conflicting components may neutralise or weaken intended effects.

6.3 Limitations and Future Research

Our study has limitations. It is imperative to validate our findings in the real world, as our experimental DCE is by far less complex than real-world DCEs regarding implemented components, design elements, and distractive features. Also, purchase behaviour is dependent on different factors, and the context is only one part of it (Parker et al., 2016). Our study is limited as we examine the effects of design components and elements within a DCE on choices, but not the underlying belief or attitude construct (Song & Zahedi, 2001) or other relevant factors. Further, we are restricted due to our experiment design choices, including a) the different images used to shift user preferences, b) the bidirectional interaction component that was implemented as a task-oriented, rule-based chatbot. Any observed effects appear statistically non-robust and likely attributable to noise. Furthermore, participant awareness of the chatbot was not verified, limiting the results' interpretability. Our male-dominated sample may introduce gender bias, limiting transferability.

In future research, we plan to investigate the interactions between chatbots using generative artificial intelligence and digital interventions, as research suggests that personalised interaction has the potential to influence the effectiveness of certain digital nudge concepts. Since configurations are not solely determined by the influence of a single variable on another, but rather by the interaction of multiple variables present in the DCE, more research is needed to determine how the DCE influences interventions and vice versa. Future research could adopt a systematic, step-by-step approach in a series of experiments to assess the impact of configurations comprising different numbers and types of components, as well as their interaction with other digital interventions in various positions. This approach could help us to understand the complexity of real-world DCEs and their configurational nature.

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