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Toward Adaptive Degrees of Freedom: An Exploratory Study of User Preference Heterogeneity in Mass Customization Toolkits

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Abstract

Mass Customization (MC) toolkits function as the primary interface between consumer heterogeneity and flexible manufacturing systems, facilitating the iterative configuration of personalized products. While widespread across industries, contemporary toolkit designs often rely on static "one-size-fits-all" frameworks that often struggle to account for the dynamic cognitive load imposed by varying solution spaces. This exploratory pilot study investigates user preferences regarding Degrees of Freedom (DoF) within MC interfaces. User interaction with a parametric lightshade configurator was examined across three distinct DoF levels (Low: 18, Medium: 23, and High: 28). The pilot observations suggest preliminary variation in user preference, and within the small exploratory sample (N=10), 4 participants showed differing preferences for the structured guidance of restricted options, while 6 participants preferred the granular control associated with high configurability. In addition, descriptive trends suggested that participants tended to prefer higher DoF levels for products perceived as more complex. The results argue the notion of a universally optimal option count and instead suggest the concept of Adaptive Degrees of Freedom (ADoF), in which toolkit complexity dynamically responds to differences in user expertise and product context. Given the small exploratory sample (N=10), these observations are descriptive and intended to generate hypotheses about adaptive interface design rather than to support statistical generalization. The primary contribution of this work is the clear illustration of user preference heterogeneity, which supports the foundational argument for developing and testing adaptive, context-aware DoF systems in future large-scale studies.

Keywords

Mass Customization Toolkits, Degrees of Freedom, Adaptive User Interfaces, Choice Overload, Progressive Disclosure.

Introduction

In the contemporary industrial landscape, characterized by the transition from Industry 4.0 to Industry 5.0, the focus of manufacturing has shifted from pure efficiency to human-centricity and resilience (Xu et al., 2021). Within this paradigm, Mass Customization (MC) has emerged not merely as a production strategy, but as a mechanism for consumer empowerment, enabling the co-creation of products that align precisely with individual functional and aesthetic requirements (Bidgoli, 2010).

However, the efficacy of MC is frequently compromised by the "*paradox of choice*." While consumers theoretically demand high customization potential, the cognitive load required to navigate extensive solution spaces can precipitate "*mass confusion*", a state of decision paralysis and diminished satisfaction (Huffman & Kahn, 1998). Traditional interface designs often present a static Degrees of Freedom (DoF), defined as the number of modifiable parameters available to the user. This static approach can limit the system's ability to accommodate the heterogeneity of user expertise: a novice may find 20 options overwhelming, while an expert may find them restrictive.

Current literature lacks a unified framework for optimizing DoF in the context of modern, algorithmic design tools. As noted by Zhao et al. (2018), there is a need for empirical heuristics that balance the informational value of options against the entropy they introduce to the user experience. This study addresses this gap through an exploratory pilot experiment. By examining user performance and preference across varying DoF levels for a lightshade toolkit, and exploring whether users tend to prefer these with product complexity, a theoretical shift toward Adaptive Degrees of Freedom (ADoF) is proposed. It is suggested that the "*optimal*" DoF is not a fixed integer but a dynamic variable, contingent upon the user's navigational capability and the product's structural complexity. While ADoF serves as a theoretical construct for balancing choice overload and restricted control, it requires a practical mechanism for execution. In this study, we operationalize ADoF as a behavior-driven system. Rather than relying on static, self-reported user profiles, a behavior-driven ADoF model dynamically adjusts the complexity of the customization toolkit by monitoring real-time user interaction metrics, such as hesitation, error rates, and task completion fluidity, to automatically expand or reduce the available degrees of freedom. This exploratory pilot asks whether preference for degrees of freedom varies by user and product context, and whether such variation might justify future adaptive interface designs.

The primary contribution of this paper is not the validation of an adaptive interface system, but rather an exploratory pilot investigation that identifies preliminary heterogeneity in user preferences regarding Degrees of Freedom (DoF) in Mass Customization toolkits. Based on these observations, the study conceptually proposes Adaptive Degrees of Freedom (ADoF) as a future research direction for adaptive customization interfaces.

Based on the foregoing literature, this exploratory study is guided by the following research questions:

RQ1: *How do preferences for the number of DoF in a customization toolkit vary within a small, heterogeneous user sample?*

RQ2: *What preliminary, descriptive trends can be observed between users' perception of product complexity and their preferred number of DoF?*

Literature Review

1. *The Solution Space and Complexity Metrics*

The core of any MC toolkit is the solution space, the set of all valid product configurations offered by the manufacturer (Hermans, 2012). Historically, the size of the solution space was viewed as a proxy for value. However, recent developments in information theory suggest that complexity should be measured not by the raw count of options (N), but by the Entropy (H) of the decision process.

2. *Mass Confusion and the Inverted U-Shape*

The relationship between option variety and user satisfaction is widely theorized to follow an inverted U-shape (Choi & Lee, 2015; Du et al., 2019; Huffman & Kahn, 1998). Satisfaction increases with variety up to a tipping point, after which "*choice overload*" degrades the experience.

- Low DoF: Limits the "*Configurability Index*", the ratio of customizable revenue to total product value (Salvador et al., 2009), potentially leading to boredom or lack of fit.
- High DoF: Increases the risk of mass confusion, where the cognitive cost of evaluation outweighs the marginal utility of the feature (Piller et al., 2005).

Extensive meta-analytic evidence confirms the robust phenomenon of choice overload, where excessive options lead to decreased satisfaction, increased choice deferral, and decision fatigue (Chernev et al., 2015; Scheibehenne et al., 2010). While the current study focuses on these established dynamics, emerging theoretical perspectives suggest that this tipping point might eventually prove malleable. For example, future implementations of AI-driven Choice Navigation systems, such as recommender algorithms and conversational agents, are hypothesized to shift the curve, potentially allowing users to navigate massive solution spaces without experiencing overload (Felfernig et al., 2024). However, empirical testing of such AI-driven systems falls outside the scope of the present research.

3. *From Static to Adaptive Interfaces*

The evolution of human-computer interaction (HCI) has witnessed a significant paradigm shift from static designs to Adaptive User Interfaces (AUIs) that prioritize universal usability and continuous personalization (Miraz et al., 2021). Recent advancements in artificial intelligence, particularly deep learning and real-time AI-powered analytics, have enabled these systems to dynamically adjust to users' cognitive loads and behavioral patterns rather than relying on rigid, one-size-fits-all layouts (Mukti & Trisilia, 2025). By leveraging these predictive technologies, modern AUIs can provide highly intuitive and tailored digital experiences that enhance overall user engagement and satisfaction (Devi et al., 2025).

At the forefront of this dynamic adaptation process is the application of Reinforcement Learning (RL), which allows interfaces to intelligently optimize layouts and interactions based on continuous, data-driven user feedback (Sun et al., 2024). To refine these systems, researchers are actively comparing various RL reward models to better align automated UI adaptations with actual user preferences (Gaspar-Figueiredo et al., 2025). Furthermore, the integration of psychological metrics, ranging from task-relevance evaluations to utilizing digital human motion for psychological decompression, highlights the growing intersection of affective computing and interface design (Gao et al., 2025). Together, these advancements underscore both the transformative potential and the ongoing challenges of accurately integrating human feedback into ethically designed adaptive systems.

4. *Conceptual Framework for Adaptive Degrees of Freedom*

The effectiveness of Mass Customization (MC) toolkits depends not only on the number of available customization options, but also on users' ability to cognitively navigate the customization process. In MC systems, Degrees of Freedom (DoF) refer to the number and variety of parameters available for user modification. Increasing DoF expands the solution space and enhances configurability; however, it may also increase the informational complexity, or entropy, of the interface. As the number and interdependence of parameters increase, users are required to process larger quantities of information and evaluate more potential outcomes.

This increase in informational complexity can elevate cognitive load during interaction. Prior research on choice overload and "*mass confusion*" suggests that excessive or poorly organized option spaces may reduce satisfaction, increase decision fatigue, and negatively affect the customization experience (Huffman & Kahn, 1998; Scheibehenne et al., 2010; Chernev et al., 2015). Importantly, the threshold at which configurability becomes overwhelming is unlikely to be universal, as users differ in technical familiarity, design confidence, and tolerance for complexity. From this perspective, mass confusion can be understood as a mismatch between interface complexity and user navigational capability rather than simply the result of a high number of options.

To address this challenge, this study proposes Adaptive Degrees of Freedom (ADoF) as a conceptual framework in which the quantity, visibility, organization, or complexity of customization parameters may dynamically adapt according to user context and perceived cognitive burden (Figure 1). Within this framework, adaptive interfaces and choice-navigation systems function as mechanisms for regulating visible complexity through approaches such as progressive disclosure, parameter prioritization, and interface simplification. Rather than exposing all parameters simultaneously, ADoF conceptually operates as an adaptive layer between the full backend solution space and the user-facing interface.

Accordingly, the "*optimal*" DoF is not conceptualized as a fixed numerical threshold, but rather as a context-dependent condition that may vary across users, products, and interaction scenarios. Recent developments in adaptive interfaces and generative AI suggest possible future pathways for implementing such systems by translating high-level user intent into parametric adjustments. However, the present study does not evaluate an operational adaptive system. Instead, it explores whether preliminary heterogeneity in user preference regarding DoF exists and whether such variation may support future investigation into adaptive and context-aware customization interfaces.

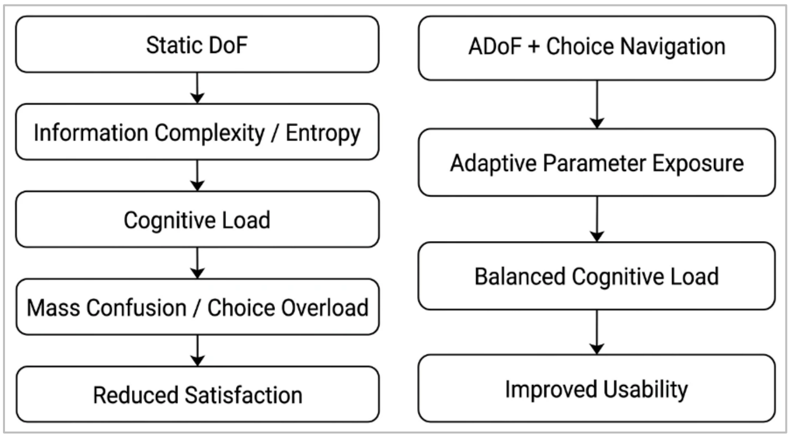

Figure 1: *Static complexity vs adaptive design in mass customization toolkits.*

Methodology

To investigate the relationship between DoF and user satisfaction, a mixed-methods exploratory pilot study is employed. This approach was chosen to generate foundational hypotheses regarding user preference heterogeneity prior to large-scale quantitative validation.

1. *Participants and Incentives*

A sample of 10 participants was recruited. While small sample sizes (N=10) limit statistical power for population-level generalization, they are sufficient for identifying usability barriers and distinct preference clusters in HCI "*pilot*" contexts (Nielsen & Landauer, 1993). Participants were recruited through convenience sampling from university-affiliated individuals with varying levels of familiarity with digital interfaces and parametric design tools. Prior to participation, individuals completed a short demographic and experience questionnaire assessing age range, prior experience with 3D software, and self-reported technical proficiency. Users with no prior experience using parametric modeling or 3D configuration systems were classified as novice, while those reporting occasional familiarity with digital design tools or customization interfaces were categorized as intermediate.

Participants ranged from 20 to 27 years old, and prior experience with 3D modeling and digital customization tools varied from none to moderate familiarity. Based on these responses, participants were broadly categorized as novice or intermediate users. No expert users were included in this pilot study.

Incentive Structure: To simulate high-engagement "*Hedonic*" customization, participants were entered into a lottery to win the physical lightshade they designed. This incentive structure was intended to increase ecological engagement with the customization process and reduce hypothetical bias commonly observed in survey-only studies. However, the incentive may also have introduced motivational bias by encouraging participants to maximize feature exploration, particularly within higher DoF conditions. Consequently, user preference observations should be interpreted cautiously.

All participants provided informed consent prior to participation. The study involved minimal risk and collected no sensitive personal data. Ethical procedures were conducted in accordance with institutional guidelines for exploratory usability research.

2. *Experimental Stimuli: The Lightshade Toolkit*

A custom web-based parametric configurator was developed (Figure 2), allowing users to manipulate geometric properties (radius, twist, tessellation) of a 3D-printed lightshade. Three versions of the interface were created to test discrete DoF levels:

- **Low DoF (18 parameters):** Restricted to basic shape and color.
- **Medium DoF (23 parameters):** Added texture and simple pattern controls.
- **High DoF (28 parameters):** Included advanced "*physics*" visualization, complex tessellation, and transparency controls.

Consequently, the High DoF condition differed not only in parameter quantity but also in interaction modality and visual feedback richness. This confounding factor limits the isolation of the independent effect of DoF and should be controlled in future experimental designs.

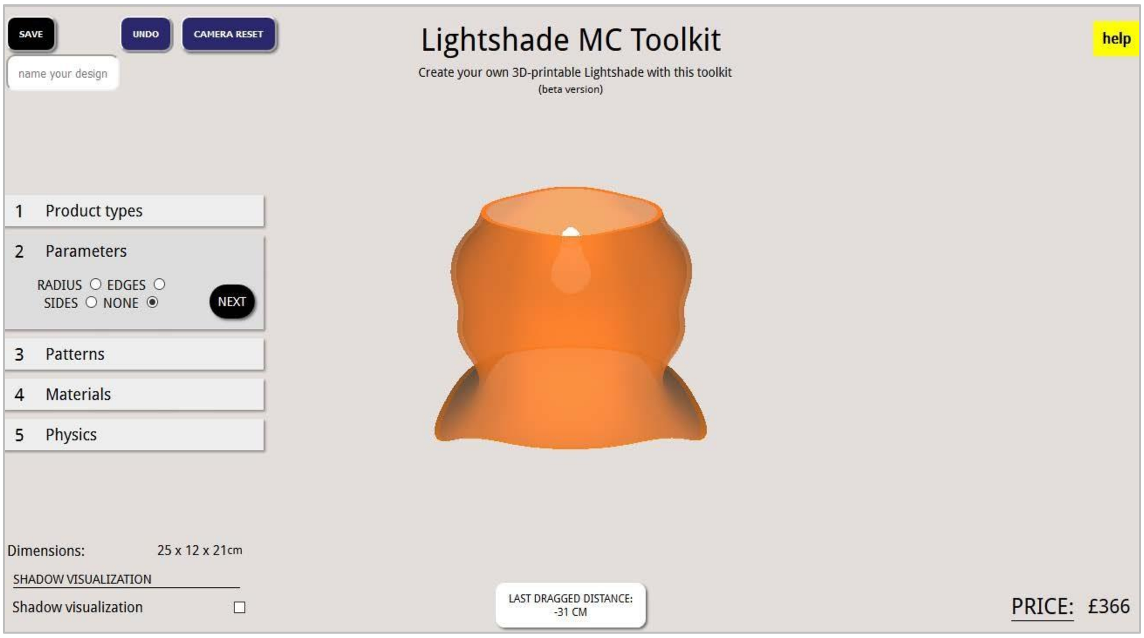

Figure 2: *The user interface of the lightshade toolkit.*

The selected DoF levels were intended as exploratory interface conditions rather than formally validated cognitive-load categories. No standardized cognitive load instrument (e.g., NASA-TLX) was administered in this pilot study. Future work should empirically validate the relationship between parameter count and perceived cognitive burden.

3. *Procedure*

The study utilized a within-subjects design component where participants interacted with the toolkit variations to establish a baseline of understanding, followed by a comparative evaluation.

- **Task 1 (Interaction):** Participants configured lightshades using the varying DoF levels.
- **Task 2 (Preference):** Participants selected their preferred toolkit version for a final "*production-ready*" design.
- **Task 3 (Complexity Extrapolation):** Participants completed a structured survey indicating their preferred DoF for products of varying complexity (Ring, Chair, Shoe, Laptop, and Car).

The presentation order of the three toolkit conditions was fixed rather than counterbalanced. As a result, learning effects, familiarity accumulation, and participant fatigue may have influenced responses. Future studies should employ randomized or Latin-square counterbalancing procedures.

Participants interacted with each toolkit condition for approximately 10-15 minutes, with total session durations ranging between 30 and 45 minutes.

Given the exploratory nature of the pilot study, the primary dependent observations consisted of self-reported toolkit preference, qualitative participant feedback, and descriptive responses regarding perceived appropriateness of DoF across product categories. Objective usability metrics such as task completion time, error rate, or standardized satisfaction scales were not formally collected.

4. *Operationalizing ADoF*

To transition ADoF from a conceptual framework to an actionable toolkit design, it is essential to define its operational mechanics. Specifically, how a system detects user competence, the triggers that dictate parameter adjustments, and the UI mechanisms used for adaptation. The proposed ADoF model operates primarily on a behavior-driven basis. Instead of requiring users to self-identify as novices or experts, which is often prone to bias or inaccuracy, the toolkit assesses competence continuously through implicit interaction metrics.

Competence in a behavior-driven ADoF system is quantified through real-time telemetry. The system monitors specific behavioral indicators, including: (1) fluidity of interaction (the speed and decisiveness of parameter adjustments), (2) error and iteration rates (the frequency of ‘undo’ commands, resets, or abandoned changes), and (3) hesitation metrics (cursor idling or prolonged hovering over tooltips). High fluidity and low iteration rates indicate high competence and clear intent, whereas high iteration rates or hesitation suggest cognitive overload or lack of expertise.

The adaptation of the toolkit is governed by predefined behavioral thresholds.

- **Expansion Triggers:** If a user demonstrates high competence, for example, successfully modifying three basic parameters (e.g., color, primary dimensions) within a specific timeframe without utilizing the ‘undo’ function, the system crosses an expansion threshold. This triggers the toolkit to unlock higher Degrees of Freedom (DoF).
- **Reduction Triggers:** Conversely, if the system detects overload, evidenced by the user repeatedly toggling the same parameter back and forth, excessively using the ‘undo’ function, or idling for an extended period, a reduction threshold is crossed. The system then reduces the DoF to prevent decision fatigue.

The actual adaptation occurs through the UI/UX principle of progressive disclosure. The system does not overwhelm the user by reloading entirely new interfaces. Instead, when an expansion is triggered, the toolkit fluidly unhides “*Advanced Settings*” or micro-parameters (e.g., allowing specific corner-radius adjustments instead of just general shape selection). When a reduction is triggered, the system gracefully collapses these advanced menus or actively prompts the user with simplified, pre-configured design templates, thereby restricting the DoF back to a manageable, macro-level state.

Results

Given the exploratory nature of this pilot study (the following results are entirely descriptive. They are intended to generate hypotheses regarding user behavior rather than establish statistical significance.

1. *Divergent Preferences for DoF*

The pilot observations indicated variation in user preference, challenging the existence of a single "optimal" DoF.

- **4 out of 10 preferred Medium DoF (23 options):** These users cited ease of use and decision confidence. Several participants subjectively described the High DoF interface as difficult to navigate or cognitively demanding. However, no standardized cognitive-load instrument was employed, and these observations therefore remain qualitative and self-reported.
- **6 out of 10 preferred High DoF (28 options):** These users valued the creative agency. Several participants reported that the possibility of winning the fabricated product encouraged deeper exploration of available customization features. This suggests that the incentive structure may have influenced engagement patterns and potentially biased preferences toward higher configurability conditions.

While drawn from a small pilot sample, this 4-to-6 split provides a preliminary observation that a static toolkit fixed at 25 options may not optimally serve a diverse user base, potentially being perceived as either too complex or too restrictive depending on the user. This observed heterogeneity provides an initial, exploratory rationale for testing adaptive systems in future research.

2. *Exploratory Observations Regarding Product Complexity and Desired Freedom*

Participant survey responses suggested a possible tendency for users to associate more complex products with greater desired configurability (Figure 3). Given the limited sample size and absence of inferential statistical testing, this observation should be interpreted cautiously as exploratory rather than correlational evidence. The selected product categories (e.g., ring, shoe, car) were used as illustrative examples of differing perceived complexity levels and were not derived from a validated product-complexity taxonomy.

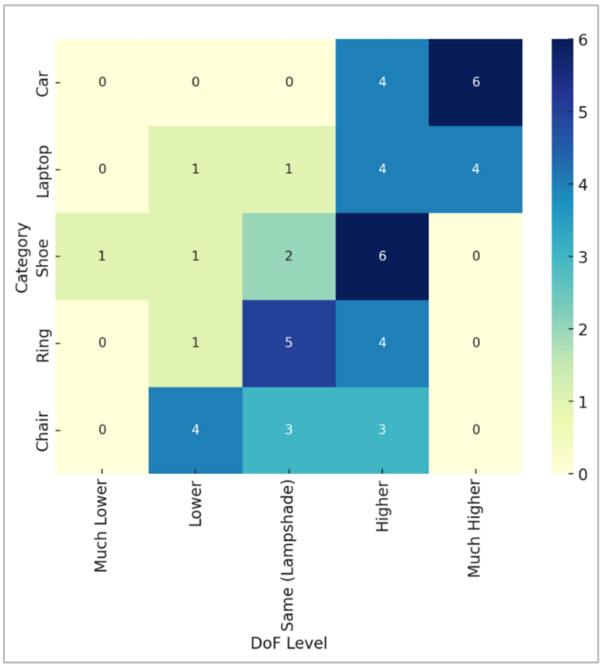

Figure 3: *Heatmap comparing the perceived Degrees of Freedom (DoF) of various product categories relative to a baseline product (Lampshade).*

- **Low Complexity (Chair, Ring):** Users preferred Low DoF (<15 options).
- **Medium Complexity (Shoe):** Users preferred Medium-High DoF (20-25 options).
- **High Complexity (Car, Laptop):** Users demanded Maximal DoF (>30 options).

3. *Qualitative Feedback*

An informal inductive thematic review of participant comments was conducted to identify recurring perceptions related to confusion, creative control, and interface organization. One participant stated that the High DoF interface "*felt powerful but difficult to organize mentally*," while another described the Medium DoF version as "easier to control without losing creativity."

Given the exploratory pilot nature of the study and limited sample size, formal inter-rater reliability measures and structured coding protocols were not employed. Qualitative feedback indicates that 'Mass Confusion' is less about the sheer count of parameters, aligning with meta-analyses showing that choice volume alone does not dictate overload (Scheibehenne et al., 2010; Chernev et al., 2015), and more about the lack of Choice Navigation support.

Discussion

Given the exploratory nature of the pilot study and the absence of a tested adaptive interface, the following discussion should be interpreted as hypothesis-generating and conceptual rather than confirmatory.

1. *The Imperative for Adaptive Degrees of Freedom (ADoF)*

The observations from this pilot study lead us to hypothesize that the "*Optimal DoF*" is a moving target. The observed variation in this pilot sample provides a preliminary rationale for investigating adaptive systems in future large-scale studies. These exploratory observations provide a preliminary rationale for investigating whether adaptive DoF systems could improve usability across heterogeneous user groups. The observations from this exploratory pilot suggest the possibility that the optimal DoF may vary across users and contexts.

2. *AI-Driven Choice Navigation*

The following discussion is conceptual and speculative in nature, as no AI-driven adaptive system was implemented or evaluated within the present study.

In the context of recent technology, AI-driven Choice Navigation can decouple solution space size from cognitive load. Generative AI agents can act as "*interpreters*," allowing users to express high-level intent ("*Make it look modern*"), which the system translates into specific parametric adjustments. This effectively allows for an Infinite Backend DoF while maintaining a Low Frontend DoF, solving the 'Inverted-U' trade-off identified in early literature and validated in comprehensive models of choice overload (Chernev et al., 2015; Scheibehenne et al., 2010).

Operationally, this means the system could generate a virtually limitless number of design permutations (the "*backend*"), but the user is only ever presented with a small, curated subset of relevant options at any one time (the "*frontend*"), thus avoiding choice overload. Such architectures may eventually help mitigate the trade-off between configurability and cognitive burden identified in the choice-overload literature.

3. *Technical Feasibility of Behavior-driven AdoF*

From a practical standpoint, the behavior-driven operationalization of ADoF is highly feasible within modern web-based customization toolkits. By utilizing standard event listeners (tracking clicks, time-on-task, and undo states) combined with basic logic thresholds, designers can implement dynamic progressive disclosure without the need for computationally heavy predictive AI algorithms. This allows firms to provide highly personalized, scalable co-creation experiences that autonomously adapt to the learning curve of each user.

Conclusion

This study provides preliminary observations suggesting that user preference for design freedom may be heterogeneous and context-dependent. While the pilot observations suggested that several participants preferred Medium-to-High DoF configurations within the specific lightshade scenario, the broader findings primarily highlight the heterogeneity and context-dependency of user preferences rather than supporting a single optimal DoF range.

1. *Preliminary Design Implications*

- **Abandon the Static Number:** Future toolkit designers may benefit from avoiding reliance on a single fixed number of options and instead exploring tiered or adaptive interaction structures.
- **Contextual Scaling:** The pilot observations tentatively suggest that perceived product complexity may influence users' desired level of configurability.
- **Invest in Navigation:** The qualitative feedback suggests that navigational support and interface organization may play an important role in moderating perceived choice overload.

Because these insights are derived from pilot data, they are presented as hypotheses to guide the future development and empirical testing of adaptive toolkits.

2. *Limitations and Future Work*

This study contains several limitations. First, the small pilot sample prevents statistical inference and limits the transferability of observations. Second, the experimental conditions simultaneously varied parameter counts and interface functionality, preventing isolation of pure DoF effects. Third, the absence of standardized usability and cognitive-load instruments limits measurement reliability. Fourth, the fixed presentation order may have introduced learning and fatigue effects. Fifth, the incentive structure may have biased participants toward greater feature exploration. Consequently, the findings should be interpreted as exploratory and hypothesis-generating rather than confirmatory. Sixth, the practical implementation of Adaptive Degrees of Freedom (ADoF) systems presents several unresolved challenges. These include accurately modeling user expertise, determining appropriate adaptation timing, maintaining interface transparency, preventing user disorientation caused by dynamic UI changes, and balancing personalization with system predictability. The present study did not implement an operational adaptive system, and therefore, these engineering and usability considerations remain important directions for future research. Finally, investigating the role of Generative AI as a mediator between user intent and parametric controls represents a promising direction for future investigation in Mass Customization research.

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