Psychologically Grounded Chatbots in Online Furniture Retail

DOI
https://doi.org/10.18690/um.fov.4.2026.16

ISBN
978-961-299-152-4

CLAUDIA PEDRON, ESTHER FEDERSPIEL

OST – Eastern Switzerland University of Applied Sciences, Institute for Information and Process Management (IPM), St. Gallen, Switzerland
claudia.pedron@ost.ch, esther.federspiel@ost.ch

High-involvement online purchase decisions are characterized by extensive information processing, perceived risk, and uncertainty. These challenges are particularly visible in furniture retail, where financial investment, long usage cycles, limited physical experience, and symbolic relevance make the purchase decision particularly complex. Although conversational AI is increasingly used in digital commerce, many chatbots remain transaction-oriented and insufficiently address psychological decision dynamics. Using a design-oriented conceptual research approach informed by design science principles, this article develops a phase-sensitive conceptual reference model for psychologically grounded conversational AI in high-involvement online purchasing. Furniture retail serves as an illustrative application context. Chatbots are conceptualized as dialogical decision companions whose roles evolve across the purchasing process, from preference exploration and risk reduction to trade-off moderation and decision stabilization. The model integrates psychological factors such as perceived risk, trust, aesthetic preferences, and sustainability values, as well as chatbot-related design factors such as personalization, usefulness, and interaction quality.

Keywords:
conversational AI,
high-involvement purchase decisions,
chatbot-based decision support,
consumer purchase decision process,
psychologically grounded design,
design science research

University of Maribor Press

1 Introduction

Electronic markets have fundamentally changed how consumers search for information, compare alternatives, and make purchase decisions by reducing search costs, increasing transparency, and enabling data-driven personalization (Huang & Rust, 2021; Verhoef et al., 2021; Wedel & Kannan, 2016). These developments are particularly relevant for high-involvement online purchase decisions, which, in contrast to low-involvement decisions, require extensive information processing and are characterized by financial, functional, and social uncertainty. In online settings, such challenges are intensified by the lack of physical product experience and by uncertainty regarding quality, fit, and return processes (Yu et al., 2023; Zhang et al., 2022). Accordingly, digital interaction systems increasingly serve to support consumers, foster trust, and reduce perceived uncertainty.

AI-supported chatbots have become established in service and sales contexts as interactive systems that structure information and guide consumer decision-making. Prior research shows that such systems can improve personalization, responsiveness, and decision confidence (Huang & Rust, 2021; Luo et al., 2019; Verhagen et al., 2014). Yet existing applications largely focus on efficiency, automation, and product-centered recommendation logic, while psychological decision dynamics such as risk perception, preference construction, and affective stabilization remain insufficiently addressed. Similarly, prior research on AI-supported chatbots in e-commerce mainly examines adoption factors, specific design cues, performance outcomes, or operational implementation models (Iniesta & López, 2025; Li et al., 2025; Sidlauskiene et al., 2023; Skuridin & Wynn, 2024). Consequently, limited guidance exists on how chatbots can address consumers' changing psychological needs as they vary across the phases of high-involvement purchase decisions. Thus, there is a need for a theory-based conceptual model that links psychological decision factors to phase-specific chatbot design principles in high-involvement online purchase decisions. This article addresses this gap and examines the following research question:

RQ1: How can a theory-based conceptual reference model be developed for designing psychologically grounded, phase-sensitive chatbots for high-involvement online purchase decisions?

To operationalize this question, two sub-questions are examined:

- RQ1a: Which psychological factors are relevant to high-involvement online purchase decisions?
- RQ1b: How can these factors be systematically integrated into the design of an AI-supported chatbot across the phases of the purchasing process?

Furniture retail is used as an illustrative application context because furniture purchases typically involve high cognitive effort, intensive information processing, long decision times, and considerable financial risk (Pepels, 2013). In addition, furniture often carries symbolic and social meaning by shaping living spaces and expressing lifestyle and identity (Foscht et al., 2017). Thus, the context is suitable for developing a transferable conceptual reference model for high-involvement online purchasing.

The remainder of the article is structured as follows: Section 2 presents the theoretical framework, Section 3 describes the research design, Section 4 introduces the conceptual reference model, and Section 5 discusses the implications and concludes the article.

2 Theoretical Background

The development of the conceptual reference model combines a process perspective on purchasing decisions with a psychological impact perspective. To this end, the Engel-Kollat-Blackwell (EKB) model is used to structure the decision-making process, while the stimulus-organism-response (S-O-R) model explains the internal mechanisms through which external stimuli shape decision-related responses. These perspectives are complemented by psychological factors relevant to high-involvement online purchases and by selected chatbot-related design factors derived from prior research. Together, they provide the conceptual foundation for the model developed in this study.

2.1 The S-O-R model as a psychological impact perspective

The S-O-R model explains purchasing behavior as the result of internal processing triggered by external stimuli (Kotler et al., 2007). Stimuli such as product information, prices, interface cues, or social signals are processed cognitively and affectively and may lead to observable responses such as purchase, continued search, or decision abandonment. A key implication is that consumer behavior is shaped not by objective product characteristics alone, but by their subjective interpretation.

In chatbot-supported purchasing, this means that chatbots do not directly determine decisions, but can influence pre-decisional factors such as trust, perceived usefulness, motivation, and perceived risk.

2.2 The EKB model as a process perspective on purchasing

While the S-O-R model explains how external stimuli are internally processed, the EKB model structures purchasing as a sequence of decision phases, from problem recognition to information search, evaluation of alternatives, purchase, and post-purchase evaluation (Kotler et al., 2007; Pepels, 2013). This process perspective is particularly relevant in high-involvement online purchasing, where decisions develop over time and involve repeated comparison, reassessment, and justification (Huang & Rust, 2021; Luo et al., 2019). The EKB model therefore provides the temporal structure within which chatbot support can be conceptualized.

2.3 Psychological factors influencing high-involvement online purchases

To apply these perspectives to chatbot-supported purchasing, it is necessary to identify the psychological factors that are particularly relevant in high-involvement online decisions. In this study, three interrelated categories are distinguished: cognitive, affective, and value-based factors.

Cognitive factors refer to rational, information-based evaluation and judgment processes through which consumers assess alternatives, uncertainty, costs, and expected benefits (Rani, 2014). In high-involvement online purchases, they are especially relevant during information search and evaluation. Perceived risk is particularly salient when product quality cannot be physically inspected in advance

(Zhang et al., 2022). Performance risk, financial risk, and uncertainty about fit or logistics intensify information search and comparison, while trust helps reduce uncertainty and stabilize decision-making. Transparent product information, warranties, origin disclosures, and clear service information can strengthen perceived trustworthiness (Yu et al., 2023).

Affective factors refer to emotional reactions and feeling-based evaluations that shape how consumers perceive alternatives and form preferences beyond purely functional assessment (Rani, 2014). They are especially relevant in high-involvement purchases that involve identity, aspiration, or symbolic meaning. Emotional resonance, aesthetic liking, and the anticipation of comfort or status influence both the attractiveness of alternatives and the formation of preferences. In furniture retail, as an illustrative context, these mechanisms are particularly visible because design and aesthetic perception are core parts of the decision itself (Balicka & Niedbała, 2022).

Value-based factors refer to relatively stable beliefs, priorities, and normative orientations that guide how consumers frame, justify, and evaluate consumption choices over time (Rani, 2014). They extend beyond immediate product appraisal and influence both problem framing and post-purchase justification. Sustainability considerations, ownership preferences, and materialistic orientations may shape what consumers regard as an acceptable or desirable solution.

2.4 Chatbot-related design factors

In addition to these psychological decision factors, prior chatbot research highlights several design-related perceptions that shape whether and how chatbot support is used. Relevant constructs include information value, performance expectancy, perceived usefulness, effort expectancy, facilitating conditions, perceived risk, anthropomorphism (i.e., the extent to which the chatbot is perceived as human-like), and perceived competence (Bansal et al., 2026; Kumar et al., 2025; Le, 2023). These constructs do not replace cognitive, affective, and value-based factors; rather, they describe design conditions through which chatbot interaction can influence them.

From a cognitive perspective, information quality, usefulness, ease of use, and performance expectancy are particularly relevant for uncertainty reduction and information support (Le, 2023).

From an affective perspective, communication style and anthropomorphic design may shape perceived warmth, authenticity, competence, and engagement (Kumar et al., 2025).

From a value-related perspective, facilitating conditions (e.g., ease of use and system support) and recommendation competence (i.e., the ability to provide relevant and preference-consistent suggestions) can support the alignment between chatbot interaction and consumers' broader priorities and preferences.

Advanced AI capabilities can further shape these effects by influencing perceived interaction quality, personalization, and decision support through S-O-R-related mechanisms (Bansal et al., 2026).

3 Research design

This study adopts a design-oriented conceptual research approach informed by design science research (DSR) principles (Hevner et al., 2004; Peffers et al., 2007). Rather than presenting a fully implemented and empirically validated DSR artifact, the study develops a conceptual reference model that can guide the future design and evaluation of psychologically grounded chatbot systems for high-involvement online purchasing. Furniture retail is used as an illustrative application context to ground the model development.

Following the DSR process model proposed by Peffers et al. (2007), five steps were undertaken:

– 1. Problem identification: The practical problem was specified through an exploratory market analysis of AI-supported applications in online furniture and interior retail. Relevant tools were identified through structured web searches using keywords such as *AI furniture chatbot*, *AI interior design tool*, *AI room planner*, and *AI furniture recommendation*. Provider websites, app store entries, and third-party overview pages were screened iteratively, with additional cases identified through cross-referencing until no substantially new tool categories emerged. Tools were included if they offered recognizable AI-supported functionality related to furniture or interior decision-making. The final sample comprised around 20 tools and platforms and was assessed using predefined categories covering AI functionality, support across purchase phases, and psychologically relevant support features; the aim was analytical coverage rather than statistical representativeness. The analysis showed that existing applications provide various forms of AI support but offer limited integrated support for psychologically relevant decision processes across purchase phases. A summary of the analyzed tools and assessment criteria is provided in Appendix Table A1.

– 2. Objective definition: Based on the identified discrepancy between theoretically relevant decision dynamics and the functional scope of existing systems, the design objective was defined as the development of a phase-sensitive conceptual reference model for AI-supported chatbot design. The model is intended to support consumers not only at the transactional level, but also in psychologically relevant processes such as uncertainty reduction, preference clarification, confidence building, and post-purchase support.
– 3. Design and development: The conceptual reference model was developed by integrating the theoretical foundations discussed in Section 2, namely the EKB model as a phase structure of the purchase process, the S-O-R framework as an explanatory lens for internal processing, psychological factors relevant to high-involvement online purchase decisions, and chatbot-related design factors. The market analysis served as a practical benchmark for identifying which support functions are already addressed in existing AI-based applications and which remain underrepresented. Based on these theoretical and practical insights, phase-specific chatbot roles and corresponding design requirements were derived.
– 4. Conceptual demonstration: The resulting model was conceptually demonstrated through illustrative decision scenarios in online furniture retail. These scenarios are reflected in Section 4, where the model illustrates how phase-specific chatbot functions address uncertainty about product fit, difficulties in comparing alternatives, low confidence before purchase completion, and the need for reassurance after purchase. The

demonstration shows how the proposed model extends existing product- and transaction-oriented systems by integrating psychologically grounded support across purchase phases.

- 5. Conceptual evaluation: The model was evaluated conceptually in terms of internal consistency, theoretical coherence, and practical plausibility, following Gregor and Hevner (2013). Specifically, the evaluation examined the alignment between decision phases, psychological mechanisms, and chatbot functions, the consistency of the model with its theoretical foundations, and its plausibility in light of the market analysis. Practical plausibility was additionally informed by discussions with representatives of an interior-design software company and interior design consultants. As the study develops a conceptual model, the evaluation remains analytical rather than empirical and provides a basis for future prototypical implementation, empirical validation, and subsequent design science iterations.

4 A phase-sensitive model of psychologically integrated chatbot support

The conceptual reference model integrates the theoretical foundations with insights from the exploratory market analysis. It conceptualizes chatbot interaction as phase-sensitive decision support across the purchase journey. While existing AI-supported applications mainly address inspiration, visualization, product discovery, and transaction-related assistance, the model focuses on psychologically demanding decision processes that remain insufficiently covered in current systems.

The model is structured along the five phases of the purchase process and links each phase to dominant decision requirements. Accordingly, the chatbot's role changes over time: from clarifying preferences and structuring information to moderating trade-offs, stabilizing the purchase decision, and supporting post-purchase evaluation. Figure 1 summarizes this logic by linking the phases of the purchase process to dominant psychological decision requirements and corresponding chatbot roles.

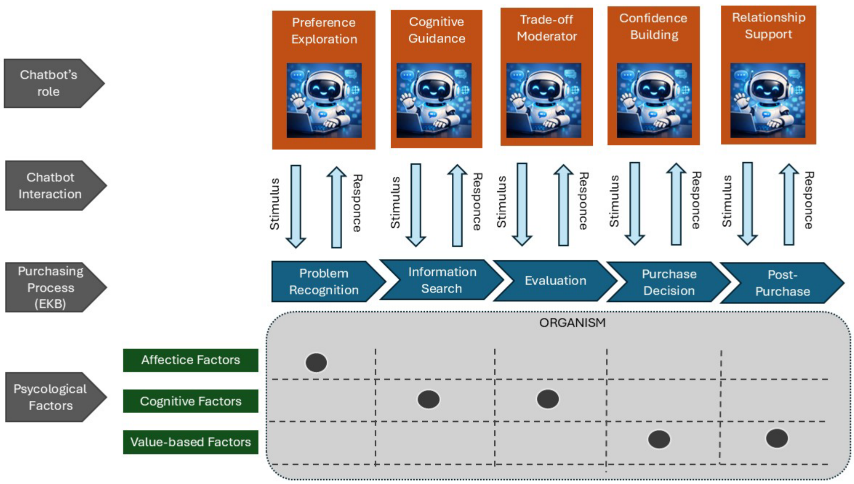

Figure 1: Phase-sensitive conceptual reference model for psychologically integrated chatbot support

Source: Own Illustration

4.1 Problem identification: Elicitation of latent needs and contextual framing

In the problem-identification phase, the chatbot helps consumers articulate diffuse and often affective needs in more explicit preference terms. Rather than recommending products immediately, it supports the clarification of latent preferences by translating moods, atmospheres, and contextual cues into decision-relevant criteria. This role builds on the affective and value-based factors discussed in Section 2.3, as these factors are particularly relevant when consumers have not yet translated subjective needs into explicit decision criteria.

For example, a desire for "coziness" may be specified in terms of preferred materials, colors, or stylistic directions. Style categories and situational cues, such as usage context or life stage, can further support this clarification. The outcome of this phase is therefore not product selection, but the development of a coherent preference structure.

4.2 Information search: Reducing perceived risk and building trust

In the information-search phase, the chatbot acts as a structuring information broker. Its task is to reduce uncertainty by presenting relevant product and service information in a clear, comprehensible, and decision-relevant way. Instead of merely listing product attributes, the chatbot translates them into functional implications and can clarify delivery conditions, return policies, warranties, or sustainability-related aspects. This role reflects the cognitive factors discussed in Section 2.3, particularly perceived risk, information processing, and trust formation, as well as chatbot-related constructs such as information value and perceived usefulness discussed in Section 2.4.

The primary objective in this phase is to make information easier to evaluate and to reduce uncertainty before alternatives are compared more closely.

4.3 Evaluation of alternatives: Moderation of goal conflicts and social dynamics

In the evaluation phase, the chatbot supports consumers in comparing alternatives across criteria such as design, price, quality, sustainability, and usage context. Rather than hierarchically ranking options, it contextualizes alternatives in relation to the consumer's previously articulated preferences. This role reflects the cognitive, affective, and value-based factors discussed in Section 2.3, particularly comparison, preference formation, aesthetic evaluation, and value-related considerations, as well as chatbot-related constructs such as recommendation competence and perceived usefulness discussed in Section 2.4.

For instance, the chatbot may contrast a product with stronger aesthetic appeal with another option that is more robust and easier to maintain, and thus more suitable for households with children. Since furniture purchases are often made jointly, the chatbot can also act as a neutral mediator by highlighting differing preferences and structuring compromise options. Its role in this phase is therefore to support preference-consistent trade-off reasoning rather than to prescribe a single optimal choice.

4.4 Purchase decision: Legitimation and development of decision confidence

Shortly before purchase completion, the chatbot supports decision stabilization by linking the chosen option to previously articulated preferences and by providing transparency about the practical conditions of purchase. For example, it may summarize how the selected product fits the consumer's priorities regarding design, sustainability, and budget, while also clarifying delivery times and return options. This role is grounded in the importance of trust, perceived risk reduction, and decision confidence in high-involvement purchase decisions (Section 2.3), as well as in chatbot-related design factors such as transparency, perceived usefulness, and interaction quality (Section 2.4).

The purpose of chatbot support in this phase is not to reopen comparison, but to reinforce confidence in the selected option. By synthesizing relevant criteria and making residual conditions transparent, the chatbot helps legitimize the decision and reduce lingering uncertainty.

4.5 Transition to the post-purchase phase: Preventive dissonance reduction

At the transition to the post-purchase phase, the chatbot supports consumers by reaffirming the fit between the final choice and the needs and preferences articulated earlier in the process. For instance, it may confirm that the selected product corresponds to the consumer's preference for a warm and calm atmosphere. This role reflects the importance of reassurance and decision confidence in high-involvement purchase decisions, as discussed in Section 2.3, and is further supported by chatbot-related design factors such as perceived competence and consistent communication (Section 2.4).

At this stage, the chatbot should not encourage further comparison, but help consumers feel confident about the decision already made. By summarizing the reasons for the choice and making its consistency with earlier preferences explicit, the chatbot can reduce post-decisional uncertainty and support the transition from purchase completion to post-purchase evaluation.

5 Discussion, implications, and conclusion

The proposed model suggests that AI-supported chatbots in high-involvement online purchasing contexts should not be conceptualized merely as extended search or recommendation systems. In such settings, consumers face elevated perceived risk, longer evaluation cycles, and more demanding cognitive, affective, and value-based decision processes. Chatbots should therefore provide phase-sensitive support that addresses uncertainty reduction, preference clarification, structured comparison, reassurance, and decision confidence.

The study contributes to design-oriented research by developing a theory-based conceptual reference model that combines the EKB model, the S-O-R framework, psychological purchase factors, and chatbot-related design factors into a phase-sensitive design logic for high-involvement decisions. By embedding design features such as trust, personalization, anthropomorphism, and usefulness in this logic, the model extends prior chatbot research and complements more operational chatbot models with a psychologically grounded perspective across the full customer journey. It shows how chatbot roles evolve from preference elicitation to uncertainty reduction, trade-off moderation, decision stabilization, and post-purchase reassurance.

For practice, this implies designing chatbots as strategic interaction systems rather than isolated automation tools. The market analysis indicates that current systems mainly support inspiration, visualization, and transaction efficiency, while deeper psychological support remains limited. Effective chatbot design should therefore support trust building, trade-off moderation, reassurance, and post-purchase stabilization, while ensuring transparency and argumentative clarity to avoid perceptions of manipulation. Implementation also requires enriched data structures that extend beyond product attributes to include semantic and contextual metadata reflecting relevant psychological dimensions.

Future research should empirically validate the model and examine its effects on trust, perceived risk, decision confidence, chatbot usage, and longer-term customer relationships.

Acknowledgment

This work was supported by an Innosuisse InnoCheck project, a Swiss innovation funding instrument that supports the initial assessment of applied research and innovation ideas. The authors gratefully acknowledge the valuable discussions with Bruno Anderegg and Frank Wicht from the software company EasternGraphics (https://www.easterngraphics.com/), which helped refine the practical relevance of the proposed conceptual reference model.

AI-based language tools (ChatGPT, OpenAI) were used to improve the linguistic quality of the manuscript. All intellectual contributions remain the responsibility of the authors.

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About the authors

Claudia Pedron

Claudia Pedron, Prof. Dr., is Professor of Business Information Systems at the Institute for Information and Process Management (IPM), OST – Eastern Switzerland University of Applied Sciences, St. Gallen, Switzerland. She has extensive experience in business process management, process automation, IT and management systems, and digitalization. She has acquired and led numerous research and service projects in process management, digital transformation, real estate technology, and decision-support systems. She holds a Ph.D. from ETH Zurich and an Executive Master in Business Engineering from the University of St. Gallen. Her publications address process-oriented decision support, digital services, e-health, and technology-supported management systems.

Esther Federspiel

Esther Federspiel, lic.phil., is a lecturer and project manager at the Institute for Information and Process Management (IPM), OST – Eastern Switzerland University of Applied Sciences, St. Gallen, Switzerland. Her professional background includes teaching, project management, marketing management, communication, and public relations. She studied journalism/public communication and psychology at the University of Zurich and holds a MAS in Communication Management from Lucerne University of Applied Sciences and Arts. Her work focuses on innovation culture, customer and employee relationships, customer integration in innovation and value creation processes, online communities, gamification, and decision processes under uncertainty.

Summary

This paper develops a theory-based conceptual reference model for designing AI-supported chatbots in high-involvement purchase contexts, using online furniture retail as an illustrative case. While existing chatbot systems primarily focus on product recommendations and transactional efficiency, they rarely integrate psychological decision dynamics. Building on the Stimulus–Organism–Response framework and the five-stage consumer decision process, the study conceptualizes chatbots as psychologically grounded, phase-sensitive decision companions. The proposed model outlines how chatbots can support preference exploration, risk reduction, trade-off moderation, and decision stabilization. By integrating psychological determinants into conversational design, the paper extends decision support research in electronic markets and provides a foundation for future empirical validation.

Appendix A: Summary of Findings from the Exploratory Market Analysis

Appendix A summarizes the findings of the exploratory market analysis of AI-supported tools and platforms in the furniture and interior context. The table consolidates the observed functionalities of the analyzed tools and assesses how they support the five phases of the purchase decision process as well as selected psychological factors. The overview is intended to document the empirical basis for identifying the practical gap addressed by the conceptual reference model.

Table A1: Summary of Market Analysis Findings on AI-Supported Tools Across Purchase Phases and Psychological Factors

	Product name	Website / source	Brief tool description (AI focus)	Assessment across the five phases and psychological factors
1	Houzz	https://www.houzz.com/	AI-supported inspiration and product platform for home and interior design; personalizes ideas, products, and professionals based on style preferences and usage signals.	Strong in phases 1-3 (problem recognition, information search, evaluation of alternatives), moderate in phase 4, weak in phase 5. Psychological factors: aesthetics/inspiration strong; trust through community and experts moderate; sustainability/environmental orientation only selectively visible.
2	DesignMyRoom	https://apps.apple.com/us/app/design-my-room-official/id1664182248	AI app for rapid room redesigns based on a photo; generates several style variants for the visual exploration of interior design ideas.	Strong in phases 1-2, moderate in phase 3, weak in phases 4-5. Psychological factors: visual need exploration strong; risk, trust, social dynamics, and environmental aspects largely not integrated.
3	Homestyler	https://www.homestyler.com/	Cloud-based 3D planning platform with AI for floor-plan conversion, furnishing, and photorealistic visualization; supports style selection and scenarios.	Strong in phases 1-3, moderate in phase 4, weak in phase 5. Psychological factors: aesthetics, preference exploration, and comparison strong; perceived risk can be partially reduced through 3D visualization; sustainability largely not addressed systematically.
4	RoomsGPT	https://www.roomsgpt.io/	Generative AI for room redesign based on a photo; creates	Strong in phases 1-2, moderate in phase 3, weak in phases 4-5.

	Product name	Website / source	Brief tool description (AI focus)	Assessment across the five phases and psychological factors
			stylized alternatives for different room types within seconds.	Psychological factors: emotional resonance and style discovery strong; risk, trust, and sustainability dimensions only very limited.
5	Planner 5D	https://planner5d.com/	2D/3D home and room planner with AI for floor-plan recognition, layout suggestions, and furnishing; combines visualization with planning functions.	Strong in phases 1-3, moderate to strong in phase 4, weak in phase 5. Psychological factors: comparison, spatial confidence, and functional fit good; affective and social factors partially addressed; sustainability not central.
6	Havenly	https://havenly.com/	Digital interior design platform with personalized suggestions, 3D visualizations, and purchasing options; AI supports matching and personalization.	Strong in phases 1-4, moderate in phase 5. Psychological factors: style, budget, and advisory needs are well addressed; trust is stronger through designer involvement than in purely AI-based tools; environmental aspects only limited.
7	Modsy (historical / integrated into Lennar)	https://www.modsy.com/	Historical 3D interior design solution with AI-supported room layouts and shoppable design suggestions; according to the website, integrated into Lennar since 2023.	Historically strong in phases 1-4, weak in phase 5. Psychological factors: visual confidence, comparison, and decision confidence relatively good; sustainability and deeper psychological/social modelling limited.
8	AiHouse	https://my.aihouse.com/	AI-supported 3D interior and manufacturing platform with room planning, renderings, and automatic structure recognition; more professionally oriented.	Strong in phases 2-4, moderate in phase 1, weak in phase 5. Psychological factors: risk and functional assessment good; emotional need exploration and environmental values less strong; more planning-oriented than dialogue-oriented.
9	Design Flex	https://www.cyncly.com/products/design-flex/	Described in the market document as an interactive 3D environment with real-time	According to the document description, strong in phases 2-3, moderate in phases 1 and 4, weak in phase 5.

	Product name	Website / source	Brief tool description (AI focus)	Assessment across the five phases and psychological factors
			visualization, automatic furniture arrangement, and AI suggestions.	Psychological factors: functional visualization good, but no clear evidence of trust, social moderation, or environmental aspects.
10	Home Design AI	https://home-design.ai/	AI tool for redesigning interiors and floor plans based on photos and prompts; quickly and accessibly generates design ideas and layout variants.	Strong in phases 1-2, moderate in phase 3, weak in phases 4-5. Psychological factors: need exploration and aesthetics strong; trust, risk reduction, sustainability, and post-purchase support hardly developed.
11	Wayfair	https://www.wayfair.com/	Large online furniture retailer using AI for search, recommendations, assortment personalization, and marketing optimization across the digital purchase process.	Strong in phases 2-4, moderate in phases 1 and 5. Psychological factors: personalization, convenience, and choice reduction strong; deeper psychological dialogue guidance, social negotiation, and sustainability integration only partial.
12	Ashley Furniture	https://www.ashleyfurniture.com/	Furniture retailer with widely used AI/digital applications for commerce, assortment, marketing, and customer experience; focus is more operational-commercial.	Moderate to strong in phases 2-4, weak to moderate in phases 1 and 5. Psychological factors: convenience and product search supported; phase-sensitive decision guidance and environmental values not prominent.
13	Coleman Furniture	https://colemanfurniture.com/	Online furniture retailer with visual product search and “shop the look” approaches; AI primarily supports discovery and inspirational product exploration.	Strong in phases 1-3, moderate in phase 4, weak in phase 5. Psychological factors: visual inspiration and comparison of alternatives good; trust, risk reduction, and sustainability only selectively addressed.
14	Freedom Furniture	https://www.freedom.com.au/	Omnichannel furniture retailer with AI-supported search and personalization to improve discovery, relevance, and cart value.	Moderate to strong in phases 2-4, moderate in phase 1, weak in phase 5. Psychological factors: personalization good, but psychological depth models, social

	Product name	Website / source	Brief tool description (AI focus)	Assessment across the five phases and psychological factors
				moderation, and environmental factors are not comprehensively visible.
15	Temple & Webster	https://www.templeandwebster.com.au/	Online retailer using AI in customer service, logistics, product creation, and personalization; focused on scaled commerce support.	Moderate to strong in phases 2-4, weak to moderate in phases 1 and 5. Psychological factors: search and service efficiency present; deeper preference exploration, risk dialogue, and sustainability advice rather limited.
16	Sofology	https://www.sofology.co.uk/	Sofa retailer with visual image search or AI-supported product search to find suitable models based on inspirational references.	Strong in phases 1-3, moderate in phase 4, weak in phase 5. Psychological factors: style and image preferences good, but little evidence of comprehensive trust, environmental, or social decision support.
17	IKEA (including IKEA Kreativ)	https://www.ikea.com/c/en/home-design/	Global furniture provider with virtual room planning, AR/scan functions, and IKEA Kreativ as an AI-supported room designer for budget- and style-related product selection.	Strong in phases 1-4, moderate in phase 5. Psychological factors: good combination of inspiration, risk reduction, and budget orientation; sustainability more visible at brand level than in many other cases, but not deeply integrated in a dialogic manner.
18	Blueport	https://www.blueport.com/about-us	Omnichannel e-commerce platform for big-ticket retail that provides furniture retailers with personalized digital shopping experiences and commerce functions.	Indirect fit: strong for phases 2-4 on the retailer side, but not an end-customer chatbot. Psychological factors are technologically supported, but not implemented as an independent dialogical decision companion with an environmental/value layer.
19	Vaimo	https://www.vaimo.com/	Digital commerce and experience provider; illustrates how AI search, recommendation, and advisory logic can be	Indirect fit: strong for phases 2-4 as enablement, weaker for phases 1 and 5. Psychological and environmental factors are more implementation

	Product name	Website / source	Brief tool description (AI focus)	Assessment across the five phases and psychological factors
			integrated into retailer ecosystems.	options than a visible core function of the product.
20	Quin AI	https://www.quinengine.com/	Generative AI platform for real-time behavioral predictions and personalized website/app experiences; optimizes engagement and conversion in-session.	Strong in phases 2-4, moderate in phase 1, weak in phase 5. Psychological factors: behavior and intent are anticipated in a data-driven way; explicit sustainability or socio-cultural reflection remains limited.

Source: Own elaboration