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Integrating AI into Startups' Design Thinking

Stefan Waitzinger*

HTWG Konstanz University of Applied Sciences, Alfred-Wachtel-Straße 8, 78462 Konstanz, Germany.
E-mail: stefan.waitzinger@htwg-konstanz.de

Christina Ungerer

HTWG Konstanz University of Applied Sciences, Alfred-Wachtel-Straße 8, 78462 Konstanz, Germany
E-mail christina.ungerer@htwg-konstanz.de

Klara Beigel

HTWG Konstanz University of Applied Sciences, Alfred-Wachtel-Straße 8, 78462 Konstanz, Germany
E-mail klara.beigel@hotmail.de

* Corresponding author

Abstract: Startups face substantial innovation challenges rooted in resource constraints, limited customer data, and time pressure. Design Thinking (DT) offers a structured, human-centered response to these challenges, with further potential to enhance its effectiveness through the integration of analytical and creative capacity. This paper investigates how Artificial Intelligence (AI) can be systematically integrated into the DT process to increase innovation efficiency in startup contexts. Drawing on a qualitative, inductive study combining a narrative literature review with semi-structured interviews with startup founders and DT/AI experts, we develop an empirically grounded framework that maps nine specific AI applications across the three core DT stages of empathizing, ideating, and prototyping. The framework differentiates between AI as augmentation and automation and identifies two critical boundary conditions: data quality and the preservation of human empathy and creativity. Our findings contribute a novel framework to the emerging literature on AI-enabled innovation management in startups.

Keywords: Artificial Intelligence; Design Thinking; Startups; Innovation Efficiency; Framework; Human-AI Collaboration.

1 The Case for AI-Augmented Innovation

Startups are widely recognized as key drivers of economic growth and technological innovation. Yet they operate under conditions that fundamentally differ from those of

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established firms: constrained budgets, limited market presence, and insufficient customer data restrict their capacity to invest in technology, scale operations, and engage in systematic R&D (McElheran et al. 2023; Madrid-Guijarro et al., 2009). At the same time, innovativeness is critical to startup survival, with highly innovative startups significantly outperforming their less innovative peers (Aminova & Marchi, 2021; Arcuri et al., 2024).

Design Thinking (DT) has emerged as a structured, human-centered approach that helps organizations navigate these innovation challenges. Its iterative and user-centric logic enables startups to develop solutions that respond to real market needs, even under conditions of uncertainty and resource constraints (Brown, 2008; Sheppard et al., 2018).

At the same time, Artificial Intelligence (AI) is rapidly reshaping how innovation processes are designed and executed. While AI adoption has accelerated significantly in recent years, it remains unevenly distributed: by 2023, 30.4% of large enterprises had integrated AI into their operations compared to only 6.4% of small firms (Eurostat, 2024). This disparity points to a significant and largely unexplored opportunity for startups to leverage AI in overcoming resource constraints in innovation processes.

Despite growing interest in both DT and AI, their intersection in startup contexts remains under-researched. Existing research either examines AI in innovation processes without accounting for the specific constraints of startups or focuses on DT in startup environments without incorporating AI. As Cai et al. (2023) note, investigating how digital technologies can be embedded in DT represents an essential and open research direction.

This paper addresses this gap by developing an empirically grounded framework that systematically integrates AI into the DT process in startup contexts. Drawing on a qualitative, inductive research design combining a narrative literature review with semi-structured interviews, the framework maps nine specific AI applications across the three core DT stages of empathizing, ideating, and prototyping. It further distinguishes between augmentation and automation as two modes of AI deployment and identifies two critical boundary conditions – data quality and the preservation of human empathy and creativity – that determine whether AI enhances or undermines innovation outcomes.

By doing so, the paper makes two contributions: First, it provides a structured and operationalizable framework that specifies where and how AI can be integrated into DT processes in resource-constraint startup environments. Second, it extends research on human-AI collaboration by highlighting the organizational and team-level implications of AI integration, particularly the risk that over-reliance on AI may erode team ownership, intrinsic motivation, and cohesion in early-stage innovation processes.

Against this background, the study is guided by the following research question: How can DT practices within startups be optimized by implementing AI?

2 Building Blocks: Design Thinking, Startup Constraints & AI Capabilities

Design Thinking (DT) is a structured, human-centered approach to innovation that prioritizes deep user understanding, iterative experimentation, and cross-functional collaboration. Rooted in Simon's (1969) conception of design as a cognitive, problem-solving discipline, DT has been defined by Brown (2008, p. 2) as a methodology that drives innovation through a thorough understanding of user needs. In practice, DT is represented through various process models, including Brown's (2008) three-phase inspiration-ideation-implementation cycle, the Design Council's Double Diamond and Plattner et al.'s (2011) divergent-convergent framework. We follow Loderer's (2023) consolidation of models into three core stages: (1) empathizing and recognition of user needs, (2) collecting and generating ideas, and (3) prototyping and testing of ideas. Across these stages, DT is guided by four key principles: human-centeredness, multidisciplinary teamwork, iterative procedure, and the cultivation of a creative environment (Sreenivasan & Suresh, 2024).

For startups, DT offers a particularly compelling fit. Startups are characterized by high innovation potential, rapid scaling ambitions, and conditions of extreme uncertainty (Ries, 2011; Olek, 2023). Their agility enables fast prototyping and iteration, yet structural constraints limit the effectiveness of their innovation processes. Data analytics remains underutilized in early-stage ventures due to limited data volume and a lack of analytical expertise (Berg et al., 2018), while financial constraints restrict investments in R&D and skilled personnel (McElheran et al. 2023). At the same time, difficulties in obtaining deep customer insights hinders informed decision-making throughout the innovation process (Berg et al., 2018). These constraints create a clear tension: startups have a strong incentive to innovate systematically but lack the resources to do so at scale.

AI technologies offer a promising path to resolving this tension. Three technology clusters are of particular relevance in this context. Machine Learning (ML) enables systems to identify patterns in large datasets and generate predictions with minimal human intervention. Natural Language Processing (NLP) and especially Large Language Models (LLMs) such as GPT enable machines to understand, generate, and analyze human language at scale, opening up capabilities from automated sentiment analysis to generative ideation (Saleh et al., 2025). Computer vision extends these capabilities into the visual domain, supporting image-based user research and automated prototype evaluation.

Crucially, AI can be deployed in two distinct modes: automation, where tasks are fully delegated to the machine, and augmentation, where AI enhances human capabilities without replacing them (Davenport & Kirby, 2016). As Füller et al. (2024) note, organizations must balance both modes deliberately, ensuring that AI complements rather than constrains human ingenuity in innovation processes. Research by Johnson et al. (2022) confirms that augmentation currently dominates AI use in R&D contexts, with 55% of applications designed to support human decision-making rather than substitute it.

Despite growing interest in both DT and AI, empirically grounded frameworks that operationalize their integration specifically for startups remain absent from the literature. Existing studies either address AI in innovation processes broadly without accounting for the resource constraints of startups or focus on DT in startup contexts without incorporating AI. As Cai et al. (2023, p. 16) note, investigating how digital technologies can be embedded in DT represents an essential and open research direction. This paper directly responds to this gap by developing a structured framework for AI integration in startups' DT processes.

3 Methodology

This study adopts a qualitative, inductive research design, deemed suitable to exploring the underexamined intersection of AI, Design Thinking, and startup innovation and enabling the development of a contextually grounded framework (Saunders et al., 2019).

The research proceeded in two phases. First, a narrative literature review was conducted to map the current state of knowledge on DT, AI technologies, and startup innovation. Following Baumeister and Leary (1997), sources were selected based on their relevance to the research questions and their contribution to identifying key themes and gaps. This resulted in a preliminary framework that guided the empirical phase.

In the second phase, six semi-structured interviews were conducted with purposefully selected participants: four startup founders and two domain experts in DT and AI, capturing both practical and expert perspectives. Semi-structured interviews allowed for flexible exploration while maintaining thematic consistency allowing the interview guide to adapt to the specific context and experience of each participant while maintaining thematic coherence across conversations (Saunders et al., 2019; Patton, 2015). The interview guides were tailored to the respective roles of participants. Anonymity was preserved throughout. The sample follows a purposive sampling strategy prioritizing information richness over statistical representativeness, as common in qualitative research (Patton, 2015).

Interview data was transcribed and analyzed using reflexive thematic analysis, following the six-phase framework developed by Braun and Clarke (2006) and further refined in their more recent methodological work (Braun & Clarke, 2024). The analysis moved from initial familiarization to systematic coding and theme development. Codes were organized along three analytical dimensions derived from the preliminary framework: (1) whether insights related to the problem space or solution space of each DT stage, (2) whether they reflected obstacles or potentials of AI integration, and (3) whether AI was deployed in augmentation or automation mode. This structured coding approach enabled a systematic refinement of the preliminary framework into the final AI-enabled DT framework.

4 An AI-Enabled Design Thinking Framework

The framework presented in this section integrates findings from the narrative literature review with insights derived from the qualitative interview study. The literature review provided an initial structure by identifying core DT stages and relevant AI capabilities in innovation processes, resulting in a preliminary mapping of AI applications. This structure was subsequently refined through interview insights, which provided concrete examples of AI use, highlighted practical limitations, and revealed how AI is deployed in real startup contexts.

Through the thematic analysis, AI applications were systematically consolidated along three dimensions: their position within the DT process, their functional role, and their mode of deployment, i.e., augmentation or automation. This iterative process resulted in the identification of nine distinct AI applications across the three core DT stages, while also revealing two overarching conditions shaping the effectiveness of AI integration across all stages: data quality and the preservation of human-centeredness.

The resulting framework maps these applications across the stages of empathizing, ideating, and prototyping, and specifies for each application whether it is primarily deployed in an automated or augmented mode, as well as its key benefits and associated risks. Table 1 provides a condensed overview.

Table 1 Framework of AI in the Design Thinking Process for Startups

Stage	*Goal of the Stage*	*AI Application*	*Mode*	*Benefits / Opportunities*	*Downsides / Risks*
Stage 1 Empathizing & Recognition of User Needs	*Build deep understanding of users and problem space; synthesize and define a specific problem.*	Data Clustering	Augmented	Structures large volumes of consumer and feedback data; scopes problem space precisely; expands informational base beyond human analytical capacity.	No guarantee of data representativeness or authenticity (e.g. faked reviews, insufficient sample sizes).
		Sentiment Analysis	Automated	Gains deep insights into user attitudes; predicts customer satisfaction; analyzes brand perception; anticipates market trends to inform strategic decisions.	Risk of limited access to relevant or sufficiently representative data.
		Questionnaire & Interview Template Creation	Augmented	Generates bias-minimized, contextually adapted research instruments; improves question clarity and neutrality; increases respondent satisfaction.	No direct risks identified; quality depends on specificity of human input.
		Quantitative Persona Creation (QPC)	Augmented	Produces statistically representative, replicable user archetypes from large datasets; supports data-driven decision-making at scale.	Risk of data-caused bias and overgeneralization; minority groups and behavioral outliers may be overlooked.
Stage 2 Collecting & Generating of Ideas	*Generate a broad range of creative ideas; explore the solution space.*	AI-based Ideation	Automated	Continuous idea flow without social inhibition; stimulates creativity with novel inputs; broadens solution space; reduces cognitive load; maintains brainstorming momentum.	Risk of limiting depth of creative thinking; reduced team ownership of ideas; potential erosion of intrinsic motivation and team cohesion.
		Computational Co-Creation	Augmented	Enables structured human-AI turn-taking; generates wider array of ideas; accelerates iterations; expands the design solution space explored.	Human biases may lead to undervaluing AI-generated ideas due to non-human communication style.
		AI as Information & Fact-Checking Source	Augmented	Convenient, real-time retrieval of domain knowledge; supports and accelerates creative sessions	No direct risks identified; checking for hallucination and false sources

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				without substituting human judgment.	should generally be done.
		Challenging of Ideas	Augmented	Prompts critical reflection through targeted questions; identifies blind spots without supplying replacement solutions; preserves human creative ownership.	No direct risks identified.
Stage 3 Prototyping & Testing of Ideas	*Transform ideas into tangible, testable prototypes; gather feedback to refine concepts.*	Prototyping & Visualization	Automated	Rapid transformation of sketches or text into functional prototypes without design expertise; significant time savings; democratizes prototyping for small teams.	AI-generated outputs frequently inferior to human-made designs; limited usefulness for complex interaction flows.
		Future Scenario Generation	Automated	Provides data-grounded foresight; simulates strategic outcomes; supports future-oriented decision-making under uncertainty.	Speculative nature of futures thinking; risk of overlooking human intuition and non-quantifiable variables.
		AI-based Testing	Augmented	Enables simulated user feedback via AI personas before real-user tests; narrows concept directions early; reduces iteration costs.	AI-based synthetic users cannot replicate real user interaction behavior, especially in app-based testing contexts.

Source: Authors

The distinction between augmentation and automation carries significant managerial weight. Automated applications delegate tasks fully to AI systems and are particularly effective for structured, data-intensive activities such as sentiment analysis or scenario generation. Augmented applications, in contrast, position AI as a collaborative enhancer of human judgment: the AI contributes inputs, suggestions, or analytical support, while the human retains interpretive control and decision-making authority. For startups in particular, choosing the appropriate mode is not a technical decision but a strategic one. Deploying automation where augmentation is warranted risks eroding the human-centered foundation that DT depends on, while under-utilizing automation where it is appropriate squanders the efficiency gains that AI uniquely enables for resource-constrained teams.

Stage 1: Empathizing and Recognition of User Needs

The first stage of the DT process focuses on building a deep understanding of users, their needs, and the broader problem space. AI offers several concrete entry points here. Data clustering, powered by NLP and ML algorithms, enables teams to process large volumes of consumer behavior and feedback data from diverse sources, identifying patterns and structuring the problem space in ways that exceed human analytical capacity (Tschepe, 2024). This application operates in augmentation mode, expanding the team's informational base without replacing human interpretation. Sentiment analysis, by contrast, functions as an automated tool: it computationally processes text from social media, customer feedback, and news sources to determine user attitudes and predict market trends, enabling startups to access customer insights they could not otherwise afford to generate at scale (Hartmann et al., 2023).

Two further AI applications strengthen the empathize. AI-supported questionnaire and interview template creation uses generative AI to design research instruments that minimize bias, improve question clarity, and adapt to specific target groups, thereby improving the quality of subsequent human-led user research (Zou et al., 2024). Quantitative Persona Creation (QPC) applies algorithmic methods to derive statistically representative user archetypes from large datasets, offering a data-driven alternative to small-sample qualitative personas that many startups rely on by default (Aoyama, 2005; Brickey et al., 2012). Interview participants emphasized the value of these tools for early-stage user research, while consistently cautioning that data quality and representativeness remain critical constraints: AI-generated insights are only as reliable as the underlying data.

Stage 2: Collecting and Generating of Ideas

At the ideation stage, AI contributes in multiple ways that expand and structure the creative process. AI-based ideation uses generative models to produce continuous, uninhibited flows of ideas during brainstorming sessions, mitigating social inhibition and production blocking in group settings (Bouschery et al., 2024). Research shows that hybrid human-AI brainstorming groups generate both more and more creative ideas than purely human teams (Bouschery et al., 2024), with LLMs performing particularly well in divergent thinking tasks (Joosten et al., 2024). Computational co-creation extends this dynamic through structured turn-taking between human and AI agents, enabling teams to explore broader design solution spaces and iterate more rapidly (Pescher et al., 2025).

Additional applications serve more targeted roles. Using AI can function as an information and fact-checking source, enabling rapid retrieval of relevant knowledge during creative sessions without replacing human judgment. Similarly, AI can be used to challenge ideas by prompting critical reflection and identifying blind spots without directly supplying alternative solutions. Notably, most applications in this stage operate in augmentation mode. Interview participants highlighted this as especially relevant for startups, which are prone to echo-chamber thinking in early-stage development. They further suggest human-led ideation should precede AI involvement, as early reliance on AI risks limiting depth of thinking, reducing team ownership of ideas, and weakening intrinsic motivation.

Stage 3: Prototyping and Testing of Ideas

In the third stage, AI offers some of the most immediate and tangible efficiency. AI-assisted prototyping and visualization tools transform textual or sketch-based descriptions into functional prototypes without requiring design or coding expertise, enabling startup teams to rapidly externalize and test ideas that would previously have required specialist skills or outsourcing (Bilgram & Laarmann, 2023). Interview participants reported substantial time savings, with tasks previously requiring days of design work completed within hours and resulting prototypes receiving positive market feedback.

AI-based future scenario generation enables startups to simulate potential outcomes of concepts using data-driven foresight, supporting decision-making under uncertainty (Tschepe, 2024). AI-based testing complements this by allowing teams to gather initial simulated user feedback through AI personas before conducting resource-intensive real-user tests, thereby reducing iteration costs. However, participants also noted limitations: AI-generated images and logos often fall short of human quality, and synthetic users cannot fully replicate the real user behaviour in app-based testing contexts.

Across all three stages, a consistent pattern emerges: AI generates the highest value when deployed as an accelerator and expander of human cognitive capacity, rather than as a replacement for it. The distinction between augmentation and automation is therefore not merely technical but managerial, and its effective application depends on the nature and sensitivity of the task.

5 Critical Boundary Conditions Identified

The framework presented in the previous section maps where AI can accelerate and augment the DT process for startups. As introduced earlier, the effectiveness of AI integration is not unconditional. The findings reveal two boundary conditions that consistently emerge from both the literature and the interview data as decisive for whether AI deployment in DT generates value or undermines it: the preservation of empathy and human-centeredness, and the quality of data on which AI applications rely.

Preservation of Empathy and Human-Centeredness

Design Thinking is, at its core, a human-centered discipline. Empathy is not merely one of its principles but its animating logic: without a deep, lived understanding of user needs, neither the problem definition nor the solution space can be reliably grounded (Brown, 2008; Liedtka, 2014). The interview findings underscore this with particular force. Participants consistently emphasized that AI cannot substitute for direct human interaction in the empathize stage, viewing AI-generated personas as a useful supplement rather than a replacement for real user encounters. This scepticism toward full AI substitution in empathy-building tasks is not merely a preference but reflects DT's methodological commitment to human insight.

A dimension that the existing literature largely overlooks, but that emerged prominently from the interviews, concerns the internal consequences of over-relying on AI in the ideation stage. When teams delegate idea generation too extensively to AI, they risk losing ownership of and identification with the resulting concepts. As one expert participant noted, this erosion of intrinsic motivation can weaken team cohesion precisely when startup teams need to be most unified behind their vision. Given that team disintegration ranks among the most cited causes of startup failure (Olek, 2023), this risk carries direct strategic weight. The implication is clear: AI should enter the ideation process after humans have already invested in developing and internalizing the problem space, not before.

More broadly, participants framed AI's role across all stages as that of a sparring partner or co-pilot, never as the primary driver of creative or empathic work. This positioning aligns with the augmentation paradigm described by Füller et al. (2024): the goal is to keep human judgment and emotional engagement at the center, while AI expands the informational and generative capacity of the team.

Data Quality

The second critical boundary condition concerns the quality of data on which AI applications depend. Across the empathize and ideation stages in particular, the value of AI outputs is directly contingent on the representativeness, authenticity, and relevance of the data fed into the system. Interview participants raised specific concerns about the reliability of social media data, the risk of AI-generated reviews corrupting training inputs, and the danger that small or unrepresentative datasets produce personas and sentiment analyses that do not reflect actual user populations (Berg et al., 2018). These are not theoretical concerns but practical constraints that startups, with their typically limited early-stage data volumes, face acutely.

The literature highlights an additional dimension that practitioners did not raise directly: the ethical risk of data-caused bias. When AI systems trained on non-representative data are used to define user needs or segment target groups, minority perspectives and behavioral outliers may be systematically excluded (Ray, 2023). For startups developing products for diverse user populations, this exclusion carries both ethical and commercial consequences. The combined view from interviews and literature thus suggests a clear operating principle: AI-generated insights in the DT process should be treated as hypotheses to be validated through human-led research, not as conclusions to be acted upon directly.

Together, these two boundary conditions define the governance layer that must accompany any framework for AI integration in DT. Technical capability alone does not determine the value of AI in innovation processes; it is the conditions under which that capability is deployed that ultimately determine whether AI accelerates innovation or distorts it.

6 Discussion and Implications

Theoretical Contribution

This paper addresses a clearly identified gap at the intersection of three fields that have each received substantial scholarly attention individually – AI, Design Thinking, and startup innovation – by developing an empirically grounded framework for integrating AI into the DT process in resource-constrained startup contexts. The findings extend prior work on human-AI collaboration by introducing a team cohesion dimension. While research exists on AI in general innovation management (Füller et al., 2024; Tekic & Füller, 2023) and on DT as a methodology for human-centered problem-solving (Sreenivasan & Suresh, 2024; Cai et al., 2023), no prior work has provided an empirically grounded framework that operationalizes AI integration specifically within the DT process of resource-constrained startups.

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Specifically, the paper contributes (1) an empirically grounded framework that maps AI applications across DT stages, (2) the identification of boundary conditions that shape the effectiveness of AI integration, and (3) insights into the team-level implications of AI use in early-stage innovation processes.

Beyond closing the gap, the study contributes a further theoretical insight that is absent from the existing literature: the internal team dimension of AI integration in DT. The finding that over-reliance on AI in ideation can erode team ownership, reduce intrinsic motivation, and ultimately threaten startup team cohesion adds a human-organizational perspective to a discourse that has largely focused on efficiency and output quality. This finding reframes AI integration not only as a process design challenge but as a leadership and team management challenge for startup founders.

The augmentation-automation distinction embedded in the framework also constitutes a theoretical contribution. Rather than treating AI as a uniform capability, the framework systematically differentiates between applications that enhance human judgment and those that replace specific task outputs entirely. This granular mapping provides a conceptual tool for researchers studying human-AI collaboration in creative and innovation contexts more broadly.

Practical Implications

For startup founders and innovation managers, the framework offers concrete, stage-specific guidance for embedding AI into DT workflows. In the empathize stage, AI tools for data clustering, sentiment analysis, and quantitative persona creation can dramatically reduce the time and expertise required to generate user insights, directly addressing the resource constraints that limit startup innovation capacity. In the ideation stage, AI is most valuably deployed as a challenging and fact-checking partner, deployed after initial human ideation rather than before it, to preserve team ownership and creative depth. In the prototyping and testing stage, generative AI tools offer the most immediate democratization effect, enabling startup teams without design expertise to rapidly externalize and test concepts at a fraction of traditional costs.

For corporate entrepreneurship units and innovation managers in larger organizations working with or alongside startups, the framework provides a transferable reference for structuring AI-enabled innovation processes that maintain human-centered principles under operational pressure.

Limitations and Future Research

This study has three principal limitations that future research should address. First, the study is based on a small, purposefully selected sample, which limits the generalizability of the findings. Larger-scale quantitative studies or comparative case research across startup sectors and geographies would strengthen the empirical foundation of the framework. Second, the framework has not yet been empirically tested in real-world startup settings. Implementation studies using key performance indicators or controlled design sprint observations would provide the validation necessary to assess its practical effectiveness and identify refinements. Third, the study does not address the organizational capabilities, technological infrastructure, or founder competencies required for successful

AI integration. Future research into these prerequisites would complement the framework and give startups more complete guidance on building toward AI-enabled DT practice.

References and Notes

Aminova, M. and Marchi, E. (2021) 'The role of innovation on start-up failure vs. its success', *International Journal of Business Ethics and Governance*, 4(1), pp. 41–72.

Aoyama, M. (2005) 'Persona-and-scenario based requirements engineering for software embedded in digital consumer products', *Proceedings of the 13th IEEE International Conference on Requirements Engineering*, pp. 85–94.

Arcuri, M. C., Russo, I. and Gandolfi, G. (2024) 'Productivity of innovation: the effect of innovativeness on start-up survival', *The Journal of Technology Transfer*. Available at: https://doi.org/10.1007/s10961-024-10069-7.

Baumeister, R. F. and Leary, M. R. (1997) 'Writing narrative literature reviews', *Review of General Psychology*, 1(3), pp. 311–320.

Berg, V., Birkeland, J., Pappas, I. O. and Jaccheri, L. (2018) 'The role of data analytics in startup companies: exploring challenges and barriers', *Lecture Notes in Computer Science*, pp. 205–216.

Bilgram, V. and Laarmann, F. (2023) 'Accelerating innovation with generative AI: AI-augmented digital prototyping and innovation methods', *IEEE Engineering Management Review*, 51(2), pp. 18–25.

Bouschery, S. G., Blazevic, V. and Piller, F. T. (2024) 'Artificial intelligence-augmented brainstorming: how humans and AI beat humans alone', *Social Science Research Network*. Available at: https://doi.org/10.2139/ssrn.4724068.

Braun, V. and Clarke, V. (2006) 'Using thematic analysis in psychology', *Qualitative Research in Psychology*, 3(2), pp. 77–101.

Braun, V. and Clarke, V. (2024) 'Supporting best practice in reflexive thematic analysis reporting in Palliative Medicine: a review of published research and introduction to the Reflexive Thematic Analysis Reporting Guidelines (RTARG)', *Palliative Medicine*, 38(6), pp. 608–616.

Brickey, J., Walczak, S. and Burgess, T. (2012) 'Comparing semi-automated clustering methods for persona development', *IEEE Transactions on Software Engineering*, 38(3), pp. 537–546.

Brown, T. (2008) 'Design thinking', *Harvard Business Review*, 86(6), pp. 84–92.

Brown, T. and Katz, B. (2011) 'Change by design', *Journal of Product Innovation Management*, 28(3), pp. 381–383.

Cai, Y., Lin, J. and Zhang, R. (2023) 'When and how to implement design thinking in the innovation process: a longitudinal case study', *Technovation*, 126, p. 102816.

Davenport, T. H. and Kirby, J. (2016) *Only Humans Need Apply: Winners and Losers in the Age of Smart Machines*. New York: Harper Business.

Eurostat (2024) *Use of Artificial Intelligence in Enterprises*. Available at: https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Use_of_artificial_intelligence_in_enterprises (Accessed: 24 July 2024).

Füller, J., Tekic, Z. and Hutter, K. (2024) 'Rethinking innovation management: how AI is changing the way we innovate', *The Journal of Applied Behavioral Science*, 60(4), pp. 603–612.

Hartmann, J., Heitmann, M., Siebert, C. and Schamp, C. (2023) 'More than a feeling: accuracy and application of sentiment analysis', *International Journal of Research in Marketing*, 40(1), pp. 75–87.

Johnson, P. C., Laurell, C., Ots, M. and Sandström, C. (2022) 'Digital innovation and the effects of artificial intelligence on firms' research and development: automation or augmentation, exploration or exploitation?', *Technological Forecasting and Social Change*, 179, p. 121636.

Joosten, J., Bilgram, V., Hahn, A. and Totzek, D. (2024) 'Comparing the ideation quality of humans with generative artificial intelligence', *IEEE Engineering Management Review*, 52(2), pp. 153–164.

Liedtka, J. (2014) 'Perspective: linking design thinking with innovation outcomes through cognitive bias reduction', *Journal of Product Innovation Management*, 32(6), pp. 925–938.

Loderer, M. B. (2023) *Der Einfluss von Design Thinking Praktiken im Unternehmens- und Kooperationskontext: Eine empirische Untersuchung*. PhD dissertation, Technische Universität Darmstadt.

Madrid-Guijarro, A., Garcia, D. and Van Auken, H. (2009) 'Barriers to innovation among Spanish manufacturing SMEs', *Journal of Small Business Management*, 47(4), pp. 465–488.

McElheran, K., Li, J. F., Brynjolfsson, E., Kroff, Z., Dinlersoz, E., Foster, L. and Zolas, N. J. (2023) 'AI adoption in America: who, what, and where', *Social Science Research Network*, pp. 375–415.

Olek, K. (2023) 'Startups and lean startup approach in building innovative companies creating unique market values: theoretical considerations', *Procedia Computer Science*, 225, pp. 3745–3753.

Patton, M. Q. (2015) *Qualitative Research and Evaluation Methods*. 4th edn. Thousand Oaks: SAGE Publications.

Pescher, C., Bell, J. J., Tellis, G. J. and Füller, J. (2025) 'The role of artificial intelligence in the ideation process', *Journal of Product Innovation Management*. Available at: https://doi.org/10.1111/jpim.12791.

Plattner, H., Meinel, C. and Leifer, L. (eds.) (2011) *Design Thinking: Understand – Improve – Apply*. Berlin: Springer.

Ray, P. P. (2023) 'ChatGPT: a comprehensive review on background, applications, key challenges, bias, ethics, limitations and future scope', *Internet of Things and Cyber-Physical Systems*, 3, pp. 121–154.

Ries, E. (2011) *The Lean Startup: How Today's Entrepreneurs Use Continuous Innovation to Create Radically Successful Businesses*. New York: Crown Business.

Saleh, Y., Abu Talib, M., Nasir, Q. and Dakalbab, F. (2025) 'Evaluating large language models: a systematic review of efficiency, applications, and future directions', *Frontiers in Computer Science*, 7, p. 1523699.

Saunders, M. N. K., Lewis, P. and Thornhill, A. (2019) *Research Methods for Business Students*. 8th edn. Harlow: Pearson Education.

Sheppard, B., Kouyoumjian, G., Sarrazin, H. and Dore, F. (2018) 'The business value of design', *McKinsey Quarterly*, October. Available at: https://www.mckinsey.com/capabilities/mckinsey-design/our-insights/the-business-value-of-design (Accessed: 25 August 2024).

Simon, H. A. (1969) *The Sciences of the Artificial*. Cambridge: MIT Press.

Sreenivasan, A. and Suresh, M. (2024) 'Design thinking and artificial intelligence: a systematic literature review exploring synergies', *International Journal of Innovation Studies*. Available at: https://doi.org/10.1016/j.ijis.2024.05.001.

Tekic, Z. and Füller, J. (2023) 'Managing innovation in the era of AI', *Technology in Society*, 73, p. 102254.

Tschepe, S. (2024) *AI-Enhanced Design Thinking*. Potsdam: HPI D-school.

Zou, Z., Mubin, O., Alnajjar, F. and Ali, L. (2024) 'A pilot study of measuring emotional response and perception of LLM-generated questionnaire and human-generated questionnaires', *Scientific Reports*, 14(1). Available at: https://doi.org/10.1038/s41598-024-53255-1.