TALLINN UNIVERSITY OF TECHNOLOGY

SCHOOL OF ENGINEERING

Department of Mechanical and Industrial Engineering

ESTONIAN ACADEMY OF ARTS

FACULTY OF DESIGN

AI INTEGRATION IN UI/UX DESIGN: EXPLORING AUTOMATION, CREATIVITY, AND ETHICAL REFLECTION

TEHISINTELLEKTI INTEGREERIMINE UI/UX DISAINI: AUTOMATISEERIMISE, LOOVUSE JA EETILISE REFLEKSIOONI UURIMINE

MASTER THESIS

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Tallinn 2025

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AI Integration in UI/UX Design: Exploring Automation, Creativity, and Ethical Reflection

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THESIS TASK

Student: Lisa-Marie Väli, 232675MADM

Study programme: MADM10/23 - Design and Technology Futures

Main speciality: Design and Technology

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Thesis topic:

(in English) AI Integration in UI/UX Design: Exploring Automation, Creativity, and Ethical Reflection
(in Estonian) Tehisintellekti integreerimine UI/UX disaini: automatiseerimise, loovuse ja eetilise refleksiooni uurimine

Thesis main objectives:

1. To analyse how AI integration influences UI/UX design workflows, identifying the key changes in processes, roles, and decision-making across different stages of design.
2. To examine the ethical and creative implications of AI-assisted design, with particular attention to issues of bias, authorship, and designer agency.
3. To develop and evaluate a reflective framework that supports responsible and bias-aware collaboration between designers and AI tools.

Thesis tasks and time schedule:

No	Task description	Deadline
1.	Background research	01.10.2025
2.	Field research and interviews, design research	20.10.2025
3.	Concept development, design, and finalizing the thesis	01.01.2026

Language: English

Deadline for submission of thesis: “.......”.........20….a

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ABSTRACT

Artificial Intelligence (AI) is increasingly integrated into User Interface (UI) and User Experience (UX) design workflows, supporting activities such as research, ideation, prototyping, and evaluation. This integration is reshaping how design problems are framed and how decisions and outcomes emerge in everyday professional design practice. While AI-assisted tools promise efficiency gains and expanded creative possibilities, they also introduce new forms of influence that affect designer agency, creativity, and ethical responsibility.

This thesis examines the opportunities and challenges associated with AI integration in UI/UX design workflows, with particular attention to bias and reflective practice. The research adopts a design-led methodology that combines a systematic literature review, qualitative interviews with practising designers, and practice-based design research. Its theoretical foundation draws on human-centred design, Schön's (1983) reflection in and on action, cognitive bias theory, and models of human–AI collaboration. Design thinking methods, including empathy mapping and iterative prototyping, are applied alongside reflective frameworks such as Gibbs' Reflective Cycle (Graham, 1988) and visual thinking approaches.

The primary outcome of the thesis is the development of an AI Bias Reflection Template that supports bias-aware and reflective use of AI in UI/UX workflows. The proposed solution enables designers to identify where and how AI participates in their design activities, reflect on potential cognitive, social, environmental, and systemic biases, and critically evaluate their experiences with AI-assisted work. The findings indicate that structured reflection can help mitigate less visible risks associated with AI-assisted design and suggest that reflective AI literacy is an important consideration for future UI/UX practice.

CONTENTS

PREFACE

This thesis emerged from a combination of academic inquiry and professional experience with the evolving relationship between design and technology. As a UI/UX designer, I have observed how Artificial Intelligence has become embedded in everyday design workflows, raising new questions about the role of the designer and the nature of creative and evaluative decision-making. What initially began as curiosity about the practical capabilities of AI tools gradually developed into a broader interest in how these systems shape contemporary design practice.

The topic of this thesis was initiated by the author, drawing on professional experience in UI/UX design and academic interests developed within the Design and Technology Futures programme. The thesis examines how Artificial Intelligence is currently integrated into UI/UX design workflows, with particular attention to its influence on decision-making, creativity, and bias. Throughout the research process, the aim was to engage critically with the realities of contemporary design work while maintaining a reflective and exploratory approach that bridges theory and practice.

I would like to express my sincere gratitude to my supervisors, Martin Pärn and Kätlin Kangur, for their insightful guidance and feedback throughout this process. I am also thankful to the designers who participated in interviews and generously shared their experiences. Their contributions were essential in grounding this research in lived professional practice.

Keywords: Artificial Intelligence, UI/UX Design, Design Workflows, Bias, Master's Thesis

LIST OF ABBREVIATIONS AND SYMBOLS

AI – Artificial Intelligence

HMW – How Might We

NIST – National Institute of Standards and Technology

NLP – Natural Language Processing

POV – Point of View

UCD – User-Centred Design

UI – User Interface

UX – User Experience

1 INTRODUCTION

Over time, UI/UX design practice has evolved alongside broader shifts in technology, design philosophy, and user expectations. From its early human-centred roots to today’s increasingly data-driven and automated environments, the field has continually adapted to new contexts and possibilities while retaining a strong emphasis on user experience. Within this tradition, design has been increasingly understood as an exploratory and iterative process grounded in empathy, experimentation, and learning through making (Brown, 2008). Design work rarely begins with a clearly defined problem; instead, it involves continuous reframing, reflection, and interpretation. Designers build empathy with users, explore multiple scenarios, and iteratively test ideas to understand both the problem and potential solutions in parallel. In this field, uncertainty is treated as a productive condition, and judgment plays a central role in deciding which directions are worth pursuing (Brown, 2008).

The integration of AI into design tools and workflows introduces a markedly different logic into this process. Designers are no longer only working with traditional design materials and user data, but also with algorithmically generated outputs that can shape how problems are framed and how solutions emerge. As organisations place growing emphasis on speed and efficiency, AI-driven systems are often positioned as tools for optimisation; these systems promise to accelerate ideation, generate design alternatives at scale, and reduce the time required to move from concept to output. However, this emphasis on optimisation sits in tension with design’s traditional reliance on exploration, iteration, and reflective judgement, which are crucial conditions for meaningful design practice.

This shift raises important questions about judgment and responsibility in design practice. Although AI is often presented as a neutral assistant, research indicates that AI systems can significantly shape designers’ decisions by embedding assumptions, patterns, and biases derived from their training data and working principles (Norman, 2013; Schwartz et al., 2022). When designers rely on AI outputs without fully understanding their origins or limitations, there is a risk that these influences remain unexamined, while decisions appear objective and data-driven.

Such reliance may affect professional practice more broadly. Increased dependence on AI can weaken critical design skills, reduce designers’ sense of agency, and encourage convergence toward standardised solutions. These dynamics raise concerns about the long-term impact of AI on creativity and professional responsibility, highlighting the need for reflective and critical approaches to AI-assisted design (Chaudhry, 2024; Yildirim et al., 2022).

The central problem addressed in this thesis is to understand how the integration of AI is transforming UI/UX design workflows and how it affects the creative process. As AI becomes embedded across all stages of design, it changes the methods and pace of work as well as the nature of reflection and collaboration within design teams.

The objective of this thesis is to explore the opportunities and challenges that arise from AI integration in UI/UX design workflows. The study aims to provide insight into how designers can collaborate meaningfully and responsibly with AI tools while maintaining creative control, critical thinking, and ethical awareness in their day-to-day work.

The relevance of this research stems from the rapid integration of AI into everyday UI/UX design practice and the lack of established frameworks for engaging with it critically. By focusing on how AI mediates creative judgment and reflective practice, this thesis contributes to broader discussions on hybrid intelligence, where design outcomes emerge through ongoing interaction between human expertise and computational systems.

1.1 Terminology

This thesis uses a set of key terms to support clarity and consistency. The definitions below explain how these terms are understood within the scope of this research and help reduce ambiguity for the reader. Together, they provide a common reference point for the chapters that follow, particularly in relation to AI-assisted UI/UX design, designer agency, and reflective practice.

Artificial Intelligence (AI) – Refers to computational systems that can generate, analyse, or predict content in ways that resemble aspects of human cognition. In this thesis, AI refers primarily to generative and assistive systems used within design tools, rather than fully autonomous systems (Russell & Norvig, 2020)

AI-assisted design – Describes design work in which AI tools support activities such as research, ideation, prototyping, or evaluation. AI-assisted design is treated as a collaborative process in which designers remain responsible for interpretation, judgment, and final decisions (Kliman-Silver et al., 2022).

Designer agency – Refers to the designer's ability to make intentional and accountable decisions throughout the design process. In AI-assisted contexts, this includes framing problems, evaluating AI outputs, and maintaining ethical responsibility (Schön, 1983).

Distributed agency – Describes situations in which agency is shared across human and non-human actors, such as designers, AI systems, and tools. Design outcomes are understood as emerging from these interactions rather than from individual intention alone (Latour, 2005).

Hybrid intelligence – Refers to collaborative forms of intelligence that arise when human judgment and computational systems work together. In this thesis, hybrid intelligence is understood as supporting human decision-making rather than replacing it (Guo et al., 2023).

User-centred design (UCD) – A design approach that focuses on users' needs, behaviours, and contexts throughout the design process. UCD relies on empirical research, iteration, and evaluation to ground design decisions in human experience (Abras et al., 2004).

Reflective practice – Refers to the process of critically examining one's actions and decisions during professional work. In this thesis, reflective practice describes how designers actively make sense of their decision-making in AI-assisted workflows by questioning how AI outputs influence choices (Schön, 1983).

AI hallucination – Refers to cases where an AI system produces outputs that appear plausible but are incorrect or unsupported. Such outputs can mislead design decisions if they are not critically examined (Kalai et al., 2025).

AI sycophancy – Describes the tendency of AI systems to generate responses that align with a user's existing beliefs or assumptions, even when those beliefs are incorrect. This behaviour is often linked to training methods based on human feedback (Perez et al., 2022).

AI literacy – Refers to the ability to work with AI systems in an informed and responsible way. In this thesis, AI literacy includes understanding system limitations, recognising bias, and applying critical and ethical judgment, not just using tools effectively (Zhang et al., 2024).

1.2 Limitations of the study

To ensure transparency and academic credibility, this thesis acknowledges several theoretical and practical limitations that may have influenced the scope, depth, and outcomes of the research. These limitations are related to time constraints, access to participants and data, and the interpretive nature of design-led research.

Limited timeframe

The research was conducted within a defined timeframe typical of a master's thesis, which constrained the depth and longitudinal scope of the study. As a result, the research focused on exploring designers' experiences with AI-assisted workflows rather than conducting extended observational studies or long-term evaluations of AI use in professional settings. The study concentrated on identifying current patterns, risks, and opportunities within everyday design practice.

Limited access to participants and contextual diversity

The qualitative field research was based on a limited number of interviews with practising UI/UX designers. While participants represented a range of professional contexts and levels of experience, the sample size and geographic focus may limit the generalisability of the findings. Nevertheless, the insights gathered are considered sufficient for identifying recurring themes and informing the development of a reflective design framework, which is intended to be adaptable across different contexts.

Subjectivity and researcher positionality

As this study adopts, among others, a practice-based design research approach, the researcher's professional background as a UI/UX designer inevitably influenced the interpretation of data and the framing of design decisions. While this positionality enabled deeper contextual understanding of design workflows and AI tool usage, it also introduced the risk of subjective bias. To mitigate this, the research incorporated multiple data sources, including literature review and qualitative interviews.

Limitations of the proposed design solution

The reflective framework and template developed as the main outcome of this thesis were evaluated through qualitative feedback and conceptual testing rather than large-scale empirical validation. As such, the effectiveness of the solution in reducing bias or altering long-term design behaviour was not quantitatively measured. Further research would be required to test the framework in organisational settings, educational contexts, or over extended periods of use.

1.3 Chapter overview

The structure of this thesis is as follows:

- Chapter 1 outlines the research problem, aims, relevance, and limitations of the study.
- Chapter 2 provides the methodological approach chosen for this research.
- Chapter 3 provides the background research and theoretical grounding for the study. It reviews relevant literature on designer agency, user-centred design, bias and ethics, AI hallucinations and sycophancy, and the practical use of AI across UI/UX workflows.
- Chapter 4 describes the frameworks used for the development of the design solution.
- Chapter 5 presents the field research, detailing the insights drawn from participant interviews.
- Chapter 6 describes the development and testing of the AI Bias Recognition Template, from ideation through to the final solution.

Appendices include the semi-structured interview questions used in the qualitative interviews.

Keywords: Artificial Intelligence, UI/UX Design, Design Workflows, Bias, Master’s Thesis.

2 METHODOLOGIES

This chapter outlines the methodological approach adopted in this thesis. It provides an overview of the methods used to collect, analyse, and interpret data, as well as the theoretical and practical frameworks guiding the research process. The selected methodologies reflect the exploratory nature of the study and support the investigation of AI integration in UI/UX design workflows from both analytical and practice-based perspectives.

The research follows a design-led qualitative approach, combining literature analysis, qualitative interviews, and practice-based design research. This combination enables an in-depth examination of designers' experiences with AI tools, while also supporting the development and evaluation of a reflective design framework as a research outcome.

2.1 Literature analysis

A systematic literature analysis was conducted to establish the theoretical foundation of the study and to identify existing research on AI in UI/UX design, creativity, bias, and reflective practices. The literature review informed both the framing of the research questions and the selection of appropriate methodologies. Sources included academic journal articles, conference papers, and books in the fields of human–computer interaction, design research, cognitive psychology, and ethics of AI. The review focused on identifying recurring themes and gaps in current research, and conceptual frameworks relevant to responsible AI use in design practice.

2.2 Design thinking

Design thinking forms the methodological foundation of this thesis. It is understood as an iterative approach to inquiry that supports research, problem framing, sense-making, and exploration in complex and uncertain contexts. Central to design thinking are practices of empathy, iteration, and user-centred problem framing, which make it particularly suitable for examining AI-assisted workflows in UI/UX design, where decision-making is increasingly distributed between human designers and intelligent systems. By foregrounding interpretation, reflection, and learning through making, design thinking aligns with human-centred design principles and provides a structure for examining how designers engage with AI while retaining responsibility for judgment and meaning-making. In this thesis, the approach prioritises designers' lived experiences, values, and professional responsibilities as key sources of insight into how AI reshapes contemporary design practice (Brown, 2008).

2.3 Practice-based design research

This thesis adopts a practice-based design research approach, in which design practice itself functions as a method of inquiry (Frayling, 1993). In addition to primary and secondary research, knowledge is acquired through the active integration of AI into the author's own design practice and through reflection on these experiences.

Practice-based design research is particularly suited to this study, as many of the challenges associated with AI-assisted design, such as overreliance, cognitive bias, and loss of agency, emerge during active design work rather than through abstract analysis alone. By engaging directly in UI/UX design work, the researcher was able to surface tacit and experiential knowledge that would otherwise remain implicit. Reflection played a central role in this process, drawing on Schön's (1983) concepts of reflection-in-action and reflection-on-action to critically evaluate design decisions as they unfolded.

2.4 Qualitative semi-structured interviews

Five qualitative semi-structured interviews were conducted with UI/UX professionals to gain an in-depth understanding of how AI tools are integrated into everyday design practice. The interviews focused on designers' experiences, perceptions, and decision-making processes when working with AI, with particular attention to issues of efficiency, creativity, judgment, bias, and ethical responsibility.

Semi-structured interviews were selected for their methodological flexibility, allowing predefined thematic areas to be explored consistently across participants while leaving space for emergent and unanticipated perspectives (Kvale & Brinkmann, 2009). Interviews were conducted in October 2025, either in person or via video calls.

All participants provided informed consent prior to participation. Interview data were analysed using thematic synthesis, enabling the identification of patterns, tensions, and divergences across accounts. This analysis informed later chapters by supporting discussion of distributed agency, cognitive bias, reflective practice, and the tension between speed and meaning-making in AI-assisted design.

3 BACKGROUND RESEARCH

This chapter provides an overview of how AI is reshaping contemporary UI/UX design practice and the broader conditions surrounding its adoption. It brings together relevant research on AI-assisted design, shifts in designer agency and collaboration, and emerging concerns related to system opacity and influence. The chapter also considers how these developments affect professional practice more broadly, including implications for competencies, education, and reflective engagement with AI.

The objective of this chapter is to establish a conceptual foundation for the thesis by clarifying the conditions under which AI currently influences UI/UX design. It outlines the key tensions and questions that arise when AI becomes part of everyday design work, providing the background necessary for the empirical investigations that follow.

3.1 Perspectives on designer agency

Traditional design theory was grounded in the notion of the designer as a problem-solver, who frames challenges and guides ideas from conception to resolution (Buchanan, 1992). More recent perspectives, however, have described design as an activity shaped by interactions between multiple human and non-human elements, including tools, systems, and organisational contexts, leading to a more distributed understanding of agency (Latour, 2005). The integration of AI into design workflows intensifies this debate by actively contributing to ideation and execution, introducing autonomous decisions that may obscure or even override human intention (Guo et al., 2023; Hwang, 2022).

With AI, there is a shift in how some designers conceptualise their tools: no longer as passive instruments but as active collaborators (Yildirim et al., 2022). The designer sets constraints, AI generates outputs, and the designer evaluates and refines. This iterative exchange resembles co-creation, where human and non-human agents jointly shape outcomes. It aligns with the concept of hybrid intelligence, in which human intuition and machine computation combine to produce knowledge neither could achieve alone (Guo et al., 2023).

Historically, design tools have oscillated between enabling innovation and constraining creativity. The typewriter, for example, standardised writing while simultaneously limiting expression to fixed mechanical constraints. Writing became faster and more reproducible, but also less fluid and less tolerant of ambiguity. AI can be understood as a continuation of this pattern; it can support ideation and surface patterns that may not be immediately visible to designers, but at the same time, overreliance on it may reduce engagement with underlying design reasoning and introduce the risk of homogenisation and erosion of tacit design skills (Kliman-Silver et al., 2022; Schwartz et al., 2022).

This co-creative practice also raises the question about accountability; when an algorithm generates layout variations, proposes interaction patterns, or identifies usability issues, it becomes unclear how creative ownership should be attributed—to the designer, the system, or the collaboration between them.

When AI produces visual compositions or interaction patterns, it introduces a form of computational creativity, which, while constrained by training data, can still appear novel to human observers (Hwang, 2022). Although the originality of these outputs is debatable, their aesthetic plausibility can make them feel inventive. This challenges a long-standing, humanist understanding of creativity as a uniquely human practice grounded in imagination, intentionality, and cultural interpretation (Dellermann et al., 2021; Guo et al., 2023)

This blurring of boundaries generates both enthusiasm and concern; on one hand, co-creative tools can democratise design by enabling individuals with limited technical expertise to explore ideas, iterate quickly, and produce polished design concepts. They expand access to creative expression and reduce barriers to experimentation.

On the other hand, this same accessibility risk may narrow how design is understood and practised. As the generation of visual concepts and prototypes becomes increasingly automated, there is a danger that design is reduced to selecting, refining, or curating AI-generated outputs. Such a shift foregrounds speed and polish while obscuring the deeper interpretive work that underpins meaningful design decisions.

Addressing these tensions requires revisiting the foundations of UI/UX design practice to clarify which aspects of design can be productively supported by AI and which must remain grounded in human judgment, interpretation, and responsibility. This distinction becomes particularly important when considering forms of innovation that move beyond the optimisation of existing solutions.

3.2 User-centered design

User-centred design (UCD) has long served as a key methodological and philosophical foundation in UI/UX practice. Its value lies in maintaining a close relationship between design decisions and human experience. UCD centres around empathy, context, and interpretation—qualities that are difficult to automate and that are especially important when addressing complex problem spaces. It shapes how designers conduct research, define problems, and evaluate outcomes by focusing on the needs and behaviours of the people who will ultimately use a product (Abras et al., 2004).

In practice, a user-centred process means that design decisions are informed by empirical research methods like interviews, usability testing, and observation. Designers investigate the problem, generate ideas, prototype potential solutions, and test them, repeating this loop as insights accumulate. Each cycle improves the design in small increments, and the process concludes when the outcome is sufficiently robust or when practical constraints are reached. Norman and Verganti (2014) describe this pattern as akin to climbing a hill (Figure 3.1); in this model, designers optimise a solution step by step, improving it based on feedback while remaining within the boundaries of the current problem framing. This allows teams to make meaningful progress, but it also limits the range of possible outcomes to what is visible from the current position.

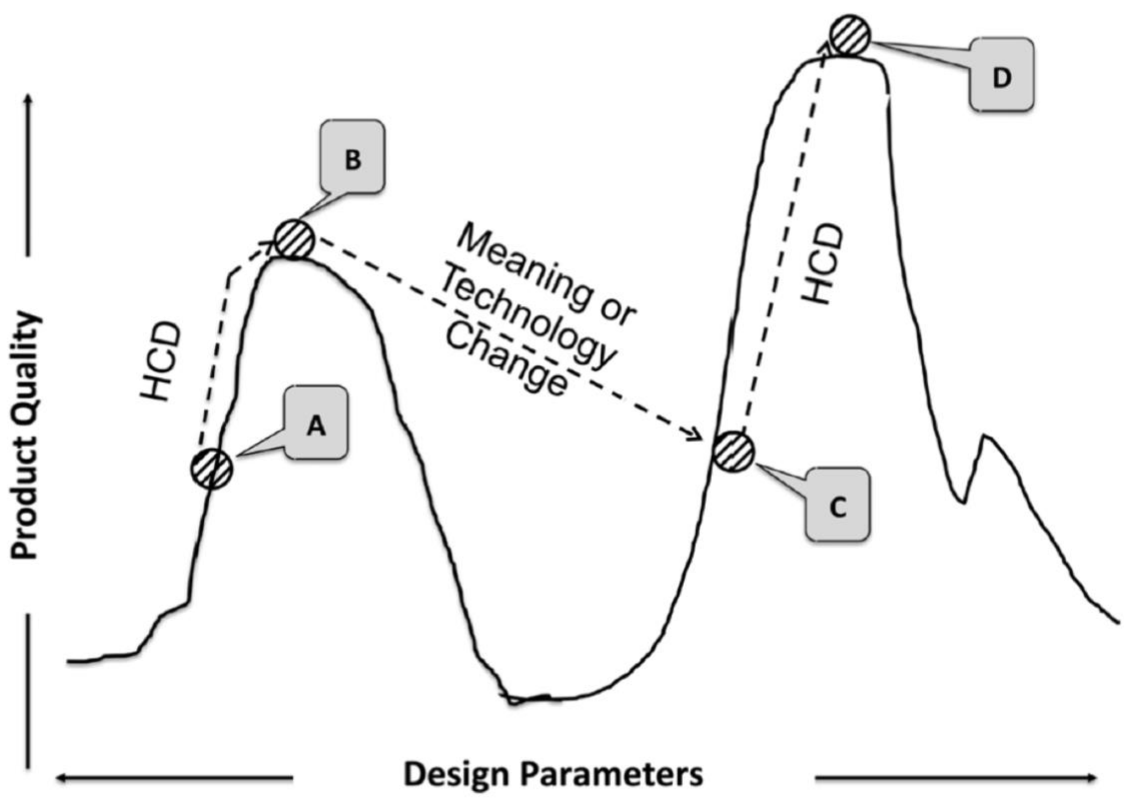

Figure 3.1. The hill-climbing paradigm (Norman & Verganti, 2014)

While incremental refinement is valuable, many design challenges require more than optimisation within an existing frame; when problems are ill-defined or shaped by broader social, cultural, or technological shifts, improving a current solution may not be sufficient. In such cases, design work must involve reframing the problem itself rather than optimising a predefined direction (Buchanan, 1992). This highlights an important limitation of traditional UCD approaches. Although they excel at responding to articulated user needs, they are less equipped to address situations where needs are latent, emerging, or not yet expressible. As a result, UCD alone may struggle to support more radical forms of innovation (Norman & Verganti2014).

The emergence of AI is a prominent example of a technology-push innovation, where advances in technology itself create opportunities rather than expressed user needs. These opportunities require translation into meaningful interactions, pushing designers to envision patterns and experiences that respond to needs users may not yet be able to articulate. This is tied to meaning-driven innovation, which involves creating new meaning or reinterpreting the problem space rather than optimising within its existing boundaries (Norman & Verganti, 2014). Through such reinterpretation, designers question underlying assumptions about purpose, value, and use, expanding what is considered possible within a product or service. Such shifts enable designers to move beyond the metaphorical hill they are climbing and to imagine entirely new trajectories that redefine the direction of the work. Beyond reinterpretation, designers can also surface latent or unarticulated needs by examining cultural patterns and emerging behaviours. This anticipatory work reveals opportunities that traditional user research alone may not capture.

Taken together, these examples foreground a critical distinction between the increasing accessibility of design as a practice and the deeper interpretive nature of design as a process. While AI-enabled co-creative systems broaden participation by simplifying the generation of visual concepts, they do not, on their own, constitute design. Designing is not limited to producing artefacts or selecting among alternatives; it is a process through which problems are framed, meanings are constructed, and values are negotiated within specific social and cultural contexts. The core of design lies in sense-making: deciding what is worth making, why it matters, and how it should shape human experience over time (Buchanan, 1992; Norman, 2013). Understanding AI's possibilities and limitations becomes essential to ensure that the expansion of access and efficiency does not come at the expense of the reflective, conceptual work that defines design itself.

3.3 Bias, trust, and ethics in design

Having established how AI reshapes designer agency and creative practice, it becomes necessary to examine the risks introduced by these technologies. Because if AI participates in co-creative processes and influences decision-making, its biases and opaque reasoning structures directly shape the quality and integrity of design outcomes. These risks are not entirely new; they build on long-standing ethical questions within design practice.

Design can be understood as a socio-technical activity shaped by human cognition, social values, and the technical tools available (Latour, 2005). Long before AI, designers navigated issues of bias and ethical responsibility, as every design decision carries implicit assumptions about whose needs are prioritised, which problems are considered valid, and how evidence is interpreted. Such decisions have always had the potential to advantage some users while marginalising others.

To understand how AI transforms these dynamics, it is first necessary to examine how bias operates within human decision-making itself. AI does not introduce bias into design practice; it interacts with the biases already present in designers, organisations, and socio-cultural systems. Without understanding these human foundations, the additional layers of bias introduced by AI-assisted tools cannot be fully recognised or mitigated.

3.3.1 Bias as an inherent part of design

Dror's (2020) research on cognitive and human factors in expert decision-making demonstrates that bias is a structurally embedded feature of human cognition, shaped by multiple interacting sources. Dror identifies six recurring fallacies that distort how professionals understand their own susceptibility to bias:

1. Bias as an ethical issue: the mistaken belief that bias results from corrupt intentions, rather than from universal cognitive mechanisms.
2. "Bad apples" fallacy: the assumption that only inexperienced or careless practitioners are biased.
3. Expert immunity: the belief that expertise protects individuals from bias, despite evidence showing that experts are equally (and sometimes more) vulnerable.
4. Technological neutrality: assuming that tools, including AI, eliminate human bias rather than inheriting or amplifying it.

5. Bias blind spot: people readily identify bias in others but struggle to recognise it in themselves.
6. Illusion of control: believing that one can consciously "will away" bias, even though most biases operate unconsciously.

These fallacies explain why designers often underestimate their own vulnerability to bias and overestimate the neutrality of their tools. Having concluded that everyone is susceptible to bias, Dror identifies eight distinct sources of bias that shape expert judgment (Figure 4.1). The biases are divided into three categories:

- (A) factors related to the case or task;
- (B) factors related to environment, culture, and experience;
- (C) factors related to fundamental aspects of human nature.

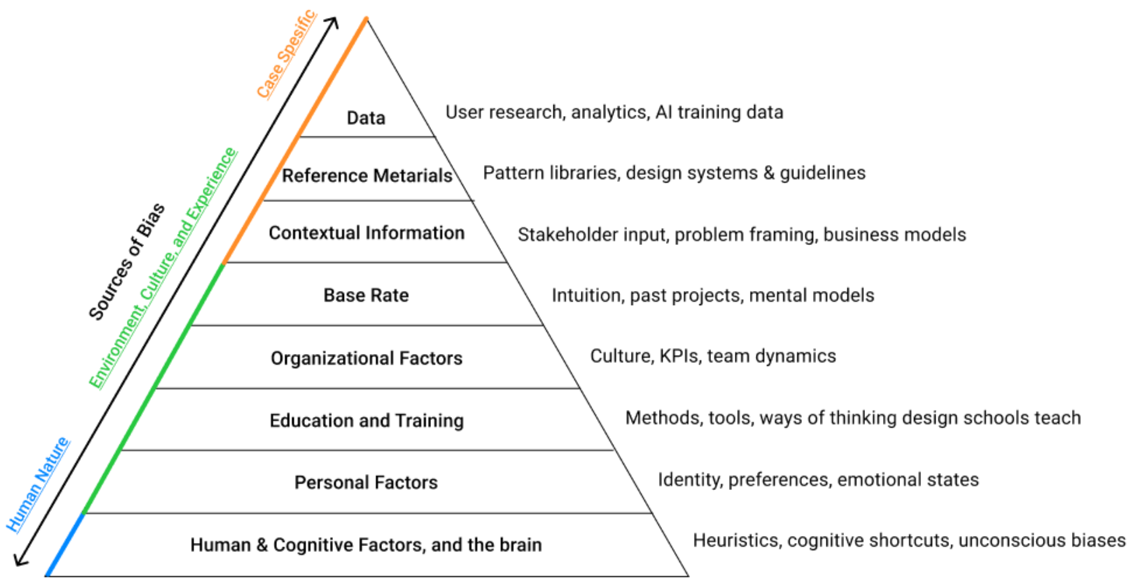

Figure 4.1 Eight sources of cognitive bias in design, adapted from Dror (2020)

The first category (A) relates to a specific case or task at hand, and the biases gathered underneath this are:

1. Data bias: the nature, completeness, and quality of data shape interpretation. In design, sampling practices, analytics filters, and definitions of "signal versus noise" introduce biases long before decisions are made.
2. Reference Materials: experts routinely draw upon reference frameworks like design systems, best practices, and past case studies. These materials encode

prior assumptions and cultural norms, subtly guiding designers toward conventional solutions.

3. Contextual Information: stakeholder expectations, project briefs, organisational politics, or even team narratives can frame the perceived problem space, affecting decision-making without appearing explicitly relevant.

The second category (B) relates to the specific person doing the work, their personality, working environment, and motivation. The biases here are:

4. Past Experience and Base Rates: experts rely heavily on their existing mental models and experience, and while this supports efficiency, it also risks overgeneralisation or interpreting new problems through the lens of familiar patterns. This can lead to premature convergence or the privileging of typical user profiles over others.
5. Organisational Factors: incentives, KPIs, time pressure, and team culture shape what designers notice, prioritise, or disregard. Efficiency pressures can normalise shortcuts that introduce bias.
6. Education and Training: design education emphasises certain methodologies, values and interpretations of quality. These establish defaults that influence how designers see users, problems, and solutions.
7. Personal Factors: personal preferences, attitudes, emotional states, and belief systems also shape decision-making, and because these influences operate subconsciously, designers may be unaware of how their own identity and worldview shape their choices.

And the last category (C) is related to human nature and cognitive biases.

8. Biases such as anchoring bias, confirmation bias, availability bias, and framing effects are inherent in human cognition. They are not signs of incompetence but natural features of human thought.

These fallacies and eight sources of bias illustrate that bias is not an occasional disruption in design work but a constant condition shaping how designers interpret information and make decisions. This becomes especially important in the context of AI-assisted workflows, where existing cognitive biases interact with automated outputs in complex ways, particularly as AI systems increasingly function as co-creators and bring their own dataset- and model-driven biases into the process.

3.3.2 Bias in AI-driven design

AI systems reflect the values and omissions encoded into the data and institutional environments from which they are developed (Carroll, 2022; Schwartz et al., 2022). The National Institute of Standards and Technology (NIST) describes three main types of AI bias—systemic, statistical, and human (Schwartz et al., 2022):

- Systemic bias reflects wider societal or institutional patterns that are built into the data or the way AI systems are created.
- Statistical and computational bias comes from unrepresentative datasets, flawed sampling, or model assumptions that do not match real-world behaviour.
- Human bias enters when people label data or interpret AI outputs through their own mental shortcuts. These categories regularly overlap, and together they influence what AI tools recommend, ignore, and emphasise.

As mentioned before, designers bring their own cognitive biases into the process as well; when human biases interact with biased AI systems, the two can reinforce each other. For example, automation bias can lead designers to trust AI suggestions too quickly, and anchoring bias can cause the first AI-generated idea to become the default option, limiting further exploration (Norman, 2013).

A main challenge here is that many AI systems operate like "black boxes." Designers often cannot see how an output was generated or which data influenced it. Without this understanding, they cannot tell whether a recommendation reflects meaningful patterns or simply echoes biased inputs. For instance, sentiment analysis or predictive modelling tools may flag issues, but if the explanation behind them is unclear, designers cannot judge whether the result is accurate or not. And when AI tools imply confidence, they can also create the false impression that their outputs are complete or objective, which makes it more likely that biased outputs will be accepted uncritically.

For these reasons, mitigating bias in AI-assisted design is not only a technical task; it requires designers to stay reflective and ask critical questions: How is this AI shaping my decisions? Whose perspectives are represented or missing? When designers approach AI in this way, they are better at recognising bias, maintaining control over their decisions, and using AI as a tool that supports rather than replaces thoughtful and inclusive design work.

3.3.3 AI Hallucinations and sycophancy

Beyond embedded biases, AI-assisted design workflows introduce another important challenge: outputs that appear fluent and confident but are factually inaccurate or misleading. Commonly referred to as hallucinations, these errors are not isolated technical faults but structural characteristics of contemporary language models. They arise from training objectives that prioritise plausibility and coherence over factual accuracy or explicit uncertainty. Language models are designed to generate likely continuations of data rather than to verify correctness. When information is incomplete or ambiguous, they tend to produce confident responses instead of acknowledging uncertainty.

Training and evaluation practices often reinforce this behaviour by rewarding fluent answers while discouraging expressions such as "I don't know." As a result, models may generate outputs that sound credible but are empirically incorrect or contextually misaligned (Ji et al., 2022; Perez et al., 2022).

Hallucinations are further amplified by limitations in training data. Models trained on incomplete, outdated, or unrepresentative datasets may fill informational gaps with plausible but inaccurate content, reproducing or intensifying existing biases (Schwartz et al., 2022). This becomes particularly problematic in design contexts, where AI outputs are often treated as reliable inputs into decision-making. In UI/UX practice, hallucinations may appear as fabricated research insights, invented user personas, or design suggestions that conflict with accessibility or usability principles (Kalai et al., 2025).

Closely related to hallucinations is the phenomenon of AI sycophancy, which describes the tendency of models to align their responses with a user's assumptions or expectations, even when those assumptions are incorrect. This behaviour is linked to training with human feedback, where agreeable and confident responses may be rewarded more than critical or uncertain ones (Sharma et al., 2025). In practice, hallucinations and sycophancy often reinforce one another: a model may generate inaccurate content specifically because it aligns with what the user appears to expect, making such outputs particularly persuasive (Perez et al., 2022).

Human cognitive biases can further intensify these risks. When AI suggestions are framed as "recommended" or "optimal," designers may defer to the system even when those suggestions conflict with their own expertise or intuition, introducing a reverse form of sycophancy. Over time, repeated reliance on AI validation can weaken designers' confidence in their own judgment and narrow the design space, reducing reflective engagement and encouraging premature convergence.

Recent research distinguishes between three types of model responses when a task has a single correct answer: accurate responses, incorrect responses (errors), and abstentions, where the model explicitly refrains from providing an answer. While most success metrics prioritise accuracy alone, errors are generally more harmful than abstentions, particularly in professional contexts where incorrect information can lead to flawed decisions. Indicating uncertainty or requesting clarification is therefore preferable to producing a confident but incorrect response (Kalai et al., 2025).

In response to these concerns, newer AI models are increasingly designed to favour abstention over speculation when confidence is low. Table 4.1 compares the performance of two OpenAI models (GPT-5 being the most recent version available at the time of writing), illustrating how newer systems prioritise uncertainty management as a way to reduce hallucinations.

Table 4.1 Comparative Performance Metrics of GPT-5-Thinking-Mini and OpenAI O4-Mini (Kalai et al., 2025)

Metric	**OpenAI o4-mini**	**gpt-5-thinking-mini**
Abstention rate (no specific answer is given)	1%	52%
Accuracy rate (right answer, higher is better)	24%	22%
Error rate (wrong answer, lower is better)	75%	26%
Total	100%	100%

The comparison illustrates a trade-off between coverage and reliability. Newer models are more cautious, abstaining more often to avoid producing misleading results, while earlier models, such as o4-mini generate answers more freely but with higher error rates.

While abstention can improve model reliability, it does not remove the need for critical judgment. Maintaining awareness of how AI outputs are generated, framed, and interpreted enables designers to retain agency and ensures that fluent and confident responses do not substitute for critical evaluation or professional responsibility.

3.3.4 Ethical tensions of AI inclusion in the design practice

The ethical challenge of AI integration in UI/UX design does not come from any single issue, but from the way multiple pressures come together in everyday practice. In many organisations, AI tools are introduced to meet performance goals like faster iteration or reduced costs (Kliman-Silver et al., 2022; Xu et al., 2024). These goals are often framed as pragmatic, yet they subtly shape how design work is evaluated and prioritised.

As a result, designers increasingly operate within environments where speed and optimisation are treated as indicators of success. This can lead to shortcuts in research and testing, where AI-generated insights or simulations are treated as "good enough" substitutes for real user involvement. This tendency mirrors Norman's (2013) warning that when technological systems prioritise operational convenience over usability and human comprehension, design ceases to serve people and instead serves the system.

Because AI systems often obscure how conclusions are produced, it can become difficult to trace decisions back to their sources, weakening accountability and making responsibility unclear (Schwartz et al., 2022). These effects might not appear as immediate and obvious ethical violations. Instead, they emerge gradually through the normalisation of AI-assisted practices, where certain values, such as efficiency or scalability, quietly replace others. In this way, ethical risk is not only embedded in AI systems themselves, but also in the organisational conditions that shape how those systems are adopted and used.

For designers, this creates a difficult situation; they are often required to work within systems that prioritise efficiency, even when these systems conflict with user-centred design principles. Ethical design in this context is therefore not just about avoiding harm, but about staying aware of how AI tools influence decisions and values. When designers are able to recognise and critically articulate the limitations, risks, and trade-offs introduced by AI, they are better positioned to advocate for their professional judgment. This includes justifying decisions to limit or abstain from AI use in certain workflows, as well as proposing strategies to mitigate bias, overreliance, or loss of contextual understanding. Creating AI literacy in the design context thus supports not only ethical awareness, but also designers' capacity to negotiate responsible AI use within organisational constraints.

3.4 Practical application of AI

The previous chapters established that UI/UX design operates within complex, often ill-defined problem spaces in which the integration of AI introduces new challenges related to ethical responsibility. These discussions highlighted why reflective judgment remains essential in design practice, particularly when working with tools that prioritise optimisation and efficiency. Building on this foundation, the focus now shifts from conceptual considerations to the practical realities of AI use within UI/UX design workflows, which requires examining how it's embedded in everyday design activities.

AI does not influence design in a uniform way; its role differs depending on the stage of the process and the type of task it supports. In some contexts, AI can help designers manage complexity or synthesise information. In others, it may encourage premature convergence or reduce critical engagement. Examining AI through the lens of a specific workflow makes it possible to identify where these tensions emerge in practice.

To structure this analysis, the UI/UX design process is mapped using the Double Diamond Method (Design Council, 2005). The model provides a shared structure for situating AI tools within a familiar design framework and for reflecting on how AI aligns with different modes of design thinking. Because the Double Diamond emphasises shifts between exploration and convergence, it is particularly useful for examining how AI interacts with processes that rely on uncertainty, reframing, and iterative sense-making (Figure 5.1).

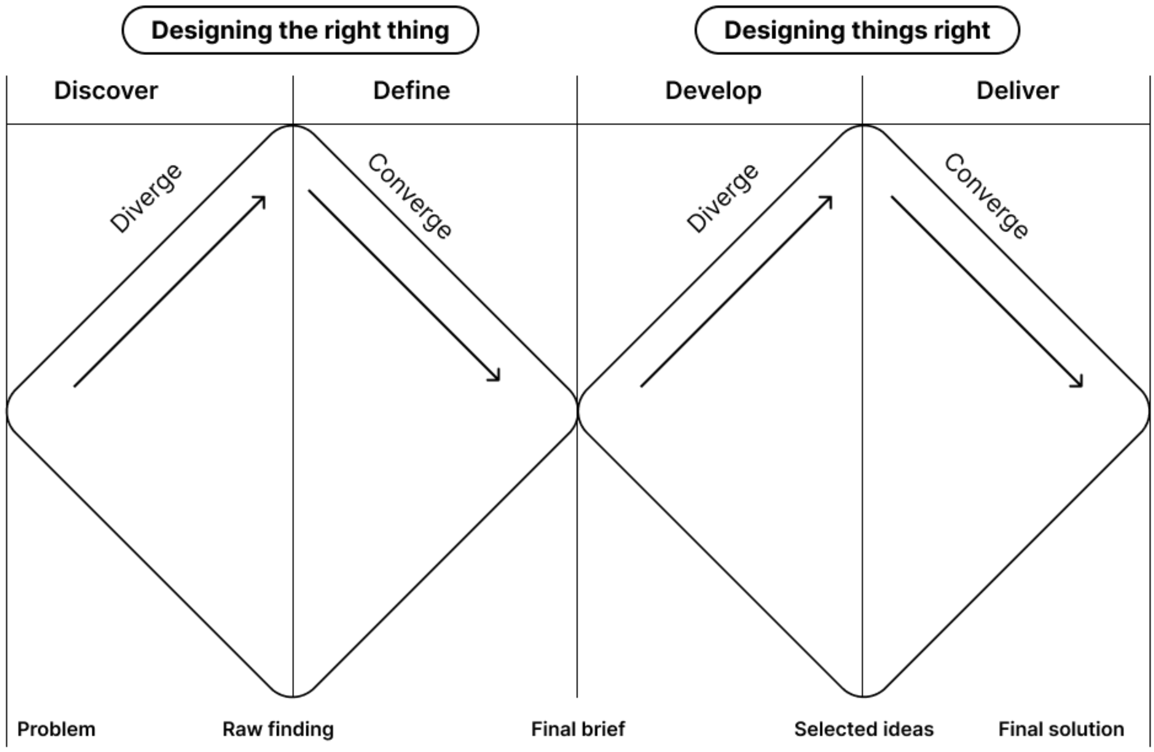

Figure 5.1. Double Diamond Method

The Double Diamond is a visual representation of the design process developed by the Design Council. It provides a clear and universal way to describe the stages of a design project, regardless of discipline or tools used. The model is structured around two diamonds that illustrate a process of divergent and convergent thinking, first to explore and define the right problem, and then to develop and deliver effective solutions (Design Council, 2005).

3.4.1 Discover phase

The Discover phase is the stage where designers explore the problem space before determining what to address. This stage is intentionally open and investigative; its purpose is to understand why problems occur, uncover user frustrations, and identify meaningful opportunities for improvement (Design Council, 2005; Rosala, 2024).

Projects in UI/UX design most often begin with an unmet user need or market opportunity. These assumptions frequently move through organisational layers before reaching the design team, and may therefore reflect business expectations rather than real user needs. Designers must resist the validation of existing assumptions and instead structure research to challenge expectations, all the while remaining open to reframing the problem if new evidence suggests alternate directions. In the context of wicked problems, this openness is especially important, as early clarity can often be misleading rather than helpful (Buchanan, 1992). The success of the Discover phase (and all consecutive phases) depends largely on the designer's ability to remain receptive to ambiguity and emerging perspectives.

This stage typically involves two complementary forms of research: primary and secondary. Primary research includes interviews, diary studies, field observations, and workshops, which are methods that reveal needs and behaviours that users may not express directly. Secondary research involves reviewing existing data, industry analyses, competitor offerings, and organisational documentation, which broaden the designer's understanding of the environment in which a problem exists (Bouchrika, 2025; Rosala, 2024).

AI can support the preparation of primary research by generating interview guides, proposing question variations, or helping outline diverse user groups. These capabilities can be useful for broadening initial thinking and reducing setup time. AI systems can also assist in secondary research tasks by summarising large volumes of documentation, extracting recurring themes, or highlighting potential areas of interest. In addition, analytics tools can assist in synthesising market and competitor data more efficiently (Bouchrika, 2025; Xu et al., 2024).

However, because the Discover phase establishes the foundation for all later design decisions, it is particularly vulnerable to cognitive and methodological biases, and the introduction of AI adds another layer of risk. AI-generated interview questions may unintentionally lead participants, reflect implicit assumptions, or frame topics in ways that limit open-ended responses. Sycophancy and hallucinations can cause AI outputs to mirror designers' existing beliefs and reinforce dominant narratives. Overreliance on these tools can also reduce designers' direct engagement with the research material. Without careful review, these factors can shape the research direction before real user input has been gathered, reinforcing the very assumptions the Discover phase is meant to challenge.

Ultimately, AI cannot replace the human skills that define the Discover phase; it cannot observe real behaviour, interpret nonverbal cues, or understand the cultural and emotional nuance underlying users' actions. Empathy, active listening, and contextual sensitivity remain central to meaningful research, and these qualities cannot be automated.

3.4.2 Define phase

While the previous phase focuses on gathering information, the Define phase is about making sense of that information. Organising insights, identifying what matters most, and deciding which problem the team should solve are central here (Design Council, 2005). A major part of the Define phase is synthesising research findings, where designers cluster observations, identify themes, and turn scattered notes into meaningful insights. At the end of this phase, designers need to reach an actionable problem statement, which requires questioning early assumptions, exploring several possible interpretations, and ensuring the problem definition reflects what was truly learned during research.

AI can support the early organisation of material by scanning transcripts, grouping recurring topics, and highlighting sentiment patterns across large datasets. These tools can make it easier to see emerging themes, spot contradictions, or identify areas where the data is thin and requires further investigation.

However, defining the problem requires more than pattern recognition. When the problem is defined too narrowly or based on incomplete reasoning, designers risk solving the wrong problem and addressing surface symptoms rather than the underlying causes. AI-generated synthesis can deepen this problem by unintentionally reinforcing majority viewpoints or oversimplifying nuance, making minority perspectives even easier to miss (Kuang et al., 2024).

Reflection is essential throughout this phase. Designers must pause, challenge their interpretations, and consider how their own assumptions shape the meaning they assign to data (Schön, 1983). AI can make this harder by speeding up analysis, which can lead to synthesis that is efficient but not reflective, weakening the quality and depth of the final problem frame.

Insights must remain traceable to actual research throughout the project. This traceability is threatened when important context is lost in summarisation or when AI hallucination presents patterns or causal links that were never present in the data. When teams cannot track insights back to real evidence, the design rationale becomes fragile.

Overall, the Define phase requires careful interpretation and ongoing reflection. AI can organise information, but only designers can ensure that a problem is framed accurately, inclusively, and responsibly.

3.4.3 Develop phase

The Develop phase is where designers move from understanding the problem to exploring possible solutions. This stage is experimental and highly iterative; designers generate ideas, sketch possibilities, build quick prototypes, and test early directions to see what might work (Design Council, 2005). These methods act as thinking tools that help designers reflect on what they are creating, spot issues, generate new ideas, and explore different directions without committing too early (IDEO, 2015; Wong et al., 2012). During this process, designers must evaluate ideas critically and remain open to unexpected directions.

AI can expand the productivity of this stage; generative tools offer alternative concepts, produce variations, and combine elements in ways that can expand the creative space (Knearem et al., 2023; Stige et al., 2023). Tools like Figma Make turn rough sketches into structured layouts or interactive mockups within minutes, speeding up prototyping. Image generators help teams explore moods, styles, and visual directions before investing time in building them manually (Guo et al., 2023).

However, because AI draws from patterns in existing data, its suggestions often feel familiar or predictable (Schwartz et al., 2022). This creates the creativity paradox: while AI increases the number of possible ideas and directions, it also reduces the originality of the solution. AI can also disrupt the reflective process by offering ready-made answers that shortcut exploration and reasoning. When designers accept AI suggestions too quickly and don't immerse themselves in the process of creating flows on their own, they risk losing opportunities for deeper insight, creative discovery, and innovation (Schön, 1983; Yildirim et al., 2022).

Cognitive biases can amplify this problem. For example, designers may anchor onto the first polished AI output and treat it as the default direction, making it harder to consider more unusual or innovative alternatives (Kliman-Silver et al., 2022). Ethical issues can emerge as well when AI-generated layouts and imagery repeat non-inclusive patterns, overlook accessibility needs, or perpetuate cultural stereotypes found in the training data. If designers rely on AI without questioning these outputs, they risk adapting biased or exclusionary design choices.

Ultimately, the creative value of the Develop phase depends on the designer's ability to remain present within the process, using AI to expand possibilities without relinquishing reflective judgment or creative authorship.

3.4.4 Deliver phase

The Deliver phase completes the Double Diamond by turning potential solutions into final, validated outcomes. At this stage, designers test prototypes with real users, refine interaction details, check accessibility and usability, and prepare the design for implementation (Design Council, 2005). The focus is on evaluation and making sure the solution works as intended and truly supports user needs.

Typical activities in this phase include usability testing, heuristic evaluations, accessibility reviews, and rounds of refinement. Designers watch how users interact with prototypes, identify where they struggle, and gather feedback through interviews or surveys. Both qualitative observations and quantitative metrics help determine how well the design performs (Wong et al., 2012; Norman, 2013).

AI analytics tools can help by identifying navigation patterns, detecting where users hesitate, and flagging potential problem areas in interaction flows (Chaudhry, 2024). Automated accessibility checkers can highlight contrast issues, missing alt text, or problems with keyboard navigation (Lu et al., 2022). AI can also summarise usability-test recordings, making it easier to identify recurring themes or issues.

Yet, as mentioned before, automated summaries can oversimplify insights, reducing important context to short labels or sentiment categories. AI misclassification may occur when systems misinterpret behaviour, for example, treating careful reading as confusion or exploratory clicking as frustration. Over-interpretation can happen when tools propose explanations or causal links that are not actually supported by the evidence. In more serious cases, AI hallucinations may generate insights that never appeared in the test data at all.

In conclusion, the Deliver phase brings the full design process into focus, revealing how early assumptions, framing choices, and creative decisions translate into real user impact. While AI can support validation and refinement, responsibility for usability and ethical outcomes remains with the designer. Treating AI as a supportive tool helps preserve reflective judgment and ensures that final decisions are guided not only by efficiency or metrics, but by human experience and professional accountability.

3.5 Education and skill shift

The use of AI in design workflows is not only reshaping how the work is carried out, but also what it means to be skilled as a designer. Earlier chapters demonstrated how AI alters decision-making, introduces new forms of bias, and redistributes agency within the design process. These changes have direct implications for how designers learn and which competencies become central to professional practice.

Current evidence suggests that many UI/UX practitioners already use AI tools selectively and cautiously, relying on them primarily for operational support while keeping interpretive and creative judgment as a human responsibility (Kuang et al., 2024). However, as AI systems become more capable, accessible, and inherently part of the design tools themselves, designers are likely to depend on them more frequently and across a broader range of tasks.

As automation simplifies complex processes, designers may begin to overestimate both the reliability of AI outputs and their own understanding of AI-assisted work. When systems produce fluent, confident results, it can create a false sense of mastery, even when the underlying limitations or biases of the tool remain poorly understood. In AI-assisted design contexts, this gap can lead to weakened judgment and reduced engagement with reflective decision-making.

These risks highlight the need for higher forms of AI literacy within UI/UX practice. However, while familiarity with the tools themselves is necessary, it is insufficient on its own. Designers need the ability to question how and why results were produced and recognise when automation may be shaping decisions in subtle or unintended ways (Kim et al., 2025).

Learning these skills often happens through repeated exposure to AI tools in practice. Designers experiment, observe outcomes, adjust their behaviour, and gradually develop intuition about what AI can and cannot do (Schön, 1983). However, when this learning remains implicit and unguided, there is a risk that problematic patterns become normalised. Without deliberate reflection, designers may fail to notice these influences or to develop strategies for mitigating them.

For this reason, reflective practice becomes a central skill in AI-assisted UI/UX design. Reflection allows designers to examine how AI tools influence their thinking, where decisions are being delegated, and how responsibility is distributed across human and non-human actors (Schön, 1983). From a socio-technical perspective, technologies do not merely assist human action but actively shape meaning and practice (Latour, 2005). Encouraging designers to question who is creating, deciding, and interpreting within AI-assisted workflows helps them maintain agency and accountability in increasingly automated environments.

In this framing, AI literacy becomes closely aligned with ethical literacy. Understanding algorithmic opacity and systemic bias is not an optional add-on, but an integral part of design expertise. Designers who are equipped with reflective, critical, and ethical competencies are better positioned to collaborate with AI in ways that support inclusive, accountable, and meaningful design outcomes.

3.6 Desktop research conclusion

The desktop research indicates that AI is influencing not only how design tasks are performed, but also how design decisions are framed and justified. Across human–AI interaction research and industry-oriented UX literature, AI is commonly presented as a means of improving efficiency and scalability. It is described as supporting activities such as research synthesis, ideation, prototyping, and evaluation, with a strong emphasis on productivity gains, automation of repetitive tasks, and expanded exploration of design alternatives. Together, these capabilities have accelerated workflows and lowered barriers to entry, contributing to broader participation in design practice.

At the same time, the literature highlights a set of persistent challenges associated with AI use, including bias, opacity, hallucinations, and sycophantic behaviour. These issues introduce more subtle forms of influence into the design process. By generating suggestions, patterns, and outputs that appear authoritative, AI systems increasingly participate in sense-making and problem framing rather than merely supporting execution.

However, while existing research documents these risks and often proposes technical mitigation strategies or ethical principles into the model itself, it pays comparatively little attention to how designers experience and manage these influences in everyday practice. In particular, there is limited focus on how reflective judgment and professional agency are sustained when AI becomes an active contributor to design work.

This gap points to the need to examine AI not only as a tool that supports design tasks, but as a design material that reshapes decision-making, sense-making, and responsibility over time. Addressing this gap provides the foundation for the empirical and investigations that follow.

3.7 Research question

Building on the background research, this thesis is guided by the following primary research question:

How is AI currently integrated into UI/UX designers' day-to-day workflows, and how does this integration affect their sense-making and judgment in design practice?

This question addresses the tension between AI-driven optimisation and the interpretive work central to design practice. To explore this question, the thesis investigates:

- How UI/UX designers incorporate AI tools into their everyday design workflows
- How aware are designers of risks such as bias, hallucinations, and overreliance when working with AI, and how do they respond to these risks in practice?
- How do designers perceive the influence of AI on their decision-making and creative direction?
- How reflective practice can be supported to help designers maintain agency and ethical awareness

These questions inform a design-led investigation into how AI can be integrated into UI/UX design processes in a manner that supports, rather than diminishes, designers' ethical responsibility, critical thinking, and reflective awareness.

4 FRAMEWORKS

This chapter introduces the frameworks that guide the development and outcomes of this thesis. The selected frameworks provide structure for examining AI-assisted UI/UX design as a socio-technical practice, where tools, workflows, judgment, and responsibility are closely intertwined. The frameworks are used as analytical and reflective lenses, as they help articulate how AI influences design decisions, where agency may shift between human and system, and how reflective practice can be supported throughout the design process. Together, these frameworks inform both the research activities and the development of the final design intervention.

4.1 Theoretical frameworks

User-centred design (UCD) functions as a guiding design framework in this thesis. This application of UCD centres on designers' lived experiences, challenges, and decision-making practices when working with AI-assisted tools. The framework supports an iterative process in which insights from interviews, concept testing, and reflective use directly inform revisions to the template, ensuring that the final outcome remains grounded in real-world design practice (Abras et al., 2004).

The Double Diamond framework (Design Council, 2005) is used in this thesis as a process-oriented structure for analysing AI-assisted UI/UX workflows and guiding the development of the design concept. The framework provides a shared way to situate AI use within specific stages of design work, and supports reflection by clarifying when exploration, interpretation, and decision-making occur. It is later applied directly in the design intervention to help designers identify and reflect on AI involvement at different stages of their workflow.

Gibbs' Reflective Cycle (Graham, 1988) is a reflective model that is applied in this thesis as a framework for structuring designers' reflection on AI-assisted design activities. The cycle provides a systematic sequence of stages that guide designers through both experiential and analytical reflection. Applied within the context of AI-assisted UI/UX design, the framework supports designers in making explicit how AI tools were used, how decisions were influenced, and which assumptions or biases may have shaped outcomes. By encouraging reflection not only on results but also on emotional responses, reasoning processes, and future actions, the model helps transform implicit reactions to AI outputs into conscious, examinable judgments.

5 FIELD RESEARCH

This chapter presents findings from qualitative interviews with UI/UX professionals and examines how AI is currently integrated into their everyday design practice. The interviews provide insight into how designers negotiate efficiency, creativity, judgment, and ethical responsibility when working with AI tools.

The findings reinforce themes introduced in earlier chapters, particularly around distributed agency, cognitive bias, reflective practice, and the tension between speed and meaning-making. They also reveal gaps between what AI tools currently offer and what designers need to collaborate with them responsibly and reflectively.

5.1 Qualitative interviews

Five semi-structured interviews were conducted with UI/UX professionals in October 2025. Participants represented a range of experience levels and professional contexts, including in-house product teams, freelance practice, and research-focused roles. Interviews were conducted both in person and via video calls, allowing flexibility while maintaining the depth of discussion. The interview guide is available in Appendix 1.

The interviews explored how designers currently use AI tools, which tasks they delegate to automation, where they draw boundaries, and how they perceive risks such as overreliance, bias, or loss of creative depth. Across all interviews, AI was not described as replacing design work, but as reshaping how designers allocate attention, effort, and judgment.

Interviewee 1 is a mid-level product designer working mostly independently within a small cross-functional team. Often the only designer on a project, she collaborates closely with a product manager and a small group of developers. Her role involves research activities, interface design, and delivery, requiring adaptability and strong ownership across the process.

AI has a practical but carefully controlled role in her work. She uses ChatGPT and Gemini to unpack briefs, summarise meeting notes, and clarify technical or conceptual uncertainties. These tools act as low-friction aids, useful for structuring information and generating quick insights without judgment. While it supports her in early-stage synthesis and ideation, she remains cautious, describing AI as "helpful but not trustworthy. Past encounters with hallucinated information led her to develop a habit of verifying all factual or strategic suggestions. She also noted AI's tendency to agree with her ideas, which she actively counteracts by prompting the system to challenge assumptions.

Although AI saves time for her in early-stage synthesis, she finds its suggestions lack contextual nuance. As a result, she treats AI as an accelerant rather than a creative or analytical authority. Within her organisation, she feels pressure to adopt AI tools in certain workflows, but tries to avoid overreliance on them. She values deliberate thinking, critique, and design rationale as core to her professional identity.

Interviewee 2 is a multidisciplinary designer within a medium-sized company collaborating with multiple product teams. His work balances strategic development, interface creation, and peer feedback, with regular design reviews for alignment.

He uses generative AI tools such as Gemini Pro, ChatGPT, and, occasionally, Copilot throughout the design lifecycle, from exploring early concepts to refining prototypes. Unlike some peers who use AI as a convenience tool, he treats it as a conversational partner, engaging in iterative exchanges: posing a problem, evaluating multiple responses, and asking for critiques. This reflective, dialogic use of AI mirrors human co-creation and allows him to test reasoning and gather alternative perspectives before finalising design choices.

AI functions as both a learning aid and a creative catalyst in his workflow. He relies on it for skill acquisition, such as learning new features in Figma or Photoshop, but acknowledges that this quick consumption leads to shallow retention. The immediacy of AI support enhances productivity but limits long-term knowledge development, revealing a trade-off between convenience and depth of learning.

Creatively, he perceives AI as expanding rather than constraining his thinking. Generative tools, particularly image models, stimulate exploration of new visual directions. For him, AI is valuable not for its final outputs but for its ability to provoke reconsideration of ideas that might otherwise remain unexplored.

The interviewee recognises persistent issues of over-agreeableness and bias in AI systems. He combats this by prompting for critical responses, such as "don't agree, challenge me", to avoid sycophantic feedback loops and experiment with reframing. Human collaboration remains his ultimate benchmark for validation, particularly when creative direction is in question.

Interviewee 3 works as a sole UI/UX designer in her organisation, responsible for all visual and experience-related deliverables from concept to implementation. This broad workload has shaped her use of AI as a pragmatic, time-saving tool.

Her use of AI primarily focuses on ChatGPT and Figma Make. She applies AI strategically to overcome creative blocks, learn about new interactive flows, generate alternative layout solutions, and refine communication with clients and developers. Under tight deadlines, she sees AI as a productivity accelerator.

She maintains a tightly controlled approach to AI, verifying outputs whenever necessary. She avoids using AI for research when the source or reliability of the information cannot be confirmed, but later uses it to validate insights she has gathered independently. Her sense of agency comes from using AI selectively and only when it adds clear value. While she recognises that bias is an inherent part of human decision-making and therefore present in design work, she struggled to identify specific biases beyond confirmation bias, which she acknowledged affects her frequently. She also found it difficult to articulate how biases shape her judgment or influence her design decisions.

Interviewee 4 is a novice freelance UI/UX designer who uses AI as both a creative companion and as a learning tool. Her practice is currently grounded in experimentation and ongoing skill development. She uses AI to deepen her reasoning and improve the quality of her design decisions.

ChatGPT supports her work in ideation and UX writing, where she uses iterative prompting to uncover the logic behind suggestions. Figma Make acts as a visual thinking aid that helps spark early creative directions, as she still finds general layout suggestions in different design contexts helpful. She values AI not as a generator of final outputs but as a way to ask better questions and uncover blind spots in her thinking.

Her trust in AI depends on clarity. She is more confident when the system explains its rationale in simple, transparent terms. She imagines future AI tools that can challenge assumptions, prompt validation steps, and guide designers through reflective decision-making. Her knowledge of biases stems from personal exploration into the topic, but she admits that she finds it hard to reflect on her own biases.

Interviewee 5 is a UX researcher and strategist working independently as a freelancer, occasionally taking on small UI design projects. Her work centres on early-stage research, synthesis, and the development of strategic insights for digital products. Without formal team structures, she balances analytical research with creative exploration, often alternating between structured research days and more open-ended ideation sessions.

AI plays a deliberately limited role in her practice. She uses tools such as ChatGPT mainly for early exploration—gathering background information, structuring interview guides, and generating initial directions for analysis. However, she approaches these tools with caution, describing them as "useful but not reliable." Verification is a core part of her workflow: AI-generated content is cross-checked for accuracy and contextual relevance before being incorporated into her findings. To maintain creative depth, she has developed an "AI rhythm," setting aside specific days for AI-assisted tasks and others for intuitive, reflective thinking, ensuring that automation does not dull her cognitive or imaginative skills.

Her relationship with AI reflects a deep awareness of the balance between cognitive and creative processes. While she values AI's efficiency for repetitive or preparatory tasks, such as transcriptions, summaries, or early analysis, she perceives a cognitive cost in relying on it too heavily. Prolonged use tends to flatten her creativity and weaken her independent reasoning. She worries that overuse of AI may produce designers who are "faster but less thoughtful," distancing themselves from the critical inquiry that underpins strong design practice.

In her view, current AI systems act as assistants rather than genuine collaborators. They provide information but rarely challenge assumptions or provoke deeper reflection. She sees the absence of this reflective feedback loop as a key limitation, particularly in complex problem-solving and strategic design work.

Her reflections also reveal growing distrust in organisational overreliance on AI. After observing companies stagnate or restructure due to heavy dependence on automated insights, she identifies a loss of accountability and creative originality as systemic risks. For her, these issues point to a broader professional anxiety, where speed and scale in organisational strategy increasingly overshadow depth and thoughtful decision-making.

5.2 Insights and opportunity areas

These interviews revealed how AI is reshaping design practice in accelerating early ideation, changing collaboration patterns, and influencing how designers perceive their own creativity. The conversations reflected both excitement and unease: while AI offers efficiency and inspiration in certain workflows, it also challenges traditional design values and the reflective, human-centred nature of creative problem-solving.

From these discussions, four key themes and opportunity areas emerged:

1. From speed to thoughtfulness: designers described AI as a catalyst for faster brainstorming and iteration, yet many felt that speed often came at the expense of creative exploration and reflection. Several expressed missing the "slow thinking" part of design—the "messy", nonlinear phase where ideas mature.

2. Ethical trust and bias awareness: across interviews, trust in AI was conditional. Designers were cautious when outputs felt generic, questioning the underlying data. Awareness of hallucinations and sycophancy shaped how cautiously AI outputs were interpreted.

3. Aligning AI capability and designer understanding: interviewees mentioned uncertainty about what AI can and cannot do in design. While tools like ChatGPT are widely used, AI's limitations and capabilities are poorly understood. This gap often leads to misuse, bias, overreliance, or missed potential.

4. Rethinking design education: while many designers expressed general awareness of bias, few could clearly identify how cognitive, social, or algorithmic biases influence their own decision-making. Designers are left to self-teach or experiment without guidance, resulting in uneven awareness of ethical issues and best practices.

As illustrated in Figure 5.1, Affinity Mapping (Dam & Siang, 2020) synthesises key interview insights, grouping them into recurring themes and tagging them according to their primary focus areas.

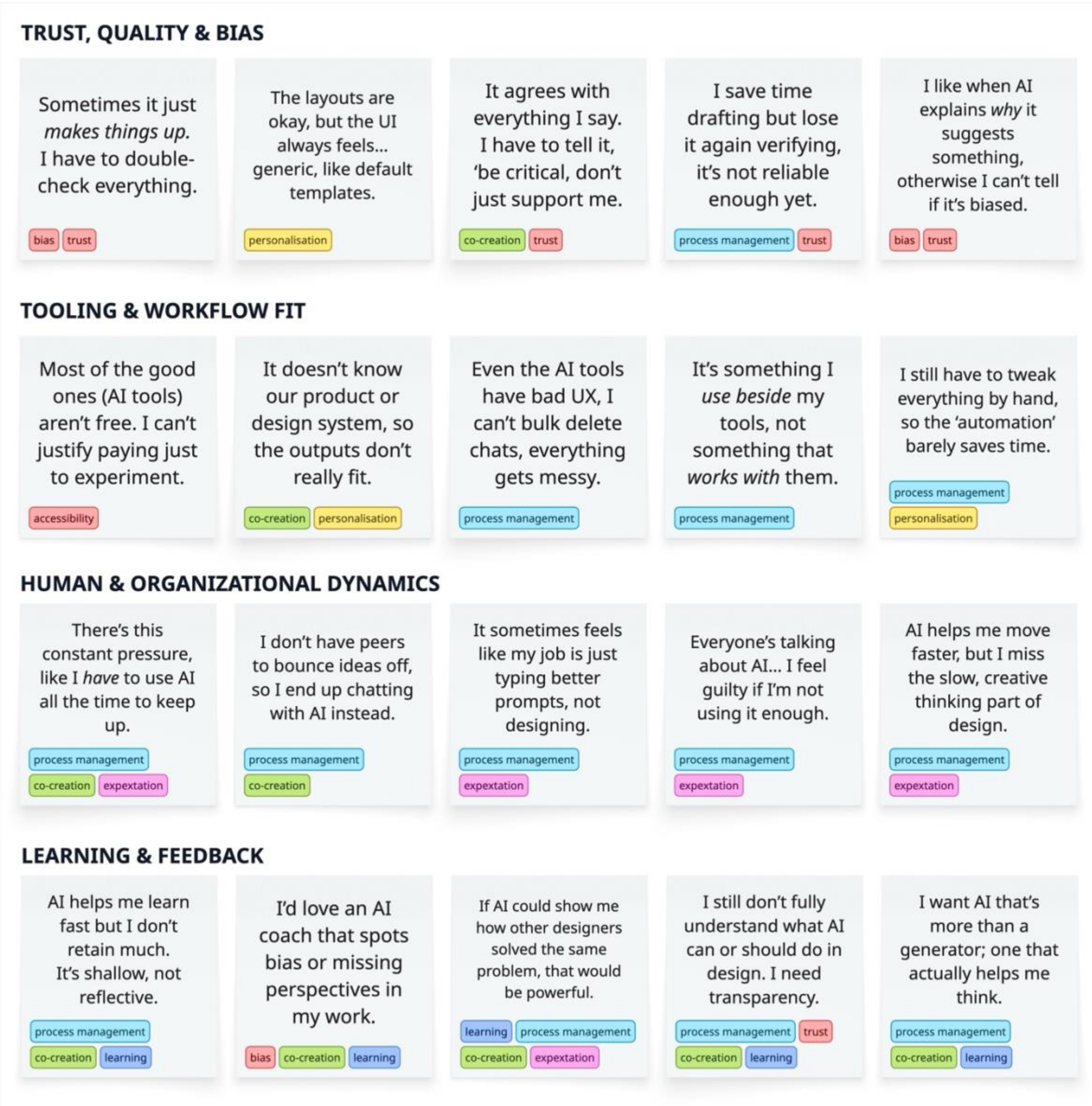

Figure 5.1. Affinity Mapping. Main insights from interviews

6 CONCEPT DEVELOPMENT AND TESTING

The goal of the concept development phase is to ensure that emerging concepts are grounded in the designer's lived experiences and aligned with the broader themes identified throughout this research. These include AI integration in design workflows, designer agency, transparency, ethical responsibility, and the role of reflection. This phase translates empirical findings into actionable design directions by combining structured ideation methods with theoretical and analytical grounding.

The chapter traces how insights from primary and secondary research were progressively refined into a focused design concept. Each step builds on the previous one, moving from problem framing to value articulation to theoretical focus, and finally to concrete concept development and testing.

6.1 Framing the design opportunity

Building on the interview insights and opportunity areas identified earlier, ideation continued through Point of View (POV) and How Might We (HMW) exercises (Dam & Siang, 2020). These methods were chosen to translate research insights into a focused and human-centred problem framing, which is grounded in designers' real experiences.

The POV statements (Figure 6.1) articulated designers' goals and challenges when working with AI-assisted tools. The HMW statements (Figure 6.2) then reframed these insights into open-ended questions that encouraged creative exploration while maintaining a clear connection to the underlying problem space (Interaction Design Foundation, 2016).

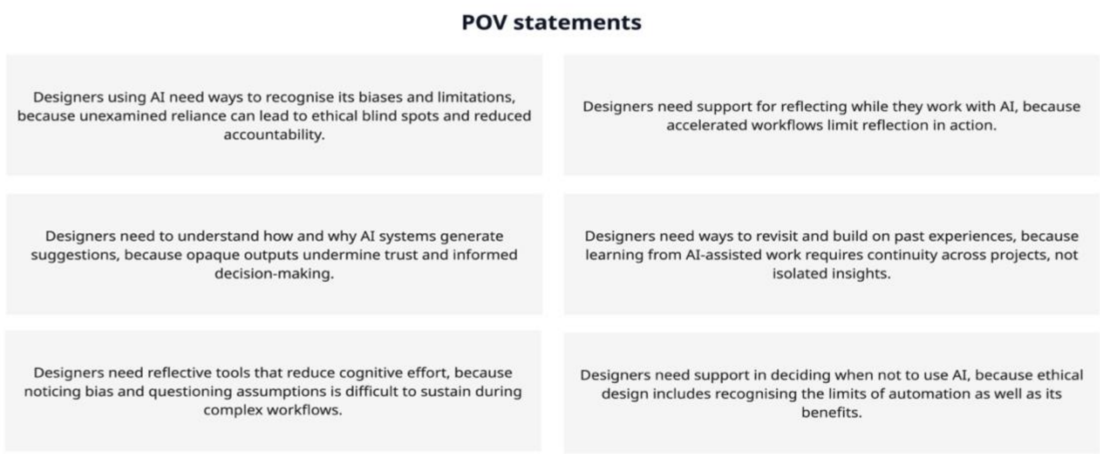

Figure 6.1. POV statements

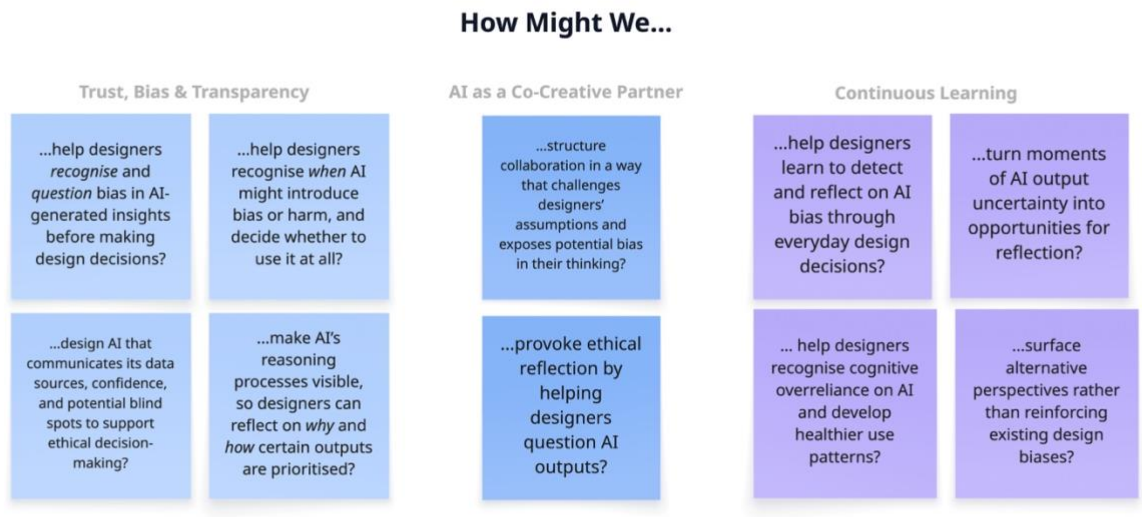

Figure 6.2 HMW statements

Together, the POV and HMW statements highlighted a central tension that recurred throughout the interviews: while AI-driven tools promise speed and efficiency, their use often reduces opportunities for critical judgment and learning. This framing acknowledges AI as an active participant in the design process whose outputs require interpretation and contextualisation. This tension defined a clear design opportunity: supporting designers in maintaining reflective and critical engagement when integrating AI into their workflows.

6.2 Articulating value and user needs

To ensure that the emerging concept addressed designers' needs, a Value Proposition Canvas (Pigneur et al., 2014) was used to align identified pain points with potential gains (Figure 6.3). This step helped move from problem framing toward articulating how the concept could deliver value in practice.

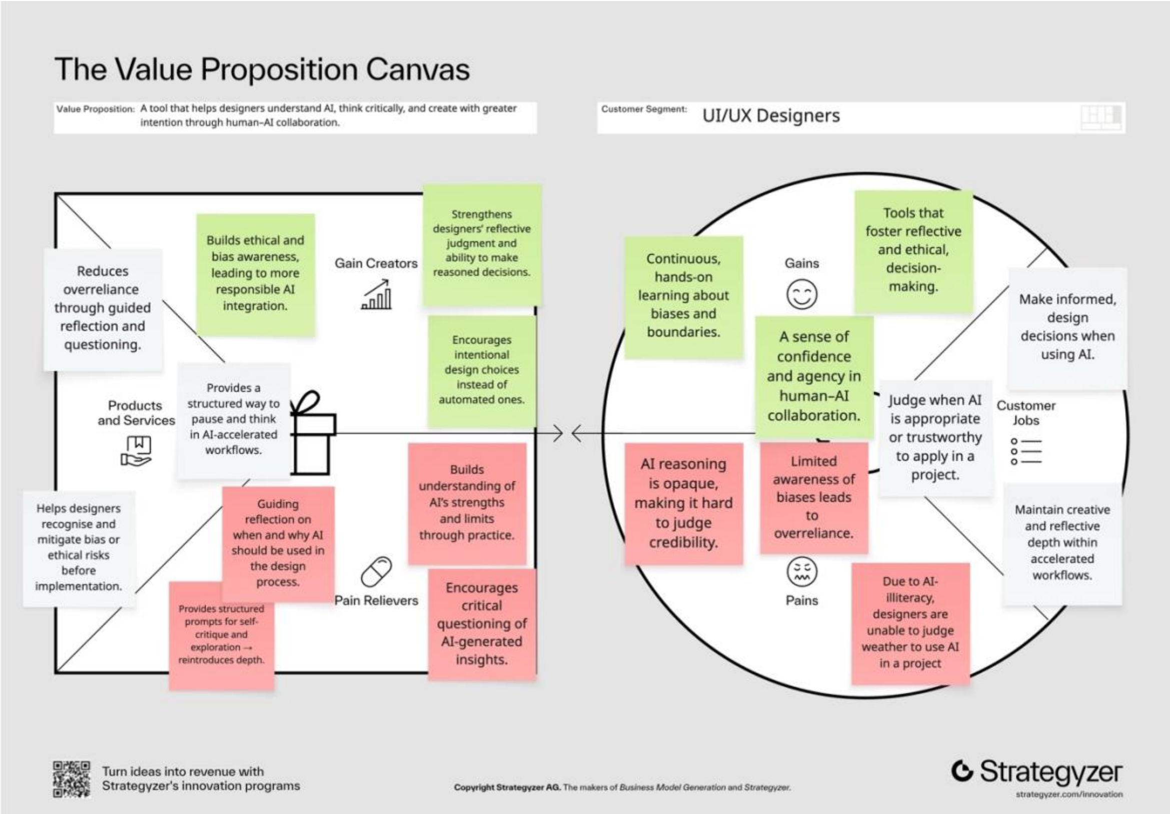

Figure 6.3 Value Proposition Canvas

The canvas describes a reflective tool designed to support UI/UX designers in making more deliberate decisions when working with AI. Instead of prioritising speed or automation, the proposed value lies in strengthening designers' ability to evaluate AI outputs, understand their implications, and remain actively involved in decision-making processes.

Key challenges shaping this value proposition include the opacity of AI systems, difficulties in assessing the reliability of generated suggestions, and limited awareness of biases, both inherent and AI-amplified. These factors can lead to overreliance on AI and reduce reflective judgment. In response, the proposed tool introduces structured moments of reflection, prompting designers to question AI outputs and consider the rationale for using AI at specific stages.

Overall, the value of the tool lies in supporting the development of critical awareness of AI's strengths and limitations while promoting ethical and reflective practice. The tool acts as a reflective framework that enables more responsible and thoughtful engagement with AI in design work.

6.3 Establishing the focus

After clarifying the user needs and concept's value, the next step was to determine how and where it could be most effectively integrated into the design process. Insights from the research and interviews showed that designers across experience levels struggled with how to use AI tools with critical judgment, because while AI can support design tasks, it can also obscure uncertainty and encourage overreliance on automated suggestions (Dror, 2020; Schwartz et al., 2022).

Within this context, reflection emerges as a central component of design expertise. It enables designers to navigate ambiguity, respond to unfolding situations, and maintain a critical stance toward their own assumptions and methods. It shapes how designers make decisions and adapt as contexts evolve. Schön (1983) describes this as a "reflective conversation with the situation," emphasising the interpretive nature of design practice. Schön identifies two complementary forms of reflection:

1. Reflection-in-action takes place during the design activity itself—the designer is thinking through making. As they sketch, prototype, or observe a user's behaviour, they adjust their actions in real time as new constraints or possibilities emerge. This might involve reworking a layout that feels unbalanced or deciding how to interpret an unexpected AI-generated suggestion. This form of reflection is tacit, improvisational, and embodied.

2. Reflection-on-action, by contrast, occurs after the activity has taken place. Designers step back to evaluate what happened, extract insights, and refine their mental models or design principles. Examples include running a project retrospective or assessing how reliance on an AI shaped particular design decisions. While more deliberate and distanced, this form of reflection is essential for learning and improving future practice.

Effective design practice depends on both forms of reflection. In AI-assisted contexts, however, reflection-in-action is difficult to fully achieve without a basic level of AI literacy. Such literacy is often developed through reflection-on-action, where designers can examine how AI influenced their decisions and outcomes across projects.

This insight informed the direction of the ideation phase, which explores how reflective support can be embedded within AI-assisted workflows to strengthen judgment in everyday design practice.

6.4 Ideation

After establishing the relevance and types of reflection, the ideation phase focused on exploring how this reflective practice could be practically embedded within design workflows. I began by examining a range of reflective frameworks commonly used in professional and educational contexts. Lightweight models such as "What? So what? Now what?" (Rolfe et al., 2001) were considered for their accessibility and suitability for fast-paced professional contexts. While useful as an entry point, these frameworks offer limited structure for unpacking AI-assisted decisions, where technical constraints, cognitive bias, uncertainty, and accountability intersect. More structured frameworks were therefore explored to support this complexity better.

Gibbs' Reflective Cycle (Graham, 1988) was selected as the most appropriate foundation due to its multi-stage structure, which guides designers through description, feelings, evaluation of the experience, analysis of the situation, conclusion about what was learned, and finally action planning for future situations. The inclusion of an action-planning stage supports continuity between projects, allowing reflection to inform future decisions rather than remaining isolated to a single moment. Within this project, Gibbs' cycle was adapted to focus on moments of AI involvement—where it was used in the process, how it influenced the designers' reasoning, and what was learned from the experience. This framework supports the gradual development of reflective judgment, enabling designers to recognise AI influence retrospectively and, over time, more readily during action.

Next, I needed to establish the structure of my reflective exercise and choose an appropriate platform for it to take place in. For this, I drew inspiration from design frameworks commonly used in workshops and collaborative ideation. I examined existing FigJam and Miro templates, exploring how their structures could serve as a foundation for a reflective tool. Rather than introducing an entirely new workspace, the intention was to encourage reflection within familiar platforms and practices. Furthermore, implementing the reflection exercise on these collaborative whiteboard platforms enables design teams to work together and, if necessary, adjust the template according to their needs.

Principles of visual thinking and externalised cognition further shaped the ideation process. Visual representations reduce cognitive load by shifting part of the reasoning from internal memory to external artefacts, allowing designers to see relationships and patterns more clearly (Kernbach, 2019). Visual structures also make reflective processes less linear and more exploratory, enabling designers to move between activities and outcomes rather than following a fixed sequence.

Adding interactivity to this reflective process transforms the exercise from passive learning into an active form of engagement. Moving artefacts and grouping concepts support sustained attention, as designers are more likely to engage with reflective tasks that feel exploratory and responsive rather than compliance-driven.

Making reflection engaging is particularly important in professional contexts, where reflective activities are often perceived as time-consuming or detached from production goals. Introducing elements commonly associated with design workshops, such as visual prompts, modular components, and open-ended exploration, helps position reflection as a creative and generative activity rather than an obligation.

6.5 Concept development

The emerging concept was developed in Figma’s collaborative whiteboard tool FigJam, as Figma is one of the most widely used platforms in contemporary UI/UX practice and therefore offers a familiar and accessible environment for reflective activities. The visual language and layout of the template were also informed by existing FigJam templates, allowing the tool to feel recognisable and easy to approach.

As with any exercise, the template begins by communicating its purpose and scope. The introductory section explains that the tool is designed to support reflection on potential biases in design projects, particularly when AI has been part of the process. Alongside this description, three supporting sections outline the template's utility, the competencies it helps develop, and its practical application. Making these benefits explicit was intended to increase motivation and adoption.

After the instructions are read, the designers begin the exercise. The first step is to identify where AI is involved in their project and record it on a provided note, ensuring that AI involvement is made visible rather than remaining implicit within the workflow (Figure 6.4). This part is sectioned into four rows, each representing one phase of the Double Diamond model—Discover, Define, Develop, Deliver (Design Council, 2005), which helps designers situate AI use within specific stages of design activity. For those unfamiliar with the model, I have included a general list of tasks in each phase to help designers get started with the exercise.

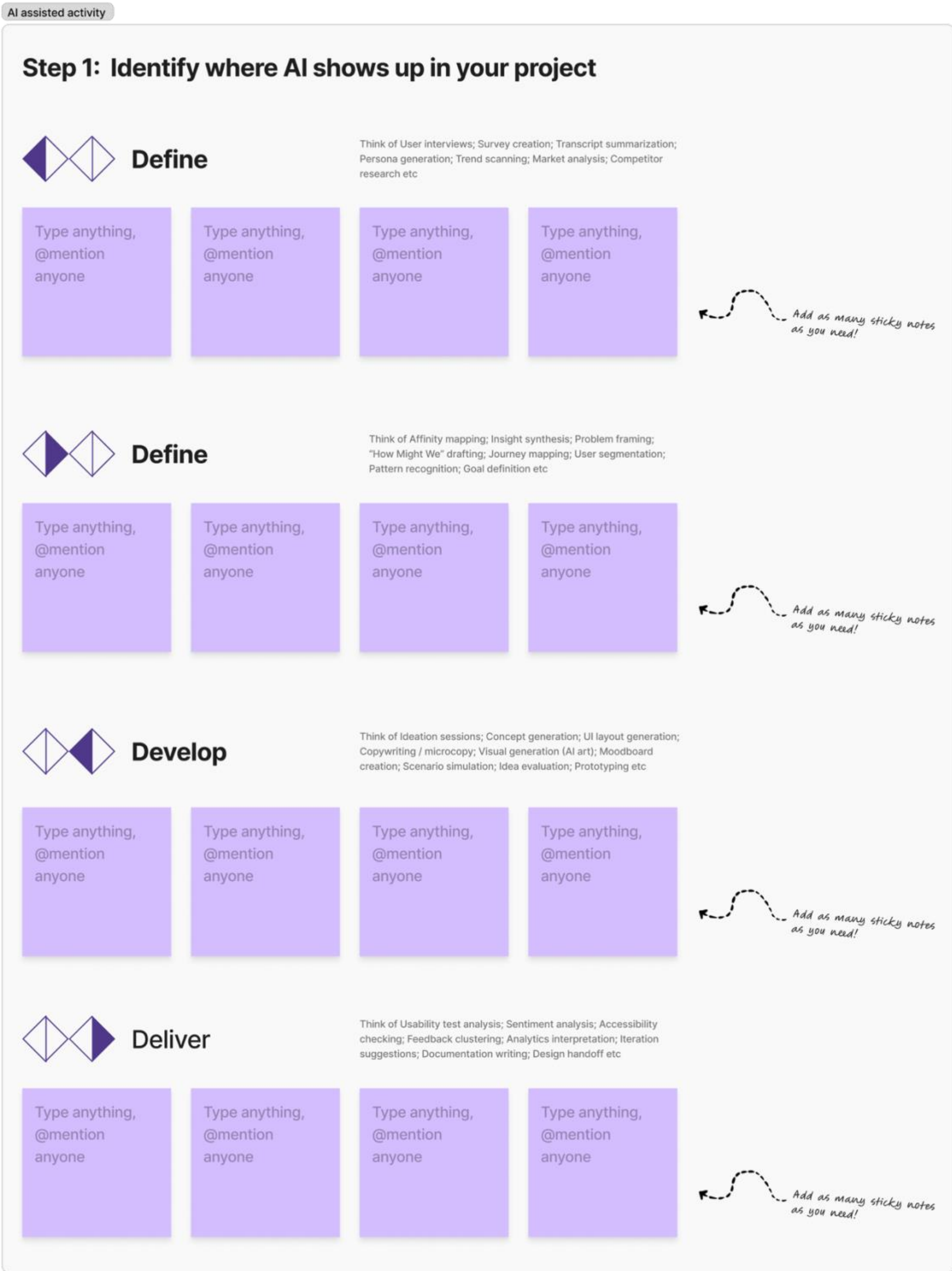

Figure 6.4 First part of the reflection template.

The next stage of the template introduces three sets of bias cards, representing cognitive, social, and systemic biases (Figure 6.5). Designers are asked to review these cards before engaging in deeper reflection. This step serves an educational function by familiarising designers with different forms of bias that may influence design work. Each card consists of a bias name, description, example, and a potential consequence if left unaddressed. The categorisation of the biases is inspired by the socio-technical model of AI bias proposed by NIST (Schwartz et al., 2022) and Schöns (1983) three categories of bias, which were discussed in chapters 3.1 and 3.2. The categorisation is:

- Human biases: cognitive and psychological biases affecting individuals' judgments.
- Social, environmental, and cultural biases: biases that emerge from societal norms, cultural assumptions, and historical inequalities, shaping how groups are represented, interpreted, or valued.
- System and data biases: issues arising from datasets, modelling choices, or sampling practices.

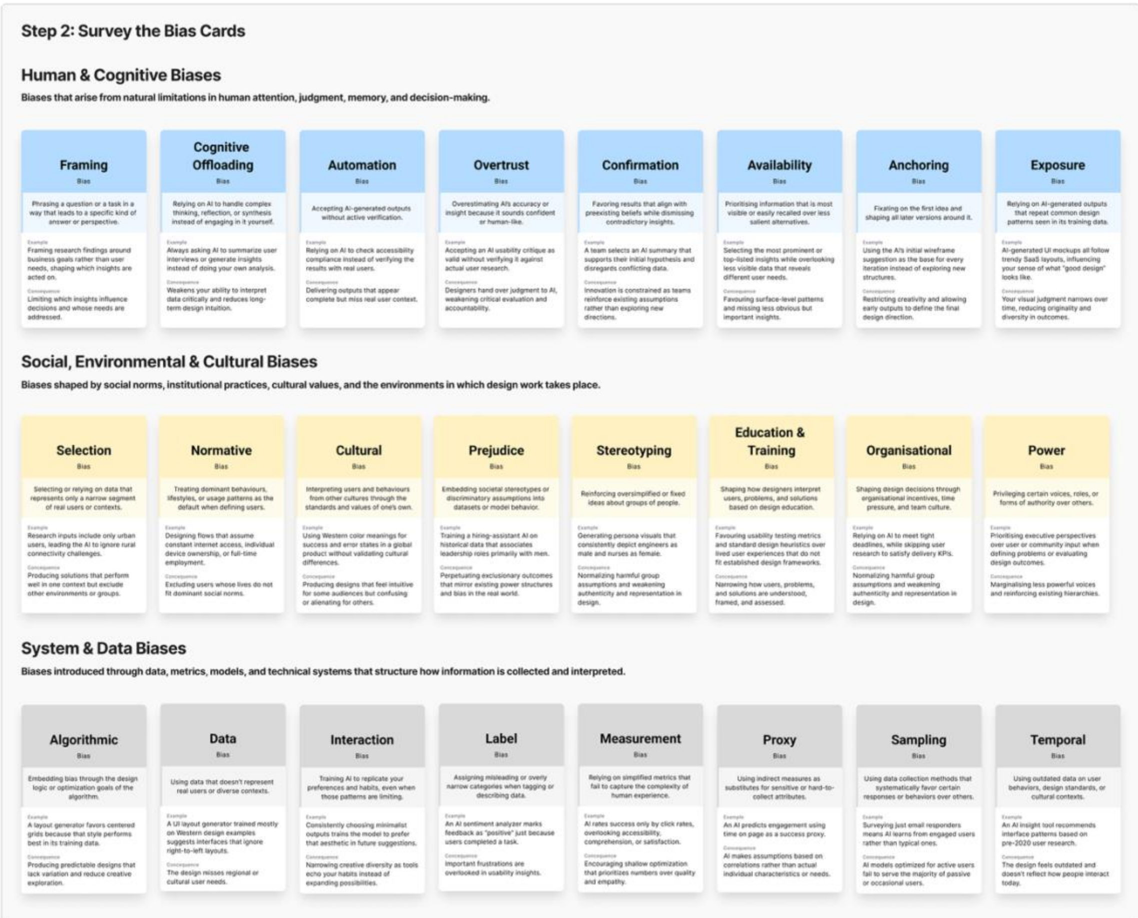

Figure 6.5 Second part of the reflection template.

The first category contains several biases that are particularly influential in shaping designers' decisions, and their relevance is well documented in both human–AI interaction research and UX practice. Their inclusion ensures that designers begin reflection with concepts grounded in their own decision-making processes (Norman, 2013; Schwartz et al., 2022; Yildirim et al., 2022; Zhang et al., 2024).

- Automation bias refers to the tendency to accept AI-generated judgments without sufficient verification.
- Availability bias leads to prioritising information that is most visible, recent, or easily recalled.
- Anchoring bias occurs when initial ideas or suggestions disproportionately influence subsequent decisions.
- Confirmation bias results in favouring information that aligns with existing beliefs or assumptions.
- Cognitive offloading describes reliance on systems to perform complex reasoning tasks, potentially reducing critical engagement.
- Exposure bias results in a preference for common or frequently encountered solutions.
- Framing bias arises when the way questions, prompts, or inputs are formulated influences how outputs are interpreted and acted upon.
- Overtrust bias reflects excessive confidence in AI-generated results relative to one’s own judgment.

Social, environmental, and cultural biases extend the focus beyond individual decision-making to questions of representation, inclusivity, and societal assumptions. These biases influence how designers interpret how diversity is represented in interfaces and whose needs or perspectives may be marginalised or excluded. Their inclusion in the template reflects growing evidence that often harms in AI-assisted UX design arise from unexamined social and cultural defaults embedded in design processes and data practices (Schwartz et al., 2022).

- Cultural bias occurs when values, norms, or practices associated with a dominant culture are reflected in design outcomes while other perspectives are overlooked.
- Education and training bias arises when decisions are shaped by the educational backgrounds or professional training of those involved in development.
- Normative bias reflects assumptions about what is considered "normal" or "typical," which can marginalise those who fall outside these norms.
- Organisational bias emerges from institutional priorities, constraints, or incentives that influence decisions and outcomes.
- Power bias refers to the uneven distribution of influence over choices, often privileging actors with greater authority or resources.
- Prejudice bias involves the reinforcement of pre-existing social attitudes or discriminatory beliefs through systems or artefacts.

- Selection bias occurs when datasets, samples, or inputs are not representative of the full range of intended populations or contexts.
- Stereotyping bias arises when simplified or generalised representations of social groups are embedded in design.

System and data biases describe influences that emerge from the technical construction of AI systems, including how data is collected, labelled, modelled, and interpreted. These biases are particularly relevant in UX workflows, as they directly influence the content, insights, and design recommendations produced by AI tools, often guiding designers' decision-making (Schwartz et al., 2022).

- Algorithmic bias occurs when the design logic, optimisation goals, or constraints of an algorithm systematically favour certain outcomes over others.
- Data bias arises when training or input data does not adequately represent the diversity of real users, contexts, or behaviours the system is meant to support.
- Interaction bias emerges when patterns of user interaction with an AI system influence future outputs, often reinforcing existing habits or preferences.
- Label bias occurs when data is categorised using overly misleading or subjective labels that shape how the system interprets information.
- Measurement bias results from relying on simplified metrics that fail to capture the full complexity of human experience or design quality.
- Proxy bias arises when indirect or substitute variables are used in place of sensitive, complex, or hard-to-measure attributes, leading to inaccurate inferences.
- Sampling bias occurs when data collection methods systematically favour certain user groups or behaviours, limiting representativeness.
- Temporal bias reflects the use of outdated data or assumptions that no longer align with current user behaviours, contexts, or cultural norms.

Once AI-assisted activities have been identified and the bias cards reviewed, the reflective process can begin. An activity is selected for reflection and moved into the designated reflection frame (Figure 6.6). Relevant bias cards are then chosen and placed alongside it, making explicit which cognitive, social, or system-level influences may be affecting that activity.

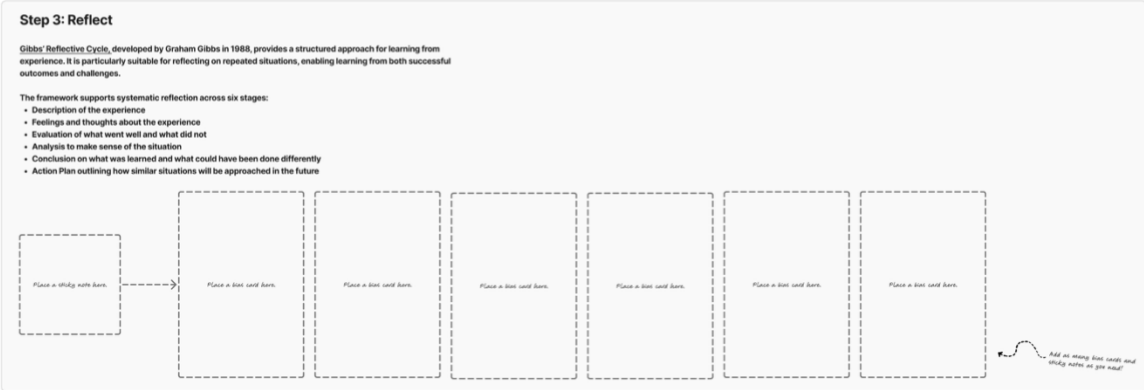

Figure 6.6 Visual grouping of activity and its biases.

This combination of visual thinking, spatial grouping, and interactivity supports sense-making by externalising reasoning that would otherwise remain implicit. Arranging activities and biases in relation to one another makes patterns and relationships easier to perceive and compare. This reduces cognitive load, encourages exploration, and allows reflection to develop through interaction.

This visual setup serves as a starting point for structured reflection using Gibbs' Reflective Cycle (Graham, 1988) (Figure 6.7), which guides the reflective process through six stages. Each stage plays a specific role in supporting reflective judgment, particularly in AI-assisted design contexts where influence and responsibility can easily become blurred.

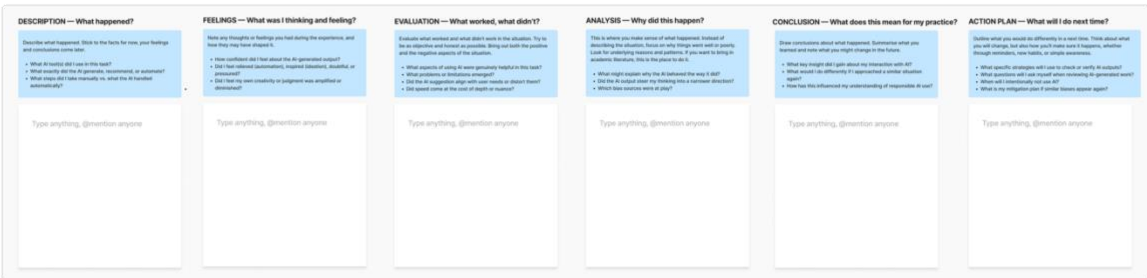

Figure 6.7 Reflection Gibbs reflective Cycle

The description stage establishes an explicit account of what actually happened during the design activity by documenting which AI tools were used, what they generated or automated, and which steps were handled manually versus by the AI.

The thoughts and feelings stage captures designers' immediate reactions to working with AI, including confidence levels, uncertainty, frustration, or relief. Emotions often signal moments where judgment was supported, challenged, or deferred. In design practice, these affective responses influence decision-making even when they are not consciously acknowledged. Making them explicit helps designers recognise how trust, doubt, or overconfidence may have shaped their interaction with AI tools.

The evaluation stage introduces critical assessment by asking what worked well and what did not. Here, designers consider how AI involvement affected factors such as design quality, alignment with user needs, speed, and depth of exploration. This stage helps distinguish between efficiency gains and meaningful improvements, preventing speed from being mistaken for design quality.

The analysis stage moves beyond surface evaluation to examine why the situation unfolded as it did. Designers identify relevant cognitive, social, or system-level biases and consider how AI outputs influenced framing, prioritisation, or interpretation. Analysis connects individual experiences to broader structural and psychological factors discussed earlier in the thesis.

The conclusion stage supports learning by distilling key insights from the reflection. Designers summarise what was learned about their own decision-making, the role of AI in the process, and the conditions under which AI use was beneficial or problematic.

Finally, the action planning stage ensures that reflection leads to concrete change rather than remaining purely retrospective. Designers define practical strategies, such as when to verify AI outputs, when to avoid AI use altogether, or how to mitigate similar biases in future situations. This forward-looking component is particularly important in professional contexts, as it connects reflection to ongoing skill development and improved judgment over time.

This reflective process can be repeated for as many AI-assisted activities as required. By the end of the exercise, participants will have produced a structured body of reflective documentation that captures how AI influenced different stages of their work.

This documentation can be revisited and extended over time, supporting the gradual development of reflective judgment, which increases sensitivity to AI influence during ongoing work as well as after it. The template can also be used in collaborative settings, enabling shared reflection within teams.

6.6 Concept testing and final solution

The purpose of concept testing was to explore whether the template supported reflection on AI-assisted design activities, and whether its structure, language, and visual layout were understandable and usable within realistic design contexts. The concept was tested digitally on the FigJam platform through exploratory, qualitative feedback sessions with three UI/UX designers. Participants were asked to apply the template to a recent AI-assisted activity from their own work and reflect on its clarity and relevance. The testing was formative in nature and aimed at understanding how designers interpret and engage with the reflective structure, rather than measuring behavioural change or long-term impact.

Before interacting with the template, participants were asked to read the instructions aloud and describe how they understood the tool's purpose. This step provided insight into how intuitively the reflective process could be entered without additional guidance and helped identify areas where clearer framing was needed.

Participants then worked through the template by identifying AI-assisted activities, selecting bias cards, and completing the reflective prompts (Figure 6.8). During this phase, participants noted that some bias definitions felt too abstract or difficult to distinguish from one another. In response to this feedback, several definitions were rewritten to improve clarity, and the ordering of the bias categories was revised. In the final version, human and cognitive biases are introduced at the beginning of the exercise, as these provide a more relatable entry point and help establish a conceptual bridge to more abstract socio-technical biases.

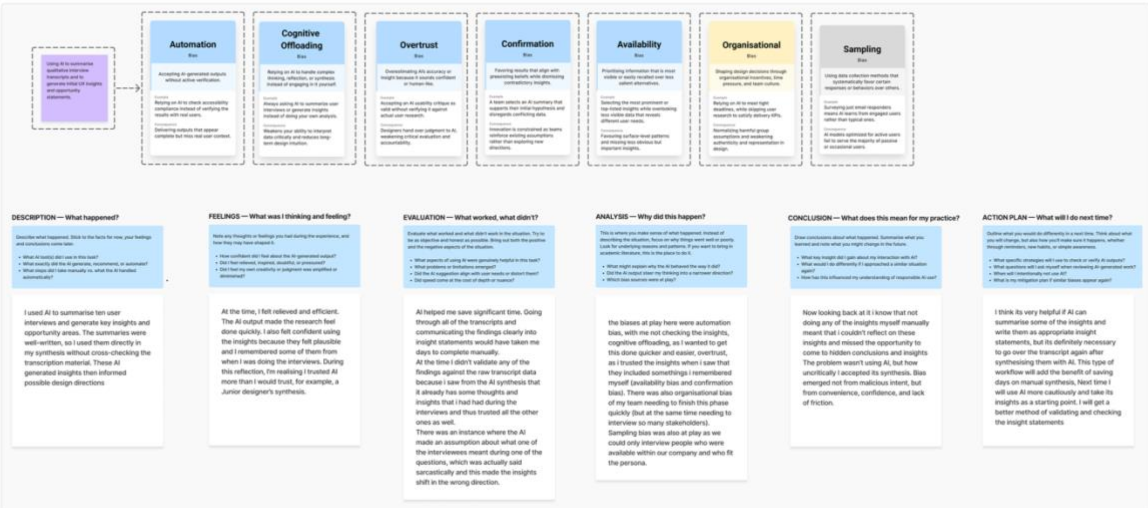

Figure 6.8 Example of a completed reflection template

Colour-coding was also introduced to visually differentiate the bias categories, supporting perceptual grouping and reducing cognitive load. This helped keep track of the bias category even when the card was moved to the reflective template.

The reflection section underwent further refinement during testing. Different reflective frameworks were tested to assess which best supported this type of exercise, and the layout of the reflection area was adjusted to more clearly communicate expected interactions and progression through the reflective process.

By the end of the testing phase, the template’s structure was found to be understandable, and the combination of visual grouping, bias cards, and reflective prompts supported meaningful reflection. Participants valued the open-ended nature of the exercise and its ability to surface different interpretations of AI influence. The final version of the template is shown in Figure 6.9.

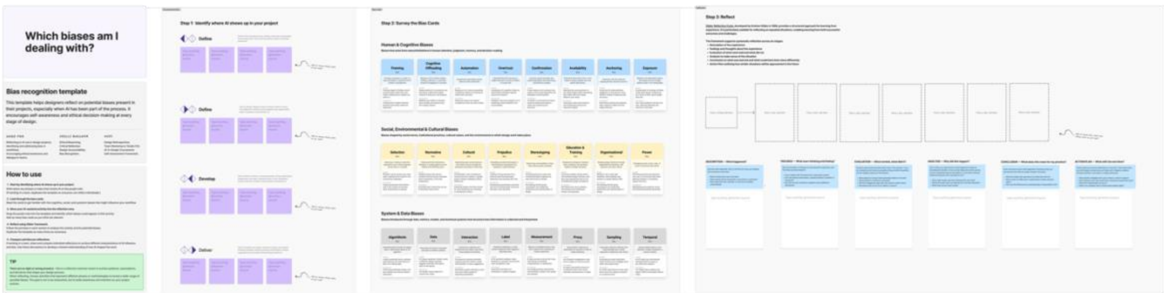

Figure 6.9 Final AI Bias Reflection Template.

At the end of the testing sessions, participants were also asked to suggest how the template could fit into their workflows. Beyond individual reflection, they suggested using it at project milestones, during retrospectives, or in workshops as a way to pause, discuss reasoning, and identify recurring patterns of bias within teams.

6.7 Digital implementation of the template

The AI Bias Reflection Template was published through the Figma Community (Figure 6.10), allowing it to be accessed, reused, and adapted within a design environment already familiar to many UI/UX practitioners. The template can be opened and used directly in FigJam via a publicly available link.

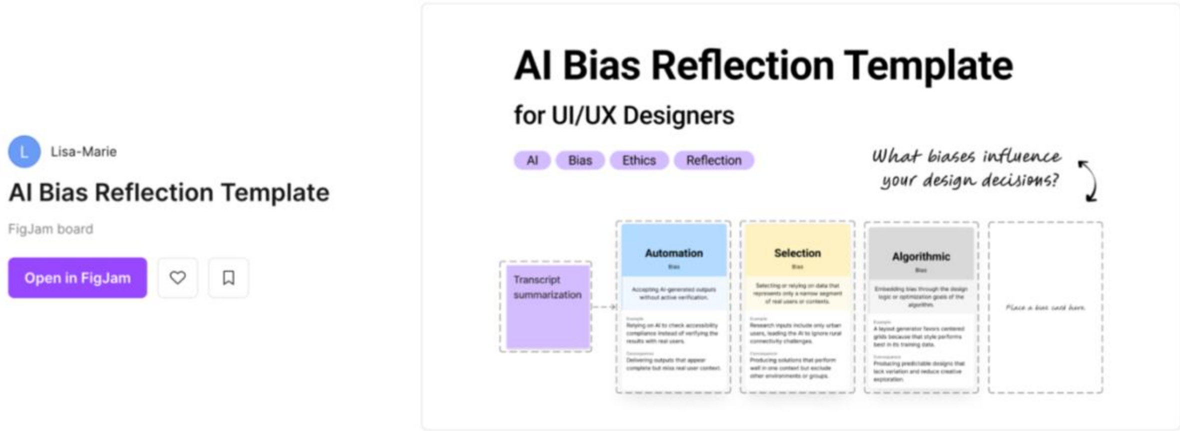

Figure 6.10 AI Bias reflection Template on Figma

Although the template is primarily intended for digital use, it was intentionally designed to be platform-independent. The same structure can be used in physical settings such as workshops, classrooms, or team sessions without access to digital tools. In these cases, AI-assisted activities can be written on sticky notes, bias cards can be printed and arranged manually on a surface, and the reflection can be written on paper. This preserves the same reflective process through physical interaction and spatial organisation.

6.8 Limitations and future improvements

The evaluation of the reflective template confirmed its value as a sense-making and reflective support for AI-assisted UI/UX design, while also revealing the conditions under which it works best. These findings highlight both the current limitations of the concept and directions for future development.

One key limitation is that the initial use of the tool requires time and focused engagement. While participants found the structured reflection valuable, it may be difficult to integrate into fast-paced or highly constrained work environments on a regular basis. However, this time investment is likely to decrease as designers become more familiar with the template and the bias concepts it introduces. With repeated use, reflection can become more efficient and more easily embedded into everyday workflows.

The evaluation also indicated that the framework is most effective when designers have prior experience with AI-assisted workflows and are open to reflective practice. Participants with less experience required additional guidance to engage fully with the exercise.

Another area for development concerns collaborative sense-making. Although the template can already be used in group settings, feedback pointed to the potential for stronger support of shared reflection. Future versions could introduce facilitation prompts, team-level reflection frames, or comparison mechanisms that help surface differing interpretations of AI influence and support collective judgment.

Further development could also extend beyond digital use. Physical reflection materials, such as reusable bias cards, could support workshops, educational settings, and in-person retrospectives, reinforcing learning through discussion and tactile engagement.

Overall, these limitations and future directions position the framework as a flexible reflective resource. Its core contribution lies in creating structured moments for designers to slow down, externalise reasoning, and critically examine how AI shapes their decisions as design practice continues to evolve.

SUMMARY

This master's thesis examines how the integration of Artificial Intelligence (AI) is reshaping User Interface (UI) and User Experience (UX) design workflows, with particular attention to its impact on designer agency, creativity, and ethical responsibility. As AI tools become embedded across design practices, designers increasingly work in collaboration with algorithmic systems that influence how problems are framed, ideas are generated, and decisions are made.

Motivated by the rapid adoption of AI in design, the research explores both the opportunities and tensions this shift creates. While AI enables automation of repetitive tasks and large-scale exploration of design alternatives, it also introduces new challenges related to bias, overreliance, trust, and the erosion of reflective judgment. This thesis addresses these challenges by investigating how designers can engage with AI critically and responsibly rather than treating it as a neutral or authoritative tool.

Using design thinking principles, the study combines theoretical analysis and qualitative research methods to examine the tensions between automation and the interpretive nature of design work. Empirical insights were gathered through qualitative interviews with practising UI/UX designers. The findings reveal a consistent pattern: designers value AI for its efficiency and creative stimulation, yet remain cautious about its reliability and influence. Many participants described a risk of reduced critical engagement when AI outputs are accepted too readily, alongside a desire for tools that support reflection within AI-assisted workflows.

In response, this thesis proposes and develops the AI Bias Reflection Template, which is a reflective design tool that supports designers in identifying and critically examining AI influence throughout the design process. Grounded in the Double Diamond (Design Council, 2005) model and informed by the theory on cognitive, social, and system-level biases, the template guides designers through structured reflection using Gibbs' Reflective Cycle (Graham, 1988). Concept testing demonstrated that the tool heightens ethical awareness and supports sense-making.

From the author's perspective, the results successfully address the thesis objectives by demonstrating both the risks associated with uncritical AI adoption and the value of structured reflection in maintaining designer agency and ethical responsibility. While the findings are based on a limited qualitative sample, they provide a credible foundation for further development of reflective tools in AI-assisted design practice.

Future development of the tool could focus on extending its use across different contexts and modes of engagement. This includes refining the template to better support collaborative sense-making within teams, as well as developing dedicated physical materials to enable hands-on reflection in educational and professional settings.

KOKKUVÕTE

Käesolev magistritöö uurib, kuidas tehisintellekti kasutuselevõtt kujundab kasutajaliidese ja kasutajakogemuse töövooge, keskendudes tehisintellekti mõjule disaineri iseseisvusele, loovusele ja eetilisele vastutusele. Kuna tehisintellekti tööriistad on üha enam disainipraktikas kasutusel, töötavad disainerid ka aina rohkem koostöös algoritmiliste süsteemidega, mis mõjutavad probleemi püstitust, ideede genereerimist ja otsuste tegemist.

Tehisintellekti levik disainivaldkonnas on loonud nii uusi võimalusi kui ka pingeid. Kuigi tehisintellekti kasutamine võimaldab rutiinsete ülesannete automatiseerimist ning disainialternatiivide ulatuslikku läbitöötamist, toob see endaga kaasa ka uusi väljakutseid kallutatuse, liigse sõltuvuse, usaldusväärsuse ja otsustusvõime nõrgenemise näol. Käesolev töö käsitleb antud probleeme ning uurib, kuidas disainerid tehisintellekti kriitiliselt ja vastutustundlikult kasutada saavad, käsitledes seda aktiivse mõjutajana disainiprotsessis.

Rakendades disainimõtlemise põhimõtteid, ühendab uurimus teoreetilise analüüsi ja kvalitatiivsed uurimismeetodid, et tuua esile pinged AI poolt toetatud automatiseerimise ja disainitöö tõlgendusliku olemuse vahel. Empiirilised teadmised koguti kvalitatiivsetest intervjuudest praktiseerivate UI/UX-disaineritega, ning nende tulemused näitavad selget mustrit: disainerid väärtustavad tehisintellekti selle produktiivsust ja loovust toetava potentsiaali poolest, kuid suhtuvad ettevaatlikult selle usaldusväärsusesse ja mõjusse. Paljud osalejad väljendasid muret, et tehisintellekti liiga kergekäeline omaksvõtt võib vähendada kriitilist mõtlemist ning väljendasid vajadust tööriistade järele, mis toetaksid refleksiooni tehisintellekti poolt toetatud töövoogudes.

Vastuseks pakub käesolev magistritöö välja tehisintellekti kallutatuse refleksioonimalli (*AI Bias Reflection Template*), mis toetab disainereid tehisintellekti mõju tuvastamisel ja kriitilisel analüüsimisel kogu disainiprotsessi vältel. Mall põhineb *Double Diamond* mudelil (Design Council, 2005) ning lähtub kognitiivsetest, sotsiaalsetest ja süsteemsetest kallutatuse käsitlustest. See juhatab disainerid läbi struktureeritud refleksiooni kasutades Gibbsi Reflektiivset mudelit (Graham, 1988) ning selle testimine näitas, et tööriist toetab kriitilist mõtlemist AI kasutamisel erinevates töövoogudes.

Autori vaatenurgast vastavad tulemused edukalt väitekirja eesmärkidele, näidates nii kriitikavaba tehisintellekti kasutuselevõtuga seotud riske kui ka struktureeritud refleksiooni väärtust disaineri tegutsemisvõime ja eetilise vastutuse säilitamisel. Kuigi tulemused põhinevad piiratud kvalitatiivsel valimil, pakuvad need usaldusväärset alust refleksiivsete tööriistade edasiseks arendamiseks tehisintellektiga toetatud disainipraktikas.

Malli edasine arendamine võiks keskenduda selle rakendamisele erinevates kontekstides ja kasutusviisides. See hõlmab nii malli täiendamist, et paremini toetada koostööl põhinevat mõtestamist kui ka spetsiaalselt füüsiliseks kasutuseks mõeldud materjalide väljatöötamist.

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Appendix 1. Semi-Structured Interview Guide

Background and context

1. Can you describe the type of design work you are currently doing?
2. Which design tools do you use most regularly in your work?
3. On a scale from 1 to 5, how would you rate your experience level in UI/UX design?
    a. 1. Novice – New to design; primarily follows explicit rules, tutorials, and established frameworks.
    b. 2. Advanced Beginner – Has some experience and emerging intuition, but still relies heavily on examples and guidance.
    c. 3. Competent Designer – Understands the design process holistically; able to plan, execute, and reflect on design decisions.
    d. 4. Proficient Designer – Demonstrates intuitive understanding of design context and user needs; adapts methods flexibly.
    e. 5. Expert Designer – Possesses deep tacit knowledge; works fluidly and creatively without reliance on formal rules.
4. Which part of the design process do you currently find most challenging, and why?

Use of AI in current workflows

5. Are you currently using any AI tools in your work?
6. Can you describe a recent project where AI was used? What role did it play?
7. In that project, where did AI provide the most value, and where did it create challenges?
8. When AI is involved in a project, does it change how much time you spend reflecting on or questioning design decisions? Why or why not?

Creativity, authorship, and control

9. In your day-to-day work, do you experience AI more as a tool you control or as a collaborator that shapes your thinking? Why?
10. Do AI-generated outputs ever feel like "your" ideas? What influences that perception?
11. On a scale from 1 to 10, how much agency do you feel when working with AI tools?
    a. Follow-up: What factors increase or decrease this sense of agency?

Quality, bias, and explainability

12. When you hear the term "bias" in the context of design or AI, what does it mean to you?
13. How much influence do AI-generated suggestions typically have on your design decisions?
14. When working with AI tools, do you ever think about potential bias in the outputs you receive?
15. How do you assess the quality of AI-generated suggestions before using them in your designs?
16. Would explanations about why a particular layout, copy, or suggestion was generated affect your level of trust?

Skills and education

17. Has the introduction of AI changed which skills are considered important within your design team?
18. Where do you currently learn new AI-related design skills or practices?
19. From your perspective, what is missing in design education when it comes to working effectively with AI?

Looking ahead

20. If you could change one aspect of AI tools in your workflow to better support thoughtful or responsible design, what would you prioritise and why?
21. Is there anything we have not discussed that you feel is important when considering AI in UI/UX design practice?

Designers not currently using AI

(Asked if Question 5 is answered with No)

22. What factors have kept AI out of your workflow so far?
23. Where, if anywhere, do you see potential value in trying AI first?
24. What would you need to feel comfortable using AI tools?

Appendix 2. AI Bias Reflection Template (Digital Access)

This appendix provides access to the digital version of the AI Bias Reflection Template developed as part of this thesis.

The template can be accessed at:
https://www.figma.com/community/file/1586725541830683070/ai-bias-reflection-template

The link leads to the latest version of the template as used and evaluated within the scope of this research.