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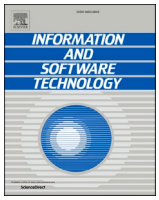

Gender-based cognitive bias and design thinking in the work of Finnish IT professionals

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ABSTRACT

Context: Cognitive bias is a concern in artificial intelligence (AI) development. Research shows the prominence of cognitive bias within algorithms. We argue that cognitive bias is more than training data, but rather development team composition. Design Thinking (DT) is an approach used to reduce bias via multidisciplinary expertise. The article presents a study examining DT in addressing gender-based cognitive bias in the Finnish information technology industry.
Objective: The aim was to examine how the gender of IT professionals influences familiarity with and use of DT, coupled with awareness and addressing of cognitive bias in IT development processes.
Method: A mixed method questionnaire was used to collect data from $N = 93$ participants. Questions probed familiarity with DT, use of DT, and cognitive bias handling in participants' organizations. Non-parametric tests were used to analyze quantitative data, due to abnormal distributions. Atlas.ti was used to code and analyze the qualitative data. Categorization determined whether participants recognized bias in their work, and the importance they attributed towards dealing with gender-based bias in IT.
Results: Women were more likely to view gender-based cognitive bias as relevant. Women were significantly more familiar with DT as a methodology ($p = 0.028$), men were significantly more likely to engage in user studies ($p = 0.018$). Older participants showed a tendency to emphasize the importance of open discussion more than other participant groups, with some analyses indicating a trend-level difference ($p = 0.085$). Qualitative responses indicated the importance of discussion in development teams to avoid or mitigate bias, suggesting the need for organizational psychological safety.
Conclusion: The paper provides novel contributions to the human dimension of bias in AI and IT in general. Results show that men and women IT professionals were aware of DT, yet men professionals were more likely to mitigate bias through collecting insight from end-users.

1. Introduction

The effects of cognitive bias among software professionals have been of concern for the past few decades. Whether shrinking-and-pinking for so-called 'feminine design', or featuring women's voices in assistant-like systems, gender stereotypes, combined with assumed gender roles and capabilities, have drawn critique, indicating imbalance from the perspective of development teams. In their field study, Chattopadhyay et al. [1] for instance found that the hardwired behaviors typified as cognitive biases impact up to 70 % of developer behaviour. This holds even when information technology (IT) professionals consider their preferred tools and practices to actively address biases themselves. The cognitive biases, or 'thought short-cuts' that tend to lean towards information that confirms our beliefs, positioning and reasoning (see e.g., [2]), observed in the field during problem-solving activities included: lack of exploration – superficial research; reduced sense-making – lack of reasoning when trouble-shooting; context loss – not maintaining knowledge of the key underpinnings of certain applications, use purposes and circumstances; and misplaced attention – failing to identify critical details in the software development due to focusing on irrelevant aspects [1]. Thus, common software development cognitive biases include: confirmation bias, availability bias, anchoring bias and overconfidence bias [1].

Cognitive biases present in the development of software already pose

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serious concerns. Yet, in the instance of the increasingly prevalent artificial intelligence (AI) development, cognitive biases have begun to manifest in different ways. From metrics chosen to reinforce specific outcomes and presentation, framing and expressing results in ways designed to *fit* stakeholder expectations, to illusory correlations (ascertaining data patterns that many not be statistically valid), and normality biases (assuming that training data effectively represents real-world phenomena), the technology that is currently in mass production and is further more being *relied upon* to produce more IT, poses unsurmountable challenges due to these biases [3]. It was through concern for these development behaviors that skew the ways in which the technology performs, combined with the growing prevalence of AI in the IT industry, that scholars such as Kronqvist and Rousi [4] saw the need to investigate and address the current state of scholarship pertaining to ethics, gender, design thinking and AI.

Whether due to text-based generative pre-trained transformers (GPTs) and large language models (LLMs) that attribute particular roles and attributes to members of specific genders, ethnicities or abilities in textual or image-based representations, or decisions to grant loans or insurance coverages, the phenomenon is having a distinct impact on the integrity of the algorithms (see e.g., [5,6]). Moreover, cognitive bias is known for being one of the main ethical concerns related to AI [7–10]. In addition to the previously mentioned cognitive biases, other challenges have been observed in relation to: biased training data – over-representation of certain cultures, languages, and standpoints in online data bases, and underrepresentation of *others* [11,12]; programming errors reflecting insufficient coder and development team knowledge [13]; and algorithmic bias – repetitive flaws resulting from training data that amplify cognitive bias in their behavior (i.e., magnifying representation of certain groups, societal norms and ideas etc.) [13–15] . In fact, a conceptual study by Ho et al. [16] on chatbot architecture and LLMs, highlighted architectural shortcomings in AI systems. These shortcomings led to much-publicised scandals such as the infamous Amazon recruitment gender bias in which women were excluded from potential candidates, and gendered assumptions of 'good' (men) versus 'bad' (women) leaders. There is also note that much of these biased technological actions stem from unbalanced power relations in development, both in physical representation of predominantly man-based teams, as well as ideologically – reinforcing long-harbored stereotypes [17]. Overall, the challenge with cognitive bias in IT, is that this form of bias functionally and behaviourally manifests flawed human thought, perceptions and power relations [13]. For example, voice assistants such as Siri and Alexa with default female personas or recommendation systems trained on biased historical data have been shown to reinforce gender stereotypes [7,15–17] . These stereotypes also apply for healthcare system applications that offer under or misdiagnoses to women based on the over representation of men in training data, and little to no training data obtained from women [18,19]. Even, the Apple Card credit system faced scrutiny when it offered up to 20 times more credit to husbands than wives [20]. These outcomes illustrate how unexamined gender assumptions in design and development teams can directly shape discriminatory or exclusionary technologies. Here we see the results of processes in which multi-faceted understandings of gender are not taken into account when developing algorithms for AI systems. Yet, what about the environments, representations, and human social dynamics that are embedded within and around the development of AI systems (i.e., the teams themselves)?

Our article contributes to a growing body of knowledge dedicated to unravelling the root causes of cognitive biases within the algorithms. We acknowledge that these biases are products of greater sociological dynamics and discourse that are played out within societies and cultures. While in this study we do not directly present empirical evidence tracing development team composition and design approaches to tangible output, the results reveal patterns in design practices that can be argued contribute to biased system design and algorithmic behavior further on. Here, we emphasize that team composition (i.e., levels of homogeneity versus heterogeneity) and design choices made (especially methodological) during early stages of development, shape facets such as data representations, model assumptions, and evaluation criteria that affect algorithmic outcomes [21]. As noted by Sánchez-Gordón & Colomo-Palacios [22], diversity in teams does not always lead to success when considering intersectional perspectives in software engineering. This is due to a number of factors, none-the-least the diversity itself in posing challenges pertaining to, for instance, cultural and communicational barriers, and the very complexity of intersectionality (i.e., one 'diverse' label does not fit all). However, their work does emphasize the importance in formulating means (i.e., frameworks) for conducting intersectional collaboration.

It is humans who imagine and create AI systems as instruments, who embody and endow the technological systems with prevailing values, priorities, and biases. Thus, in an effort to re-frame the challenge of cognitive bias, we approached the present study by investigating one of the root causes of bias within the systems – the human beings developing them. Based on our decades' worth of experience in working, as women, in the IT field, our aim was to understand how practitioners of different genders (in this case, for sample reasons, men and women) experience cognitive bias, through their own positioning within the IT industry landscape. While not all respondents in the present study worked directly on AI systems, all were involved in design or development roles within software-producing organizations. This reflects the broader technological ecosystem in which AI solutions are embedded and shaped.

We were interested in understanding how familiar professionals were with using the human-centred methodology of Design Thinking (DT) that aims to balance bias through combining numerous multidisciplinary and multi-professional viewpoints in design and development processes [23]. We specifically focus on the IDEO and Stanford d.School DT methodology. This was chosen as it is a popular approach among industry professionals and teams under various packages and terminology (i.e., Double-Diamond approach and/or Six Sigma, or combined with Agile and Scrum) [24]. Organizations and practitioners often claim that this multidisciplinary and multi-professional approach enhances the ethicality (or moral responsibility) taken in development processes [25]. DT was selected for this study because of its industry-wide popularity and its focus on user empathy, rapid ideation, and iterative problem-solving. Compared to other human-centered approaches such as participatory design or co-design, DT offers a structured and replicable framework for managing multidisciplinary collaboration in early-stage development. While participatory design emphasizes user inclusion, fewer studies have examined DT's effectiveness and limitations in addressing gender-based cognitive bias specifically [26,27]. Other creativity-based techniques, while useful for idea generation, often lack the iterative structure and user validation features that make DT suitable for bias detection and correction [28].

We formulated our inquiry on the IDEO model in an effort to frame what we meant by DT methods intended to address and mitigate cognitive bias in design. Furthermore, in anticipation of not all respondents being either familiar with the methodology per se, or only utilizing components of its framework (e.g., empathy/user inquiry, testing etc.), we used the model to isolate what respondents knew of the approach, and/or how various components were used by participating professionals. Our argument as researchers and practitioners was that despite the intention behind the method (see e.g., [28]), the representational (i.e., gender as well as other special interests such as ethnicity, religion, ability etc.) distribution of the development team is crucial when seeking to mitigate vulnerabilities such as cognitive bias [29].

Moreover, not only do we see gender distribution as an active risk within the integrity of utilizing DT and related methods to address cognitive bias, but we also see that gender could potentially influence how familiar one is with the methodology and its application. Therefore, our main research question is:

RQ1. How does gender affect IT practitioner familiarity with and utilization of DT and related methods in their design and development work to mitigate gender-based cognitive bias?

By *gender-based* bias, we refer to patterns and tendencies towards prioritizing certain behavior, traits and information via our lived experience as a representative of and within a particular 'gendered' group. Thus, we understand 'gender-based' as comprising gendered social, cultural and psychological conditioning of beliefs about oneself and others that are engrained within one's subconscious. This occurs in a way that certain roles, approaches and assumptions seem *normal* (i.e., normative [30). The current article goes beyond simply looking at gender-based bias in AI systems. Rather, through focusing on the thought of professionals in the development teams, observing the ecosystems in which AI exists and is formed – i.e., the human designer-user development systems, as well as surrounding technological ecosystems – we aim to reveal how cognitive bias is incubated within development. This is achieved by probing IT professionals' conceptions of cognitive bias in their own work, and how they attempt to mitigate this bias in their practice.

The article proceeds by describing cognitive bias and the situation of gender-based bias, leading to an explanation of how this is witnessed in the development of IT products such as AI. The article then accounts for the state of research addressing gender in DT by describing the nature of DT as a science-based method for multidisciplinary collaboration in design and problem-solving [31]. We additionally, cite our contribution, addressing the manifestation of gender-based bias held by practitioners while engaging in DT processes. The method is presented alongside results that reveal compelling intersections between participants' awareness of DT processes and methodology, and the ways that IT practitioners of different genders engage in human-centered design. The discussion offers some interpretations of the results, while outlining limitations of the study. The discussion also outlines the possible implications that this knowledge has of future development processes and practices implemented to reduce cognitive bias in software engineering for AI (SE4AI). The article ends with reflection over future research that would serve to advance understanding of gender-based cognitive bias, stemming from design and development teams.

The main contributions of this study are as follows: (1) It reveals gendered patterns in awareness and application of DT among IT professionals; (2) it identifies differences in bias mitigation strategies by gender and experience; and (3) it provides empirical insights into how gender-based cognitive bias is conceptualized and addressed in professional IT contexts.

2. Background

Gender-based bias among other biases (racial, ableist, religious etc.) are some of the hottest topics in AI ethics [8,32]. Yet, these seemingly technological issues do not exist in isolation. Rather, they stem from more historical sociological and socio-technical issues that are intrinsically embedded within the fabrics of our societal structures. Matters of equality in the workforce have been an area for debate for well over a century [32]. Gender equality, as with all equalities in areas of product and service development, not only accounts for who can undertake what position, under what conditions, and at what pay level, but signifies the strength of voice regarding critical decision-making within design and development processes [33,34] . For this reason, the current section focuses on prior research in IT development on gender-based bias, and then more specifically how gender has been accounted for in DT processes.

2.1. Gender-based bias

Cognitive biases are systematic ways of operating that deviate from decision-making based on rational thought [7]. These biases are usually caused by the brain's need to simplify and code information for its processing. Common cognitive biases are for instance: 1) confirmation bias – basing one's judgment and assumptions on one's own preconceptions; 2) anchoring bias – becoming stuck or fixated with initial ideas, even if new information arises; and 3) survivorship bias – focusing on successful decisions and ignoring failures [35].

When considering gender, significant cognitive biases arise in for example: 1) gender stereotyping – the desire to see the function and competence of people belonging to a specific gender through stereotypical perceptions attributed to that gender; 2) confirmation bias – where information is searched for and interpreted via the understanding and perceptions of one's own gender; and 3) affinity bias – favoring people and things that are similar to oneself, or through which one can identify, ignoring diversity or plurality [36,37] . Gender-based biases and perceptions of gender-related abilities stem from early childhood, easily directing thought at later stages of life [38,39] .

Within IT development and its related design (and designer) thinking, it is important to note the effects of the practitioner's gender (thought, approaches and biases) and their impact on the design's end product. In an earlier study, Batya Friedman and Helen Nissenbaum [36] demonstrated that gender-based biases in system design resulted in extensive usability challenges within technology. Although cognitive bias, gender bias, and DT are often addressed as separate topics in research, their intersection is particularly relevant in software and AI development. DT, while intended to reduce bias through empathy and iterative feedback, is not immune to the influence of team composition and internalized norms [21,32]. When teams lack gender diversity, or practitioners are unaware of their own cognitive filters, even DT processes can reproduce bias under the guise of human-centered design. In the development of AI for instance, it has become increasingly important to recognize biases as they often lead to major ethical issues [40]. One example of gendered thinking can be seen in instances of identifiably woman-gendered AI-driven chatbots and assistants [15]. Liu considers why the role of 'assistant' is often designated to women, and how this reflects the ways in which women are conceptualized in design and development overall.

In industrial processes of IT design and development, it is recognized that arriving at functional solutions to problems are not easy feats. Attempts have been made to aid in problem-solving and development processes to ensure that essential issues are taken into account. However, no one can fully escape their own internal thought patterns, and this inevitably affects the ways in which professionals are able to facilitate the processing of large sets of information. Despite adherence to processes and methods designed to integrate various factors into design, cognitive biases continue to persist [38]. The first step to reducing the impact of cognitive biases in design work is to acknowledge their existence and try to identify the types of cognitive biases people within the development team may have [39].

In cases where design processes aim to identify and account for gender-based cognitive biases that potentially stem from the composition of the practitioners within the design and development team(s), it is possible to develop products, services and systems that increase inclusiveness or possess traits that are more inclusive to a broader population of users. This results in social and economic ripple effects, as the technology we live by should increasingly provide diverse user groups with a sense of inclusion and belonging within and among the systems [32,40]. Thus, the acceptability of the technology is increased and subsequently also is its value, or worth [41,41], through its ability to serve diverse user groups.

Concrete examples of biased outcomes in design include popular voice assistants like Siri or Alexa, which often default to submissive woman personas willing to please - reinforcing traditional gender roles [15]. Another case is Amazon's AI recruiting tool, which was decommissioned after it systematically rated men applicants more favorably than women applicants for technical roles [42]. These cases illustrate how gender bias can become embedded in software tools not only

through data, but also through design assumptions and team-level cognitive biases.

2.2. Design thinking and gender

The life span of DT can be separated into two distinct time periods: 1) psychological inquiry and experimentation of multidisciplinary thought (problem-solving, reasoning, communication) encompassing creativity, visual research, perceptual and cultural factors, 'blocks' and design philosophy [43,44] from the 1950s to the 1990s; and 2) scholarly and practice-based inquiry on developing DT as an actionable approach for multi-disciplinary problem-solving (seen through IDEO, [44,45]). Thus, since the 1950s, DT has evolved as a means of understanding cognition (ways of thinking and approaching problems) in design and development processes across a range of multi-disciplinary and multi-professional settings. Additionally, it has served as a tangible and approachable framework for developing human-centred products and combining diverse areas of expertise [46–48] . Auernhammer and colleagues [44] go further to split DT's development into four separate periods: 1) Beginning – creative thinking and human values (1957–1964); 2) Growth and entrepreneurship – visual thinking and human values (1965–1985); 3) Design thinking – ambidextrous thinking and design as a social process (1986–2005); and Design thinking today (2006-onwards) – not covered by the paper, yet continuing IDEO-style traditions.

The earlier phase is largely attributed to the work of psychologist and engineer Professor John E. Arnold in 1957 at the Department of Mechanical Engineering and Graduate School of Business, in Stanford University's Joint Program in Design and Design Division. Arnold saw the need to both generate an understanding of how thought works in situations that require diverse expert knowledge to solve problems, as well as to develop techniques to bridge the diversity of thought and approaches. Arnold collaborated with the likes of Abraham Maslow, J.P. Guilford, Henry Dreyfuss and Matthew Kahn in attempts to isolate creativity of thought across the disciplines, while understanding what types of creativity and inquiry are necessary at which particular moments of problem-solving [49,50].

As seen in the latest two periods described by Auernhammer and colleagues [44], DT takes on a more concretized notion, being implemented as a tool to guide human-centred multi-disciplinary development processes. Notedly, the method is largely recognized for three integral components [43]: a) need-finding or problem-scoping; b) brainstorming; and c) creating prototypes in multidisciplinary teams. The main objective for its usage is to facilitate creativity while overcoming obstacles such as cognitive bias [43,51,52] . Recent research has begun to map how DT is used in software and AI development. For example, Sreenivasan and Suresh [25] identified both synergies and gaps in combining DT with AI pipelines, noting ethical and inclusivity challenges. Similarly, Parizi et al. [26] found that while DT is often embedded in agile or UX processes, its application to mitigate bias - especially gender-based cognitive bias - remains limited and under-theorized.

For this reason, DT as a tool for incorporating consideration for traits and aspects regarding e.g., gender, racial or age-related biases to name some, would appear to be ideal. However, knowing that DT is only as strong as the practitioners and their team undertaking it, in 2023 the authors sought to investigate what types of challenges DT faces from a gender and ethics perspective in the development of AI systems [27]. Their literature review revealed that while DT is promoted as a method and means of human-centred design process that has the potential to account for ethical considerations within process, the issue of cognitive bias within the teams and practitioners engaging in DT is relatively neglected. Most studies highlight the effectiveness of the method in reducing cognitive bias (see e.g., [51]). Yet, very few studies (i.e., [52]), examine the biases that may exist within DT teams themselves, particularly in light of the composition of the team members.[1] That is, homogeneity on some levels, i.e., in respective to gender, cultural identity, socio-economic circumstances, language etc. may pose challenges in terms of identifying and overcoming hidden biases that are subsequently manifested within designs.

For this reason, we sought to study how IT design and development practitioners, as representatives of their genders, recognize and utilize DT within their work. It was our hope to reveal commonalities and differences in terms of how they approach DT, and how its characteristics are integrated within their work. Table 1 presents a comparison of key studies on DT and bias mitigation in software development. The comparison serves to highlight the timely contribution of this study, both in terms of scarcity and temporal currency, as well as in the lack of empirical investigations in the IT field pertaining to this specific topic on mitigation of gender-based cognitive bias.

None of the papers cited in the comparative Table 1, except Kronqvist and Rousi [4] and the current paper directly address the issue of gender-based bias, the team composition of IT developers, or the use of DT as a means of tackling gender-based bias in the development of software products (including AI). Research is highly focused on systematic mapping and conceptual development, without the collection of actual experiences from the field (i.e., empirical questionnaire studies).

3. Method

A mixed method [55] approach was used to collect data via an online questionnaire supported by Webropol, between March and June 2024. A pilot study was conducted with three participants prior to the main data collection. The responses from the pilot participants were not included in the final analysis. No major changes were made to the questionnaire based on the pilot; only some wording was clarified to improve readability. Professionals - professionals working in development within the IT sector in Finland and/Finnish companies - were recruited via public social media postings and Author 1′s internal business communication channels. The reason for this broad approach in participant recruitment stems from the ecosystemic nature of cognitive bias cultivation. This sampling strategy is grounded on the basis of prior scholarship in technology ethics and organizational behavior (see, e.g., [56,57]), underscoring that systemic bias in AI is deeply engrained in institutional structures. This goes beyond technical workflows and position titles. We justify our approach, through alignment with a more holistic understanding of how gender-based bias emerges and persists in socio-technical systems. AI systems are not developed, nor do they exist, in isolation. Rather, they are rooted in organizational ecosystems that comprise cultures, diverse teams (i.e., product teams), engineering divisions, and workflows. Gender dynamics in teams and leadership affect core structural and interpersonal dimensions, leading to decision-making hierarchies, *voice*, dissent, norms surrounding inclusion, and even mentorship that leads to career advancement. These are important ambient conditions that contribute to fostering environments in which AI is developed. Thus, our rationale is that it is important to gain insight into the conditions and approaches of professionals across the IT field, rather than limiting the scope to those directly responsible for design and development of the AI systems. Here, we have been able to grasp contextual factors that either reinforce or mitigate gender-based cognitive biases within AI development teams.

In total, 181 individuals opened the questionnaire, 129 started responding, and 93 completed it. These 93 responses form the final dataset analyzed in this study. Of the 93 respondents, two identified as

[1] Interestingly one Masters' thesis [53] acknowledges the risk of bias existing within DT teams.

Table 1
Overview of related work on design thinking and bias mitigation in software development.

Study	Focus	Method	Context	Bias Addressed	Gaps Identified
Sreenivasan & Suresh (2024) [25]	DT + AI	Systematic Literature Review	AI Systems	Cognitive Bias	Weak ethical integration
Parizi et al. (2022) [26]	DT in Software Development	Systematic Mapping	Software Projects	Process-related Bias	Limited attention to inclusion
Kronqvist & Rousi (2022) [4]	DT + Ethics + Gender	Literature Review	AI/IT Ethics	Gender Bias	Team composition rarely analyzed
Current Study	DT + Gender + Cognition	Mixed-Method Survey	Finnish IT Professionals	Gender-based Cognitive Bias	Lack of awareness inside DT teams
Mohanani et al. (2018) [9]	Cognitive biases in software engineering	Systematic Mapping + Literature Review	Software Engineering	47 types of Cognitive Bias	Scarcity of mitigation techniques; weak theoretical foundations
Sanchez Ruelas et al. (2021) [54]	Decision models to reduce bias in design processes	Model Development + Pilot Study	Engineering Design & Strategic Planning	Decision-making Bias	Lack of integration with DT frameworks
Sánchez-Gordón & Colomo-Palacios (2021) [22]	Intersectionality in SE	Conceptual Framework	Software Engineering	Structural & Identity-Based Bias	Lack of practical integration with DT and SE processes

non-binary and were excluded from comparative statistical analyses. Thus, the gender-based analyses are based on $N = 91$. The survey announcement reached approximately 3600 professionals through public LinkedIn posts (2279 views) and internal business communications (1320 recipients). The open-access nature of the recruitment process and the sensitivity of the topic likely contributed to the dropout numbers and the modest completion rate. Questions addressing DT and cognitive bias are presented in Table 2.

Participants were eligible if they were employed in IT development roles in Finland or Finnish companies abroad, including but not limited to software developers, UX designers, architects, team leads, and consultants. No strict role-based or experience-level exclusions were applied. The study was openly advertised as targeting professionals involved in design and development activities. As such, the participant pool included individuals with a range of design responsibilities - from full involvement in user-centered design to partial engagement due to role-specific constraints. Because of the open recruitment, no prescreening for Design Thinking familiarity or AI-specific project work was undertaken.

Table 2
Questions addressing DT and cognitive bias in the online questionnaire.

Theme	Question type	Response type	Target variable
Familiarity with DT	How familiar are you with the DT model?	Likert scale 0 to 5 - Not at all – I know well	DT familiarity level
Use of DT	Have you used the model in your design work?	Multiple choice - Yes/No/I do not know	DT usage
Bias mitigation practices	How do you mitigate the possible effects of cognitive bias in your design work?	Multiple choice - Options: We do nothing; we discuss about biases; we aim to collect diverse user information; something else, what?	Mitigation strategy
Gender influence on design	Have you noticed your gender influencing your design decisions and if so, how?	Open-ended question	Self-perceived gender influence
Recommendations for mitigating bias	In what ways should cognitive bias be addressed in design?	Open-ended question	Recommendations for bias mitigation

We recognize that the relatively high proportion of women respondents ($N = 54$ women, $N = 37$ men, $N = 2$ non-binary) is atypical for the IT industry. However, this reflects a possible self-selection effect where women - often underrepresented in design - may have been particularly motivated to share their experiences regarding gender-based bias and team practices. In other words, women may have felt compelled to have their voices heard.

Through the questionnaire, we collected data regarding the participants' familiarity and experiences with the earlier six step Stanford d. School/IDEO Design Thinking model ([48,51,52], see Fig. 1). The steps were explained in the six-step diagram provided to participants as: empathize – user studies uncovering stories and data about the stakeholders; define – re-framing the problem and creating problem-statements; ideate – brainstorming; prototype – low-resolution (rough) objects to test ideas; test – testing, embracing failure and making improvements; and assess – validation stage.

The questionnaire progressed to focus on the participants' own observations of the effects of cognitive bias, its significance and how to pay attention to it within design work. These queries were made with the research assumption that cognitive bias pertaining to gender experience would affect how practitioners engage with Design Thinking, and how it affects the approaches made within development work. The questionnaire was built via utilizing the observations and findings obtained in an earlier study [4].

The current study focused on collecting both quantitative and qualitative data. The quantitative data was transferred to the SPSS tool for statistical analysis. Because data was not normally distributed, non-parametric tests were used. Mann-Whitney U tests were used for two-group comparisons (e.g., men vs. women), and Kruskal-Wallis H tests for comparisons across multiple experience or age groups. Chi-square tests were used for categorical associations. Kruskal-Wallis H tests were applied only when each comparison group contained at least five observations. For comparisons between two groups, Mann-Whitney U tests were used. Categories with insufficient group size were reported descriptively and excluded from inferential tests (see Table 3).

Code frequencies from the qualitative analysis were exported into SPSS and analyzed in relation to demographic variables, enabling triangulation between participants' written responses and their quantitative background data. Table 3 presents variable groupings, group labels and group sizes. The qualitative data collected via the open field questions was transferred into Atlas.ti for narrative analysis [58]. The textual responses were categorized into specific sub-categories and the responses were coded according to these. A grounded theory approach was taken for the open coding [59,60], whereby the objective was to discover what concepts arose when participants described their thoughts of and approaches to addressing gender-based cognitive bias, in relation to DT. Pre-defined categories were not referred to during this process, as the goal was to observe the concepts that emerged while participants

Fig. 1. Acknowledgement of bias relevance.

Table 3
This table summarizes the group sizes used in the statistical analyses to verify that the assumptions for Mann-Whitney U (2 groups) and Kruskal-Wallis ($\geq$ 3 groups, $n \geq 5$) are met.

Variable Grouping	Group Labels	Group Sizes (N)
Gender (used in Mann-Whitney U)	Women, Men	54, 37
Age groups (used in Kruskal-Wallis)	21–30, 31–40, 41–50, 51–60, 61+	16, 32, 33, 8, 4
Experience groups (used in Kruskal-Wallis)	<5, 6–10, 11–15, 16–20, 21–25, >26 years	20, 27, 11, 11, 11, 13
Bias relevance coding (Chi-square)	Sees gender relevant, irrelevant	40, 51
Bias mitigation importance (Chi-square)	Important, Not important, No opinion	69, 2, 20
Mitigation strategy (Chi-square)	Discussion, Collection, Other	15, 43, 7 (varies by item)

qualitatively expressed their positioning and approaches. Here, Author 1 initiated the process by: 1) becoming familiarized with the full qualitative data set, initial open coding then took place. Author 2 then reviewed and compared the codes to the data, and the two authors discussed and refined the codes. It was only upon interpretation of the codes, that the authors compared the findings to the DT model and previous research.

Open coding was performed by Author 1 to identify meaningful statements in the responses. The process was inductive, Author 2 reviewed the codes, offering suggestions for refinement or re-coding. These were then grouped by Author 1 through axial coding into themes such as bias awareness, mitigation strategies, and perceived relevance, which were then once more reviewed by Author 2. In total, seven main categories were formed. Both researchers, Author 1 and Author 2, collaboratively reviewed the codes once more to enhance consistency and reduce interpretation bias. The frequencies of the codes were exported to SPSS to enable triangulation with quantitative variables such as gender, age, and experience. The qualitative analysis was guided by two core questions embedded in the open-ended survey items. Open coding was used to identify meaningful statements, which were then grouped into themes through axial coding [60]. The coding resulted in two overarching categories: (1) personal views of bias relevance and importance; and (2) ways to mitigate gender-related cognitive bias. Within each code, responses were further distinguished by values (e.g., yes/no/no opinion), which represent whether participants' statements explicitly acknowledged, rejected, or did not address the theme. The final codes and themes used in the analysis are presented in Table 4.

Table 4
The final codes and themes derived from the analysis, accompanied by their descriptions.

Theme	Code	Description
Perceived bias importance	Cognitive bias is important factor	Participant considers gender-based cognitive bias important in their design work.
Perceived relevance	Sees gender relevant in design	Participant perceives their own gender as relevant to their design decisions.
Ways to mitigate gender-related cognitive bias	Familiarize with user groups	Participant mitigates bias by actively gathering input from diverse users.
	Open discussion	Participant describes discussing bias openly within their team or project context.
	Acknowledge bias existence	Participant mentions acknowledging the bias as mean to address bias
	Usage of diverse design groups	Participant sees the design group composition as important mean to address bias
	Added information about bias	Participant stated that information about exiting biases and the phenomenon should be added
	Psychologically safe information	Participant emphasizes the importance of safe discussion environment in design groups

3.1. Participants

In total, $N = 93$ IT-sector development and design practitioners participated in the study. These comprised $N = 54$ women, $N = 37$ men, and $N = 2$ non-binary. Because there were only two participants in the non-binary category, their responses were excluded from the analysis. This was due to the inability to make comparisons with the other groups, or any generalizations overall. The respondents represented the following age groups: 1) 21–30 years old (16); 2) 31–40 years old (32); 3) 41–50 years old (33); 5) 51–60 years old (8); and 6) over 61 years old (4). Thus, the largest respondent groups were 2 and 3. Groups five and six were combined for analysis due to the low number of participants in group 6. Additionally, participants were divided into groups according to how long they had worked in the IT field: 1) <5 years (20), 2) 6–10 years (27), 3) 11–15 years (11), 4) 16–20 years (11), 5) 21–25 years (11) and 4) over 26 years (13). The largest group of respondents had worked in the field for six to 10 years.

3.2. Research ethics

In compliance with the Finnish National Board on Research Integrity

(TENK), the University's own guidelines for ethical research, and in compliance with the General Data Protection Regulation (GDPR) all participants were, before commencing the study participants informed about why we were collecting the data, how we would be using it, how it would be stored, and for how long. Participants could opt out after reading this information. All data was collected anonymously, and questions had been carefully formatted to ensure that participants could not be identified either by personal characteristics, or characteristics of their place of employment.

4. Results

The first part of the questionnaire focused on familiarity with the Design Thinking model. Here, participants were asked about how familiar they were with this six-step method and whether they had used it in their professional practice. The familiarity with the design thinking model was addressed by the question: "How familiar is the model to you?" Usage was inquired via the question: "Have you used the model or parts of it in your work?" alternatives being "yes", "no", and "I cannot say". The next questions concentrated on gender-based cognitive bias: how it is addressed by the participants and their organizations; how they use DT to address and/or mitigate gender-based cognitive bias; and how they acknowledge gender-based cognitive bias in their work as IT development professionals. The section progresses by presenting the results of the quantitative analyses, and then moves on to describe the results of the qualitative questions that focused on: acknowledgement of the relevant of gender-based cognitive bias; and how important the respondents feel that the mitigation of gender-based cognitive bias is in the design and development work of IT. The results are as follows.

4.1. Familiarity and DT usage

The SPSS analysis reveals notable gender-related differences in familiarity with the design approach and approaches to addressing cognitive biases (see Table 5). A Mann–Whitney U test indicated that women reported significantly higher familiarity with the design approach (mean rank = 52.06) compared to men (mean rank = 37.15), $U = 671.5$, $Z = -2.692$, $p = 0.007$. These results confirm that women were more familiar with the DT model than men. However, there was no statistically significant association between gender and the use of DT in design and development work ($\chi^2 = 0.332$, $p = 0.847$). Both genders reported similar usage levels, with 51.9 % of women and 45.9 % of men indicating that they had used the model.

A Kruskal-Wallis H Test was performed to examine differences in familiarity with the DT process among age groups, as the data was not normally distributed. The study found no statistically significant differences between age groups (Kruskal-Wallis $H = 2.640$, $p = 0.650$). The high p-value indicates that familiarity levels do not vary significantly across the groups. No post hoc tests were conducted, as the Kruskal-Wallis H Test did not reveal significant differences. Also, no significant differences in familiarity with the model were found across experience groups (Kruskal-Wallis $H = 2.545$, $p = 0.770$). This suggests that familiarity with the DT model is relatively consistent regardless of the length of professional experience. Similarly, no significant differences in model usage were observed across experience groups (Kruskal-Wallis $H = 4.877$, $p = 0.431$). The results indicate that professional experience does not significantly influence familiarity with DT or its application in design and development work.

Table 5
Familiarity and DT usage.

Variable	Chi-square	p-value	Difference
Gender and Usage of Design Thinking Model	0.332	$p = 0.847$	
Gender and Familiarity with Design Thinking Model	Mann-Whitney $U = 671.5$; $Z = -2.692$	$\boldsymbol{p = 0.007}$	Women scoring higher
Familiarity with Design Process by Age Groups	Kruskal-Wallis H Test $H = 1.640$	$p = 0.650$	
Familiarity with the Model by Experience Groups	$H = 2.545$	$p = 0.770$	
Model Usage by Experience Groups	$H = 4.877$	$p = 0.431$	

4.2. Addressing cognitive bias

A multiple-choice question was featured in the questionnaire to ascertain how cognitive bias is addressed in the design and development work in participants' organizations. This is shown in Table 6.

Regarding approaches to addressing cognitive biases, there was no statistically significant association between gender and whether participants addressed cognitive biases in their design processes ($\chi^2 = 3.361$, $p = 0.067$). However, the results (see Table 7) suggest a trend-level difference, with women more likely to report not addressing cognitive biases (51.9 %) compared to men (32.4 %). Men, on the other hand, were significantly more likely to report collecting information from diverse user groups during the design process ($\chi^2 = 5.561$, $p = 0.018$). This finding highlights a gender-related difference in bias mitigation strategies, where men prioritize gathering diverse user data more frequently than women.

No significant differences were found between genders in terms of openly discussing cognitive biases ($\chi^2 = 0.003$, $p = 0.955$) or using other methods to handle biases ($\chi^2 = 0.854$, $p = 0.355$). Overall, the analysis highlights significant gender-related patterns in the DT model familiarity and specific bias mitigation strategies, such as collecting diverse user information, while showing no substantial differences in other approaches, including open discussions and alternative methods.

However, a statistically significant difference was identified in the likelihood of engaging in open discussions about cognitive biases (Kruskal-Wallis $H = 12.575$, $p = 0.014$). The oldest age group (61+) showed the highest mean rank (72.63) in this category, suggesting that they are significantly more likely to discuss cognitive biases openly to avoid their impact on design outcomes. Due to the low number of cases in the 61+ age group, the two oldest groups (51–60 and 61+) were combined for analysis. When comparing combined age groups, the Kruskal–Wallis tests did not reveal statistically significant differences in bias mitigation practices. For neglecting cognitive bias, the overall test approached significance ($H = 6.850$, df = 3, $p = 0.077$), and for open discussion of cognitive biases the effect also showed a trend-level difference ($H = 6.617$, df = 3, $p = 0.085$), with the oldest group (51+) displaying the highest mean ranks. However, these effects did not meet the conventional threshold for statistical significance. No significant differences were found for the practice of collecting diverse user information ($H = 1.458$, df = 3, $p = 0.692$). Post hoc pairwise comparisons (Mann–Whitney U tests) suggested that most age groups did not differ significantly from each other, but some patterns emerged. Respondents in the oldest group (51+) reported significantly lower levels of 'not addressing cognitive bias' compared to the youngest group (21–30 years; $p = 0.022$) and expressed significantly higher levels of engaging in open discussions compared to the 41–50-year-old group ($p = 0.023$). In

Table 6
Multiple choice question on how cognitive bias is addressed.

Option No.	How do you consider the possible effects of cognitive bias in your design work?
1	We do nothing
2	We discuss cognitive biases openly to avoid their impact on the outcome
3	We use a triangulation approach, i.e., we collect data in several different ways to ensure the right understanding
4	Some other way

Table 7
Addressing cognitive bias.

Variable	Chi-square	p-value	Difference
Gender and Not Addressing Cognitive Biases	$\chi^2 = 3.361$	$p = 0.067$	Women scoring higher
Gender and Collecting Diverse User Information	$\chi^2 = 5.561$	$\mathbf{p = 0.018}$	Men scoring higher
Gender and Openly Discussing Cognitive Biases	$\chi^2 = 0.003$	$p = 0.955$	
Gender and Using Other Methods for Bias Handling	$\chi^2 = 0.854$	$p = 0.355$	
Variable	Kruskal-Wallis	p-value	Difference
Age and Open Discussions about Cognitive Biases (51+ compared to others)	$H = 6.617$	$p = 0.085$	Age group 51+ trending higher than others
Age and Neglecting Addressing Cognitive Biases (51–60 and 61+ compared to others)	$H = 6.850$	$p = 0.077$	51+ trending lower to neglect
Experience and Collecting Diverse User Information (11–15 and 21–25 years of experience compared to others)	$H = 13.823$	$\mathbf{p = 0.014}$	11–15 years and 21–25 years of experience reported significantly higher

addition, a significant difference was observed between the 31–40-year-old group and the oldest combined group (51+), where the older group more frequently reported open discussion of bias ($p = 0.014$). These findings indicate that while overall tests did not reach significance, the oldest respondents showed a clearer tendency to actively discuss cognitive biases and to avoid neglecting them, compared to younger groups

When comparing years of experience in relation to addressing the impacts of cognitive bias, the Kruskal-Wallis H Test revealed statistically significant differences between experience groups in their likelihood to collect diverse user information ($H = 13.823$, $p = 0.017$). Participants with 11–15 years and 21–25 years of experience reported significantly higher mean ranks for comprehensively collecting user information compared to those with less than five years of experience. This suggests that mid-career professionals are more likely to prioritize gathering diverse user information in design processes than those with limited experience. Although no post hoc tests were conducted in this analysis, the results indicate a trend where more experienced professionals generally place greater emphasis on user data collection. Notably, the group with less than five years of experience reported the lowest mean rank for this practice, while those with 21–25 years of experience reported among the highest ranks.

Table 8

Mann–Whitney U tests were used to compare DT familiarity (0–5 scale) between those who reported collecting diverse user information and those who did not. For the full sample, no statistically significant difference was observed ($U = 855.5$, $p = 0.153$), although the direction suggested slightly higher familiarity among those collecting user data. When analyzed by gender, a significant difference emerged among women ($U = 194.5$, $p = 0.008$). This exhibited that women who collect user information reported significantly higher familiarity with the DT model than those who did not. Among men, no such association was found ($U = 156.5$, $p = 0.884$). These findings refine the earlier chi-square results, suggesting that familiarity with the DT model is linked to user data collection practices primarily among women.

A Mann-Whitney U test indicated that participants who reported not addressing cognitive bias had significantly lower familiarity with the DT model ($U = 803.0$, $p = 0.042$). When analyzed by gender, the effect was particularly strong among women ($U = 188.0$, $p = 0.002$), whereas no significant association was observed among men ($U = 127.0$, $p = 0.439$). These results suggest that lower DT familiarity is linked to neglecting cognitive bias, especially among women respondents. A Mann–Whitney U test indicated a trend-level association between DT familiarity and reporting open discussion of cognitive bias ($U = 439.0$, $p = 0.067$). When analyzed by gender, the effect was significant among men ($U = 45.5$, $p = 0.043$), with those who reported open discussions showing higher familiarity (mean rank = 26.9) than those who did not (mean rank = 17.5). Among women, no such association was found ($U = 155.5$, $p = 0.266$). These results suggest that higher DT familiarity is linked to a greater likelihood of engaging in open discussion about cognitive bias, particularly among men respondents.

Table 8
DT familiarity and addressing cognitive bias.

Variable	Group	Chi-square	p-value	Difference
Not addressing cognitive bias	All ($N = 93$)	$U = 803.0$, $Z = -2.030$	$p = 0.042$	Lower familiarity among those not addressing bias
	Women ($N = 54$)	$U = 188.0$, $Z = -3.104$	$\mathbf{p = 0.002}$	Women not addressing bias have significantly lower familiarity
	Men ($N = 37$)	$U = 127.0$, $Z = -0.773$	$p = 0.439$	No difference
Collecting user information	All ($N = 91$)	$U = 855.5$, $Z = -1.427$	$p = 0.153$	No significant difference, trend
	Women ($N = 54$)	$U = 194.5$, $Z = -2.655$	$p = 0.008$	Women who have higher familiarity collect more often user information
	Men ($N = 37$)	$U = 156.5$, $Z = -0.146$	$p = 0.884$	No difference
Open discussion about cognitive bias	All ($N = 93$)	$U = 439.0$, $Z = -1.834$	$p = 0.067$	Trend: discussion linked to higher familiarity
	Women ($N = 54$)	$U = 155.5$, $Z = -1.111$	$p = 0.266$	No difference
	Men ($N = 37$)	$U = 45.5$, $Z = -2.029$	$p = 0.043$	Men who discuss bias have higher familiarity

4.3. Convergence between DT familiarity / usage and open-ended references to user research

To examine whether open-ended response references to user research aligned with participants' reported DT familiarity, we compared familiarity scores (0–5) between those who mentioned user research in open-ended questions and those who did not. Descriptive statistics suggested slightly higher familiarity among those who mentioned user research (median = 2, IQR = 1–4; mean rank = 48.8) compared to those who did not (median = 1, IQR = 0–4; mean rank = 43.4). However, the difference was not statistically significant (Mann–Whitney $U = 913.0$, $Z = -0.978$, $p = 0.328$). These results indicate that while user research is conceptually central to DT, in this sample open-ended references to it were not strongly associated with higher self-reported DT model familiarity.

Table 9

A chi-square test examined whether participants who reported using DT were more likely to mention user research in their open-ended responses. The analysis showed no significant association ($\chi^2(2, N = 91) =$

Table 9
DT familiarity in relation to participants open-ended response mentions of user research.

Familiarize with user groups	N	Median	IQR	Mean rank	U	Z	p
Not mentioned	47	1.0	0–4	43.43			
Mentioned	44	2.0	1–4	48.75	913.0	−0.978	0.328

0.90, $p = 0.637$). Overall, 52 % of those who mentioned user research also reported using DT, compared to 47 % of those who did not. These results suggest that while user research is a central principle of DT, open-ended references to it did not systematically align with self-reported DT use in this sample.

Table 10

4.4. Analysis of open-field questions

The open-ended survey responses were analyzed using an inductive open coding process. Importantly, although the questionnaire also included a closed multiple-choice item on bias mitigation practices, these predefined categories were not used in the coding of open responses. Instead, codes were generated directly from the participants' own wording without reliance on the survey alternatives. The coding proceeded iteratively, grouping similar expressions together and gradually forming broader categories and themes. This approach follows the principles of thematic analysis, where meaning patterns are identified from the data in a bottom-up manner. The procedure was carried out as part of the broader qualitative phase of the doctoral research project, in which the same open coding strategy has been applied consistently.

Answers to two open-ended questions were analyzed in Atlas.ti: 1) "What do you think should be done to take cognitive bias into account in your design work? Share your ideas, thoughts and experiences"; and 2) "In what ways have you found that the design decisions and solutions you make are influenced by your own gender, and the resulting understanding or lack of understanding of user needs?". The resulting code tables were exported to SPSS for further analysis.

4.5. Acknowledgement of gender-based cognitive bias relevance

The answers were coded based on how well the cognitive bias of the practitioners themselves was acknowledged as a possible factor affecting design results. The division of codes is visible in Fig. 2. Further statistical analysis in SPSS reveals significant gender differences in acknowledging bias existence and noticing gender affecting design. Out of 93 valid responses, 23 participants (25 %) explicitly considered gender relevant, 62 (67 %) stated that gender was not relevant, and 8 (9 %) gave no opinion. Gender-disaggregated analysis (only women and men included, $N = 91$) showed very similar patterns: 24 % of women and 22 % of men acknowledged gender relevance, while 67 % of women and 70 % of men reported gender as irrelevant, and around 9 % in both groups gave no opinion. A chi-square test confirmed no significant differences between women and men ($\chi^2(2, N = 91) = 0.13$, $p = 0.936$)

The relevance of gender can be understood through the following comment made by a man participant,

> "I didn't even think that my gender could be connected to how I take users' needs into account. Come to think of it, I notice *that my assumption is that user needs are not dependent on gender. Of course, gender plays a role, but I just didn't think of it." – Man P22, age 41 to 50, Familiarity with DT=0, Has not used DT*

This comment reflects a lack of awareness of the impact of one's own gender and identity on the human-centred design process. The participant acknowledges its importance yet also admits to a lack of self-reflexivity on the issue. The next comment takes a different, more assertive perspective, emphasizing majority voice,

> *"Men decide, women follow. Majority decides (in IT men are still majority)" – Woman P33, age 51 to 60, Familiarity with DT=3, Has used DT*

*The statement above gives a matter-of-fact assertion that there is power imbalance within the IT development field, and that it is those who are there within the development processes (*i.e.*, the man majority) who have a say on how products and services are developed. The statement is made in an ambivalent way, not placing the indivdiual themselves within the position of the 'man majority'. They stress the direct relationship between those who are present and contributing to development, and those who remain in a secondary position (*i.e.*, women, users, others) after decisions have been made. Interestingly, another participant does ackowledge their role as a white man designer in the following comment,*

> *"As my understanding of structural chauvinism/patriarchy/racism, etc. increases, I have tried to take into better account the fact that my own background as a white man distorts my own view and understanding of how different things are used or need to be used, and I try my best to take that into account." – Man P31, age 41 to 50, Familiarity with DT=4, Has used DT*

P31's statement projects an awareness of tensions and imbalance of gender in technological development alongside how one's own demographics influence cognition and approach towards design and development. This statement may offer insight on the quantitative findings indicating that men are seeking more information about target end-users than women. There is a recognition of imminent bias, and strategies to mitigate this.

However, other statements seemed contrary to this trend. Two participants argued that their gender was irrelevant, and as one of these participants explained:

> *"I don't feel that my gender or my experience of it have influenced my design decisions. My area of design consists of technical descriptions and these types of things, which are not dependent on user groups."* Woman P9, age 21 to 30, Familiarity with DT=4, Has not used DT.

In this comment, P9 exemplifies a strain of thought that dislocates technical back-end decisions from holistic acknowledgement of gender and its implications in the overall design. Shepperd et al. [61] describe this in terms of "anchoring bias" when making estimations. Moreover, Hehn and Mendez [62] emphasize that DT is imperative to technical development as diverse user needs are also implicated within the inner workings of the systems.

> *"I don't feel that my design decisions or solutions have had anything to do with gender."* Man P23, age 21 to 30, Familiarity with DT=1, Has used DT

Another participant simply states,

> *"Why does gender matter?"* Man P10, age 41 to 50, Familiarity with DT=0, Has not used DT

Thus, there are differences of opinions among even men respondents regarding the role of their own gender in design and development processes, and how this affects their design decisions. There is the acknowledgement of internal cognitive biases of designers that operate in conjunction with structural gender-based biases, and then there is the sentiment that gender has no effect on design or decision-making.

4.5.1. The importance of cognitive bias mitigation

The answers to the question, "What do you think should be done to take cognitive bias into account in your design work? Share your ideas, thoughts and experiences?" were coded based on how important the respondent found the mitigation of cognitive bias. The codes are visible in Fig. 2. After coding, the data was exported to SPSS for further statistical analysis.

SPSS chi-square analysis showed no statistically significant gender

Table 10
DT use (survey) × User research mention (open-ended).

Familiarize with user groups	DT use: yes	DT Use: No	IQR	Did not know	Total
Not mentioned	47	1.0	0–4	43.43	
Mentioned	44	2.0	1–4	48.75	913.0

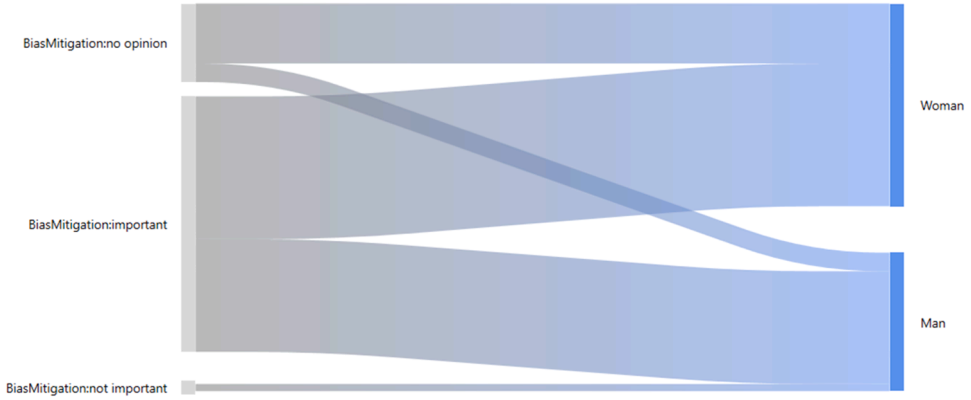

Fig. 2. Importance of cognitive bias mitigation.

differences in perceptions of the importance of bias mitigation, $\chi^2(2, N = 91) = 3.39$, $p = 0.183$. A majority of both women (74 %) and men (76 %) rated mitigation as important, while around one-quarter of women (26 %) and one fifth of men (19 %) expressed no opinion. Only two men (5 %) and no women considered mitigation not important. These findings indicate that both genders largely agreed on the importance of bias mitigation, with no meaningful gender-based differences observed.

Table 11

The importance of cognitive bias mitigation was expressed in the following comments that demonstrate a form of reflexivity regarding the success of design projects in light of concern for the lack of target user knowledge, as well as inadequacies regarding cognitive biases and their incubation within development teams,

> *"Generally, in design and collaboration, the endeavour to arrive at a common goal seems left behind. With sufficient background material, a sample of users and their needs could be obtained. In design, I would ask for each proposal or decision to consider this question, "What do I assume the user knows/ is capable of, in order to complete this step?"* – Woman P9, age 41 to 50, Familiarity with DT=1, Did not indicate DT use

Another participant states,

> *" People need to learn to be able to identify biases, and designers should be different people and projects should foster a safe culture, in which biases and their effects can be discussed." – Man P17, age 21 to 30, Familiarity with DT=2, Has used DT*

One participant advocated for a systematic approach towards detecting, identifying and dealing with gender-based cognitive biases,

> *"It should be more visible, and larger decision-making processes should have a clear stage in which to examine biases."* – Man P23, age 21 to 30, Familiarity with DT=1, Has used DT

Contrasting opinions were also expressed by other participants who did not view the mitigation of cognitive bias as particularly important. This can be seen in the following comments that state,

> *"I can't say, I don't experience the matter as significant."* – Man P13, age 31 to 40, Familiarity with DT=0, Did not indicate DT use

> *"Yeees… This matter has not perhaps had such great significance in the organisation/systems of my own career."* – Man P15 age 41 to 50, Familiarity with DT=0, Has used DT

Table 11
Differences in perceptions of bias mitigation importance between genders.

Response option	Women ($n = 54$)	Men ($n = 37$)	χ^2	p-value
Mitigation important	40 (74 %)	**28 (76 %)**	3.39	0.183
Mitigation not important	0 (0 %)	2 (19 %)		
Does not have an opinion	14 (26 %)	7 (19 %)		

From these responses, we can interpret that participants in some cases either do not see gender and gender-based biases as playing a significant role in their development work, or that they do not perceive that the types of tasks they undertake are affected by gender in any way. This is a point that requires deeper scrutiny and complimentary research, as potentially there are cognitive bias-related blind spots preventing professionals from understanding the relevance of gender in assumedly technical tasks for instance.

4.5.2. Ways to tackle gender-based cognitive bias

In the Atlas.ti analysis we examined the ideas for tackling gender-related cognitive biases. The responses were coded according to proposed actions. These results can be seen in Fig. 3, whereby the division of the proposed actions between genders are presented. In total, 75 participants provided open-ended responses. Several mitigation actions were sometimes mentioned in single responses. In the open-ended responses ($N = 91$), the most frequent action was familiarizing with user groups (45/93, 48 %), acknowledging bias existence (11/93, 12 %), and open discussion (11/93, 12 %). Less frequent were forming diverse design groups (9/93, 10 %), calls for more information about bias (4/93, 4 %), and psychological safety (3/93, 3 %). When analyzing the data in SPSS, gender comparisons revealed that men were significantly more likely than women to acknowledge bias existence (22 % vs. 4 %, $\chi^2 = 7.21$, $p = 0.007$). By contrast, no significant gender differences were found in the likelihood of mentioning user-group familiarization (57 % vs. 43 %, $\chi^2 = 1.76$, $p = 0.184$) or in any of the other themes.

These findings partially converge with the survey data, where men more frequently reported collecting user information in response to the multiple-choice question. In the open-ended responses, no significant gender differences were found in references to user research, although

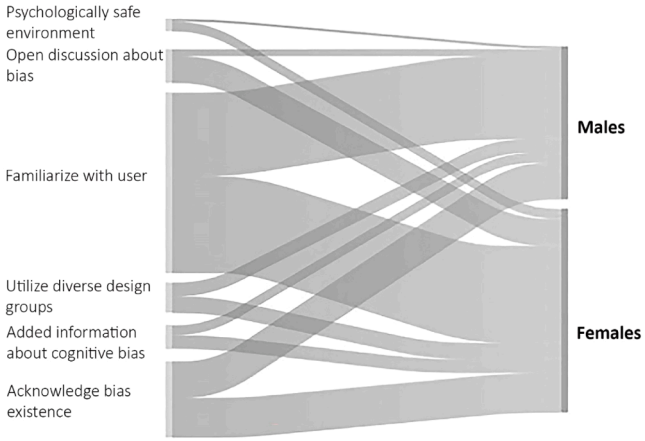

Fig. 3. Ways to tackle gender-based cognitive bias.

the distribution showed a slight tendency for men to mention it more often. Taken together, the results suggest that while the quantitative data clearly indicate a stronger emphasis on user-focused approaches among men, the qualitative data provide only limited support for this pattern, with women more often highlighting other aspects of bias.

Thus, the results show that the five common themes for addressing gender-based cognitive bias were to: (1) create a psychologically safe environment; (2) engage in open discussion about bias and how it manifests; (3) familiarize oneself with the user – i.e., engage in human-centered inquiry; utilize groups comprising diversity (i.e., gender, culture, age etc.) in design and development; (4) seek more information about cognitive bias and factors influencing it; (5) and acknowledge that bias exists and will always exist within individuals and teams – yet, the key to acknowledging this is to directly address it. This aspect is also contingent on the team's and organisation's culture, as a certain level of psychological safety is required for professionals to engage in identifying, acknowledging and discussing various gender-based cognitive biases. The fact that those affecting and affected by gender-based cognitive bias are inevitably within the team (i.e., team members always represent a gender of some form) renders this as a topic that demands sensitivity. One of the statements mentioned above by Participant 17 emphasises this characteristic in that teams and projects should house safe cultures in which to identify and discuss biases.

Among the statements offered by respondents were clear proposals on how to mitigate cognitive bias. These included,

> " *Perhaps by bringing up one's own preconceived notions, thoughts and feelings before starting the design work. In this way, they will perhaps become more visible, and it is possible to critically examine what the perceptions comprise and whether they correspond with reality?"* – Man P22, age 41 to 50, Familiarity with DT=0, Has not used DT

> *"The first step is to note its existence. It is important to speak about and remind about these."* – Man P 38, age 31 to 40, Familiarity with DT=0, Has not used DT

This first notion carries sentiment regarding the inevitability of possessing cognitive biases within and among team members. It taps into acknowledging bias existence, and through this acknowledgment, increasing visibility of the issue, which enables the team to deal with its elements within development complexities. Similarly, the second statement above also promotes this perspective. From this micro-view on detection, identification and acknowledgement, we see a proposal to understand the broader societal structural causes influencing these biases.

> *"To develop one's own understanding first of the structural problems that occur in society in general and how they affect your own thoughts and attitudes. Of course, the goal is (within budget) to try to involve as many people as possible in one way or another in the design work in order to correct the bias."* – Man P 31, age 41 to 50, Familiarity with DT=4, Has used DT

Being aware of the societal and structural problems contributing to cognitive bias aids in the understanding of not only how they are generated on the individual level, but how they manifest on the socio-technical level. By carefully analysing core components that contribute to cognitive bias in a pragmatic way, designers and developers are better equipped to practically intervene and inform future design decisions in a way that prevents or hinders bias-related patterns in future technological iterations.

Then, from the team composition perspective another participant pointed out that,

> *"By forming as diverse a design team as possible, while asking for experiences/ideas from as many stakeholders as possible."* – Man P 31, age 41 to 50, Familiarity with DT=4, Has used DT

While increasing the experience pool to as large as possible both from the perspectives of designer diversity and stakeholder input may seem obvious, often practitioners forget the urgency of this practice. Societies, cultures and conditions are in constant flux, influencing the experience of individuals and communities in profound ways. During times of hard deadlines and limited budgets, professionals may consider that their previous reading, knowledge and even current media-seeking suffice as adequate information sources. However, sources do not reveal the burgeoning challenges faced by respective stakeholder groups during unfolding eras.

We can see that the results indicate that the role of DT in mitigating gender-based cognitive bias expressed by participants remains inconclusive. Some of the participants reported that they engaged with DT within their processes, yet the extent to which this engagement influenced gender-based cognitive bias-related outcomes seems to vary. In particular, the diversity of professional roles of participants poses one confounding factor. Those who work in backend roles for instance, might not have access to users or human-centred, user-facing processes. The differences in role-based engagement should be ascertained when interpreting the results. Thus, it would have been ideal to have collected more detail about the participants' professional roles and their relationship to user-centered tasks. We note that this limitation holds implications for the broader interpretation of our findings, which we also raise in the limitations section of the article.

5. Discussion

The article has focused on understanding IT designer and developer awareness of gender-based cognitive bias, and how they address it within their work and organization. The main idea was to understand these dynamics within the ecosystemic context of AI development, i.e., SE4AI. As a methodology that has been specifically developed to decrease bias by increasing understanding across multiple disciplines, DT was chosen as a design process model through which to probe IT professionals' approach to human-centred design. By examining how professional questionnaire respondents experienced their gender as affecting their work and potential existent cognitive biases, and how they address and mitigate potential concerns within development projects, we were able to ascertain the interrelationship between individual professional and gender-based cognitive bias sensitivity within design and development projects. Moreover, we measured professional awareness of DT as a methodology, and how professionals implemented aspects of the model within their work in an effort to identify and mitigate bias.

Statistical analysis of the data indicated that women possessed greater familiarity and awareness of the DT model than men. The difference between genders was significant. However, there was no significant difference in acknowledging the application of DT between the genders, as almost half of both gender groups reported using the methodology. Furthermore, in relation to age groups there was no visible significant difference in terms of familiarity with the DT model. There were also no significant statistical differences between gender groups regarding whether the respondents actively addressed gender-based cognitive biases in their work. Men were significantly more likely to report collecting information from diverse users in the multiple-choice question, but no significant differences were found in the open-ended data. Based on the results, men acknowledged bias existence significantly more than women. However, the qualitative responses revealed variation: while some men explicitly acknowledged their own positionality and bias, others strongly downplayed or denied gender relevance. This divergence highlights the complexity of bias awareness across individuals. Thus, in practice, men more frequently reported engaging in specific human-centred components of the DT model, such as user research and bias acknowledgement, while women demonstrated higher overall familiarity with the model. Moreover, the qualitative findings shed light on a form of 'self-awareness' among some of the men respondents who intellectually, and practically, attempt to mitigate the

'power positioning' (i.e., as white, male development professionals) by acknowledging their own identity in tangent with learning more about structural biases. These results hold implications for future AI and IT development, particularly regarding development team construction and facilitation, as what can be seen is that the men are ready to engage in 'designer-developer reflexivity' (i.e., the acknowledgement and examination of socio-cultural positioning) yet need a space to express this. Likewise, women development professionals may benefit from engaging in these moments of 'designer-developer reflexivity' with men and professionals identifying as other gender, to promote a more active awareness of critical aspects of their own design and development practices, i.e., the persistent need to understand *other(ed)* perspectives in relation to technologies and their discourses.

Pertinently, these results call for a need to *challenge gender stereotypes*, rather than defaulting to the assumption that behind all IT development is a 'brogrammer' culture. We should acknowledge that there have been blind spots also held by professionals falling outside the white, youngish, masculine criteria of the stereotypical tech professional. There is evidence here to suggest that stereotypes of women more actively engaging in tasks to increase empathy and reduce cognitive bias in IT development should be challenged. We should not assume that empathy in itself is gendered. Additionally, the findings open the floor to the understanding that more knowledge is needed regarding nuanced gender dynamics in the algorithms and in the development teams that produce them. Some aspects that should be further examined include the exploration of how gendered socialization of professional roles operates, in addition to matters such as identity politics in human-centered design methods.

These findings are in line with previous studies that suggest DT alone is not sufficient in mitigating bias if underlying team dynamics remain unexamined. Kronqvist and Rousi [4] argue that while DT is often promoted as a tool for ethical and inclusive development, issues related to gender awareness and power structures are often inadequately addressed in practice. Similarly, Liedtka [31] and Dorst [27] emphasize that although DT provides cognitive tools for bias reduction through structured collaboration, the actual outcomes depend heavily on how the methodology is adopted and by whom. Our results resonate with this observation: while women demonstrated higher familiarity with DT as a human-centered methodological model, it was often men who reported engaging in bias mitigation activities, particularly by acknowledging bias existence. Clarke, Marks, and Lykins [29] further support this by identifying gender-based differences in empathy and emotional engagement in professional contexts—factors that may shape how individuals interpret and respond to the idea of bias. These comparisons reinforce the view that DT is not a neutral process, but a socially situated practice influenced by professional identity, gender, and experience. This may indeed be one reason why men seem to be more active in collecting data from end users, as they possess an active awareness of their normatively seemingly privileged position.

By analyzing the open-ended responses regarding how important respondents feel gender-based cognitive bias mitigation is, no statistically significant differences were found between women and men. A majority of both groups rated mitigation as important, while only a minority selected 'not important.' These results indicate that perceptions of the importance of bias mitigation are broadly shared across genders. In terms of age, groups representing mid-career professionals (11–15 and 21–25 years of experience) indicated significantly more that they have used modes of end-user data collection in their design processes. From an age perspective, professionals over 51 years of age saw it more important to openly discuss gender-based cognitive biases in their processes and within their teams, and demonstrated lower trend-level differences in regard to neglecting cognitive bias in development work.

Although the statistical tests did not reveal significant gender differences in how respondents rated the overall relevance of gender in design work, the qualitative and textual analyses provide a more nuanced picture. Several men explicitly downplayed gender relevance, whereas women were less likely to do so. In particular, men were more inclined to state that gender was not relevant to their own design practice, even while acknowledging the broader importance of mitigating gender-based cognitive bias. Women, by contrast, were less likely to reject gender relevance, which may reflect a different experiential relationship to bias and marginalization in professional contexts. Taken together, these findings suggest a distinction between recognizing bias in principle and perceiving it as personally relevant in one's own work.

5.1. Implications

While this study did not directly provide empirical evidence of cause-consequence relationships between team composition, design approach, and tangible SE4AI outputs, the findings reveal patterns in professional practices that may contribute to biased system design and algorithmic behavior. In our sample, men were more likely than women to report engaging in user research in the multiple-choice responses, whereas women reported higher familiarity with the DT framework. Although not consistent across all data types, this pattern challenges stereotypes of disengaged men and emphasizes the importance of ongoing user-centered inquiry by all professionals.

Development environments and teams in IT companies - including those responsible for AI systems - are crucial for identifying, addressing, and mitigating gender-based cognitive biases in early design stages. Imbalanced ways of understanding phenomena are not created by technological organizations, but are reflected and reinforced through the individuals and collectives working within them. This is shaped further by organizational culture and structural characteristics. On this basis, we recommend deliberate efforts to compose teams with diverse backgrounds and for leadership to promote environments where members feel comfortable to express ideas and opinions without criticism or stereotypical assumptions. Regarding ways to minimize cognitive bias, participants most often pointed to gaining information from diverse user groups, alongside recognition of their own cognitive biases and open discussion of these issues. Based on these findings, IT teams could implement short reflective design check-ins, where practitioners share assumptions and discuss potential blind spots. Encouraging multidisciplinary reviews and supporting communication practices that foster openness - for example, training on psychological safety, as suggested in prior research - can further help integrate bias awareness into routine development work.

5.2. Limitations

While the sample of $N = 91$ (minus two non-binary) responses may be considered adequate when considering the study of a specific professional population within a national context, it is not comprehensive in terms of capturing the overall state of gender-based cognitive bias and its treatment among professionals in the entire IT industry. Moreover, a limitation of the questionnaire itself pertained to the fact that the respondents' specific professional roles were not asked. During the design phase of the questionnaire, we the authors deliberated over how much detail we should obtain from the respondents. The choice to not ask role information was for confidentiality reasons – Finland's professional pool is relatively small, and key details such as role, combined with gender and organizational size, can render participants identifiable. We tried to encourage participation through heightening anonymity in the data, complying with GDPR requirements. However, upon analysis of the data we see that the professional role would have given more of an indication of how cognitive bias plays out on the organizational level, particularly if, for instance, a woman is trained in and serving in the role of user experience, yet feels that she does not need to seek user insight. Or, that the women respondents were in roles in which they did not need to gather user insight (software developers not participating in actual design, e.g. backend or integration developers). Among the respondents there were apparently individuals who did not regularly participate in

design work or were able to participate only partly during their professional career. The length and time during an individual's career in which they could participate in design work may have influenced the responses.

Another issue pertained to the representation of gender groups. As mentioned above, only two non-binary individuals participated in the study, and there were no indications of transgender participants. This too should be accounted for in future research samples. While gender was the focus of this study, other identity-related factors such as cultural background, ethnicity, and organizational hierarchy likely also influence bias perception and mitigation behavior. Moreover, cultural framing, roles and perceptions of gender are additionally pertinent to the logic of technological systems, and designed use – implementation and relevance. This is a complex issue that extends beyond mere discussion on cognitive bias. As women, located in Finland, we are operating and researching in an environment that is seemingly utilitarian to its approach towards gender equality [63] – women are expected to be in the workforce (dual-earner families), utilizing technology, maybe developing it (the topic of this research) - while in other contexts perspectives on women in relation to technology and other societal dimensions may be far different. These dimensions were not directly examined in this study but may intersect with gender in shaping how DT is understood and applied. Future research should incorporate these variables and account for the complexity of gender and its socio-cultural make-up (structures and perceptions) to gain a fuller picture of cognitive bias in design work. Connected to this, is the added societal structural features and dynamics of socio-economic and ethnic hierarchies – even within nations – as well as the ethical implications of attempting to evaluate the properties of other socio-cultural practices undertaken internationally via our *privileged Western gaze* [64]. Embarking on research that isolates and analyses these facets would itself be a sizeable body of research.

A further limitation of this study concerns the measurement of Design Thinking use. The survey item "Have you used the model or parts of it in your work?" offered only three response options ("Yes," "No," and "I cannot say"). These categories are relatively broad and do not capture the range, intensity, or specific forms of DT use - for instance, whether participants applied the full process systematically or only adopted selected tools occasionally. As a result, the measure may underestimate the diversity of participants' DT experience. Future studies should employ more fine-grained items that differentiate between levels and types of DT adoption to better capture the variety of professional practice

Moreover, while we were able to probe the issues of gender-related cognitive bias in the questionnaire via open field questions, these types of inquiries are never as effective as either semi-structured interviews, or ethnographic inquiry that would see the examination of evidence chains progressing from the development team and early design choices, through production to deployment. In the case of semi-structured interviews, the participants always have an opportunity to raise varying issues and viewpoints that have not been considered from the perspective of the researcher(s). In particular, we noticed that more research should be undertaken to analyse the role of gender in diverse development domains (i.e., back-end, front-end, type of IT being developed, for whom and what context etc.). Some partial non-responses were observed in open-ended items, particularly in questions about personal design approaches and gender influence. However, no systematic dropout pattern was detected. Given the sensitivity of the topic and the social norms around gender and ethics, it is possible that some responses were affected by social desirability bias, or where people feel the need to respond to questions in a way they perceive would be favorable to others [65]. This may have particularly influenced participants' willingness to acknowledge cognitive bias or the role of gender in their work.

Another limitation of the present study applies to the inconclusive role of DT in mitigating gender-based cognitive bias among participants. DT was present in some participants' workflows, yet it can be claimed that its impact varied, and with the present data, the impact cannot not be reliably isolated. One reason for this is due to the diversity of professional roles within the sample. Participants with backend roles and tasks such as developers or software testers will have limited contact with user-facing processes. Data collection or persona development for instance, where gender-based cognitive bias is more likely to surface, may not be included in the participant's tasks. Thus, without greater granularity in role-specific data, it is difficult to ascertain how exposure to human-centered practices may correlate with gender-based bias awareness, or even mitigation in relation to the developed systems. Future research must include the collection of detailed data regarding participants' roles and responsibilities in order to better understand how cognitive bias manifests in relation to various points within the development process. This limitation limits both the interpretation and the findings, as well as the generalizability of the results.

6. Future research

Thus, several interesting future research directions can be noticed, and one basic element of all future studies should be the increase in granularity of job roles and tasks undertaken by participants. In addition to increasing the opportunity to generalize results, this type of detailed data can aid in pinpointing nodes within the development pipeline at which important decisions are made that subsequently influence the likelihood of specific cognitive biases within the systems. Yet, in relation to other worthwhile research directions, it would be fruitful to engage in more thorough and intensive qualitative inquiry via interviews, field observations (watching design and development teams in practice), and analyzing end results of Design Thinking processes. From a cognitive scientific perspective, a rich analysis incorporating triangulation [66] of designer/developer traits (gender, age, culture etc.), qualitative and quantitative self-reporting, plus visual, formalistic (form plus function) and user analysis of Design Thinking end results (products, services, systems) could uncover the ways in which cognitive bias manifest in practice. Observations of team meetings and development processes may shed further light on differences in approaches to gender-based cognitive bias detection, identification, and mitigation – i.e., how soon they are noticed and acted upon, the types of action and communication surrounding the activities. This is particularly since the Design Thinking approach is supposed to reduce bias via communication and collaboration, serving as a frame in which to uncover and explicate cognitive biases that are often innately subconscious among hegemonic (normatively dominant) designers and users [67].

7. Conclusion

The current article presented a study in which we examined how gender affects the ways in which IT design and development professionals (in Finland and Finnish companies) within the SE4AI development ecosystem recognize and utilize DT and related methods in their design and development work. This was coupled with gaining insight regarding awareness and mitigation of gender-based cognitive bias within development processes. The main research question was: *How does gender affect the way IT practitioners utilize DT and related methods in their design and development work?* The results reveal some interesting statistically significant results:

- While men acknowledged gender-based cognitive bias as an issue in design work, qualitative responses suggested that they were less likely to consider it a problem within their own processes.
- While women were significantly more familiar with DT as a model and methodological framework, men were more likely to engage in human-centered research – undertaking studies to attain more information about diverse target user groups.

- There was a significant difference between age groups, whereby practitioners 51 years old and over were more likely to address cognitive bias through engaging in discussion.

These results lead to considerations for investigating their interpretations on a deeper level. This pertains to future research efforts engaging in: a) the sense of self-efficacy (competence and confidence) practitioners of various genders have towards their own knowledge accounting for cognitive bias; b) members of particular marginalized populations and their sense of *knowing* or *need* to engage in human-centered research of other diverse groups; and c) generational differences in approaches to multi-professional, multidisciplinary problem-solving. Six key points arose from the results regarding practical ways to address and mitigate gender-based cognitive bias in IT design and development processes. These are to:

- create a psychologically safe environment;
- engage in open discussion about bias and how it manifests;
- familiarize oneself with the user – i.e., engage in human-centered inquiry;
- utilize groups comprising diversity (i.e., gender, culture, age etc.) in design and development;
- seek more information about cognitive bias and factors influencing it;
- and acknowledge that bias exists and will always exist within individuals and teams.

The current study makes several significant contributions. It observes how the gender of IT development professionals influences their knowledge of DT, gender-based cognitive biases, and how DT is considered in relation to the mitigation of gender-based cognitive biases. It also examines how professionals report their actual activities regarding gender-based cognitive bias mitigation. Some men IT development professionals expressed increased acknowledgement of their positioning in relation to end-users, reflecting a degree of reflexivity, though this was not consistent across the group. The results shed insight on six key points for mitigating cognitive bias within design and development processes, highlighting psychological safety as the important attribute of a work environment in which IT solutions are developed. Through psychological safety, professionals are afforded the security to be able to voice concerns in a supportive and supported way, allowing for interventions to be made at earlier stages of development.

When considering DT and its qualities of uniting professionals from multiple disciplines these aspects of psychological safety become even more profound, as the communication differences and languages of reasons vary, necessitating higher levels of interpersonal skills encompassing patience and empathy. On this note, we would like to end with a quote by Tim Brown [43] who stated: “Design thinking is neither art nor science nor religion. It is the capacity, ultimately, for integrative thinking” (p. 9). DT is as important within the inner workings of technical development as it is for the overall design and realisation of the user interface and use culture surrounding the system, including the dynamics manifested in the algorithms of data-driven systems [13]. Unfortunately, similarly to the current findings, previous research has also found that developers are prone to instilling bias when engaging in making estimations within technical specifications [38]. Even when developing back-end systems, estimations riddled with cognitive bias can propagate errors throughout the software development lifecycle, influencing user-facing outcomes such as: system resource allocation; performance optimizations; and selection of libraries or integration approaches. Unfortunately, all too often backend teams spend too little time investigating problem spaces [38,39].

It is therefore critical to foster diverse teams and promote psychological safety (openness, supportive and encouraging attitude, and growth mindset) when composing teams to counter cognitive bias. Even from a backend perspective, a diverse development team that engages in DT [68], or similar methodology such as user requirements gathering, can significantly improve: resource and time estimations; selection of architectures and frameworks; and alignment between technical implementation and user needs.

It is therefore critical to foster teams of diversity while instilling psychological safety (openness, supportive and encouraging attitude, and growth mindset) when composing teams to counter cognitive bias. Even from a back-end perspective, a diverse development team that engages in DT, or similar methodology such as user requirements gathering, can significantly improve: resource and time estimations; selection of architectures and frameworks; and alignment between technical implementation and user needs.

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During the preparation of this work the author(s) used Open AI’s Chat GPT in order to improve English language. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

CRediT authorship contribution statement

Aila Kronqvist: Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Rebekah Rousi:** Writing – review & editing, Writing – original draft, Visualization, Supervision, Methodology, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

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Data availability

Data will be made available on request.

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