Ethics in AI through the Developer’s Prism: A Socio-Technical Grounded Theory Literature Review and Guidelines

Aastha Pant, Rashina Hoda, Chakkrit Tantithamthavorn, Burak Turhan

Abstract— The term ‘ethics’ is widely used, explored, and debated in the context of developing Artificial Intelligence (AI) systems. In recent years, there have been numerous incidents that have raised the profile of ethical issues in AI development and led to public concerns about the proliferation of AI technology in our everyday lives. But what do we know about the views and experiences of those who develop these systems – the AI developers? We conducted a Socio-Technical Grounded Theory Literature Review (ST-GTLR) of 30 primary empirical studies that included AI developers’ views on ethics in AI to derive five categories that discuss AI developers’ views on AI ethics: developer’s awareness, perception, needs, challenges, and approach. These are underpinned by multiple codes and concepts that we explain with evidence from the included studies. Through the steps of advanced theory development, we also derived a set of relationships between these categories and presented them as five hypotheses, leading to the ‘theory of ethics in AI through the developer’s prism’ which explains that developers’ awareness of AI ethics directly leads to their perception about AI ethics and its implementation as well as to identifying their needs, and indirectly leads to identifying their challenges and coming up with approaches (applied and potential strategies) to overcome them. The theory provides a landscape view of the key aspects that concern AI developers when it comes to ethics in AI. We also share an agenda for future research studies and recommendations for developers, managers, and organisations to help in their efforts to better implement ethics in AI.

Index Terms—Grounded theory literature review, GTLR, artificial intelligence, ethics, AI ethics, socio-technical grounded theory, STGT, socio-technical grounded theory literature review, ST-GTLR, developers, software engineering

1 INTRODUCTION

Ethics refers to “the moral principles that govern the behaviors or activities of a person or a group of people” [1]. Ethics can also be defined as “the way an individual behaves and the values they hold” [2]. Ethics can be applied to computers and machines. The process of attributing moral values and ethical principles to machines to resolve ethical issues they encounter, and enabling them to operate ethically is a form of applied ethics [3]. ‘AI ethics’ refers to “the principles of developing AI to interact with other AIs and humans ethically and function ethically in society” [4].

Ethical consideration in AI is very important [5] as demonstrated by several prominent incidents in recent years where lack of ethical consideration has resulted in severe consequences. In a recent example, software developers were upset due to GitHub’s unauthorised and unlicensed use of copyright source code as training data for their machine learning powered GitHub Copilot product. It is an example of an ethical issue as the product was injecting source code derived from copyright sources into the customers’ software without informing them of the license of the original source code [6].

In another case, the founder of the Algorithmic Justice League (AJL) found that facial recognition algorithms work best on white men and worst on black women. The head of AJL mentioned that there is no guarantee that such issues are solved as there are no accountability mechanisms. The case study reported the issue of racial bias as well as accountability issues in AI [7]. In 2018, Amazon Inc. ceased its new recruitment tool when the machine learning specialists of the company found out that the tool was biased against women. The tool preferred male candidates over female candidates during the recruitment process [8]. Likewise, in the Netherlands, the court passed a law to restrict the government from deploying the AI-based social security fraud detection system as it was not transparent on how the model calculated the fraud risks. This lack of transparency of the model violated the people’s fundamental rights [9].

These and many such case studies compelled us to believe that ethical consideration in the development of AI is significant and necessary in today’s time and motivated us to explore the area of ethics in AI. We were interested in exploring the broader context of ethics in AI to understand the lay of the land, and inform future studies into more focused areas. In particular, we were interested in exploring this important area from the perspective of those closest to it, and indeed in one of the best positions to bring about changes and improvements, – the AI developers. Given the increasing prominence of the topic of ethics in AI, and growing research interest, exploring existing literature to gain an understanding seemed like a reasonable approach.

To understand developers’ views on AI ethics as presented in literature, we conducted a socio-technical grounded theory literature review or ST-GTLR, a literature
We applied GTLR’s five step framework of **define, search, select, analyse, and present** with concrete data analysis and theory development steps of socio-technical grounded theory. Our experience suggests that while an ST-GTLR can be conducted for most contexts, it is particularly suited to niche and emerging topics where there may not be enough literature accumulated over time to conduct a systematic literature review but where the topic is significant for the practice and research communities to fundamentally understand and unpack. An added advantage of the method is its focus on rigorous analysis and the development of evidence-based theoretical concepts or mature theory, to guide research and practice in the area. Another reason for conducting an ST-GTLR is its methodological alignment with empirical socio-technical grounded theory (STGT) studies [10], since that is the next step of our wider research program.

We first defined the overarching question, **What do we know from literature about how developers view ethics in AI?** Then, we developed an ST-GTLR protocol to find and analyse primary empirical studies investigating developers’ views on AI ethics. After rounds of searching and filtering, we rigorously analysed data from 30 primary empirical studies using STGT techniques such as open coding, targeted coding, constant comparison, and memoing and advanced theory development [10].

GTLR studies have been conducted in domains such as health [12], [13], [14], banking [15], and education [16]. GTLR has also been used to study topics in information systems research [17], on the use of information and communication technology (ICT) such as the techniques used by social media influencers and their potential for influencing the public regarding environmental awareness [18], and national ICT policy challenges for developing countries [19].

To the best of our knowledge, this is the first ST-GTLR, and as such we present the **guidelines** for conducting an ST-GTLR, including describing its context of use, steps and procedures, as well as details of our **application** in this review study, in Section 3. This is followed by presenting the findings of our ST-GTLR, including five categories discussing AI developers’ views on AI ethics: awareness, perception, needs, challenges, and approach, detailed in Section 4. We derived a set of relationships between these categories in five hypotheses that, together with the key categories, make up the ‘theory of ethics in AI through the developers’ prism’, explained in Section 5 (H1-H5). The hypotheses lead to the **theory of ethics in AI through the developer’s prism**, which we visually represent using the developer’s prism metaphor. We also present insights and recommendations in Section 6, followed by reflections in Section 7, evaluation is Section 8, threats and limitations in Section 9 and conclusion in Section 10.

The main contributions of this paper are:

- A source of gathered information on AI developers’ views on and understanding of ethics in AI.
- A **theory of ethics in AI through the developer’s prism** that presents the key categories as developers’ awareness, perception, needs, challenges, and approach, and associated hypotheses.
- A guidance for practitioners who require a better understanding of the requirements and factors affecting ethics implementation in AI.
- A set of recommendations for future research in the area of ethics implementation in AI from developers’ perspective.
- Guidelines for socio-technical grounded theory literature review (ST-GTLR) through an example application.

### 2 Background – Ethics in AI

There are numerous and divergent views on the topic of ethics in AI [G4], [20], [21], as it has being increasingly applied in various contexts and industries [G20]. AI practitioners and researchers seem to have mixed perspectives about AI ethics. Some believe that there is no rush to consider AI related ethical issues as AI has a long way from being comparable to human capabilities and behaviours [4]. While others conclude that AI systems must be developed by considering ethics as they can have enormous societal impact [5], [22]. Although the viewpoints vary from practitioner to practitioner, most conclude that AI ethics is an emerging and widely discussed topic and a current relevant issue of the real world [23].

A number of studies conducted in the area of ethics in AI have been conceptual and theoretical in nature [G15]. Critically, there are copious numbers of guidelines on AI ethics, making it challenging for AI developers to decide which guidelines to follow. Unsurprisingly, studies have been conducted to analyse the ever-growing list of specific AI principles [G10], [G17], [4]. For example, Jobin et al. [24] reviewed 84 ethical AI principles and concluded that only five AI ethical principles – transparency, fairness, non-maleficence, responsibility and privacy – are mostly discussed and followed. Fjeld et al. [25] reviewed 36 AI ethical principles and reported that there are eight key themes of AI ethics – privacy, accountability, safety and security, transparency and explainability, fairness and non-discrimination, human control of technology, professional responsibility, and promotion of human values. Likewise, Hagendorff [21] analysed and compared 22 AI ethical guidelines to examine their implementation in the practice of research, development, and application of AI systems. Some review studies focused on exploring the challenges and potential solutions in the area of ethics in AI, e.g. [26], [27]. The desire to set ethical guidelines in AI has been enhanced due to increased competition between organisations to develop robust AI tools [23]. Among them, only a few guidelines indicate an oversight or enforcement mechanism [28].

Another prominent area of focus have been studies that were conducted to discuss the existing gap between research and practice in the field of ethics in AI. Smith et al. [29] conducted a review study to identify gaps of ethics research and practice of ethical data-driven software development and highlighted how ethics can be integrated into the development of modern software. Similarly, Shneiderman [30] provided 15 recommendations to bridge the gap between
ethical principles of AI and practical steps for ethical governance. Overall, existing studies seem to primarily focus on either analysing the plethora of ethical AI principles or filling the gap between research and practice.

We also came across solution-based papers and papers discussing models, frameworks, and methods for AI developers to enhance their AI ethics implementation. For example, an article by Vakkuri et al. [31] presents the AI maturity model for AI software, whereas another article by Vakkuri et al. [32] discusses the ECCOLA method for implementing ethically aligned AI systems. Likewise, there are papers presenting the toolkit to address fairness in ML algorithms [33] and transparency model to design transparent AI systems [34]. However, we did not include these papers in the list of our seed papers because they do not provide insights on the developer’s views on ethics in AI.

We believe it is essential to study developers’ views and understanding about AI ethics as they are the ones developing the AI systems and are one of the best places to bring about improvements in practice. While the importance of understanding developers’ views on AI ethics has been acknowledged [G4], limited attention has been paid to investigating it. In particular, there are not enough research articles focusing on the topic to effectively conduct a systematic literature review or mapping study. For example, a keyword search on prominent SE databases resulted in under 1% return in finding relevant papers. This is mainly because there are not enough papers that primarily investigate AI developers’ views on ethics in AI. Papers that do include this as part of their findings are difficult to identify without a full read through, making it ineffective and impractical when dealing with thousands of papers. Hence, we turned to grounded theory literature review (GTLR) [11] as a review approach for this niche but significant and rapidly emerging topic. While the overarching review framework from Wolfsinkel et al. helped frame the review process, we found ourselves having to work through the concrete application details using the practices of socio-technical grounded theory (STGT).

3 REVIEW METHODOLOGY- GUIDELINES & APPLICATION

Socio-Technical Grounded Theory Literature Review (ST-GTLR) is an iterative and responsive literature review method that applies the five-step framework of define, search, select, analyse and present described in the original GTLR guidelines by Wolfswinkel et al. [11] with concrete data analysis (and optional theory development) steps of socio-technical grounded theory [10]. A GTLR is particularly well suited to studying niche and emerging research areas to gain in-depth understanding, establish theoretical foundations, and make practical recommendations.

In this section, we present the guidelines for conducting an ST-GTLR, including a definition of ST-GTLR (see definition box), the context of use, the basic steps and procedures of the ST-GTLR method and a diagram of the ST-GTLR process with elaborated analysis stage (Figure 1). We also include the details of the application of these guidelines and demonstrate how we conducted the ST-GTLR in the context of our review study.

3.1 Context of Use

We begin by listing our recommendations on when, why, and how to use the ST-GTLR method, based on our practical experiences.

- **When to use:** Due to its iterative and responsive nature, ST-GTLR is particularly suited to niche and/or new and emerging topics where there is not enough literature on the specific topic (rather, relevant information is contained within and spread across papers focusing on related topics) but where the topic is significant for the practice and research communities to fundamentally understand and pack, such as is common in the dynamic discipline of software engineering.

- **Why use:** Due to its focus on rigorous analysis and theory development, an ST-GTLR study leads to rich findings and evidence-based theories that can serve as research agendas for the emerging area and as guides for practice.

- **How to use:** ST-GTLR can be applied as a review method to produce original findings and theories, reported as standalone papers. Due to ST-GTLR’s inherent methodological alignment, it can also be used as a pre-cursor to empirical STGT studies in the same topic area.

We performed an ST-GTLR to undertake an in-depth exploration of the ethics in AI from the perspective of developers working in the field of AI. The main objective of our review study was to enable systematic and evidence-based development of a theoretical framework, understand the various facets of the practice area, to guide future research in this emerging area, and to present recommendations for practice. Figure 1 shows an overview of ST-GTLR, adapted from [11] with further details of the analyse step where STGT’s data analysis [10] is most explicitly applied.

To the best of our knowledge, this is the first ST-GTLR study in software engineering. As such, we take the opportunity to describe the details of each of the stages in the following sub-sections and reflect on our experiences.

3.2 Define

The first step is to formulate the initial review protocol, including determining the scope of the study by defining inclusion and/or exclusion criteria, publication period, and search items, followed by databases to search in, research questions, and search strings. Following this approach, we defined our inclusion and exclusion criteria, publication period, language of the articles to be included followed by the guiding research question (RQ), search string and appropriate sources and specific search items with the aim

1. The term ‘developers’ in our study include AI programmers, practitioners, engineers, specialists, experts, designers, and stakeholders. We use the terms ‘AI developers’ and ‘developers’ interchangeably throughout our study.
The RQ was formulated to gain an overall understanding of ethics in AI from the perspective of AI developers, as:

**What do we know from literature about how developers view ethics in AI?**

Four popular digital databases, namely, ACM Digital Library (ACM DL), IEEE Xplore, SpringerLink and Wiley Online Library (Wiley OL) were used as sources to identify the relevant literature. These databases have been regularly used to conduct reviews on human aspects of software engineering, e.g., [35], [36]. Initially, we searched for relevant studies of obtaining maximum relevant primary empirical studies. The RQ was formulated to gain an overall understanding of ethics in AI from the perspective of AI developers, as:

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Key terms were selected from the research title to develop search queries. The first key terms were ‘ethics’ + ‘AI’ + ‘developers’ as the aim of our study is to find AI developer’s views about ethics in AI. Then, synonyms of the key search terms were used to retrieve more relevant primary studies. The search terms were linked with ‘AND’ and ‘OR’ Boolean operators when developing the final search string. The purpose of the ‘AND’ operator was to concatenate the key terms whereas the ‘OR’ operator linked the synonyms.
Six candidate search strings were developed and executed on the four online databases before one was finalised. Table 1 shows the initial and the final search strings created for this study. As the finalised search string returned an extremely large number of primary studies (N=9,806), we restricted the publication period from January 2010 to June 2021, in all four databases, as the topic of ethics in AI has been gaining rapid prominence in the last ten years. Table 2 shows the seed protocol of this study, including inclusion and exclusion criteria. For example, an inclusion criterion was that the study should be written in English, and be empirically based, presenting evidence of AI developers’ views on ethics in AI. The exclusion criteria included: studies such as workshop articles, short papers which were less than four pages, books, gray literature, theses, unpublished and incomplete work. It also included studies written in language other than English and duplicate articles. Likewise, studies that presented only the concept of ethics in AI without empirical evidence, review papers, and studies discussing topics irrelevant to the RQ were also considered grounds for exclusion.

3.3 Search

The second stage involves performing the actual search using the review protocol defined in the first stage [11]. We performed the search using our seed review protocol presented in Table 2. The search process was iterative and time-consuming because some essential synonyms of the search terms were missing initially, and we had to revisit the define stage again and again before moving to the next stage (e.g. see the initial and final search strings developed for this study in Table 1).

3.4 Select

The selection of sample texts is done in this stage. The steps include (i) filtering out doubles, (ii) refining sample based on title and abstract, (iii) refining sample based on full text, (iv) scanning forward and backward citations, and (v) checking if new articles come up in the last step as these steps are iterative [11]. If new articles come up in the last step, researchers should go to step (i) and follow other steps accordingly. If no new articles come up, then that will be the final sample to be included in the study.

Following these guidelines, we obtained a total of 1,244 primary articles (ACM DL: 273, IEEE: 355, SpringerLink: 543 and Wiley OL: 73) using the seed review protocol as shown in Table 2 and the final search string. After filtering out the duplicates, we were left with 982 articles. As per the Wolfswinkel et al. guidelines, the next step was to refine the whole sample based on title and abstract. We tried this approach for the first 200 articles each that came up in ACM DL, IEEE and SpringerLink and all 73 articles in Wiley OL to get a sense of the number of relevant articles to our research question. We read the abstract of the articles whose title seemed relevant to our research topic and tried to apply the inclusion and exclusion criteria (in Table 2) to select the relevant articles. We quickly realised that selection based on title and abstract was not working well. This is because the presence of the key search terms (e.g., ethics AND AI AND developer) was rather common and did not imply that the paper would include the developers’ perspective on ethics in AI. We found ourselves having to scan through full texts to judge relevance to our RQ. Despite the effort involved, the return on investment was low, e.g. for every 100 papers read, we found only one or two relevant to our study, i.e., that presented the AI developers’ views on ethics in AI.

From a quick reading of 673 papers, we obtained only 10 primary articles that were relevant to our research topic. Many articles, albeit interesting, did not present the AI developers’ views on ethics in AI. So, we decided to find more relevant articles through snowballing of articles. Snowballing of those 10 articles via forward citations and backward citations was done until 31 December 2021 to find more relevant articles and enrich the quality. Snowballing seemed to work better for us than the traditional search approach. We modified the seed protocol accordingly, to include papers published in other databases and those published beyond journals and conferences, including students’ theses, reports, and papers uploaded to ArXiv. The rest of the protocol remained the same. The final review protocol used in this study is presented in Table 2. In this way, we obtained 20 more relevant articles, taking the total number of primary articles to 30.

The select step of scanning through the full contents of 673 articles was very tedious with very low return on investment (e.g. only 10 relevant studies obtained). In hindsight, we would have done better to start with a set of seed papers that were collectively known to the research team or those obtained from some quick searches on Google Scholar. What we did next by proceeding from the seed papers to cycles of snowballing, was more practical, productive, and in line with the iterative GT approach as a form of applied theoretical sampling.

3.5 Analyse

We applied Socio-Technical Grounded Theory (STGT) to conduct our review because its socio-technical research framework is customised to fit the unique socio-technical contexts of domains such as software engineering and artificial intelligence [10].

- Socio-technical phenomenon: The topic of studying ethics in AI from the developers’ viewpoint presents a distinctly socio-technical phenomenon, where “the social and technical aspects are interwoven in a way that studying one without due consideration of the other makes for an incomplete investigation and understanding” [10].
- Socio-technical domain and actors: Our domain of investigation was artificial intelligence, and we were
TABLE 2: Seed and Final ST-GTLR Protocols

| Seed ST-GTLR Protocol | Final ST-GTLR Protocol |
|-----------------------|------------------------|
| Digital Databases     | ACM Digital Library    |
|                       | IEEE Xplore            |
|                       | SpringerLink           |
|                       | Wiley Online Library   |
| Search Items          | Journal articles       |
|                       | Conference papers      |
|                       | Full Text              |
| Language              | English                |
| Publication Period     | January 2010 to June 2021 |
| Search String         | (“ethic*” OR “moral*” OR “fairness”) AND (“artificial intelligence” OR “AI” OR “machine learning” OR “data science”) AND (“software developer” OR “software practitioner” OR “programmer”) |
| Inclusion Criteria    | Each study must be a full text published journal article or conference paper |
|                       | Studies that are written in English |
|                       | Studies that are empirical |
|                       | Studies that present AI developers’ views on ethics in AI |
| Exclusion Criteria    | Workshop articles, short papers (less than 4 pages), books, gray literature, theses, unpublished and incomplete work |
|                       | Studies written in language other than English |
|                       | Review papers |
|                       | Duplicate articles |
|                       | Theoretical or conceptual studies on ethics in AI (non-empirical) |
|                       | AI related topics that do not include developers’ perspectives |

studying the viewpoints of actors in that domain, the AI developers, both being socio-technical.

- **Socio-technical researchers:** Our team included researchers with the requisite technical background in software engineering and AI, social science (e.g., traditional GT experience), empirical and qualitative research, philosophical foundations, and theory development.

- **Socio-technical data, tools, and techniques:** We were using qualitative data gathered from relevant SE/AI literature and the STGT data analysis techniques.

STGT includes basic data analysis procedures such as open coding, constant comparison, and memoing that are common to all GT variants and advanced data analysis procedures such as options of targeted data collection and analysis (DCA) and theoretical structuring or structured DCA and theoretical integration, depending on the researchers’ choice of emergent or structured modes of theory development respectively [10]. In our ST-GTLR, we applied open coding, constant comparison, memoing in the basic stage and targeted DCA and theoretical structuring in the advanced stages using the emergent mode of theory development.

The qualitative data included primarily the context and findings covered in the primary studies, including excerpts of raw underlying empirical data included in the papers. Data was analysed iteratively in small batches. At first, we analysed the qualitative data of 10 articles that were obtained in the initial phase. We used the standard techniques of STGT data analysis such as open coding, constant comparison, and memoing for those 10 articles and advanced techniques of STGT data analysis such as targeted coding on the rest 20 articles, followed by theoretical structuring. The right-hand side of Figure 1 shows the details of the data analysis in the Analyse stage of the ST-GTLR process, as applied in this study. This approach of data analysis is rigorous and helped us to obtain multidimensional results that were original, relevant and dense, as evidenced by the depth of the categories and underlying concepts (presented in Section 4). The techniques of the STGT data analysis are explained in the following section. We also obtained layered understanding and reflections through reflective practices like memo writing, which are presented in Section 6.

3.5.1 The Basic Stage – Open Coding

We performed open coding to generate codes from the qualitative data of the initial set of 10 articles. Open coding was done for each line of the Findings section of the included articles to ensure we did not miss any information and insights related to our RQ. The length of the qualitative data varied from article to article. For example, some articles had an in-depth and long Findings section whereas some had short sections. Open coding for some articles consumed a lot of time and led to hundreds of codes whereas a limited number of codes were generated for some other articles.

Similar codes were grouped into concepts and similar concepts into categories using constant comparison. Examples of the application of STGT for Data Analysis [10] to generate codes, concepts and categories are exhibited in Figure 2 and a number of quotations from the original papers are included in the Findings section, providing strength of evidence [10]. The process of developing concepts and categories was iterative. As we read more papers, we refined
The emerging concepts and categories based on the new insights obtained. The coding was performed by the first author in Google docs to begin with, followed by Google spreadsheet as the number of codes and concepts started growing. Both these formats enabled the ease of reviewing and providing feedback by the second author, and were accompanied by detailed discussions leading to refinements. Each code was numbered as C1, C2, C3, and providing feedback by the second author, and were growing. Both these formats enabled the ease of reviewing and providing feedback by the second author, and were accompanied by detailed discussions leading to refinements. Each code was numbered as C1, C2, C3 and labelled with the paper ID (e.g. G1, G2, G3) that it belonged to, to enable tracing and improve retrospective comprehension of the underlying contexts.

While the open coding led to valuable results in the form of codes, concepts, and categories, memoing helped us reflect on the insights related to the most prominent codes, concepts, and emerging categories. We also wrote reflective memos to document our reflections on the process of performing an ST-GTLR using an STGT approach. These insights and reflections are presented in Section 6. An example of a memo created for this study is presented in Figure 3.

3.5.2 Advanced Stage – Theory Development

The codes and concepts generated from open coding in the basic stage led to the emergence of five categories: Developer Awareness, Developer Perception, Developer Needs, Developer Challenges and Developer Approach. Once these categories were generated, we proceeded to identify new papers using forward and backward snowballing in the advanced stage of theory development.

Since our topic under investigation was rather broad to begin with, an emergent mode of theory development seemed appropriate in the next, advanced stage of STGT [10]. This decision was further confirmed as the categories identified were distinct and well supported but the links between them, which define the shape or structure of a theory, were still unclear. We proceeded to iteratively perform targeted data collection and analysis on more papers. Reflections captured through memoing and snowballing served as an application of theoretical sampling when dealing with published literature, similar to how it is applied in primary STGT studies.

Targeted coding involves generating codes that are relevant to the preliminary but strong concepts and categories [10]. For example, see the emergence of a new code cultural norms realisation during targeting coding that supported the concept human limitations, which in turn led to the category Developer Awareness identified in the basic stage, in Figure 3. An example of a memo arising from the code (“principles vs practice gap”) labelled [C1]

Fig. 3: An example of a memo created for this study is presented in Figure 3.

3.6 Present

The last step of the ST-GTLR process is to present the findings. The key findings are presented through textual descriptions accompanied by original quotations from the included primary studies. Furthermore, Wolfswinkel et al. recommends, “presenting findings using visualisations such as diagrams can help reach a wider audience” [11]. To visualise the findings of the 30 primary empirical studies, we created model diagrams (Figures 4 and 5).

4 FINDINGS – KEY CATEGORIES

Five key categories emerged from the analysis: (1) Developer Awareness, (2) Developer Perception, (3) Developer Needs, (4) Developer Challenges and (5) Developer Approach. Taken together, they represent the aspects AI developers are concerned with when considering ethics in AI. We describe each of the five key categories, their underlying concepts, and use quotes from the included primary studies by attributing them to paper IDs G1 to G30. Figure 4 shows a visualisation of the prism metaphor. Figure 5 shows the theory diagram.
including the five key categories, each of which are detailed in this section, and the five hypotheses, which are explained in Section 5.

4.1 Developer Awareness

The first category that emerged was Developer Awareness. This category emerged from three underlying concepts: developer awareness of AI ethics & principles, developer awareness of human limitations, and reasons for developer awareness.

4.1.1 Developer Awareness of AI Ethics & Principles

Most articles reported that the developers participating in their study were aware of ethics, including its importance [G1], [G4], [G5], [G17] and its relevance [G18] in AI.

AI developers were aware of their roles and responsibilities in implementing ethics during AI system development [G7]. They were aware that they play the most important role in shaping the ethics that is embedded in an AI system [G23]. Govia [G16] mentioned that a participant was aware of the philosophical theories of AI ethics. The participant stated the following:

> “If you’re familiar with various philosophical theories of ethics, a lot of them involve either satisfying constraints based on rules, Kantian deontological ethics, or optimising some function, Utilitarian like Mill or Bentham...now these sorts of optimisation are actually very important in computer science in general, also in artificial intelligence.” – AI specialist from [G16].

Transparency is one of the ethical principles of AI that is discussed widely by AI developers [G1], [G23] and a highlighted topic of discussion in academia [G6]. AI developers were aware of the term ‘transparent AI’ and it was recognised as a goal during AI development [G2], [G9], [G18]. Mark et al. [G17] mentioned that a participant was aware of the transparency law which helped them to determine what data needs to be public and what data needs to be private during the development of an AI system. Another participant in that study [G17] was also aware of transparency in AI and aimed at making transparent systems. The participant mentioned the following:

> “You might want to make it transparent for all citizens.” – AI expert from [G17].

AI developers are aware of the term ‘fairness’ which is an ethical principle of AI [G2]. AI developers are aware of this principle and work towards abolishing fairness issues in AI systems [G3]. Similarly, AI developers acknowledged that they are aware of accountability of AI systems and its importance [G3], [G6], and they felt responsible for the harms caused by their system [G10]. A study [G8] stated that ‘responsibility’ as an ethical principle achieved the highest rank in terms of relevance in AI and it affects other ethical principles of AI. They were also aware that they possessed sensitive customer data and so they actively considered accountability in relation to cyber-security and data management [G5].

Privacy is another ethical principle that AI developers were aware of and discussed widely. Privacy of data and information was identified as one of the major concerns of organisations [G6], [G27]. One of the participants in a study [G6] stated that:

> “And one of the first questions is privacy; that is, these algorithms that you are presenting, where are they going to be run? What will their information requirements be?” – AI practitioner from [G6].

Developers also seemed to be aware of the gap that exists between ethical principles and practice of implementing AI ethics. Ibanez et al. [G6] reported that a participant stated the following:

> “They sent two hundred pages of what it should be today from the European Union, but then in reality, what can be applied? What is the reality of companies, and what is practical?” – AI practitioner from [G6].

4.1.2 Developer Awareness of Human Limitations

Participants in a study [G7] mentioned that they were aware of their own limitations in implementing ethics in AI. They reported that sometimes the limitations of their foresight and intention resulted in the development of a faulty and unethical AI system. Orr et al. [G7] mentioned that a participant stated the following:

> “We are developing systems that are better than human ... only to discover as time goes on, that maybe they make things worse. And I don’t think that, that is a cynical thing to say. I think it is just a reflection of how every technology innovation has unfolded so far. What we need to do, as designers, is be aware that we could be designing the system that works and changes people’s lives, or you could be designing the system that makes people’s lives worse.” – AI practitioner from [G7].

On the other hand, some studies highlighted the lack of such awareness and assumed ethical behaviour, without addressing conscious and unconscious biases. For example, a study on developers’ challenges of addressing ethical issues of AI presented various challenges that AI developers face in addressing AI ethical issues [G24]. The study [G24] reported that AI developers lacked self-reflection on being able to recognise their own biases and responsibility which hampers AI ethics implementation. A participant in that study mentioned the following:

> “Most of us think we’re ethical and we operate with a very bad ethical premise that says I’m a good person and evil is caused by evil people. I’m not an evil person. So I don’t have to worry about it. So when I write the algorithm, I’m a good software engineer. I don’t even have to question this. I’m doing a fine job.” – AI engineer from [G24].

Another participant in that study mentioned that they lacked awareness about their cultural norms while making ethical decisions during AI system development:

> “The cultural norms that we have, but don’t even realise we have, that we use in order to make decisions about what’s right and wrong in context. It’s very difficult for any software system, even a really advanced one, to transcend its current context. It’s locked into however it was framed, in whatever social norms were in place amongst the developers at the time it was built.” – AI engineer from [G24].

Likewise, other participants stated that they did not always have a diverse and broad perspective to build inclusive AI technologies which affects the ethics implementation in AI:

> “I’m in a niche market and I do the photo recognition software and I’m an old white guy. So the only people I recognise are white males with beards. And that happens in the software, we know it’s happened and we’ve framed out the ethics.” – AI engineer from [G24].
Participants from another study [G25] mentioned that they are aware of their lack of knowledge about ethics and ethical guidelines to be followed during AI system development. They also mentioned that they were aware of the ways to overcome their limitations such as participating in mandatory employee training programs, attending ethics-focused design workshops to overcome, and reading published materials on ethics.

### 4.1.3 Reasons for Developer Awareness

Using the STGT data analysis procedures, in addition to the types of awareness, we were also able to identify some reasons for developer awareness. For example, several participants in a study [G3] concluded that organisational pressure is the main reason for awareness of transparency which led them to make transparent AI systems. Organisational pressure leads to transparency of the ML system which is also beneficial for the organisation. A participant of the study [G3] stated the following:

> “We have better buy-in”. – ML practitioner from [G3], when the logic of their ML systems is provided to the users.

Several studies concluded that AI developers were forced by laws and regulations to be aware of AI ethics [G10], [G5]. For example, the General Data Protection Regulation (GDPR) [G6], [G27]. Following are the statements made by the participants about GDPR in a study [G6]:

> “The first thing is the GDPR.” – AI practitioner from [G6].

> “We learned from GDPR to have sensitive data in a separate sensitive database that can only be accessed by several users or with special permissions.” – AI practitioner from [G6].

Another study [G1] concluded that medical domain has the most strict regulations which is the reason for medical AI developers to be aware of AI ethics. On the flip side, the same regulations seemed to limit their awareness of ethical issues. A participant in that study [G1] who was involved in developing a medical AI system stated that,
“We have in-house quality measurements and these regulation requirements are very strict, so therefore these things pretty much come as a given for us. And of course if you think about it the other way, we consequently think about these things [ethics] even less because we already have such clear regulations and requirements for what we do.” – AI designer from [G1].

Other reasons for AI developers’ awareness of ethics were also mentioned by participants such as AI developers’ personal interest and experiences that help them in gaining AI ethical knowledge [G6],

“The typical ones, I know them but on a personal level and [based on] curiosity.” – AI practitioner from [G6].

Another participant in a study [G6], who was the Director of AI and had 14 years of experience in Technology Consulting Services, stated the following:

“The White Paper of the European Commission on Artificial Intelligence, well, I know it in my case, but it is also a bit because of my profile and past.” – AI practitioner from [G6].

Customer complaints about AI ethical issues and negative media coverage of AI systems were other reasons for developers’ awareness about AI ethics [G2]. A participant in a study [G2] suggested a reactive approach to awareness:

“How do you know the unknowns that you’re being unfair towards? You just have to put your model out there, and then you’ll know if there’s fairness issues if someone raises hell online.” – ML practitioner from [G2].

### 4.2 Developer Perception

The second category is Developer Perception. This category emerged from four underlying concepts: developer perception of AI ethics & principles, developer perception of users, developer perception of data, and developer perception of AI systems. This category of developer perception is related to the developer awareness category (as presented in the previous section), in that awareness was a prerequisite to forming perceptions. However, the perception category goes beyond acknowledging the existence of something and captures developers’ views and opinions about it, including held notions and beliefs. For example, it includes shared perceptions about the relative importance of ethical principles in developing AI systems, who is considered accountable for applying and upholding them, and the perceived cost of implementing ethics in AI.

#### 4.2.1 Developer Perception of AI Ethics & Principles

Perception about the importance of ethics varied. Some AI developers perceived ‘ethics’ as very important in developing an AI system [G1], [G29], [G20]. A study [G1] reported that AI developers acknowledged the importance of AI ethics. In the paper, when participants were asked if ethics is useful in AI, all (N=6) of them answered “Yes”.

In contrast, many AI developers do not consider ethics as the most important element during AI system development. A study [G7] mentioned that AI developers consider only specific ethical principles important whereas another study [G9] mentioned that AI developers are less concerned about ethics as a whole in AI and more concerned about the usefulness and viability of their products. Ethics was perceived as a secondary concern [G7] and as other’s problem [G1]. The study [G10] concluded that AI developers perceive ethics as a non-functional requirement of AI systems. Yet others approached it with a minimalist approach. For example, a participant (AI practitioner) in a study [G7] shared:

“The very minimum that you have to adhere to is the law. So, we start by ensuring that everything that we do, or our clients do is legal. Then we have to decide whether or not it is appropriate, which could be considered ethical or fair.” – AI practitioner from [G7].

Developing responsible AI was seen as building positive relations between organisations and human beings by minimising inequality, improving well-being, and ensuring data protection and privacy. However, when it comes to the relative importance of the ethical principles, it was a divided house. Some AI developers think that AI systems must be fair in every way [G11]. Others think that fairness issues in AI systems must not only be minimised but completely avoided [G8]. A study [G8] concluded that protection of data privacy is the second most important principle that comes after transparency. While other studies – [G6] and [G10] – concluded that privacy is the most important ethical principle in AI system development.

There were also differing opinions about who should be responsible for ethics in AI. For example, a participant in a study [G30] mentioned that:

“When you think about who’s accountable for AI that they’re using in the public sector. When something goes bad, who do you point the finger at? If you got the human being out of the loop or maybe it’s never out of the loop? But how do you decide who bears the cost in a bad experience?” – AI practitioner from [G30].

Others had strong opinions, such as a participant of a study [G10], who stated that ethics cannot be outsourced, suggesting it is ultimately the AI developers’ responsibility. There was a notion that AI developers are responsible for maintaining data privacy in AI systems. AI developers perceived the importance of privacy from the user’s point of view. A participant in a study [G6] quoted the following:

“There you have the data of people, their addresses, you even have precious information, about when they are at home or not, private data, and making proper use of them is essential.” – AI practitioner from [G6].

Some others think that accountability issues are different for different AI systems [G6]. For example, one perception was that both users and AI developers are responsible for maintaining the accountability of an AI system [G7], [G26]. Technical knowledge of AI developers help them in producing accountability whereas lack of user’s knowledge about AI algorithms has a negative effect on accountability of an AI system. A participant in a study [G7] shared the following:

“Accountability does not come up in any of our client discussions. It does not come up as you would think. It is because they don’t understand what they don’t understand. How many people will know in detail how AI algorithms work, and who has actually practiced it to understand the nuances of an AI algorithm?” – AI practitioner from [G7].

In another study [G20], participants suggested stricter mechanisms for enforcing accountability beyond relying on individuals. They mentioned that AI is a very powerful technology which needs ethical regulations. Ethical regulations provide an ethical framework that guides them during the development of an AI system. A participant in the study
[G20] mentioned the following:

"We have regulations on all kinds of technology, and I think that there's no special reason for why AI should be less regulated than anything else." – AI expert from [G20].

Another interesting opinion shared was to do with the perceived cost of applying ethics in AI development. For example, too much ethical accountability was perceived as having a negative impact on business and organisational growth. A participant in a study [G6] stated the following:

"If I have to be very "ethical", accuracy will also be affected. Then I think there is a dilemma there, in the end, of how ethical I am and how much business I am losing." – AI practitioner from [G6].

Likewise, a study by Morley et al. [G29] reported that improvement of social impact is the benefit of a pro-ethical AI design as perceived by majority of their participants but incurring additional costs such as resource costs and additional time is a perceived disadvantage.

4.2.2 Developer Perception of Users

AI developers have perceptions about users' nature, technical abilities, drivers, and their role in the context of ethics in AI. Participants in a study [G3] perceived that users only like to communicate if there is any chance of an incident occurring. Otherwise, they don't care. Similarly, the participants in a study [G3] reported on the users' tendencies to judge an AI model based on personal factors:

"People tend to lose faith if their personally preferred risk indicators aren't in a model, even without looking at performance of results." – ML practitioner from [G3].

Some AI developers perceive that users are not curious about the working of AI systems because ethical complexities of an AI system are irrelevant to them [G5]. A participant in one study [G5] stated that:

"Nobody wants to listen to ethics-related technical stuff. It's not relevant to the users." – AI developer from [G5].

Users' lack of AI knowledge is one of the reasons that they have no interest in ethics of AI according to the perception of a participant in a study [G7]:

"Accountability doesn't come up in any of our client discussions. It doesn't come up as you would think. It is because they don't understand what they don't understand. How many people will know in detail how AI algorithms work, and who has actually practiced it to understand the nuances of an AI algorithm?" – AI practitioner from [G7].

Another study [G6] reported that users are concerned about ethics in AI and ethical issues only when it impacts their business. Likewise, a study [G14] reported that users are skeptical and worried when it comes to the publication of their personal data in AI systems:

"So, there will be a lot of scepticism, because everyone is afraid that personal data will be published. So, everyone has quite a bit of respect." – AI expert from [G14].

Participants in a study [G7] discussed the role of users in ethics in AI. An AI developer stated that it is essential to get users' needs and requirements before developing an AI system as it creates ethical parameters for them. Likewise, participants in a study [G7] perceived that the growth of an AI company is based on users. Users are likely to sue a company if ethical issues of an AI system are not addressed by the company:

"[Companies] that aren't transparent or ethical, eventually, or you would hope, end up being prosecuted or sued or you know, all citizens as a whole would choose not to engage with them because they've been identified as an untrustworthy organisation. Because, trust becomes the currency on which we trade upon. And will be more so as AI embeds itself in everything that we do." – AI practitioner from [G7].

Similarly, participants in a study [G7] perceived users as autonomous agents and stated that encounters between users and AI systems cannot be fully controlled through AI design. They perceived that users have an equal responsibility as developers for AI outcomes. A participant in that study stated the following:

"We were a technology provider, so we didn't make those decisions. It is the same as someone who builds guns for a living. You provide the gun to the guy who shoots it and kills someone in the army, but you just did your job and you made the tool." – AI practitioner from [G7].

This statement is supported by another study [G10] which concludes that users are accountable for their own safety.

4.2.3 Developer Perception of Data

AI developers consider data as an important aspect in implementing ethics in AI [G5], [G6]. A participant in a study [G5] perceived that data handling is an essential step that enhances the development of an ethical AI system:

"It's really important how you handle any kind of data that you preserve it correctly, among researchers, and don't hand it out to any government actors. I personally can't see any way to harm anyone with the data we have though." – AI developer from [G5].

The developer's naive perception of the potential for harm (or lack thereof) is worth noting in the above example.

Along with that, participants in a study [G2] highlighted the importance of data collection and curation in an AI system development. They mentioned that collecting sufficient data from sub-populations and balancing them during curation of data sets is essential to minimising ethical issues of an AI system. On the other hand, Stahl et al. [G18] reported that participants avoided getting personal data of users or minimised its collection as much as possible as so that no ethical issues related to data privacy arise during AI system development.

4.2.4 Developer Perception of AI Systems

AI developers have different perception about AI systems. The participants in a study [G1] perceived that every AI system has some ethical issues initially and they take actions to either avoid or mitigate them. The participants in another study [G3] perceived physical harm of an AI system as important and relevant but not any other harm. One of the participants mentioned the following:

"What could it affect-the distribution of funds in a region, or could it result in a school taking useless action. It does have its own risks, but no one is going to die because of it." – ML practitioner from [G3].

AI developers perceive AI as just another feature at least for considering the ethical side of the things [G4]. Whereas, participants in a study [G7] thought AI as a socio-technical system and not just a technical system:

"There is not really such a thing as an autonomous agent, it
has kind of become important to say. It is now a socio-technical system, not just a technical system.” – AI practitioner from [G7].

Orr et al. [G7] commented on the perceived limitations of AI systems, suggesting that they are so complicated that sometimes, they are not able to minimise ethical issues despite trying their best:

“Can I say, yeah OK that was a fault, but this is how we did the safety analysis. And I can see that this was missed, not because we were negligent, but just because it is so complicated. In this case, somebody died, but we did have the right ethical framework. But sometimes accidents happen. I think that is the kind of argument that you are going to have to make.” – AI practitioner from [G7].

Participants in another study [G9] also perceived AI systems as only concepts and prototypes so they did not feel accountable for the design of an AI system. These kinds of perceptions of AI developers denote that their AI systems are as ethical as the humans that create them. Likewise, studies [G12], [G14] reported that AI systems will always have some biases as humans create those systems:

“The machine will always have biases, always being created by a programmer, and the programmer has prejudices.” – AI expert from [G12].

4.3 Developer Needs

The review highlighted different needs of AI developers which can help them enhance ethics implementation in AI systems. This category was underpinned by concepts such as AI ethics & principles needs and human needs.

4.3.1 AI Ethics & Principles Needs

Developers in the included primary studies identified a number of needs. For example, the need for a universal ethics definition was highlighted, as it fulfills the gap between the on-going academic discussion and the industry and enhances AI ethics implementation [G1], [G6], [G13]. A participant in a study [G1] mentioned the following:

“I actually try to use the word ‘ethics’ as little as possible because it’s the kind of word that everyone understands in their own way, and so they can feel that it’s not relevant to what we’re doing at all.” – AI designer from [G1].

Along with that, a participant in a study [G6] stated that there is a gap between practices and principles which needs to be fulfilled:

“They sent two hundred pages of what it should be today from the European Union, but then in reality, what can be applied? What is the reality of companies, and what is practical?” – AI practitioner from [G6].

Developers in [G1] and [G6] reported that participants expressed the needs of tools or methods to translate principles into practice. A participant in that study stated the following:

“I think we read them all because they are coming out. There are many in the ‘stratosphere’. That is when you read the principles and say, how do I translate them in practice? It gets more complicated.” – AI practitioner from [G6].

Another study [G19] concluded that there is a lack of tools that supports continuous assurance of AI ethics. A participant in a study [G19] stated that it was challenging for them as they had to rely on manual practice to manage ethics principles during AI system development. The participant stated the following:

“We had to go through a lot of data and make sure that there was not a single frame with a person in it.” – AI scientist from [G19].

AI developers face communication challenges that affect ethics implementation in AI systems [G2], [G3], [G15]. Participants in studies [G2], [G3] expressed the need for tools to facilitate communication between AI model developers and data collectors. All these points conclude that there is a need of tools that can help AI developers to successfully implement ethics during AI system development.

While the lack of practical tools are repeatedly identified, other participants in a study [G6] had an opposite view on the gap between principles and practice. They expressed the need for more principles as they have much practice. A participant of that study mentioned the following,

“There is much practice but few principles.” – AI practitioner from [G6].

4.3.2 Human Needs

There are few needs related to AI developers that affect ethics implementation in an AI system. A participant in a study [G2] mentioned that there is a need for effective communication between AI developers as it supports ethics implementation. Similarly, participants in a study [G3] reported that they are in need of external perception and opinions of external parties on their AI software. It helps them to know the ethical issues of the software. On the other hand, participants in a study [G5] reported that they need more discussion of their responsibilities and AI development to help them become aware of ethical issues and minimise them. However, Chivukula et al. [G28] reported that participants didn’t feel responsible anymore as they were already doing their jobs ethically. One of the participants mentioned:

“I’m starting to feel like it’s not the responsibility of us anymore because I think all of us are already thinking from that perspective.” – AI practitioner from [G28].

4.4 Developer Challenges

The third key category is Developer Challenges. The review shows that AI developers face several challenges while implementing ethics during AI system development which are related to four underlying concepts of ethics implementation challenges, user challenges, AI system challenges, and data challenges.

4.4.1 Ethics Implementation Challenges

A number of challenges related to implementing AI ethics were reported, including knowledge gaps, gaps between principles and practice, ethical trade-offs including business value considerations, and challenges to do with implementing specific ethical principles such as transparency, privacy, and accountability.

Participants in a study [G1] reported that they have difficulty in conceptualising ethics, i.e., it is challenging for them to talk about ethics because the term ‘ethics’ is understood differently by different people. A participant in a study [G1] stated that,

“I actually try to use the word ‘ethics’ as little as possible because it’s the kind of word that everyone understands in their
own way, and so they can feel that it’s not relevant to what we’re doing at all.” – AI designer from [G1].

Likewise, Govia [G16] mentioned that it was difficult for the participants to talk about ethics because they did not have a clear concept about ethics in AI. A participant in that study stated the following:

“...it’s hard for me to talk about ethics because I don’t really understand it that well to be quite honest with you; and that’s probably the same for a lot of computer scientists, artificial intelligence researchers — that we’re not too clear on what ethics is.” – AI specialist from [G16].

Another participant acknowledged the need to possess relevant background in ethics:

“I don’t know if I am qualified yet to really make professional thoughts about it. I don’t have an ethics background. I have a computer science background which maybe gives me insight into some areas of it, but certainly does not give me the full picture.” – AI specialist from [G16].

Similarly, a participant in a study [G18] reported that they were technology experts but did not have any knowledge and background of ethics. However, they mentioned that they were extremely aware of privacy concerns in AI use, highlighting the interesting relationship between developer awareness, perception, and challenges.

Some AI developers are concerned about the lack of discussion of implementing AI ethics in the industry. Different types of challenges are mentioned and solutions are discussed in theory but there is no demonstration of those solutions in practice [G1], [G3]. Translation of AI principles into practice is a challenge for AI developers:

“I think we read them all because they are coming out. There are many in the “stratosphere”. That is when you read the principles and say, how do I translate them in practice? It gets more complicated.” – AI practitioner from [G6].

AI developers are also challenged over making ethical choices during the design of an AI system:

“Quite often we will make trade-offs naively and in line with our own experiences and expectations and fail to understand the implications of those trade-offs for others. We can assess all of the trade-offs, but we still don’t weigh them in impartial ways.” – AI practitioner from [G7].

Likewise, AI developers are challenged to implement ethics in AI as there is a lack of tools or methods for implementing ethics. For example, in a study [G1], when AI developers were asked, “Do your AI development practices take into account ethics, and if yes, how?”, all respondents (N=6) answered “No”. This indicated that AI companies lack clear tools and methods for implementing ethics in AI.

A number of challenges were mentioned to do with implementing specific ethical principles such as transparency, privacy, and accountability. For example, although transparency is perceived as an important ethical principle of AI, developers have challenges in maintaining transparency. These challenges arise both in the sense of transparency of systems and the development process [G1]. Providing transparency to customers is challenging [G6]:

“There’s generally little transparency everywhere because it is hard to make that transparent to the customer I think it is still challenging to give that security and transparency.” – AI practitioner from [G6].

A study [G3] highlighted that communicating the performance of designed AI systems is challenging sometimes due to cost and business value considerations, which hampers transparency of an AI system. Cost is one of the major challenges in maintaining transparency in AI [G26]:

“Releasing source code of AI to maintain transparency does not happen often because it costs money to do, you have to spend time to clean it up, to maintain it, to publish it and so on. Second, you decrease the commercial value of it usually.” – AI scientist from [G26].

Similarly, developers were found to be challenged to maintain accountability of an AI system:

“How to clarify responsibilities and what are the standards or regulations? A machine cannot take responsibility by itself, as a human being can.” – AI developer from [G22]. At the same time, some of them felt they did not have control over the way an AI technology is used [G26]. Dividing responsibilities among the teams was seen as one of the major challenges of AI developers [G27].

4.4.2 User Challenges

AI developers face challenges related to users and clients during the implementation of ethics in AI systems. Participants in a study [G1] mentioned that lack of interaction with end users causes uncertainty about user problems:

“So that’s of course one question: how to make it clear for them that there are some uncertainties there so that they don’t expect the information to always be perfect. But I don’t really know how much of a problem this is - I haven’t really spoken to our end users.” – AI designer from [G1].

An AI practitioner in a study [G7] reported that an imbalance is developed between AI developers and users because the priorities of their work are set by senior members of the company:

“Senior executives don’t understand machine learning models that their data scientists are producing. Here are the parameters and here is what is actually, here is what matters. You have told me to maximise profits so, it really just comes down to [maximising profit].” – AI practitioner from [G7].

4.4.3 AI System Challenges

AI systems create challenges for AI developers while implementing ethics. Unpredictability of an AI system is a major challenge for AI developers [G1], [G4], [G7] and they take actions to avoid, mitigate or prevent unpredictable behaviors that take place [G1]. A participant in a study [G1] stated that,

“An example of such an action can be ML management by means of using different sets of training data or limiting its utilisation. “...we have even cut some functionalities of the system in order to make it more predictable, which has reduced the amount of unexplained results we have gotten out of it in practice we’ve been able to explain all of the faulty results so far.” – AI designer from [G1].

Similar thought was shared by a participant in another study [G24] who mentioned that,

“In terms of unpredictability, there is a lack of work looking at scenarios of unintended consequences precisely because ‘we don’t know the unintended consequences of the decision-making of the machine.” – AI engineer from [G24].
There are external causes of AI system unpredictability such as cyber-security threats [G1]. Likewise, client’s needs such as profit maximisation and attention optimisation cause unpredictable system behaviour that ultimately develops ethical issues. A participant in the study [G7] stated the following:

\[\text{“It’s not that we thought what we were doing was safe, it’s just that, certain inbuilt desires to increase clicks, to increase attention, to maximise advertising was our primary motivation. You did not have to think about any other consequences.”} \quad \text{— AI practitioner from [G7].} \]

Not all organisations and their AI developers have fallback plans for solving ethical issues developed by an unpredictable AI system [G4]. Therefore, it can be concluded that it is challenging for AI developers to solve ethical issues that are developed by unpredictable AI system behaviours. AI developers are using some strategies to avoid such unpredictability issues of an AI system. However, there is a need for methods and tools which can mitigate or prevent unpredictable behaviour of an AI system. Such methods or tools will help in minimising AI ethical risks.

### 4.4.4 Data Challenges

Some of the challenges shared by participants across the primary studies were related to data. For example, the quality of dataset used in AI algorithms is considered one of the main factors affecting fairness of an AI system. Some AI developers mentioned that it is challenging for them to collect quality datasets as they are not given full control over the data collection process [G2]. Lack of proper engagement of users with the product also hampers the data collection process. Participants in that study also mentioned that challenges to get additional training dataset to ensure AI fairness arise due to the team’s blind spots. Holstein et al. [G2] reported that the participants recalled cases where users complained about a globally deployed AI system that recognised popular celebrities of some countries and did not recognise others. One of the participants [G2] quoted the following:

\[\text{“It sounds easy to just say like, ‘Oh, just add some more images in there,’ but there’s no person on the team that actually knows what all of [these celebrities] look like, for real if I noticed that there’s some celebrity from Taiwan that does not have enough images in there, I actually don’t know what they look like to go and fix that. But Beyoncé, I know what she looks like.”} \quad \text{— ML practitioner from [G2].} \]

On the other hand, in some cases data privacy issues were seen to induce risk aversion and impose barriers to better data usage:

\[\text{“My perception is that companies do take great care of their information, to the point that they often prefer not to generate value from information [rather] than to expose their information to a risk of leakage.”} \quad \text{— AI practitioner from [G6].} \]

### 4.5 Developer Approach

The review of empirical studies provided insights into the approaches used by AI developers to implement ethics during AI system development. This category is underpinned by two key concepts, applied strategies and possible strategies, to enhance ethics implementation in AI. Applied strategies refer to the techniques or ways that AI developers reported using to enhance the ethics implementation in AI, whereas possible strategies are the recommendations or potential solutions discussed by AI developers to enhance the ethics implementation in AI.

#### 4.5.1 Applied Strategies

AI developers use different strategies to enhance ethics implementation in AI. Participants in a study [G1] mentioned that organisations implemented proactive strategies to enhance ethics implementation in AI development. One of the strategies used was speculating socio-ethical impacts by AI developers before developing an AI system. This helped AI developers become aware of AI ethics and ethical issues that may arise in future and have a plan if the issues arise [G5]. Similarly, analysing a hypothetical situation of unpredictability was a strategy used to solve unpredictable behaviour of an AI system [G1].

Likewise, group discussion with fellow colleagues was another strategy used by AI developers to be aware of AI ethics and address AI ethical issues [G9]. Some AI developers reported merging ethical and legal considerations to ensure no illegal actions have been taken during AI system development [G7]. In this strategy, ethics remained a secondary concern. A participant in a study [G7] stated:

\[\text{“The very minimum that you have to adhere to is the law. So, we start by ensuring that everything that we do, or our clients do is legal. Then we have to decide whether or not it is appropriate, which could be considered ethical or fair.”} \quad \text{— AI practitioner from [G7].} \]

Participants in a study [G18] reported several strategies that they used to enhance ethics implementation in AI such as responsible data science, stakeholder engagement, ethics review boards, and following codes of ethics and standards of practice. AI developers were also involved in setting customised regulations in the company and played an essential role in the development of AI ethics. This strategy was used to enhance ethics implementation by developing comprehensive and well-defined guidelines of AI ethics for the company [G7]. Similarly, a participant in a study [G17] mentioned that they had an interaction and collaborative discussion with policy makers and legal teams of the company to ensure that their algorithms were abiding by the legislation. This denotes that AI companies focused on ensuring their algorithms were legally fit before deployment.

AI developers discussed some strategies and methods that they used to maintain transparency and accountability of AI systems. Code documentation was the primary proactive strategy of creating transparency during development of an AI system and to track the actions and people involved [G15]. Conducting audits was the other important strategy used by AI developers to solve transparency issues [G1], [G5]. RESOLVEDD, which stands for R: Review; E: Estimate; S: Solutions; O: Outcomes; L: Likely; V: Values; E: Evaluate; D: Decide; D: Defend, was a proactive strategy used by AI developers to increase transparency and ensure that the ethical considerations of the team members were documented. Similarly, documenting decisions made by AI developers in order to track decisions back to individuals when needed was one of the strategies used to enhance accountability [G10].
Collecting as much training data as possible was one of the proactive strategies of AI developers to minimise biases in the system [G15]. Speculating possible fairness issues in an AI system before deploying it was the other strategy used to minimise fairness issues [G2] in AI. However, some companies did not use proactive strategies to maintain transparency of AI systems but addressed transparency issues only when it impacted their business [G6]. Some AI developers just followed what is legal and shifted the ethical responsibilities to policy makers and legislative authorities [G7]. At the same time, some AI developers used the reactive strategy of apologising to customers if any unpredictable ethical issue arises [G1].

4.5.2 Potential Strategies
In addition to sharing experiences of tried and tested strategies, developers also discussed potential strategies that they thought could improve ethics in AI. A study [G10] concluded that appointing one individual to implement ethics during AI development is not a good option. The whole AI development team must be involved in the process of ethics implementation. Educating AI developers about AI ethics and including diverse people in the development team help AI developers to implement ethics in the system and build ethical AI [G21].

Having internal governance such as ethics committees in an organisation to establish AI ethical standards and employing AI auditors help AI developers were other possible strategies that can provide AI developers an opportunity to work closely with ethicists so that they can verify if ethics is being implemented appropriately during AI system development [G21]. On the other hand, a participant in a study [G28] stated that educating business owners with ethics training and education instead of them because they focus on their business growth rather than ethics in AI.

The participant said:

“More education for business owners and people in other parts of businesses to be a responsible business owner. Don’t push these agendas. You think making more money quickly is the most important part of your business.” – AI practitioner from [G28].

Similarly, a participant mentioned that organisations should work on treating ethics properly by having a cultural shift in the organisation:

“Isn’t just a designer process or designer influence at this point of time, but it’s a cultural shift that has to happen in the organisation on how they treat ethics.” – AI practitioner from [G28].

AI developers provided some potential strategies on enhancing the transparency and fairness of AI software. Recognising transparency as a goal is not sufficient, pursuing it formally is important [G5]. Likewise, a participant in a study [G10] mentioned that tackling ethical issues during design and development of an AI system to enhance system transparency is good. Using explanatory mechanisms during AI design and development phases is recommended to enhance system transparency [G6]. Hiring employees who belong to different communities and ethnic groups can enhance the chance of spotting biases within a team. Others suggested including fairness-focused quizzes in the interview processes can be useful to help people who can detect fairness issues in an AI system [G2]:

“No one person on the team [has expertise] in all types of bias especially when you take into account different cultures. It would be helpful to somehow pool knowledge of potential fairness issues in specific application domains across teams with different backgrounds, who have complementary knowledge and blind spots.” – [G2].

5 Hypotheses and Theory
A grounded theory is not limited to a set of descriptive categories – it also explains the key relationships between those categories, such as through a set of interrelated hypotheses [10], [37]. We have presented the five key categories – Developer Awareness, Developer Perception, Developer Needs, Developer Challenges and Developer Approach – in Section 4, that emerged through the data analysis of 30 primary studies. In this section, we present the relationships between those categories as five interrelated hypotheses. We also analyse how changes in one category impacts the changes in another category. By analysing the relationships between categories facilitated by memoing, we derived the grounded theory of ethics in AI through the developer’s prism. Figure 5 presents the theory diagram resulting from theoretical structuring, with key categories and hypotheses (H1-H5).

H1: Developer Awareness is an antecedent to, but does not guarantee positive, Developer Perception.
Awareness and perception are related yet distinct. AI developers’ awareness of ethics can lead to their perception but awareness does not guarantee improved perception of the importance of AI ethics. In fact, awareness about AI ethics was seen to lead to varying perception about it. For example, a participant in a study was aware of the term ‘AI ethics’ but that participant considered ‘ethics’ as a secondary concern in AI [G1].

H2: Developer Awareness can lead to identifying Developer Needs.
AI developers’ awareness about ethics can lead to a recognition of their needs. For example, their awareness about human limitations in the context of implementing AI may lead to them acknowledging the need to overcome those limitations. Similarly, awareness of the lack of foresight, broad perspective and self-reflection [G7] on the one hand can be seen to be addressed by recognising the need for effective communication to discuss AI ethics and ethical issues [G2] and the need to own responsibility of ethics implementation [G5].

H3: Developer Challenges lead to identifying Developer Needs.
AI developers’ challenges lead to identifying their needs. For example, a participant in a study [G3] mentioned about the challenge they face during ethics implementation in AI due to lack of communication between AI developers and data collectors. Therefore, a need of tools to facilitate effective communication between AI developers and data collectors was highlighted in the study [G3]. Similarly, some AI developers shared challenges in implementing ethics in AI due to lack of tools to help them during ethics implementation [G3], [G9]. At the same time, the need for tool support for ethics implementation in AI was highlighted
by participants in studies [G9], [G1] to overcome these challenges.

H4: Developer Perception can generate Developer Approach.

AI developers’ perceptions can lead to generating approaches, such as possible strategies, to enhance the process. For example, a participant in a study [G4] perceived that ethics must be implemented systematically in AI. Another study reported that developing systematic implementation guidelines can be a possible strategy to enhance AI ethics implementation [G21]. Likewise, another participant in a study [G4] perceived that ethics must not be outsourced and developers developing the AI system must implement ethics. This perception about the ethics implementation may generate a possible strategy such as providing ethics implementation training to AI developers so that they do not have to outsource the ethics implementation to the third party [G21].

H3: Developer Challenges can be overcome by Developer Approach.

AI developers’ challenges can be overcome by their approaches. For example, lack of communication between colleagues was one of the challenges mentioned by a participant in a study [G3]. Practicing group discussion with colleagues and other members of a company to discuss AI ethics and ethical issues was one of the approaches used by a participant in a study [G1]. Lack of knowledge about AI ethics was one of the challenges identified by a participant in a study [G16] which can be overcome by an approach such as setting own ethical regulations by a company to make the employees aware and knowledgeable about AI ethics, shared in [G1].

Theory of Ethics in AI through the Developer’s Prism:

Taken together, the key categories and hypotheses form the theory which explains that developers’ awareness of AI ethics directly leads to their perception about AI ethics and its implementation as well as to identifying their needs, and indirectly leads to identifying their challenges and coming up with approaches (applied and potential strategies) to overcome them. As with most grounded theories, our theory is meant to be modifiable with future empirical evidence as the landscape of ethics in AI changes over time.

6 DISCUSSION AND RECOMMENDATIONS

Our findings contribute to the academic discussion by exploring the studies that have included the views and understanding of AI developers about ethics. As we conducted an ST-GTLR and used the STGT approach for data analysis, we got an opportunity to rigorously review the primary empirical studies relevant to our research question and develop a multi-faceted theory. We now discuss some of the insights captured through memoing and team discussions, accompanied by recommendations.

Ethics in AI – whose problem is it anyway? Participants of the primary studies had a different perception of AI ethics and its implementation. Most studies included in our research concluded that AI developers perceived ethics as an essential aspect in AI [G5], [G20]. However, some participants of the primary studies had an opposite perception about ethics in AI. A participant of a study [G1] stated that discussion on AI ethics does not affect most people, except for AI ethics discussions in massive companies like Google. Likewise, we found that the participants of a study [G4] perceived ethics as a non-functional requirement in AI, and it was implemented externally [G23]. However, a participant in a study [G4] stated that ethics could not be "outsourced", and it should be implemented by AI developers who are developing the software. The diverse perspective of the participants about the implementation of ethics in AI serves to highlight the complex nature of the topic and why organisations struggle to implement AI ethics.

Likewise, there were also different views on the accountability for ethics in AI. An AI practitioner in a study [G30] mentioned the uncertainty in deciding responsible people when some ethical issues arise in AI systems. We perceive that organisations decide who to be held accountable for ethics in AI, and it varies from organisation to organisation. For example, ACM Code of Ethics clearly puts the responsibility on professionals who develop these systems. On the other hand, AI developers perceive that physical harm caused by AI systems is essential and needs to be considered rather than any other harms [G3]. This statement is alarming as it hints that developers are not worried about ethical harms in an AI system and prioritise only physical harms.

Recommendations for Practice

Given the diverse perspectives on who owns accountability of considering ethics in AI systems development and potential ethical issues arising from AI system use, it is important for AI development teams, that are usually multidisciplinary in nature, managers, and organisations at large to have open discussions about such issues at their workplace [G5]. For example, this can be done through organising discussion panels, guest seminars by ethics and ethical AI experts, and hosting open online forums for employees to discuss such topics. Another approach is to collate the challenges specific to the organisation and see how they map to selected ethical frameworks, as was conducted at the Australia’s national scientific research agency (CSIRO) [G26].

Developer discussions can be followed by strategic and organised attempts to reconcile perspectives, e.g. teams collaboratively selecting an existing or creating a bespoke ethical framework, and drafting practical approaches to implement them in their specific project contexts [G7], many of which may be application domain specific.

Following hypothesis H1 (developer awareness is an antecedent to, but does not guarantee positive, developer perception.), improved awareness may not equate to more positive perception about the importance of ethics in AI. This has implications for the efforts made in industry and research to improve the awareness of ethics in AI. Such efforts need to be carefully crafted to cater not only to those who are likely
to go away with positive perceptions but to also address the scepticism, concerns, and questions of those who may harbour negative perceptions as a result of increased awareness. In other words, awareness programs need to focus on building positive perceptions by addressing developer challenges and needs.

Guided by our review findings, we recommend proactive awareness as evidenced in our review, such as driven by personal interest and experiences [G6], organisational needs [G3], and regulations such as the General Data Protection Regulation (GDPR) [G6]. Whereas reactive awareness, driven by customer complaints about AI ethical issues and negative media coverage [G2], is not desirable.

Similarly, we recommend proactive strategies such as speculating socio-ethical impacts by AI developers prior to developing an AI system [G5], analysing hypothetical situations to solve unpredictable behaviour of an AI system [G1], following codes of ethics and standards of practice [G18], including diverse people in the development team [G21], and having internal governance such as ethics committees in an organisation to establish AI ethical standards [G21].

Finally, there is a need to consider accountability at the organisation and industry level. For example, Ibanez et al. [G6] reported that there is a need for ethical governance that can help them solve accountability issues.

**Recommendations for Education**

Educators should include the topic of ethics of AI software development in the curriculum to educate future AI developers about ethical principles, guidelines, and practical aspects as presented in this paper. They can give students the opportunities to express their perceptions about the topic through group discussions and debates.

Students should be explicitly trained about the accountability of considering ethics in AI system development. For example, through being assigned projects to develop AI systems where they are given the opportunity to decide the accountability of the ethical issues arising in the system they develop.

**Ethics-critical domains lead the way.** Comparisons were made between the medical field and the IT field in terms of the awareness of ethical regulations in AI [G5]. Participants mentioned that developers developing AI used in the medical field are more aware of ethics because the medical field has more strict laws and regulations than IT. This hints that awareness of AI ethics depends on domain specificity. Domains such as medical and health are more ethics-aware than others and lead the way in ethics awareness and implementation.

**Recommendations for Practice**

The IT domain can learn from the advances in improving the awareness of and implementing ethics in the medical domain. This includes digital, virtual, mobile, and tele-health areas, as well as AI systems developed in other domains.

Labelling certain domains as safety-critical and equating that with ethics-critical, can be a flawed argument leading to perceptions that domains traditionally considered non-safety-critical, such as gaming and social media, can be held to lower standards and expectations when it comes to ethics implementation. We know from multiple cases of cyber-bullying and intelligent games encouraging self-harm in young adults that this would be a mistake. We recommend that all domains should aim to be ethics-critical domains.

**Research can help in fundamental and practical ways.** We found that AI developers have different perceptions about AI systems that affect the implementation of ethics. A participant of a study perceived the AI system as a socio-technical system and not just a technical system. So, the participant considered ethics a vital aspect of AI [G4]. However, a participant in another study perceived AI as a highly complex system. The participant mentioned that sometimes, they could not solve the ethical issues that arise in an AI system due to its complexity. It compels them to avoid ethics and give some excuses if required to defend the issues arising in the system [G7]. The participants’ perspectives on AI systems indicate that the implementation of ethics depends on how developers perceive AI ethics.

**Recommendations for Research**

Based on our review findings and insights, we recommend research, including empirical, review, and solutions and tools development, into the following topics.

- Unpack fundamental schools of ethics (or meta-ethics theories) such as Utilitarianism, Divine Law, and how they impact developers perspectives and approaches.
- Investigating each of the facets of our theory – developer awareness, perception, challenges, needs, and approach – individually and in depth, as much remains to be understood about how these manifest in practice.
- Investigating specific ethical AI principles, such as human-central values, human societal and environmental well-being, reliability and safety, contestability – individually and in depth.
- Developing frameworks and recommender systems for appropriate ethical AI principles selection and application, suited to the unique facets of the application domain (e.g. health, cybersecurity, entertainment) and AI system.
- Reviewing tools available to AI developers to implement ethics in AI systems, including their evaluation and feedback for improvement.
- Designing solutions in terms of tools and guidelines to address the developer challenges, working in close collaboration with the developers and managers.
- Investigating and explaining the users’ view of ethics in AI, for example, through a similar ST-GTLR approach as applied in this review to address the developers’ view.
- Understanding the interplay between the role of developers and users in implementing ethics in the
development and use of AI systems, including human limitations, biases, and strengths.

- Understanding the role of rules, regulation, legislation, and laws in enforcing ethical AI principles and guidelines, including enablers and barriers, to guide policy development.

- Better understanding the reasons for developer awareness such as laws and regulations, GDPR, personal experiences, as developer awareness directly or indirectly leads to other categories like developer perception, needs, challenges and approach of ethics and its implementation in AI.

7 Reflections

7.1 Selecting a Review Method

A systematic review is defined as “a means of evaluating and interpreting all available research relevant to a particular research question, topic area, or phenomenon of interest” [38]. SLR is a popular review method in software engineering [39]. Kitchenham derived the SLR guidelines from three guidelines in the medical domain, adapting them to the specific context of software engineering research. A key feature of an SLR is its focus on comprehensive and fair reviewing achieved through systematic application of a predefined search strategy to report research that does and does not support the preferred research hypothesis. The main reasons for performing systematic reviews include summarising existing literature, identifying gaps in literature, and providing a framework to position new research [38]. The SLR process supports a top-down, carefully pre-designed, sequential, and specification driven approach to reviewing.

Initially, we wanted to conduct an SLR to analyse and synthesise existing primary studies on ethics in AI as viewed by AI developers. However, the emerging nature of the research area and niche topic meant we obtained a minimal number of studies that focused on the AI developers’ views of ethics in AI. On the other hand, if we went broad with the search terms, e.g., combinations of (“ethics” OR “trust” OR “moral” OR “fairness” OR “responsibility”) AND (“artificial intelligence” OR “AI” OR “machine learning”) AND (“software developer” OR “software practitioner” OR “data scientist” OR “machine learning” OR “software engineer” OR “programmer”), it led to too many papers to filter through manually with very low return on investment in terms of relevant papers. An SLR did not appear to be the right fit for purpose. Nevertheless, we were convinced that this new and emerging topic was worth investing deeper into. We then decided to explore Grounded Theory Literature Review (GTLR) because of its iterative approach that provides flexibility in identifying related works from within the same area and allows to refine the review protocols to accommodate related works from other areas or other credible sources of information. We started by attempting to apply the five GTLR steps proposed by Wolfswinkel et al. [11]. However, we had to work our way through the concrete application details ourselves, and ended up adapting it for implementation in our socio-technical research context.

Table 3 summarises the differences between an SLR and an ST-GTLR. Researchers interested in understanding a socio-technical research topic that is niche and emerging, and deriving evidence-based theoretical models, and potentially theories, from the findings along with recommendations for practice, are recommended to apply the ST-GTLR guidelines presented in this paper.

7.2 Implementing an ST-GTLR

While the original GTLR framework proposed by Wolfswinkel et al. [11] was a good place to start, and sample studies in other domains existed (e.g. [12], [13], [16]), many aspects of how to apply the high-level five step framework were still fuzzy. For example, it was not clear how the iterations were meant to work. Some studies were seen to apply a sequential approach [17], [13] while others attempted some iterations [18]. Similarly, while Wolfswinkel et al. noted an application of the traditional Strauss-Corbinian GT and claimed “Grounded Theory aids in building theory when performing a literature review: by focusing on phenomena through a rigorous concept-centric approach” [40], there was little concrete guidance available on how to develop theory from literature as a data source. Additionally, the analysis of the raw data – in this case derived from the empirical evidence presented in primary studies – needed a socio-technical treatment because of its socio-technical research context, described in Section 3.5. For these reasons, we turned to the concrete steps and procedures of socio-technical grounded theory for basic data analysis and advanced theory development [10]. We found ourselves working through the details guided by the team’s collective experience of conducting literature reviews (both systematic and informal) and grounded theory studies and the second author’s STGT expertise [10].

The original STGT guidelines [10] provide guidance on conducting primary empirical research studies in socio-technical contexts, where the research team both collects the empirical evidence from the source and analyses it, to: (a) derive descriptive findings through a limited application of STGT for data analysis, or (b) derive mature theories through a full STGT study. STGT studies do not work with literature as a data source. The role of literature in an STGT study is captured under the practices of lean and targeted literature reviews, conducted in the basic and advanced stages of the study respectively.

In implementing an ST-GTLR, we have extended the GTLR framework with the use of STGT analysis steps and procedures to a conduct secondary review study, where the empirical evidence was originally collected by the research teams behind the included primary studies, which in turn were selected and analysed by the review team. Combining the original GTLR five step framework with the concrete STGT analysis steps allowed us to implement an iterative yet rigorous literature review.

This process was challenging in many ways. The lack of concrete guidelines to conduct a GTLR study motivated us to develop and apply the ST-GTLR guidelines. The main challenge in this process was finding articles relevant to our research topic. Due to this, we performed forward and backward snowballing of the seed articles. This step was challenging as we had to go through every study in depth. Besides, we performed open and targeted coding
TABLE 3: Comparison of Systematic Literature Review (SLR) [38] and our Socio-Technical Grounded Theory Literature Review (ST-GTLR)*

|                           | Systematic Literature Review (SLR) | Socio-Technical Grounded Theory Literature Review (ST-GTLR) |
|---------------------------|------------------------------------|-------------------------------------------------------------|
| **Definition**            | Systematic review to present comprehensive findings on well researched topics. | Rigorous review to present multi-dimensional findings and develop theoretical foundations for niche and emerging topics. |
| **Context of use**        | Comprehensive coverage of well researched topics to establish the state-of-the-art. | In-depth coverage to establish theoretical foundations and periodic sense of the lay of the land, specially to establish an early sense of where the field is headed for niche and emerging topics. |
| **Approach**              | Top-down/deductive, mostly sequential, and specification driven. | Bottom-up/inductive, iterative, and responsive. |
| **Steps**                 | Phase 1. Planning the review | Iterative steps of: |
|                           | 1. Identify need for review | ‣ Define/refine RQ(s) and protocolb |
|                           | 2. Develop review protocol | ‣ Conduct Search |
|                           | Phase 2. Conducting the review | ‣ Select articles |
|                           | 1. Identification of research | ‣ Conduct STGT data analysis |
|                           | 2. Selection of primary studies | ‣ (optional) Develop theory or theoretical models |
|                           | 3. Study quality assessment | ‣ Present findings |
|                           | 4. Data extraction and monitoring | |
|                           | 5. Data synthesis (e.g. meta and thematic analysis) | |
|                           | Phase 3. Reporting the review | |
| **Outcomes**              | Full coverage findings and meta findings. | In-depth descriptive findings, theoretical models, and theories. |
| **Advantages**            | Repeatable, reproducible, breadth of coverage. | Credible, rigorous, theoretical, depth of findings, can work with established and new topics. |
| **Limitations**           | Considerable effort involved, possibility of biases, requires established topics, can be monotonous. | Considerable effort involved, possibility of biases, difficult to replicate outcomes. |

*Based on Wolfswinkel et al. five step review process [11] and Hoda’s STGT [10]. ⁵Protocol includes in-built quality criteria

manually in the Analyse stage. Reading each sentence of the Findings section and developing codes and concepts was time-consuming and tedious. We had to take multiple breaks and refresh our minds while doing data analysis. Our advice would be the same for those who perform the ST-GTLR as this is a rigorous review, unlike other review methods. Also, validating codes and concepts with team members is recommended to achieve better results during data analysis. Another challenge was to develop concepts and categories from the codes, as we got hundreds of codes from data analysis. Grouping similar codes to develop concepts and similar concepts into categories can be complex process. We recommend using software like Nvivo for this process to save time and energy. Overall, our experience of developing these ST-GTLR guidelines and its application allowed us to explore a new option in the space of conducting literature reviews, one especially suited to niche and emerging research areas where applying traditional systematic review approaches are particularly challenging. Using a pragmatic approach, this paper presents the ST-GTLR guidelines through sharing the concrete details of its implementation in a real project as well as presenting the findings of our ST-GTLR on ethics in AI so researchers can benefit from both – the guidelines for method application and an example outcome.

8 Evaluation

The application of STGT is evaluated using the criteria of credibility and rigour, which we define and demonstrate in the context of conducting a review below. In case of literature reviews applying STGT, these criteria still apply, but the indicative questions underlying them are adapted as follows:

- **How were the primary studies selected?** We selected the primary studies using the seed review protocol, described in Section 3 and summarised in Table 2.

- **How were the iterations applied?** Our initial iteration included 3 papers which we used to pilot our STGT data analysis, followed by another 7 papers. Together, these form the basic stage of the STGT data analysis. The advanced stage of STGT’s theory development involved the identification and analysis of the remaining 20 papers through iterations of reading the title, abstract, and full text for relevance and inclusion/exclusion, and performing snowballing on them.

- **How were memos written and used?** Memos were written throughout and used to drive theoretical sampling and theory development, as explained in Section 3 and Figure 3.

For manuscripts presenting mature theories, additional information should be provided.
- How was theoretical sampling applied? We applied theoretical sampling through forward and backward snowballing.
- How were the review protocols refined through the iterations? The search string was tried until a final string was decided upon (Table 1). Initially, we defined the search period to limit it to papers published between January 2010 and June 2021 to make the review manageable (see seed protocol in Table 2). Later, to retrieve more papers, we revised the seed review protocol to include papers up to December 2021, relaxed the inclusion criteria, and enabled snowballing (see final protocol in 2).
- Which mode of theory development was applied? We applied an emergent mode of theory development, structuring the emergent theory later in the review, as explained in Section 3.5.2.
- How was theoretical saturation achieved? When the last couple of papers served to confirm the key findings and did not lead to the identification of any significant or new insight, we finished coding for this project.
- What research paradigm was used and why? To maintain a keen focus on the real-world issues of ethics in AI, we applied a pragmatic approach.

A mature theory in a STGT study must be novel, useful, parsimonious, and modifiable according to the STGT evaluation guidelines presented by Hoda [10]. Our grounded theory of viewing ethics in AI through the developer’s prism is a mature theory as it fulfills the evaluation criteria of an STGT study as follows:

- **Novel**: Our theory presents novel findings of the five key categories and five hypotheses connecting them.
- **Useful**: Our theory will be useful to AI developers and managers in helping them understand the importance of awareness and perception as critical first steps to acknowledging needs and challenges, and leading to applied and suggested approaches to dealing with those challenges. It is useful to researchers as a research agenda to explore the key categories and their underlying concepts in future empirical studies.
- ** Parsimonious**: Our theory is parsimonious as it explains the complex phenomena of ethics in AI in a simple and elegant way using the developer’s prism metaphor. The theory breaks down the seemingly single phenomenon of ethics in AI as a set of five categories, each representing a phenomenon worthy of full investigation, and a set of five interrelated hypotheses. The theory is represented visually in Figures 4 and 5.
- **Modifiable**: Our theory can be modified in the future with new empirical evidence as developer awareness, perception, needs, challenges, and approaches to do with ethics in AI change over time.

## 9 Threats and Limitations

We now discuss some of the threats and limitations of our study. Unlike an SLR, an ST-GTLR study does not aim to achieve completeness. Rather, it focuses on capturing the ‘lay of the land’ through identifying the key aspects of the topic and presenting rich explanations and nuanced insights. As such, while the process of an ST-GTLR can be replicated, the results – the resulting descriptive findings and hypotheses – are not easily reproducible. Furthermore, our search and select steps for identifying the seed papers and subsequent snowballing may have resulted in missing some relevant papers. This threat is highly dependent on the list of keywords selected for the study and the limitations of the search engines. To minimise the risk of this threat, we used an iterative approach to develop the search strings for the study. Initially, we chose the key terms from our research title and added their synonyms to develop the final search strings which returned the most relevant studies. For example, we included ‘fairness’ in our final search string because when we used only the term ‘ethics’, we obtained zero articles in two databases (ACM DL and Wiley OL). It is one of the limitations of our study because using this term in our search string may have returned the studies focusing on developers’ views on the fairness of AI systems.

Finding enough empirical articles related to our research topic was another challenge. Due to this, we relaxed the review protocol during snowballing of articles. This led us to include the articles that were published in venues other than journals and conferences. We also had to use studies uploaded on ArXiv as our seed papers due to the lack of enough peer-reviewed studies relevant to our research topic. Given the increasing trend of researchers sharing their manuscripts early on ArXiv while they are still under review, it is a useful resource to find the latest research on emerging topics. The ability to ascertain the authors and their affiliations lends credibility to the source. Direct citations to ArXiv has increased steadily from 2000 to 2013 in Scopus indexed scholarly publications. For example, ArXiv has been cited the most by mathematicians [41].

When applying the STGT approach [10] to analyse the qualitative data of primary studies, we performed open coding and targeted coding only on the Findings sections of the studies that presented the empirical evidence we were interested in. We did not find examples of tools (software/framework/models) that AI developers use to implement ethics in AI. A study [G10] mentioned that there is an existence of various tools to enhance AI ethics implementation, however, no details about the tools were mentioned. Following a broad and inductive approach, we were not specifically looking for information on tools. However, it was still surprising that not a lot was mentioned by developers in this area. Future reviews and studies can be conducted to understand to what extent, why, and how tools are used in the context of implementing ethics in AI.

To minimise the threats associated with a single coder, the second author regularly reviewed the codes and discussed the coding process. All findings were reviewed and discussed by the four authors regularly who asked critical questions, helping develop nuanced concepts and categories. The hypotheses were derived by analysing the relationships between the five categories based on the empirical findings from 30 primary articles which limits the scope of our theory but it remains open to modification with more empirical evidence in future.
10 Conclusion and Future Work

AI systems are as ethical as the humans developing them. It is critical to understand how the humans in the trenches, the AI developers, view the topic of ethics in AI if we are to lay firm theoretical foundation for future work in this area. With this in mind, we formulated the research question: What do we know from literature about how developers view ethics in AI? To address this, we conducted a socio-technical grounded theory literature review (ST-GTLR) by applying the overarching framework of grounded theory literature review (GTLR) introduced by Wolfsinkel et al. [11] with the concrete steps of the socio-technical grounded theory (STGT) method for data analysis and theory development [10], on 30 primary empirical studies. Since there were not many empirical studies addressing our niche topic and RQ exclusively, a grounded theory-based iterative and responsive review approach worked well to identify and extract relevant content from across multiple studies (that mainly focused on related topics), while the application of STGT enabled rigour analysis and theory development. A contribution of this paper is the ST-GTLR guidelines for conducting review studies in software engineering, especially on niche and emerging topics.

Through applying STGT’s basic stage, we identified five categories of developer awareness, developer perception, developer challenges, developer challenges, and developer needs. Through applying its emergent theory development mode, we identified five hypotheses that link the categories: H1: developer awareness is an antecedent to, but does not guarantee positive, developer perception; H2: developer awareness can lead to identifying developer needs; H3: developer challenges lead to identifying developer needs; H4: developer perception can generate developer approach; H5: developer challenges can be overcome by developer approach. Taken together, the categories and hypotheses form the theory of ethics in AI through the developer’s prism that explains the seemingly single phenomenon of ethics in AI as a complex set of interrelated phenomena using the developer’s prism metaphor. The theory explains that developers’ awareness of AI ethics directly leads to their perception about AI ethics and its implementation as well as to identifying their needs, and indirectly leads to identifying their challenges and coming up with approaches (applied and potential strategies) to overcome them.

We also share practical recommendations for AI developers, managers, and organisations. The theory serves as a research agenda for the community, where future work can focus on investigating and explaining each of the phenomena of developer awareness, perception, challenges, needs, and approach. Future empirical studies can focus on improving the understanding and implementation of ethics in AI and recommend practical approaches to minimise ethical issues such as mitigating human biases in AI development through frameworks and tools development.

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Aastha Pant is a Ph.D. candidate at Monash University, Melbourne, Australia. She received her Bachelor in Computer Engineering degree from NIILM university, India. She completed her Master in Business Research from University of Southern Queensland, Australia. Prior to her Ph.D. candidature, she was in academia as a teaching assistant. Her research interests include ethics in Artificial Intelligence, socio-technical aspects of software engineering, software systems and cyber security. More details of her research can be found at, https://www.researchgate.net/profile/Aastha-Pant-3 Contact her at: aastha.pant@monash.edu.

Rashina Hoda is an Associate Professor in Software Engineering at Monash University, Australia. Rashina specialises in human-centered empirical software engineering and has introduced socio-technical grounded theory (STGT) for software engineering. She received an ACM SIGSOFT Distinguished Paper Award (2017) and Distinguished Reviewer Award (2020). She serves as an Associate Editor of the IEEE Transactions on Software Engineering and the PC co-chair of the SEIS track of ICSE2023. Previously, she served on the IEEE Software Advisory Board, as Associate Editor of Journal of Systems and Software, CHASE 2021 PC co-chair and XP2020 PC co-chair. More details on https://rashina.com. Contact her at rashina.hoda@monash.edu.

Chakkrit Tantithamthavorn is a Senior Research Fellow in the Faculty of Information Technology, Monash University, Australia. He is recognized as the most impactful early-career SE researcher based on a bibliometric assessment of software engineering (2013-2020), and received numerous prestigious awards including a 2021 ACM SIGSOFT Distinguished Paper Award, a 2020 ARC’s Discovery Early Career Researcher Award (DECRA), and a 2016 Japan Society for the Promotion of Science (JSPS-DC2) Research Fellowship. More about him and his work is available online at http://chakkrit.com. Contact him at Chakkrit@monash.edu.

Burak Turhan, PhD (Boğaziçi University), is a Professor of Software Engineering at the University of Oulu and an Adjunct Professor (Research) in the Faculty of IT at Monash University. His research focuses on empirical software engineering, software analytics, quality assurance and testing, human factors, and (agile) development processes. He is a Senior Associate Editor of Journal of Systems and Software, an Associate Editor of ACM Transactions on Software Engineering and Methodology and Automated Software Engineering, an Editorial Board Member of Empirical Software Engineering, Information and Software Technology, and Software Quality Journal, and a Senior Member of ACM and IEEE. For more information, please visit: https://turhanb.net.