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Gender Diversity, Discrimination, and Bias in AI

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Gender Diversity, Discrimination, and Bias in AI
Yapay Zekada Cinsiyet Çeşitliliği, Ayrımcılığı ve Önyargı

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ABSTRACT

In this study, I analyze the gender distribution, diversity, discrimination, and bias in AI in Turkey focusing on the workplace dynamics and algorithmic systems from the perspectives of AI developers. I aim to demonstrate “How do the AI developers in Turkey perceive gender diversity, gender discrimination, and the gender bias in AI teams and algorithms? How is the current gender distribution in the AI workforce in Turkey? Why and from which reasons the gender biases occur in AI systems according to developers’ perspectives?” I analyze my research questions by using two different methods to gain a broader perspective on gender diversity, discrimination, and bias. I conducted semi-structured interviews with 22 Turkey-based AI developers as the main method of the research to understand their perceptions on the issue. I also select quantitative data collection as a complementary method to support the research. I collect the employee data of AI startups in Turkey through LinkedIn and student data in Computer Science related departments to examine gender distribution and diversity by statistical numbers. The study shows that the rate of women in AI with technical occupations is around 9% at the AI startups in Turkey. The participants of the study, AI developers, are aware of the lack of women in the field and state their concerns about gender-related issues in society. However, they perceive that there is no common ground to discuss gender and AI together. They have a tendency to divide the technical and societal from each other in which the AI systems and algorithms belong to the “technical” world which cannot contain any kind of bias and discrimination. Therefore, according to them, gender belongs to the social world in where the societal problems about it should be solved within the culture, families, people, and society. While the perspectives of developers differentiate in some topics, it is seen that there is a consensus in some of them. In this study, I try to draw a comprehensive framework on gender diversity, discrimination, and bias in AI in Turkey looking for the perspectives of AI developers

who are the everyday creators and developers of these systems. So, I aim to contribute to the literature by featuring the perspectives of developers in the first place, bringing together the workplace gender diversity, discrimination, and bias with algorithmic bias as an interpenetrating problem and presenting a framework about gender and AI from Turkey.

Keywords: Gender diversity, gender discrimination, gender bias, Artificial Intelligence, algorithmic bias, AI in Turkey

ÖZET

Bu çalışmada, yapay zeka geliştiricilerinin bakış açılarına göre işyeri dinamikleri ve algoritmik sistemlere odaklanarak Türkiye'de yapay zekadaki cinsiyet dağılımı, çeşitliliği, ayrımcılığı ve önyargısı analiz edilmektedir. “Türkiye'deki yapay zeka geliştiricileri, yapay zeka ekiplerinde ve algoritmalarında cinsiyet çeşitliliğini, cinsiyet ayrımcılığını ve cinsiyet önyargısını nasıl algılıyor? Türkiye'de yapay zeka iş gücünün mevcut cinsiyet dağılımı nasıl? Geliştiricilerin bakış açılarına göre yapay zeka sistemlerinde cinsiyet önyargıları hangi nedenlerle ortaya çıkıyor?” sorularının yanıtlarını ortaya koymak hedeflenmektedir. Cinsiyet çeşitliliği, ayrımcılık ve önyargı konularında daha geniş bir bakış açısı kazanmak için araştırma soruları iki farklı yöntem kullanarak analiz edilmektedir. Araştırmanın ana yöntemi olarak Türkiye temelli 22 yapay zeka geliştiricisi ile konuyla ilgili algılarını anlamak için yarı yapılandırılmış mülakatlar gerçekleştirilmiştir. Ayrıca araştırmayı desteklemek için tamamlayıcı bir yöntem olarak nicel veri toplama yönteminden yararlanılmıştır. Cinsiyet dağılımını ve çeşitliliğini istatistiksel sayılarla incelemek için Türkiye'deki yapay zeka girişimlerinin çalışan verileri LinkedIn üzerinden toplanmıştır ve “Bilgisayar Bilimleri” ile ilgili departmanlardaki öğrenci verileri analiz edilmiştir. Araştırma, Türkiye'deki yapay zeka girişimlerinde yapay zeka ile ilgili teknik işlerde çalışan kadınların oranının %9 civarında olduğunu göstermektedir. Çalışmanın katılımcıları olan yapay zeka geliştiricileri, alanda kadın çalışanların sayılarının az olduğunu farkındadırlar ve toplumda mevcut olan toplumsal cinsiyetle ilgili sorunlara dair endişelerini dile getirmektedirler. Ancak, toplumsal cinsiyet ve yapay zekayı birlikte tartışmak için ortak bir zemin olmadığına dair bir algıları mevcuttur. Yapay zeka sistemleri ve algoritmalarının herhangi bir önyargı ve ayrımcılığı barındırmayan “teknik” dünyaya ait olduğu, teknik ve toplumsalı birbirinden ayırma eğilimleri olduğu görülmektedir. Bu nedenle, onlara göre toplumsal cinsiyet, toplumsal sorunların kültür,

aile, insan ve toplum içinde çözümlenmesi gereken toplumsal dünyaya aittir. Yapay zeka geliştiricilerinin bakış açıları bazı konularda farklılık gösterirken bazılarında fikir birliği olduğu görülmektedir. Bu çalışmada, bu sistemlerin günlük yaratıcıları ve geliştiricileri olan yapay zeka geliştiricilerinin bakış açılarına odaklanarak Türkiye'de yapay zeka alanında cinsiyet çeşitliliği, ayrımcılık ve önyargı hakkında kapsamlı bir çerçeve çizmek hedeflenmektedir. Bu nedenle, geliştiricilerin bakış açılarını öne çıkararak, işyeri cinsiyet çeşitliliği, ayrımcılık ve önyargı ile algoritmik önyargıyı iç içe geçmiş bir sorun olarak bir araya getirerek ve Türkiye'de toplumsal cinsiyet ve yapay zeka ile ilgili bir çerçeve sunarak literatüre katkıda bulunmak amaçlanmaktadır.

Anahtar Kelimeler: Cinsiyet çeşitliliği, cinsiyet ayrımcılığı, cinsiyet önyargısı, yapay zeka, algoritmik önyargı, Türkiye'de yapay zeka

FOREWORD

The subject of this study has emerged from my personal background about the issue. And I made this research with the purpose of taking a step in gender equality in all kinds of imbalances, discriminations, biases, and unfair practices in the world. I hope to have a better future in terms of all kinds of unfairness, especially while we are in an era of AI represents the future of technology.

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INTRODUCTION

At 2018, I started to work in an Artificial Intelligence (AI) startup as a fashion consultant. The startup that I was working at was creating a mobile application for fashion retail powered by AI to enable different kinds of recommendation systems based on users' previous shopping experiences, styles, and preferences such as the like/dislike function. Till the day I started to work there, I had no knowledge and prior experience on AI. I heard about it as the advance form of technology, the thing that "Siri" can do, the robots that will conquer the world, the technology that "Black Mirror"-ish distopian science-fiction series, movies, and books. I always thought about it as a separate being from the human touch, cannot be interfered with systemic softwares, and automated and autonomous technology away from the humanlike aspects. However, after I started to work at an AI startup, I had a chance to observe and discover the world behind of the codes in black screens and understand what AI really is and is not. While I was working there, I understood that AI is neither a mere computational algorithmic system nor a technology that will lead us a dystopian future. I observed that the most of the thing with AI is done behind of those systems, algorithms, and black screens with codes: but, at the stage of the developers, teams, startups, and companies. Because of that, in this study, I focus on the developers' side of the process of AI development by trying to understand their perceptions.

Before coming to the role of the developers and teams on AI, I would like to give more information about my experience at AI startup and it's relation with my research. While I was working at the startup for almost a year, the team was consisted of 6-8 full-time male engineers and 2 full-time female fashion consultants, and two male co-founders. There were also freelance interns, new comers and the ones that leave the work in that amount of time. But the male dominance at the AI & software development side and female dominance at the fashion side have never changed. For

one year long period, there was only one female AI intern engineer for a couple of months. So, from my first day there till the last day, I wondered how can this gender distribution occur. The division of fashion team and development (technical) team was so obvious that while women were working on fashion, men were the technical ones, developers, AI engineers. Even when the startup was growing and new team members were hired, male dominance at the technical side was never changed. Since my first day on the job, I have usually sensed that something was off between two camps at the company; something between men and women, something between engineers and fashion consultants, something about male dominance at the development side, something about the genders, perceptions, diversity, discrimination and unconscious biases. That feeling has driven me to research gender diversity, discrimination, and bias in AI.

In this study, I aimed to demonstrate the gender distribution, discrimination, and bias in AI at Turkey with the focus of workplace dynamics and algorithmic systems. Gender discussions in Artificial Intelligence have different dimensions in terms of workplace diversity and algorithmic bias. The gender diversity, discrimination, and bias in the workplaces that AI systems are developed and algorithmic bias are actually the two sides of the same problem in AI. As West et al. (2019) pointed out “many researchers have shown that bias in AI systems reflects historical patterns of discrimination. These are two manifestations of the same problem, and they must be addressed together” (S. M. West et al., 2019, p. 3). In this study, I analyze the gender diversity, discrimination and bias in the workplaces that AI systems are developed and the algorithmic bias and discrimination from the perspectives of AI developers in Turkey. So, I aim to draw a perspective about gender in AI in Turkey by looking at the environments and actors who are the primary creators of these systems. Their perspectives and evaluations on gender in relation with AI systems and workforces are important to understand their points of view about these societal

concerns as they are standing at the technical developmental side of the AI. As West et al. (2019) suggest “As the focus on AI bias and ethics grows, the scope of inquiry should expand to consider not only how AI tools can be biased technically, but how they are shaped by the environments in which they are built and the people that build them. By integrating these concerns, we can develop a more accurate understanding of how AI can be developed and employed in ways that are fair and just, and how we might be able to ensure both.” (S. M. West et al., 2019) Looking behind of the machines, systems, algorithms, and reaching out to the vivid, warm, human touch is important to understand decision mechanisms and workplace structure behind of this technology. Because, no decision is made without any humane decisions and perspectives behind it. So, if we would like to create fair and socially inclusive AI systems, we should trace back the problem to its roots. If we would like to understand why the algorithmic biases and discriminations has occurred, we should turn back the teams and actors who develop these algorithms and systems. As Jim Boerkoel defines the importance of the problem “One of the challenges is that when there’s a lack of diversity, there’s a lack of diverse thought. If the population that is creating the technology is homogeneous, we’re going to get technology that is designed by and works well for that specific population. Even if they have good intentions of serving everyone, their innate biases drive them to design toward what they are most familiar with.” (Klawe, 2020). Because all of that, I state that the important thing to do is going back to the developers of AI systems to understand their perceptions about gender in AI are vital to understand the path that leads us to the male dominance in the field and algorithmic bias and discrimination. Even though there is a growing concern in racial discrimination in real life and algorithms, the gender discrimination is more visible experience in technology field in Turkey. So, in this study, my main research questions are “How do the AI developers in Turkey perceive gender diversity, gender discrimination, and the gender bias in AI

teams and algorithms? How is the current gender distribution in the AI workforce in Turkey? Why and from which reasons the gender biases occur in AI systems according to developers' perspectives?"

I analyze my research question with using two different methods to gain a broader perspective on gender diversity, discrimination, and bias on AI in Turkey. I used semi-structured interviews with AI developers as the main method of the research to understand their perceptions on gender diversity, discrimination, and bias in AI. I interviewed with 22 participants who are Turkey-based developers and working on AI development in startups or corporate companies. I also selected the quantitative data collection and analysis as a complementary method to support the findings and analysis of the research. I collected statistical two different kinds of data from two different sources: employee data and student data. I aimed to give statistical gender distribution in AI workforce and computer science related departments at college to discover the gender diversity in the field. I analyzed the employee statistics by looking at the AI startups employee distributions via LinkedIn data. Also, I collected student data from the Higher Education Information Management System website of YOK which is the Council of Higher Education in Turkey. I aimed to see the gender distribution in the college departments which are related with the computer science and have the potential to work on AI after graduation.

The research has composed of five main chapters as Introduction, Literature Review, Methodology, Findings & Analysis, and Conclusion. In the Literature Review chapter, I examine the roots of gender discrimination and bias in the Social Identity Theory (Tajfel, 1970), stereotypes and discrimination as general concepts, and the notion of gender from different perspectives and gender discrimination. Following that, I analyze gender discrimination and bias in AI by dividing the section into historical shifts of women in AI, gender discrimination and bias from the

workplace perspective, algorithmic bias and non-binary gender perspectives. In the Methodology chapter, I give information about the methods of my research, participants of the research, and ethical considerations and limitations regarding the methodology. I elaborated the Findings and Analysis of the research into three sections: a) Introduction to AI in Turkey: The Definitions, Working Models, and Job Hierarchies, b) Gender Diversity in AI Companies, Startups, and Teams: Perceptions on Women in AI, c) Algorithmic Bias: Reasons and Solutions. In the first main category, I draw a framework about AI in Turkey using the perceptions of developers to understand how they perceive and evaluate AI as a notion and the studies and works on AI in Turkey. I wonder how the developers define Artificial Intelligence (AI) as a non-technical concept with its strengths, weaknesses, limitations and possibilities; and also the state of AI in Turkey according to the perceptions of participants. I also tried to understand the business models and hierarchical orders of the startups and companies that they work for. I aimed to draw a framework about the works in Turkey, business models and hierarchical orders of AI startups and companies in general to give a brief information about AI in Turkey before examining the gender issues. In the second chapter, I analyzed the perceptions of participants on gender in AI from an employee distribution and discrimination at the workplaces perspective. I aimed to comprehend the issue of gender discrimination and bias according to the perspectives of AI developers. In addition to that, I especially talked about their real-life experiences, perceptions, feelings, thoughts, and more importantly their stories with women participants. I also looked at the solutions perspective for the gender inequality in AI. Under this topic, the participants evaluated the women organizations and networks in AI and positive discrimination. In the final chapter, I analyzed the gender discrimination and bias from the perspective of algorithmic bias according to the participants' perceptions and evaluations about the reasons behind of the biased outcomes, how do they

distribute the responsibility for the algorithmic discriminative incidents, and finally and more importantly what can be the solutions for these incidents.

LITERATURE REVIEW

The Roots of Gender Discrimination and Bias

A. Social Identity Theory

In 1970's, Henri Tajfel introduced and developed the Social Identity Theory. Social Identity Theory explains how people "construct a sense of who they are and how they are evaluated" based on group relationships (Hogg, 2000, p. 401). Tajfel pointed out the importance of group relations and belonging to a group in the process of self identification. Our social groups help us to shape our social identity, it bonds our connection to the social world (McLeod, 2019). Tajfel and Turner (1979) indicated that there are three stages in the social identity process. The first stage is the "social categorization" which means the categorization of people, objects, intergroup and intragroup relationships to understand the social environment. According to this categorization process, we determine our social identity by defining who we are as well as who we aren't. The social categorization, as Hogg (2000) cites to Tajfel (1972) "creates and defines an individual's own place in the society" (Hogg, 2000, p. 404). The second one is "social identification". Social identification process enables us to identify ourselves with our group identity. Our sense of belonging to the group that we categorized ourselves as belong to is developed at this stage. The third and final stage is "social comparison" which means intergroup and intragroup comparisons to define and emphasize the differences between outgroup relations and the similarities between ingroup relations. At this stage, we exaggerate the differences of our group's norms, values, and rules between other groups' aspects and norms (McLeod, 2019). The individual-level comparisons help to create the norms and rules of the groups and this schema emerge the group-level

comparisons. Hogg (2000) cites to Turner (1985) "self-categorization and social comparison are mutually dependent and complementary processes in that neither can exist without the other" (Hogg, 2000, p. 409).

B. Stereotypes

In the social categorization process, people categorize every person, object, situation, knowledge and all of the other things to develop a wider idea about them. "Inevitably, our opinions cover a bigger space, a longer reach of time, a greater number of things, that we can directly observe. They have, therefore, to be pieced together out of what others have reported and what we can imagine" (Lippmann, 1997, p. 79). The individuals need to simplify and order their social affiliations to reduce the complexity of intergroup and intragroup relationships (Tajfel, 1970). We need simplification to gain insight into the people, things, events and situations in the world, since we cannot meet every person in the world one by one and we cannot obtain the knowledge of everything through our own direct observations and examinations. The culture that we live in and obtain knowledge, values, norms, and rules is an important part of our lives to gain prior knowledge about things. It defines the fundamental things for us, explains the social environment and relations to us. And, afterwards, the signs for ideas from the social environment helps us to give a meaning to things. In our intimate acquaintances with people or things, "we notice a trait which marks a well-known type, and fill in the rest of the picture by means of the stereotypes we carry about in our heads" (Lippmann, 1997). Stereotypes are preformed impressions that fill knowledge gaps about an object or a group, and help define our perception and attitude about them. In short, they are the images we create in our minds about an object or a group. People use predictions to have an idea about the world, to develop an attitude for every person they meet, every event they encounter, every object they see. Therefore, they make sense of each new person,

situation or event by categorizing rather than evaluating them separately. Social categorization, which affects our perception and interpretation of the social world, emerges as a fundamental cognitive process in the formation of stereotypes and prejudices. At this point, physical and social categories such as race, gender, religious belief, and ethnic origin are used for categorization. These functions make the social environment recognizable by simplifying the world in a sense; but in doing so, it also prepares the ground for the formation of prejudices (Göregenli, 2012).

C. Discrimination

At the social comparison process, third and final stage in “Social Identity Theory”, people make intergroup and intragroup comparisons to differentiate their groups’ values and norms from the other groups. At this point, people make upward and downward comparisons. According to Hogg (2000), people make upward comparison with people who are slightly better than themselves to satisfy self evaluation. And similar to this, people also make downward comparisons with people who are slightly worse than themselves to satisfy self enhancement. Hogg (2000) cites to Wills (1981, 1991), the prejudice and discrimination may reflect a downward comparison process (Hogg, 2000).

The prejudice and discrimination show similar characteristics in different social, cultural, and economic settings. Tajfel (1970) pointed out a dialectical relationship between object and the subject in the issue of prejudice and discrimination. He gave an example to show how this dialectical relationship works: “economic or social competition can lead to discriminatory behavior; that behavior can then in a number of ways create attitudes of prejudice; those attitudes can in turn lead to new forms of discriminatory behavior that create new economic or social disparities, and so the vicious circle is continued” (Tajfel, 1970, p.96). This dialectical relationship

between object and the subject, between the discriminatory behaviors and attitudes of prejudice create different kind of prejudices and discriminations in different social settings.

Modern law has defined all individuals as beings of equal qualifications, based on the basic concept of human rights on the basis of the principle of equality. The modern legal system is a structure that connects people who do not know each other, stand together in as a 'society', have different individual and historical characteristics. Although, many social and cultural factors cause legal principles to have different meanings in every society and to have differences in practice. Because of that we experience, observe or hear that in different social contexts, people can be discriminated because of their skin color, gender or sexual orientation, religion or ethnicity (Göregenli, 2012).

Discrimination is all negative attitudes and behaviors fueled by prejudices against a group or group members. Prejudices and discrimination lead to attitudes nurtured by negative thoughts and feelings towards a group or group members. Although discriminatory behaviors resulting from prejudices are directed at individuals individually, individuals are discriminated against due to the characteristics of the group they belong to. Prejudices are attitudes where we keep social and emotional distance from people or groups that we have prejudice. In cases where prejudices turn into behavior, discrimination occurs. Discrimination is made against groups deemed "below" and "disadvantaged" in the social hierarchy (Göregenli, 2012). Tajfel conceptualized the discrimination in ingroup and outgroup relationships. He proposed that the discriminatory behaviors are directed to the outgroups and people favors their groups. According to him, there are three main consequences of this manner. The first one is that even though a person does not have any interest or gain, he/she may direct discriminatory behavior to another group member. The second one is a person may discriminate in the absence of any prior dislike to the outgroup. The third one is people generally behave in a discriminatory manner before there was any prejudice

or negative feelings towards the outgroup. And, following this, there may be discrimination even though the person does not have a personal conflict with the outgroup and no previous hostility in intergroup relations (Tajfel, 1970).

D. Gender Discrimination: What is gender and what does gender discrimination mean?

The social construction of identity which is conceptualized in Social Identity Theory (1970) explains how human-beings make discrimination and have prejudice in their social relationships with the outgroups. In this sense, this discrimination can be made to different social classes, ethnicities, races, genders, or any other social groups. In this study, we examine the discrimination and prejudice (bias) in terms of gender. But first, we should examine the question of “what does gender mean?” before coming to the “gender discrimination”.

Many scholars, feminists, social scientists, philosophers define gender or sex from different perspectives. While some of them focuses on the biological, essential difference between two sexes, some of them focuses on the cultural and social construction of the identities of men and women. According to Butler (1990), defining “gender” as a cultural interpretation of “sex”, as a “given” meaning to the “given” nature, can mislead us to conceptualize gender as a binary concept as in parallel with sex. By doing so, the biological determinism in sex such as “biology is destiny” reflects to gender-culture relationship and eventually turns into “culture is destiny”. So, we should evaluate “gender” as a separate concept from the binary sex. When we set free gender from sex, “*man* and *masculine* might just easily signify a female body as a male one, and *woman* and *feminine* a male body as easily as a female one” (Butler, 1990, p.6). Simone de Beauvoir says “one is not born, but rather becomes, a woman” in her book, *The Second Sex* (1949). According to Butler (1999), de Beauvoir focuses on the social construction of the “women” identity with this sentence. De Beauvoir posits woman in relation to man, in a relation of contrast. According to her,

man is the “subject, absolute, essential”, but women is the “other, inessential” (De Beauvoir, 2010, p.26). According to de Beauvoir, there is a dual, contrary relationship between self and other and duality can be seen in any context from ancient mythologies to genesis stories. Groups define themselves as the one while defining the other opposite themselves. The one posits itself as the one and the other. So de Beauvoir interrogates how women has become the other and how women has subordinated to man. In other cases, the numerical majority and minority has an effect on the domination of a group. But this was not the case in women’s subordination. According to de Beauvoir, women do not have their own community to organize and get together all women such as Jews or Blacks. “They live dispersed among men, ties by homes, work, economic interests and social conditions to certain men –fathers or husbands– more closely than to other women. As bougeois women, they are in solidarity with men and not with women proletarians; as white women, they are in solidarity with white men and not with black women” (De Beauvoir, 2010, p.8). De Beauvoir makes an analogy between the relationship of man and woman with the master and slave dialectic in Hegel. And if women are not directly represents the slave, de Beauvoir sees that today women’s position is still “handicapped and disadvantage” compared to men. In terms of economic conditions and job market, women are less valued than men. Men have better jobs, positions, wages than women. Because, “the present incorporates the past, and in the past all history was made by males” (De Beauvoir, 2010, p. 30).

While in de Beauvoir, woman is the other and man is the absolute; similar to de Beauvoir in Irigaray (1995), femaleness can only be understood by the existence of male and female can be defined in relation to the male. De Beauvoir’s claim of “women as the secondary being” arouses in Irigaray. However, they seperate in the solution of the problem. While de Beauvoir sees the solution that women should own the positive traits of men like men, Irigaray points out that women

should recognize their differences from men (Butler, 1990). As told in the beginning of this chapter, gender is a complex problem that many scholars, social scientists, philosophers address and evaluate from different perspectives. The perceived and constructed differences between men and women; female and male, feminine and masculine can lead to the stereotypical assumptions about the absolute “femininity” and “masculinity”. The determinist, stable, universal understanding about these differences cause gender discrimination or discriminatory behavior and attitudes towards different genders. Although, in this study, I discuss gender discrimination from the angle of discrimination against women.

According to Convention on the Elimination of All Forms of Discrimination Against Women, Article 1, the term "discrimination against women" means “any distinction, exclusion or restriction made on the basis of sex which has the effect or purpose of impairing or nullifying the recognition, enjoyment or exercise by women, irrespective of their marital status, on a basis of equality of men and women, of human rights and fundamental freedoms in the political, economic, social, cultural, civil or any other field” (*Convention on the Elimination of All Forms of Discrimination against Women (CEDAW)*, 1979). It is based on the ground of any kind of right and freedom that women are deprived of. Limiting the participation or action areas of women to any social, political, economical or cultural areas or excluding them from any of these areas are in the scope of gender discrimination. This kind of violation of rights can be applied explicitly or implicitly. Bora (2012) differs the implicit and explicit discrimination against women in these examples: adding a condition of “military service” to a job ad is an explicit violation of rights. Because, in Turkey, the military service is only obligatory for males, so that kind of condition means that the desired candidate is male. Or sometimes the discrimination against women can be applied implicitly by ignoring their needs and conditions. For example, not having a widespread, accessible day care

center/kindergarden is an obstacle for women to work. Because, there is a common sense that women are the primary caring responsible for children and if there is no day care center service, women would be the one who give up on their career and paid job pp.178 (Bora, 2012). Bora (2012) focused on the “gender division of labour” as an important aspect which leads to gender discrimination. Because, gender division of labour does not mean an equal division in daily duties and life. Instead, it positiones the place of the women at home with houseworks and positions men to bring home the bacon. In this division of labour, the housewife role for women make the primary responsibilities of them as houseworks and unpaid domestic caring works while limiting the paid work and career opportunities for them (Bora, 2012). Even though women are work in a paid employment, it can be perceived as exceptional and from necessity as well as arbitrary and secondary. Hereby, perception and attitudes towards women –even though they are active employees in their career– are shaped by the stereotypes and prejudices about them.

To interrogate the gender discrimination, Bora (2012) asks these two questions which enlightens a very important part of my study: “So what is happening to us in the world that women seem (usually) more compassionate and timid, and men (usually) more fighter and self-opinionated? Why are there more male engineers and more female psychologists?” (Bora, 2012, p. 176). In this study, I aim to discover the answer of the same question: Why are there more male AI engineers and how does the AI systems contain gender biases?

Gender Discrimination and Bias in Artificial Intelligence (AI)

A. The Definition of Artificial Intelligence (AI)

Before examining the gender discrimination and bias in AI startups and systems, I would like to explain the concept of Artificial Intelligence (AI). At 1950, mathematician Alan Turing proposes the question of “can machines think?” in his paper *Computing Machinery and Intelligence* (Turing,

1950, p. 433). But, instead of searching for the meanings of the words of “machine” and “think”, he introduces the Turing Test to evaluate if a machine can perform as similar as human-being. Six years after Alan Turing’s article on Artificial Intelligence, John McCarthy names the science as today’s name “Artificial Intelligence”. So, what does Artificial Intelligence mean? John McCarthy answers this question as “It is the science and engineering of making intelligent machines, especially intelligent computer programs. It is related to the similar task of using computers to understand human intelligence, but AI does not have to confine itself to methods that are biologically observable.” (McCarthy, 2007, p. 2). In this definition, the technical processes used to develop Artificial Intelligence systems are emphasized as “the science and engineering of making intelligent machines, ...computer programs” (McCarthy, 2007, p. 2). Basically, AI refers to “any human-like intelligence exhibited by a computer, robot, or other machine” by mimicking the capabilities of human intelligence. Answering the customer’s question, driving a car, recommending a new book for you, optimizing or sometimes surpassing the human capacity in high velocity tasks or decision-making in credit scores are some of the tasks that AI systems can do. Machine learning and deep learning are subsets of the umbrella term of Artificial Intelligence (AI). While AI is “the entire universe of computing technology that exhibits anything remotely resembling human intelligence”, machine learning (ML) is a subset of it which performs the specific task derived from data, and deep learning (DL) is a subset of ML which learns by itself without any human intervention (*What Is Artificial Intelligence (AI)?*, 2021). There are plenty of application areas of AI that can be applied to image, speech, text, automation, robotics and more. As briefly mentioned in this section, from 1950’s until today, AI systems have different development areas and focuses in the industries and the academia. So, I will analyze the gender discrimination

and bias journey, especially focusing on women's roles in this area, perceptions towards women, and how does it reflect to the AI systems themselves.

B. Gender Equality in Technology Development: Equal or Discriminated?

a) From Women's Work to Brotherhood Culture

In the first years of computer programming and coding, there was the dominance of women especially in the perception of the stereotypical character of the job. During the Second World War, women were the majority of the software programming profession at the developments of electronic computing. When we look at the work statistics in computational professions, according to Federal Government data of USA, in 1960, the proportion of women working in these areas was 27%. In 1990s, the percentage increased to 35% and that proportion is the highest number of women in computing and mathematical professions. When we came to 2013, the proportion of women in these professions decreased to 26% (Thompson, 2019). This historical shift is highly related with the technical enhancements in computers and broadly technology itself, and also the changing perception and reputation of computer programming. In the first years of computational programming, it was seen as a procedural job to only necessitate a detailed look and follow-up abilities which are more likely to be feminine aspects. As Thompson cites to Wilkes, employers were looking for "logical, good at math and meticulous" candidates for these jobs and these characteristics were stereotypically related with women who are more familiar with the "painstaking activities" such as knitting. In a 1968 book called "Your Career in Computers" draw an analogy of "cooking from a cookbook make a good programmers" (Thompson, 2019). The job ads of the era were mostly referring feminine aspects and targeting women. As West et al. referred to Hicks (2017), "throughout history, it has often not been the content of the work but the identity of the worker performing it that determined its status"(S. M. West et al., 2019).

The historical shifts of gender distribution in professions of computational programming, computer programming or mathematical areas have also been in a relation with the student statistics of these areas. According to National Center for Education Statistics in USA, in 1983-84 academic year, women graduated with degrees in computer and information sciences were 37.1% of all students. But, from 1984 onward, the proportion of women were decreased to 17.6% in 2010 (*Digest of Education Statistics*, 2012). After Allan Fisher who is a computer scientist noticed that the proportion of women in computer science below 10%, in 1995 Jane Margolis and her colleagues started a research in Carnegie Mellon's computer-science department to understand the underlying reasons for underrepresentation of women in the field. They have found out that the male first-year students in Carnegie Mellon has significant pre-experience in computers. As Thompson (2019) refers to their book *Unlocking the Clubhouse* (2002), "boys were more than twice as likely to have been given one as a gift by their parents. And if parents bought a computer for the family, they most often put it in a son's room, not a daughter's. Sons also tended to have what amounted to an "internship" relationship with fathers, working through Basic-language manuals with them, receiving encouragement from them; the same wasn't true for daughters" (Thompson, 2019). These stereotypical attitudes towards boys and girls are reinforced by also in the first games of childhood: cars and constructive toys for boys and dolls for girls. These separation implicitly show who belongs to where. So, as Thompson (2019) cites to Margolis (2002), there is not a correlation between talent in the technical fields and gender (Thompson, 2019). According to a study conducted in United Kingdom (UK), girls and boys are nearly equally interested in STEM subjects; however the interest gap increases to 14% in favour of boys by the age of 18 (M. West et al., 2019). As Kiesler et al. (1985) indicates that the children who have the most experience with computers "will sharpen their procedural thinking and programming skills,

gain confidence with electronic devices, and have the opportunity to explore the many ways computers can be used” (Kiesler et al., 1985, p. 452). These opportunities more likely to turn into an interest area or a career path. Kiesler et al. (1985) analyzes this disparity between boys and girls interest on computers by focusing on computer camps. There is a gap in participation ratio of boys and girls. Thus, Kiesler et al. claims that “if this bias in exposure produces an equivalent bias in competence and confidence, the girls of today will have no choice but to be secondclass citizens in the computer-intensive world of tomorrow” (Kiesler et al., 1985, p. 452). Kiesler et al. (1985) also points out the importance of videogames to meet with the computers, to learn the culture of computers such as having a familiarity with the behavioral norms. Men who are the dominant figures of computer culture by “designing the video games, writing the software, selling the machines, and teaching the courses” inevitably effect the social settings (Kiesler et al., 1985, p. 453). Eventually, while girls are alienated from the computer culture, men become good at it (Kiesler et al., 1985). A 1983 study which analyzes M.I.T computer science department reveals that women are treated as they are not there for professional reasons but for personal reasons such as looking for a husband and they are encountered by negative judgments based on their gender. The subtle and overt discriminations against women in M.I.T such as exclusion of women from social relationships and creating a “locker-room culture” in social settings; low professional expactations from women students; low respect to their opinions, arguments and works and ignoring the professional expertise of women make it harder to follow a career in computer science for them. To tackle with these discriminative attitudes, women often isolate themselves, hide their femininity, leave M.I.T or drop out their professional field of computer science (Massachusetts Institute of Technology, Laboratory for Computer Science, 1983). In 1991, Ellen Spertus published a report on experiences of women students in computer programming at M.I.T.

According to report, stereotypical assumptions are reinforcing what roles girls and boys have in this world; and these roles take shape in the profession of computer science as subtle and subconscious biases towards women, determining different-level standards for women and men, and the perception of unfeminine or unattractive aspects towards women in the male-dominated areas (Spertus, 1991). As seen in the literature, from childhood to adulthood, from no-experience to graduate levels, from video games to advance coding; the sexist and discriminative attitudes towards women in computer science have not been changed in any way. The form of the sexism changes over time, but the fact that it is there has not changed. So, the reasons behind of the historical decline in the number of women in computer science come into existence in infant toys, personal computers in sons' room, computer clubs, arcades, teachers' attentions, role models and many more areas. The combination of male domination in the field, the stereotypical aspects of coders, and necessities of the job turn into a specific "culture" for coding and computer science.

So, what do the culture of computer science and high-tech say to us? This culture brings us to Silicon Valley which is the heart of the high-technology startups ecosystem. Matthews (2003) define the hub as "Silicon Valley is, and has been for a generation, the world capital of advanced technology. In and around the Santa Clara Valley are thousands of high-tech firms, a plethora of venture capitalists, and one of greatest concentrations of inventiveness and entrepreneurial energy in human history" (Matthews, 2003, p. 1-2). These aspects of Silicon Valley makes it important to understand the culture of high-technology startups, because the Silicon Valley ecosystem and its culture has been set a presedent for the startups or high-technology development in any other place in the world. As Thompson refers to Sue Gardner (2014), in Silicon Valley, "almost everyone in charge was a white or Asian man, that was the model for whom to hire; managers recognized talent only when it walked and talked as they did" (Thompson, 2019). As an example to this bias,

whiteboard challenge is a highly used hiring method for the Silicon Valley startups and it is also very similar to the classroom work at Ivy League institutions. This familiarity refers to the culture of coding, computer science, and especially of Silicon Valley that women are not the only ones who are excluded but also everyone outside of this culture (Thompson, 2019). According to USA Bureau of Labor Statistics, in 2018, the proportion of women in computer and mathematical occupations were 26%, the proportion of black employees were 8.4% and Latinos 7.5% (*Employed Persons by Detailed Occupation, Sex, Race, and Hispanic or Latino Ethnicity*, 2019). The diversity problem is not limited with the startups, many big technology companies are struggling with it. According to a research done by Recode in 2017, the proportion of women in technical occupations was 19% in Facebook, 20% in Google, and 18% in Microsoft. While the share of Black employees were only 1% and Hispanic employees were 3% in Facebook and Google, the proportion of Black employees were 2.4% and Hispanics were 4% in Microsoft. The numbers were also very similar at the other major tech companies like Twitter, Amazon, Apple, Intel (Molla, 2017). The statistics have pointed a gender and ethnic minority, but the situation in real life has been even worse. According to a former Google employee, Google suddenly changed the title of “UX Designers” to “UX Engineers” which a year after they announced the proportion of women in engineering positions as 20% in 2018. Although, almost none of them was software engineers (“Life as a Female Techie,” 2018). At Tesla, the diversity crisis show up like the other tech companies and startups. A former employee at Tesla claimed that women were less than ten percent in her working groups (Kolhatkar, 2017). When we look at the startup ecosystem, in 2016, 61% of founders claimed that there were no women in their boards (*First Round State of Startups 2016*, 2016). This lack of diversity and white-male dominant stereotype in Silicon Valley startups refers to a “brotherhood culture”. Dan Lyon at SXSW explained the “bro culture” by splitting organization

into the three types of components: “white male, no experience, no adult supervision” as CEO, management team as the “clones of the CEO, frat brothers he hires for culture fit”, and women as the “second class citizen”. And he indicated that the reason behind the “bro culture” is the Venture Capital system which seeks rapid growth rather than reliability (Clark, 2017). Many startups begins with a small “core” team with no clear rules and no human resources department. The venture capital culture which creates a “growth at any cost” system prevails startups to ignore workplace problems and ethical issues (Kolhatkar, 2017). As networks have become more important in the hiring practices, it can act as “forms of gendered social closure in a variety of ways” (Walby, 2011, p. 9). As Walby cited to Lindsay (2008), “Male subcultures in employment can act as old boys’ networks that create barriers to women in technical areas of work” (Walby, 2011, p. 9).

b) Gender Discrimination and Bias in the Industry

Gendered Practices

There is a vast amount of literature on gender distribution and relations in computational occupations, gendered work, and women’s experiences in engineering or technical jobs. The technology development labour market contain a considerable gender gap. In North America, women who have computing jobs are the one quarter compared to men. Only, 6 per cent of the mobile application and software development field are women (M. West et al., 2019). For the women and racial/ethnic minorities who succeed to get in the computational or engineering related technical occupations, the exclusion, reduction, underestimation, and sexism became a challenge during the work. Shih (2006), in her article which examines the gender and ethnic strategies in Silicon Valley, indicates that there are three forms of organizational inequality: job segregation through their prestigious levels and assign the less-prestigious ones to women and racial/ethnic minorities, “deskilling” of these individuals and groups, exclusion of them from key networks and

mentorships (Shih, 2006). McIlwee and Robinson (1992) refers to a “locker room culture” to define the majority and dominance of men in computational jobs (McIlwee & Robinson, 1992). Carter and Kirkup (1990) indicate that men colleagues often underestimate the work-related abilities of women in the workplace (Carter & Kirkup, 1990). The gender discrimination in the workplace is not only happening by “glass-ceiling” at the promotions and raises, it is also experienced through these “invisible” details of the work such as assigning the “assistantship tasks” to women employees even if everyone are in the same-level positions. As Gershgorin states “A woman employee said that “on one project she was only given tasks like booking conference rooms, taking meeting notes, and making dinner reservations despite being in a technical role” . (Gershgorin, 2019). Elephant in the Valley research conducted to understand challenges of promotion, inclusion, bias, motherhood and harassment for women who has been working in the startups, big tech companies or venture capital companies in Silicon Valley for at least ten years and more. While 84% of women have been told that they are too aggressive, also “47% have been asked to do lower-level tasks that male colleagues are not asked to do (e.g., note-taking, ordering food, etc.)” (Vassallo et al., 2017). Similar to Shih (2006), 66% of women have felt excluded from the social networking opportunities and 59% have thought they have not had the same opportunities as their male counterparts. 88% of women have experienced that they have been excluded from the work-related issues even the issues have been belong to their expertise (Vassallo et al., 2017). Gendered work and gendered workplaces are important concepts to understand the “gendered” nature, aspects, expectations, and relations in the workplace. Yancey Martin (2003) analyzed the “gendering or gendered practices” at work which they are learned through a lifetime experience from childhood. Gendered practices occurred by exclusion of women from social

relations in the workplace, seeing them as “sexual beings” rather than professional colleagues, and subordinating them in daily works (Yancey Martin, 2003).

Gender Discrimination in the Earnings and Promotion

In addition to the experiences of women through behavioral expressions of male-dominated teams, the income inequality and “glass-ceiling” are another important aspects that puts a barrier to the existence or professional development of women in these occupations. Prokos and Padavic (2005) explain the “glass ceiling” as “a transparent barrier above which women cannot advance” in the blocked possibilities for women in the workplace and the job hierarchy (Prokos & Padavic, 2005). In this sense, Ranson and Reeves (1996) analyzed the gender discrimination in the earnings and promotion in Canadian computer professionals. They indicated that the control over the access and mobility of women occurred in two types of strategy. They found out that the companies who has more than 35 percent of women did not block the entry of women to the company, but block their mobility to high-level wages and status; and the companies who has lower than 35 percent of women block the access of women by hiring a few of them, but not block their mobility in the company (Ranson & Reeves, 1996). In the high-level jobs in technology development, men are likely to be in these positions 15 per cent more than women. According to UNESCO, in the ICT sector, women are underpaid for their work in the digital sector (M. West et al., 2019). In 2015, women employees at Microsoft claimed that there is a gender bias in raises and promotion, and they are ranked below their male colleagues in biannual performance reviews (Tiku, 2019). The substantial pay disparities in high tech workers have also experinced in women of color. As West et al. cites to 2010-12 American Community Survey, “female software developers of color earn less than white, black, and Asian men, as well as white women. Latina software developers earned as much as 20% less annually than white male software developers.” (S. M. West et al., 2019).

Sexual Harrassment

The diversity problem in technology is also related with the harassment and unfair practices for ethnic, racial and gender minorities in the companies. In the recent years, big tech companies such as Google and Microsoft is alleged for their unfair HR policies, sexual harassment incidents and discriminative treatments for women. In the e-mail chain started at March 2019 at Microsoft, dozens of women have been shared the sexual harassment or discrimination incidents (Tiku, 2019). Many women shared different incidents such as sexist comments during work trips or sexual harassments by male colleagues (Gershgorn, 2019). Yet, the HR and managers did not do well in these situations, they either overlooked the incident or offer to change the position/department of the women (Tiku, 2019). In 2018, 20,000 Google employee did a mass walkout for sexual harassment allegations against top executives and demanded for a new policy for harassment. The demands include sexual harassment transparency, end pay and opportunity inequity, and change in the company's policies about these issues (Statt, 2018). In early 2017, a former software engineer at Uber Susan Fowler revealed that there was a hostile working culture in Uber for female employees and outlined that company's HR department did not punished her former manager who sexually harassed her. Later, another former software engineer made allegations against Uber for sexual harassment and racial discrimination ("Uber Investigated over Gender Discrimination," 2018). The gender discrimination, bias and harassment of women incidents are similar at Tesla. A former employee filed a lawsuit against Tesla for "sex discrimination, retaliation, and other workplace violations" (Kolhatkar, 2017). Especially in Silicon Valley, the harassment, discrimination, bias, and sexism stories of women are countless. 90% of women have been working in the Silicon Valley for more than ten years experienced sexist behavior at the outside of the company and 60% of women have reported unwanted sexual advances (Vassallo et al., 2017).

The venture capital companies, startups, big tech companies are accused for gender discrimination in payment and promotion; sexual harassment incidents such as offering or implying a sexual relationship or making sexist comments and creating environment for it. As the Harvey Weinstein incident went public on October 2017 and the sexual harassment issue became a central topic in the world, many women in Silicon Valley have been publicly standing up for their rights without a fear of being excluded or degraded in the company, got fired or forced to resign (Kolhatkar, 2017).

The Perceptions of Men and Women Towards Gender Diversity Problem

The causes behind of the diversity problem in tech were differentiated on perceptions of men and women. Men were more likely to address issues on pipeline into tech. While 8% of men claimed the cause is that poor recruitment into college STEM programs, only 1% of women address the same issue. Also, similar to this cause, 49% of men pointed the reason of not enough women and minorities going into tech. In spite of that, women were more likely to address issues on unconscious biases and lack of role models as the causes for lack of diversity in tech (*First Round State of Startups 2016*, 2016). The pipeline perspective has been frequently used approach for addressing the reasons behind of the diversity problem. When the outstanding tech companies were asked for increasing the diversity in their teams, they have pointed the issue as a difficult and improving process. For example, “Facebook has blamed a lack of qualified minority candidates” (Rangarajan, 2018). According to Romero, the Paradigm diversity consultant, “Usually companies feel like it’s more of a pipeline problem, but often, the pipeline has more diversity than the current employee population,” (Rangarajan, 2018). Even though, the numbers ethnic and gender minorities have been less than white men in technical-related majors such as computer science, the gap have not been extensive much like employee statistics in tech startups and companies. As

Rangrajan claims, minorities who hold a tech major have tended to have a job outside of the tech sector (Rangarajan, 2018).

c) Women in AI

Women have been challenged with the tech culture since the end of 1980's. But, what is the situation for Artificial Intelligence (AI)? Is there a room for women developers or technical-related jobs specifically in AI? The statistics show that the gender gap in STEM fields also exists among AI professionals. The gender gap in AI has been analyzed from the gender-binary perspective because there is no public data on other gender minorities/identities. According to The Global Gender Gap Report 2018, only 22% of AI professionals globally were female, compared to 78% who were male. Across the globe, the countries that have the most of the AI workforce were United States, India, and Germany. However, Germany was one of the countries that has the largest gender gap with 82%. Turkey ranked sixteenth line among the countries in AI talent. While the female workforce in AI was about 24%, the male talents were 76% of all. And, the remaining gender gap pointed out 76% which is above the global average (*The Global Gender Gap Report 2018*, 2018). In addition to the global proportions on AI talent, The Global Gender Gap Report 2018 also analyzed the specializations and skills set of men and women in the field. This data pointed out that women were less likely to be positioned in senior or high-level roles and skills. "Women with AI skills are more likely than men to be employed as data analysts, as well as in research, information management and teaching positions. For example, 4.2% of women in the female AI talent pool are employed as data analysts in contrast to 3.0% of men. Male AI professionals are better represented in roles such as software engineer, head of engineering, head of IT as well as business owner and chief executive officer positions that are generally more lucrative and of a more senior level" (*The Global Gender Gap Report 2018*, 2018). As we see in the statistics, the

growing field of AI has remained the gender gap in traditionally male dominated technology industry.

The gender gap in AI also appears in the academia. According to the Global AI Talent Report 2019, among 21 academic conferences, women were underrepresented with the proportion of %18 of the conference authors. Although, according to the 2018 Artificial Intelligence Index reports 80% of AI professors are men (Shoham et al., 2018). And, when they compared the academia statistics with the industry, they found out that the numbers were even worse at the industry with %16 of women (Kiser & Mantha, 2019). In the big global tech companies such as Google and Facebook, the proportions were even lower than the general situation. At Google, women were 10% of the AI researchers and Black people were only 2.5%. At Facebook, women were %15 and the proportion of black AI researchers were 4% (S. M. West et al., 2019). In this research, I examine the diversity problem from the gender perspective, but in general, diversity issue is not limited with gender, it comprises race, ethnicity, age and so on. West et al. (2019) describes the importance of diversity problem as “It affects how AI companies work, what products get built, who they are designed to serve, and who benefits from their development” (S. M. West et al., 2019, p. 5). This is important because this is not only related with the workplace diversity, it is also deeply related with how the technology that is produced by that team is developed and what are the outcomes of it, what it is effecting and whom. While thinking these questions, again we turn back to our starting point and Gina Neff asks us the question of “who is leading technology?” (Neff, 2018). West et al. (2019) also puts a similar question in interrogating the discriminating systems of AI: “Who is harmed? Who benefits? Who gets to decide?” (S. M. West et al., 2019). These questions are important because we need to think on the urgency of this problem while

designing the tomorrow's systems. Neff underlines that in 1984, the proportion of women who completed a computer science major was 37.1% and in 2014, it was 18% (Neff, 2018).

C. Bias: From Fourteenth Century to Algorithmic Bias

Bias has a long and changing history since 14th century. While in the 14th century the word “bias” had a meaning in geometry, in the 16th century the meaning and usage of the word transformed into something similar to today and meant “undue prejudice”. When we came to 20th century, it has referred to “systematic differences between the sample and a population” (The Artificial Intelligence Channel, 2017). When we have arrived today, the word of “bias” means “the action of supporting or opposing a particular person or thing in an unfair way, because of allowing personal opinions to influence your judgment” (*Bias*, n.d.).

Under the concept of the Artificial Intelligence (AI), the phenomenon of bias has been studied from the perspective of “algorithmic bias” which have discriminative and harmful outcomes for the society that is created for. Algorithmic bias or algorithm bias means “the lack of fairness that emerges from the output of a computer system” (Alake, 2020). The lack of fairness can be detected in the discrimination of a particular group because of a “specific categorical distinction” of that group (Alake, 2020). The algorithmic bias mostly appear in gender, racial, or any other kinds of discrimination.

Gender and racial bias have the risk of creating allocative harm for ethnic and racial minorities, and women. Allocative harm means a system that allocating or retaining some resources from certain groups. Easily quantifiable harms such as economic harms like automated recruitment practices, credit scores, extent of insurances and much more are in the scope of the allocative harm (The Artificial Intelligence Channel, 2017). In the literature, we see that there are a significant number of AI-enabled systems and tools which create allocative harm for its users and excludes

certain ethnic, gender, and racial groups. Obermeyer et al. (2019) analyzes the racial bias in an algorithm that is used for healthcare systems and they find that because of the algorithm uses health-care expenditures to measure “sickness”, black patients are accounted of being at lower risk than white patients (Obermeyer et al., 2019). The problem that the algorithm understated the medical needs of black people because “society spend less on black patients”(Mullainathan, 2019). Sweeney (2013) evaluates the racial discriminative connotations of black-identifying names with arrest recording suggestions in online ad delivery systems. She found that when black-identifying names are searched, 81-86 percent of names gets the suggestion of arrest-record ads in one website, and 92-95 percent of on the other website (Sweeney, 2013). In another study, it is found out that Amazon’s Prime Same-Day Delivery service does not work for neighbourhoods which are the majority of residents are Black people. It is revealed that Amazon’s Prime same-day service is fed by the historical data of residency and it mirrors the historical division of Black-residents’ neighbourhoods and White ones. Even though the company made a statement about the choice is not racial and it is decided by many parameters which one of them is the neighbourhood’s proximity to the warehouses; it is clear that “the company must decide which neighborhoods are worth the cost of service and which aren’t.” (Ingold & Soper, 2016). Besides of the locations of warehouses, the study shows that in many cities such as Boston and Atlanta, the very central or close-to-center neighbourhoods which have dominantly Black residents are also excluded (Ingold & Soper, 2016). A 2015 research conducted by Carnegie Mellon University analyzed the fairness of targetted online ads by comparing the differences of online ads for different target groups and preferences of them. To do the experiments, they developed a tool called AdFisher which creates hundreds of simulated user profiles to understand the effects of changes in the behavior and the correlations of them with online ads. They found out that in top 100 employment websites,

significantly fewer women than men were shown executive position ads paying more than \$200,000. While men saw these ads about 1,800 times, women saw only about 300 times (Spice, 2015). These difference in numbers show the gender discrimination and bias in these systems.

Biases in the AI systems also create representation harm for certain groups of people. The subordination of certain groups according to their identities causes representation harm for them. Negative attitudes such as stereotyping or creating culturally offensive labels and underrepresentation of certain groups are evaluated as representation harm (The Artificial Intelligence Channel, 2017). The gender or racial biases can create representation harm for those groups and individuals. Gender and racial bias are studied in sub-frameworks of computer vision such as facial recognition or image detection to analyze the classification and detection performances of these systems in the visual world. Buolamwini and Gebru (2018) evaluated gender and racial bias existing in automated facial recognition datasets and algorithms. They found that while the most misclassified group is dark-skinned females, the detection of lighter skinned individuals and males are the ones that are performed best in all classifiers (Buolamwini & Gebru, 2018). Kay et al. (2015) present the gender bias in image search results for occupations and they find out that there is a under-representation of women and stereotypical referrals in the results (Kay et al., 2015). According to BBC News, the UK passport application website is biased against darker skin colours. When a black person uploaded her photo to the system, the system warns the applicant that the quality of the photo is poor or her mouth is open even though it doesn't. After uploading 1,000 photographs of politicians across the world, it is found that there is a significant number of false-detection in darker-skinned people compared to lighter-skinned. Photos of darker-skinned women with the darkest skin tone were detected as "poor quality" four times more than women with the lightest skin tone (Ahmed, 2020). In 2015, the image recognition algorithms of

Google Photos misrecognized Black people as “gorillas” (Barr, 2015). In 2009, the Nikon cameras was mistakenly recognized Asian faces/eyes as they “blinked” even if they just smiled (Lee, 2009). In 2009, the facial tracking software of HP computers couldn’t follow a Black person’s face, while it could perfectly follow a White person’s face (Chen, 2009).

Gender bias is studied in word-embeddings algorithms and datasets which is a commonly used machine learning framework that build correlations and semantic relationships between different words (Garg et al., 2018). Bolukbasi et al. (2016) show that word-embeddings trained on Google News articles contain explicit gender bias which reflect the gender stereotypes of the society. According to article, the risk regarding the word-embeddings is not just reflecting the gender stereotypes, they also amplifying them through machine learning systems (Bolukbasi et al., 2016). Leavy (2018) analyzes the gender bias in machine learning and indicates the need for gender diversity to prevent algorithms from embedding the societal biases into machine learning system (Leavy, 2018). Amazon’s AI-powered experimental hiring tool rating candidates according to their gender for the technical-associated jobs. Because of the system was trained on historical job application data, the system is developed biased against women.

So, what is the problem with algorithmic bias? Why a lot of systems which some of them are part of our daily lives contain high rates of gender and racial bias? The outstanding argument that comes to front in this issue is that algorithms are not the ones which has biases, but the people and the society which develop this technology have social norms and values that contains biases. The bias in AI systems emerges mostly from the training datasets. The use of the historical data and lack of gender and racial diversity in the field are outstanding reasons for gender and racial bias in the automated systems. When a historical data is used to train algorithm, it automatically reflects historical biases into today’s “cutting-edge technology” and AI systems becomes biased against

historically discriminated groups. Because Amazon uses its historical job application data for the AI-improved hiring tool, the system inevitably ends up being biased against women. The white-male dominance in the industry also creates a one-sided perspective in the phase of developing the algorithms. Developing an AI system contains many steps such as: creating dataset from historical data or collecting data, organizing the dataset to eliminate noisy data, developing the model and training the model with the dataset. In all of these steps, human labour make the decisions of what to do, how to do, and whom to do. So, the lack of diversity is an important problem that should be fixed today before the AI systems are rolling in many more areas in our daily lives.

D. Non-Binary Gender Perspectives

So far, we discussed gender discrimination and gender bias in technology and AI with a gender binary perspective. My research, as many others, focuses on the gender discrimination and bias issue in this perspective. Because, there is no data on gender minorities in AI. Although, there are a bunch of studies focusing on gender bias within the inclusion of “trans and non-binary gender identities” (S. M. West et al., 2019). The automated and classified structure of AI systems may cause the exclusion of especially the trans people in those systems. And this exclusion is discussed around the Automatic Gender Recognition (AGR) which is a method to identify someone’s gender from a video, image or audio. According to Hamidi et al. AGR technology is “a class of algorithms that use various techniques, including facial recognition and body recognition, to classify an individual’s gender” (Hamidi et al., 2018). AGR systems are used frequently in the security systems, marketing tools, and any other services. Even though their common usage, they can “misgender” the transgender people which is “a form of structural violence” (Hamidi et al., 2018). As Hamidi et al. (2018) reveals, the transgender people has negative experiences, negative thoughts, and doubts regarding the AGR systems (Hamidi et al., 2018). Uber’s facial recognition

security system for drivers is an example for the real life negative experience and harm that AGR systems can create. Uber's system suspended the transgender drivers' accounts for cannot matching the drivers' latest photo with the previous ones. The "Real-Time ID Check" system of Uber asks drivers to take selfies occasionally to make sure that driver is matching the established identity in the system. But, transgender drivers who goes through a physical appearance change cannot match their identity with the previous photos. That's why their accounts are suspended until they declare the situation in Uber Support centers. These incidents cause an allocation harm for them because they cannot work until they solve the issue with Uber Support (Urbi, 2018). Keyes (2018) also studies on AGR systems that are used in Human-Computer Interaction (HCI) studies in the academia focuses on the social media usage and he found out that the AGR systems works in a "trans-exclusive" manner (Keyes, 2018).

In addition to the AGR systems, gender identity is also discussed around the categorization of genders in online platforms or backend systems of AI products. Bivens and Haimson (2016) analyzed the gender category systems of 10 most popular English-speaking social media platforms and revealed that most of them have a gender-binary system in their underlying categorization which cause the misrecognizing the genders (misgendering) of individuals (Bivens & Haimson, 2016).

To overcome the gender bias issue against gender minorities, data collection of those individuals and training on that data can be seen as a part of the solution. But, the permission of individuals is the vital aspect of this process. Karl Ricanek and his students tried to develop a facial recognition system for individuals who went through a hormone replacement therapy (HRT). They collected the time-lapse transitioning videos of individuals over YouTube without their permission (Vincent,

2017). So, this also creates questions regarding the privacy of those individuals, surveillance systems and their personal security.

METHODOLOGY

In this study, I gather two different methods to gain a broader perspective on gender diversity, discrimination, and bias in AI from the perceptions of AI developers in Turkey. I used semi-structured interviews and quantitative data collection that focuses on two different spectrums about gender distribution and diversity which are college education and workplaces. I selected the interview as the main method of this research, because in this study it is important to understand the perceptions, stories, evaluations of the participants with their own words. Since the topic of this research is the perceptions of AI developers about gender-related issues in AI, I would like to understand their perspectives about the social impacts of AI systems and the workplaces where these technologies are developed. As they are the developers of these novel technologies everyday, as a occupation, as a work, as a field of interest; I wonder how they evaluate the relationship between the computational, mathematical, technical, technological developments with their social impacts such as gender dynamics in the workplaces, gender discrimination and bias, and algorithmic bias. So, their words and their perceptions are the center of my research. Saldaña (2011) describes the method of interviews as “is an effective way of soliciting documenting, in their own words, an individual’s or group’s perspectives, feelings, opinions, values, attitudes, and beliefs about their personal experiences and social world, in addition to factual information about their lives.” (Saldaña, 2011). I selected the interviewees strategically since the main topic of the study is perceptions of AI developers. So, I used strategic sampling method. I determined some keywords that match with the profiles of AI engineers such as “artificial intelligence, AI, machine learning, deep learning, NLP, computer vision, computer science, computational neural networks, image

recognition, object detection etc.” and used the LinkedIn Search function to reach out a diverse sample of AI engineers. After searching via these keywords, I filter the results as “People”. Because, LinkedIn offers different kinds of results according to the searched keyword such as people, job ads, groups, companies, posts, schools, and activities. After selecting the People filter, LinkedIn gave approximately more than 2.000.000. However, there can be unrelational profiles inside of the results. So, starting from the first page of the results, I reviewed the each profile and according to their suitability, I asked them to connect on LinkedIn. After randomly connected with approximately 200 people, I send them a message about my research and asked them whether they can participate or not. 24 of the people returned positively and I conducted the pilot interviews with two of them to look for the suitability, credibility, and understandability of the question set. So, the participants of the study were 22 people who were occupied as AI developers in startups or companies. 6 of the participants were women and 16 of them were men when we demographically divide the interviewees. In the study, 18% of the participants work at the corporate companies, 4% of them work at a global tech company, and 78% of them work at the startups. I conducted the interviews from April 2020 to September 2020 in an extended amount of time. Each interview took approximately 1 to 2 hours according to the length of the participants’ narratives. Since the Covid-19 pandemic started in late 2019 and the first positive case was seen on March 2020 in Turkey; I had to conduct the interviews online via Zoom which is a common video conferencing tool. There was a partial lockdown in Turkey until June 2020 and all of the interviewees were working from home since March 2020 because of the pandemic. So, I could not conduct the interviews face-to-face. The online interviews had the risks in terms of the trustworthiness of the research and researcher and limited opportunity of observing the body language of the participant. Since I did not have a previous face-to-face acquaintance with the

participants and I did not have any referrals for them to participate in the research, some of the participants had doubts about the recording and some questions about their companies, teams, and the questions that focus on the perspectives of participants on the social issues. However, at the beginning of my interviews, I ask for their permissions to record the interviews and emphasize that they can close their cameras during the recording. I also highlighted that I will not be sharing the recordings, their identities, and any information that can be matched with their identities. All of the participants allow me to record the interviews, only some of them close their cameras during the recordings. So, I will not share any of the information, names, initials, name of their companies, and etc. I will define each participant in a numerical order such as “Participant 1, Participant 2, Participant 3...”. In addition to that, I emphasize that we can stop the interview whenever they feel uncomfortable or skip the questions that they prefer not the answer. None of the participants stop the interview before it is done. A few of the participants prefer not to answer some of the questions during the interviews. I overcame the ethical considerations about the trustworthiness of the research with these applications. The second consideration is the limited opportunity of observing the body language of the participants since I conduct the interviews online. As I mentioned before, I stated to participants that they can close their camera while recording if that makes them more comfortable. So, while I could observe some of the interviewees while answering the questions, I could not in some of them. However, I listen them very carefully with their voice tones, laughs, pauses while they were thinking, and ask more about the parts that I could not sure what the participant wanted to tell. And I noted every observation that I make during the interviews. So, even though I analyze the interviews months later, I could check my notes about what I felt, I observed, and I sensed during the interviews which was also very helpful to me. So, I overcame this obstacle by taking a lot of notes, asking more to participants, and observing not only the visual

expressions, but also audio expressions as well. There are also positive impacts of online interviews for my research. Since I conducted the interviews during the Covid-19 outbreak, it is more healthy for each actor in the research such as researcher and the participant. Also, as the participants of this research are AI developers in companies or startups, they have a full time and busy jobs. So, we could schedule interviews after or before working hours, and weekends more easily. After completing the interviews, I transcribed the audio files into writing between January 2021 and April 2021 and analyzed the interviews via the written documents.

I also selected a quantitative data collection and analysis method as a complementary method to support the findings and analysis of the research. I collected statistical two different kinds of data from two different sources: employee data and student data. Besides only focusing on the perceptions of developers, I would like to give statistical gender distribution in AI workforce and computer science related departments at college to discover the gender diversity in the field. I limit the employee data by only looking at the employee statistics in AI startups. To reach out all of the startups in Turkey, I benefit from the website of Türkiye Yapay Zeka İnisyatifi (TRAI) which is an initiative on AI in Turkey to raise awareness about the issue. TRAI publishes a Startups Map on their website and update the map in a regular basis. So, I benefit from the Startups Map February 2021 to collect the total list of the startups. According to the map, there are 150 startups in Turkey in which ten different main categories of AI methods and business solutions. These categories are Machine Learning, Optimization, Forecasting and Data Analytics, Natural Language Processing, Otonomous Vehicles, Search Engine and Search Assistants, Chatbots and Dialogic Artificial Intelligence, RPA, Smart Platforms, and Image Processing. After gathering the list of AI startups in Turkey, I collected the employee data for each startup via LinkedIn. So, I searched the each startup on LinkedIn and examine the LinkedIn pages of starups to see employee statistics. I analyze

the number of men and women employees and the professions of women employees such as technical or non-technical. Therefore, I see the total distribution of genders in AI startups and number of women working in a technical occupations. However, there are some considerations regarding the validity of employee data. I collected the startup data from the website of TRAI and it is only limited with the employee statistics of AI startups. So, the number of AI teams at big companies or corporate companies are not included to the data. Because, I could not reach a data about corporate companies which work on AI. Since the startups are leading organizational units in AI, limiting the employee statistics with startups would not effect my analysis. There is a second consideration regarding the employee statistics. As I collected the employee statics of AI startups, I could not verify if there are some employees who do not have a LinkedIn account. So, if there are some employees who do not use LinkedIn, I would left out them from the statistics. However, LinkedIn was my only choice to collect employee numbers for each startup efficiently. Because, while some of the startups have a “team” page on their websites, most of them do not have a page to give information about their teams. I use the employee statistics to support the Findings and Analysis of my research as a complementary method. Since the actual total number of employees who work on AI are not the core of the research or a determining part for my analysis, I think that this obstacle would not effect the study.

In addition to the employee statistics, I collected data from the Higher Education Information Management System website of YOK which is the Council of Higher Education in Turkey. I aimed to see the gender distribution in the college departments which are related with the computer science and have the potential to work on AI after graduation. I determined eighteen departments of “Computer Science, Computer Science and Engineering, Computer Engineering, Computer Technology and Information Systems, Computer and Information Engineering, Computer and

Software Engineering, Computer Software, Information Systems Engineering, Information Technologies Engineering, Electrical and Computer Engineering, Electrical, Electronical and Computer Engineering, Electronical and Computer Engineering, Artificial Intelligence, Artificial Intelligence Engineering, Artificial Intelligence and Robotics, Artificial Intelligence and Data Science, Software Development, Software Engineering”. I also look for the three levels in education: Bachelor’s, Master’s, and PhD. Since these are the official statistics of Council of Higher Education (YOK) in Turkey, I assume that the numbers reflect the reality with no tolerance. However, it should note that the graduates do not necessarily have to prefer to work on AI in their career paths. I analyze the gender distribution of students who are studying on any of these departments in 2019-2020 according to each level of education: Bachelor’s, Master’s, and PhD. I add this section and analysis to my research to trace back the gap between women and men in the early ages at the period of college education. I wonder when this gap is closed more and when it is extended.

Finally, I approach gender from a binary perspective which creates a limitation for my research. However, I could not reach out any non-binary gender information in Artificial Intelligence workplaces or computer science departments in Turkey. As I collected the quantitative data from LinkedIn and Council of Higher Education (YOK), there are no non-binary gender information in these sources. In addition to that, I did not ask about their genders to the participants in the interview part. When I asked about gender in AI in general, they tend to answer these kinds of questions from a gender binary perspective. So, I evaluate the gender issue from a binary perspective to reflect about their perceptions and data. However, I am aware of this situation creates an ethical challenge for my research.

FINDINGS AND ANALYSIS

Introduction to AI in Turkey: The Definitions, Working Models, and the Job Hierarchies

A. Introduction

In this study, I aimed to demonstrate the gender distribution, discrimination, and bias in AI at Turkey with the focus of workplace dynamics and algorithmic systems. As a beginning of my research, I aimed to draw a framework about AI in Turkey using the perceptions of developers to understand how they perceive and evaluate AI as a notion and the studies and works on AI in Turkey. Since AI is a technical development area for developers that they create models or systems everyday at work, I wondered how they perceive AI as a non-technical concept. Because, I would like to understand what kind of social concepts that they relate to AI besides than the technical processes or algorithmic calculations. I aimed to see how they perceive the job that they are doing everyday, what are the strenghts or weaknesses, what does AI offer and what does not, or what does it mean when they want to explain to a person that would not understand the technical details... I also asked their perceptions on AI in Turkey to light the way for AI studies and works in Turkey. Since AI is studied from the European or American perspective much, I would like to understand what kind of studies and works are done in Turkey and how AI developers consider these as the actors of these developments.

In this section, I also tried to understand the business models and hierarchical orders of the startups and companies that they work for. Artificial Intelligence is a field that technology startups takes the lead and Silicon Valley is the center for innovative technological developments in all over the world. Since the Silicon Valley is famous with its new-age way of working environment such as non-hierarchical models, no formal work clothes or formal working hours like 8 am to 5 pm as in corporate companies; I wondered that can we describe a same environment in AI startups or

While defining AI, most of the participants use phrases to emphasize the humanlike aspects of AI. Participant 20 explains this as “I interpret artificial intelligence as the ability of the only intelligent and excellent human being created in this universe to be able to repeat exactly the same functions by machines and computers and to work in a full human dimension, to be able to make every feature of a human being by machines, and even to carry human to higher levels by having some superhuman features. All the technology, all machines that enable us to do this, are actually the subject and agenda of artificial intelligence”. Participants claim that AI systems are developed to perceive, think, and act like humans in simple and complex tasks. So, it is important for AI systems to perceive an input data which can be image, voice, text or anything else; think how to perform the task and what to do; and act to give the outcome. While some of the participants are only mentioning the efforts of AI systems to perform like human-beings and their decision support mechanism for humans, some of them emphasize the superior aspects of AI systems compared to humans. According to a participant, humans are more successful to easily pick something, move and take physical actions compared to AI; although AI can be more skillful in strategic decision mechanisms such as playing chess.

The “making people’s lives easier” aspect of AI systems is emphasized by many participants. Participant 14 explains the functions of AI systems by likening it to the inventions of machines: “Normally, what is the invention of the machine, workers work, there are some jobs that are also done by physical force. Workers are employed in these. After that, machines were invented slowly. Cars have been invented and humanity has begun to turn this muscle power into a little more machine power. I also compare artificial intelligence to this. Because normally you use your eye to detect what is in an image and you process this information in your brain, and you say there are

these objects in this picture. In fact, by having this done with artificial intelligence, you will provide automation. This automation is actually a great use of artificial intelligence today.”

According to most of the participants, data is an important element for AI systems to process. Because, AI systems can work with a vast amount of data through seeing the patterns in data. “Data” and “learning” often are used together to define the continuous and autonomous learning in AI systems.

Some of the participants answer this question by explaining the historical development of Artificial Intelligence through the important figures, steps, and dates in this field. In these narratives, the participants take the Alan Turing’s “Computing Machinery and Intelligence” (1950) article as starting. Following Alan Turing’s question of “Can machines think?” in that article, naming this field as “Artificial Intelligence”, statistical learning, neural networks, big data, and deep learning are defined as important steps until today in the development of AI. In another historical narrative of AI, one participant emphasizes that the definition of AI contains different meaning in each era. For example, today’s meaning of AI is different from what it means in 1950’s. It has contained different aspects and meanings as evolved.

Some of the participants answers this question by referring the myths about AI such as “AI will cause unemployment” or “AI or robots will take over the world”. They claim that the Hollywood movies like Terminator or Netflix movies and series, in short the cultural products, create a misperception in people’s minds like “AI is equal to robots” or “AI has free will”. According to them, this hype created by the movies or series cause misperceptions in public. They emphasize that the common sense knowledge is far from the reality and the capacity of today’s AI systems is limited with human interventions. According to this thought, the AI systems make people’s lives easier instead of create danger for them. Some of the participants explain the capabilities of today’s

AI systems as the technical division of supervised learning and unsupervised learning. In supervised learning, the developers limit the action area of AI systems in a certain framework, and that is the highly used method for the systems that we are using now. The unsupervised learning part of AI is at a premature stage at the moment.

Some of the participants use the word “hype” to define the situation of AI systems today. In the narratives, there are two definitions and intentions to explain “AI hype”: The first one is the hype caused by movies and series. Participants claim that the science fiction movies and series cause a misperception in people about AI. And the fact that artificial intelligence is on the agenda so much causes that even non-experts in this field are asked about these issues, so this misperception is maintained in public. The second one is the misuse of the word of artificial intelligence. According to the participants, many people and startups develop simple softwares, promote their products as AI-powered, AI-enabled, or AI-supported even though those softwares don’t contain AI methods and are mostly rule-based such as “give X when Y comes in”. In these cases, the participants think that the definition of the artificial intelligence lost its meaning.

To sum up, while most of the participants emphasize human-like aspects of AI systems to define what is AI, the other ones focus on more technical details such as the data usage, certain methods in AI such as Machine Learning or Deep Learning, and machinery functions of AI systems. According to participants’ narratives, there are two common concerns related with AI that are mentioned in the interviews: the lost of the meaning of AI and misperceptions about AI. These two concerns are mentioned most of the interviews as the negative aspects related to AI systems today.

C. AI in Turkey: The Perceptions of Developers

I asked participants about their perceptions on Artificial Intelligence (AI) studies and works in Turkey to understand the state of AI in Turkey. While defining their perceptions about AI in Turkey, the participants emphasize the difference between academia and the industry. Because of AI is an academia-driven field, the academic researches and industrial developments are maintained hand in hand. However, some of the participants remark that the driving points, concerns, focuses, and works of academia and industry are differentiated each other in AI. Academia work on research-focused studies about AI to develop more “state of art” solutions and industry’s main concern is to make profit from AI-enabled solutions. In the industry, AI takes actions determined within those limits. The participants claim that this may cause a problem for the companies and startups to develop rule-based solutions that may go beyond the AI. According to participants, when we look at the global examples, we can see that there is the synergy between academic studies and industrial developments. They have research labs in the companies or even though they do not have, they can spare time for research. But, in Turkey, the industrial developments are not synchronised with the academic studies. So, the difference between academia and the industry draws the attention in Turkey by the participants. According to one participant's narrative, if you would like to develop an AI-driven chatbot, you create a chatbot that responses the customers’ certain queries, not the one which can bring together the words and create its own sentence by itself. So, minimizing the risk in usage and create a solution which can fix one particular problem gain importance in the industry compared to academia. Hereby, the concern of participants about misconceptualization of AI by individuals and startups to benefit from the AI hype also appears here. When I asked about the definition of AI, some participants claimed that the hype of AI in recent years cause the problem of calling almost every software as AI even

though they are not. So, when I ask about their perception on state of AI in Turkey, many participants refer to that problem again in the developments in Turkey. According to their view, some of the startups easily call their rule-based softwares as AI to benefit from this hype, to get an investment from investors and to get attention of the public. Participant 7 interprets this situation as “There are many ‘AI projects’ in Turkey which are done by corporate companies, governmental institutions or banks only for the sake of appearances”. Participants also emphasize the “adversarial” purposes to call a rule-based, non-AI system as AI. One participant says that “In fact, they produce using simple things and they say we use artificial intelligence for advertising purposes. This situation provides a serious convenience to enterprises in finding investment”.

According to most of the participants, Turkey is in a good position in terms of human resource. Participants claim that the employees and students in this field is qualified and youth has an interest in this field. For them, there are very good Turkish engineers and academics working in this field. Although, the brain drain is an important obstacle in Turkey. The qualified, succesful Master’s or PhD students often choose to go abroad to study or work in global initiatives, companies, or top universities. Many participants mention that most of the their friends go abroad to do their PhD or work in the global startups and companies. So the brain drain effects negatively the AI developments in Turkey. And this problem is subject to our interviews with most of the participants. One participant explain this problem as “I think that investments in the private sector are not enough at the moment. That is why the majority prefer to work abroad as there are no job opportunities and employment opportunities here. This actually turns out to be a great loss”. Participant 7 explain this problem as “The country has a serious brainpower. But there have been a lot of people from my circle who have recently moved to abroad. That is why the answer to the question of how much we can utilize this potential is that we cannot benefit from this very well”.

Participant 2 points out to this issue with inefficient usage of sources in Turkey: “So frankly, I see that the intelligence of artificial intelligence employees is spent inefficiently”.

The challenges that Turkey face in the development of AI systems are several in the narratives of participants. The lack of financial source or investment is mentioned in a couple of interviews. According to them, this situation effects negatively the research developments and human resource in the field. The lack of communities is another dimension mentioned in the interviews. According to some of the participants, the community understanding and working on a common project strengthen the qualities of developments. However, they claim that academics or startups are working individually on the different methodologies in AI, and so these developments stay immature. Language barrier is an important obstacle in Turkey according to participants. They assert that most of the academic publications, online courses, books, and any other sources in English. So, if people do not know English or not advance in English, they cannot develop themselves very well. In this field, people need a good English to follow the technological developments in the scientific field. A participant points out this problem in these sentences “There is a chronic problem in the field of artificial intelligence or software in Turkey, and anyone who wants to do something in this field should solve this problem first. Artificial intelligence or software is moving very fast. So we are no longer in the 1980s, not in the 1990s. Many developments are progressing very fast right now. That's why you need to know English first to be able to follow these developments. This is a serious problem in our country. English education is not very well given except for a few institutions. Or let's say people don't learn”. According to participants, there is an another problem regarding to language barrier as Turkish source. Increasing the amount of Turkish sources in the field can be a solution to convey the AI knowledge to people who does not know English. According to a participant, the Turkish sources such as

online courses, blogs, YouTube videos are increased dramatically in the last 3-4 years. Although, another participant claims that the increasing Turkish source is not the solution, eventually people needs English to develop themselves in the field.

To sum up, generally, participants claim that AI developments in Turkey are inadequate and inefficient. The startups focus on the industrial products rather than maintaining the research and development together compared to global initiatives and companies. The investments and sources are insufficient to apply researches or keep the human resource in the country. Both quantitatively and qualitatively, AI studies in Turkey cannot comparable with the top universities globally. According to the Participant 7 “If 100 projects are carried out within an institution or in a sector, more than 80% of the projects are not actually implemented in world average. If we look at the average of Turkey, this is over 95%. In other words, a very serious part of the work we do in Turkey ends without being beneficial to anything”. However, according to participants’ narratives, the country is fortunate in terms of human resource.

D. Working Models and Job Hierarchies in AI Startups and Companies

Another important topic in AI is the working models and job hierarchies in startups and AI teams at companies. AI is a fast developing area with the focus of getting quick results, trials and errors, fixing bugs, and turning the investment into profit quickly. Behind of this rapid growth strategy, there is the role model of Venture Capital system in Silicon Valley for the tech startups in the other countries (Clark, 2017). So, I analyze how AI startups and companies or AI teams at the companies shape their working models and job hierarchies while developing AI systems, are they also effected from the Venture Capital’s rapid growth strategy and how are they fitting into the casual, flexible, away from hierarchy stereotype of startups. In the study, 18% of the participants work at the corporate companies, 4% of them work at a global tech company, and 78% of them work at the

startups. When I asked about the working models and job hierarchies in their companies or teams, most of the respondents answer the question by comparing the working conditions of startups and corporate companies. Startup employees refer to the strengths of the startup culture as efficient, flexible, task-focused, and result-oriented. According to participants, most of the startups don't have a strict working hours like the corporate companies' 8 am to 5 pm working model. While some of the startups have more determined working hours than others, it still requires an understanding of above the working hours. Most of the participants state that this working model requires people to love the job and to have a curiosity in their field. And that's how they can even work at late hours or research about the job-related issues at their spare times. One participant explain this as "Since these issues are my curiosity, I mean, I work here, but I see it as a hobby, not as a work. Frankly, when I learn something new while researching something, it is not a job for me. I usually continue my research after work". As I see from the narratives of engineers, they often see their job not just as job, but also see as an area that they are interested in or as a hobby. This blurred balance between work and hobby cause dense pace of work for them. Because, even they complete their tasks, they spare time for work-related areas to develop themselves and make researches. A startup employee Participant 13 refer this as "I do not think that normal (corporate company) working hours is the right concept and I think more efficiency is obtained like startups' flexibility. We do not have any free days or we do not have to work between strict hours. Whenever we feel comfortable, we work. But, you have to work hard. Especially if you work in a startup, you work 50-60 hours a week instead of working 40 hours a week in a corporate firm. But there is no time limit or a day for this". One participant Participant 7 explain the busy working hours of AI teams by giving the example of global tech companies: "They work like animals. There are no such concepts as working hours, weekdays, weekends, I don't know, day and night, etc. There is

work, this job will be finished. By the way, it is not actually working with such a cruel employer model. Because he has such a motivation that the engineers working there are constantly trying to improve in a constant competition, constantly trying to develop better models and inevitably this is the only thing on his mind. So they are a little obsessed, usually those who work for good tech firms that work on stuff like that. He always has that job in mind and continues to go home and still do that job at home. I do not know, on the weekend, there are not many friends already, we do not work in groups in such large teams”. A participant, Participant 18, refers to this situation as a difficulty to work in a startup. He is corporate company employee, so he claims that he works more comfortable and systematic in there. He states that people misunderstood the flexible working hours of startups. According to him “You are the owner of the product, you are in charge of the product, you have to meet the expectations of your customer, you have to work harder, you are in a higher responsibility position in a startup”.

The task oriented mindset is an important asset for startups. Since there are no strict working hours, employees are obligated to complete their tasks in the determined period of time with positive or negative outputs. Establishing micro project groups inside of the startups are another common method to assign employees in different projects and roles. Another aspect of the startups is uncertainty of the roles in teams. Since startups work in small teams, the roles are not divided with sharp and precise distinctions. So, we can say there is no precise job definition especially during the busy times. Participant 13 explains the uncertainty of roles as “I am an authorized person in the field of computer vision. But we are involved in all development and improvement work, regardless of the field, and we are fully dealing with how we can make the project better. I think this is the biggest difference of startups. Nobody has some specific duties. Of course, there are

areas where everyone is an expert. But here, I can say that the general purpose is to provide the project with intensive work and to give the best efficiency”.

There are a few participants who have a working model in between of startups and corporate companies. One of them, Participant 17, works at the AI team of a corporate company. He claims that “It is close to the startup culture, but it also has an institutional structure. They are mostly trying to keep up with the Silicon Valley structure. There is hierarchy because somebody has to lead the team and we are looking at multiple projects. But this hierarchy is evident in the way of doing business, not in conversations. In places that require a lot of communication or decisions, team leaders emerge. But there is no hierarchy in meetings and task sharing amongst us”. Another participant also works at a corporate company, but states that the company has a more startup culture with some differences. According to him, they have the structured, divided into departments process in the company with the flexible working hours of the startup culture. According to him, this flexibility prevents the company and work from being in the cumbersome structure of corporate companies. A participant, Participant 13 who is an employee of a startup, asserts that they also have the same in-between working model “I can say that the working model is actually between corporate and startup. Here, our working hours are certain, our meeting hours are certain, our duties and what will happen are certain”. There are also participants who claim that even though the working hours are flexible, the duties of employees are specific and there are some workplace/business rules.

According to participants, the hierarchical models are not suitable for the technology companies and startups. Because they define this field as “new-generation”. And for them, the successful companies or startups should be leadership-oriented with small structures and teams inside of the company and allowing the employees to self-govern themselves with the feeling of having a share

in management. Otherwise, hierarchical and based on KPIs structures cannot be successful models for technology companies. From the narratives, almost all of the participants claim that there is no vertical hierarchy, there is a horizontal hierarchy in their startups or companies. Only, a few of them states that the working environment requires an hierarchy to manage the projects. Even at the corporate companies, participants claim that there is an hierarchy between titles such as specialists or engineers, managers, and CEO; but there is no hierarchy in doing business or social relations inside of the companies.

E. Subconclusion

In this chapter, I asked participants about their perceptions on what is AI and how they evaluate the studies and works that are conducted in Turkey. In addition to that, I asked the participants about their business models and job hierarchies to understand the current situation in AI startups and teams in Turkey.

In the non-technical definition of Artificial Intelligence (AI), the participants mostly refer to the human-like aspects of AI systems such as perception, thinking, action. While some of the participants are only mentioning the efforts of AI systems to perform like human-beings and their decision support mechanism for humans, some of them emphasize the superior aspects of AI systems compared to humans. The superior aspects of AI are stated as performing better in strategic decisions such as playing a chess since these systems work well in big amount of data. The comparison of AI and human capacity is one of the starting points of AI algorithms. As Turing (1950) asked the question of “Can machines think?” in his article of Computing Machinery and Intelligence, the boundaries, limits, and fantasies about AI is often compared the capabilities of human intelligence and physical actions. As in the science fiction movies about AI and robots, we often see the competition and superiority of machine intelligence over human’s. So, the narratives

of the participants are similar to these kinds of explanations. They tend to make comparisons between the capacities of AI and humans. Most of the participants define that AI systems are developed to make people's life easier. Like the invention of machines, AI help humans to take over their mundane jobs with automated systems which is a great use of AI today. Some of the participants mention the technical processes and methodologies of AI systems even though I asked about a non-technical definition. They emphasize the differences between methodologies, working mechanism of these systems, current capabilities of AI, and data as an important element for AI systems to work well. There are two main concerns that are mentioned in the interviews: the lost meaning of AI and misperceptions about AI. These two concerns are emerged because of the AI hype in recent years. According to participants, companies and startups develop non-AI, rule-based softwares and call them as AI-enabled to benefit from this hype as public attention or get investment to their initiative. So, they define that there are many products which do not contain AI models, but called as AI. And second reason that cause to lost the meaning of AI is bringing AI on the agenda so much that even non-experts in this field are asked about these issues so much. According to the participants, second important concern related to AI is the misperceptions of AI. Many of them state that the Hollywood movies and Netflix series and movies cause a misperception about AI in the public such as AI will take over our jobs or destroy the world. In addition to that, the statements of non-experts about AI also contain misinformation. Therefore, there happens a misperception and misunderstanding about AI in the public.

The state of AI in Turkey has differentiated focus points in participants' narratives. According to them, Turkey has many challenges in the development of AI in terms of lack of financial source, high rate of brain drain, language barrier, industry-focused simple solutions, quality and originality of the works, and low ratio of implementation of AI projects into products and services. As first

of the challenges, the investments and financial sources are insufficient to conduct research-focused studies and develop the “state of art” technologies in Turkey. It also creates obstacles to keep the qualified human resource in the country. So, the lack of financial sources and investments cause to the second obstacle as the high rate of brain drain. According to participants, most of the qualified, Master’s or PhD students on AI migrate abroad to work or study in global tech companies, top startups, and top universities. So, the country cannot use efficiently its brain power. Thirdly, the language is a compelling barrier for Turkish students and employees who want to work in this field. According to them, the English education is not sufficient in most of the education institutions except a few of the top institutions. And the students do not have the motivation of developing their English knowledge. But, it is impossible to improve themselves in AI without an advance English level. Therefore, this language barrier limit the capacity of Turkish developers. Fourthly, the developments on AI is limited to simple, industry-oriented and profit-focused solutions in Turkey. Since the financial source is limited, the number of innovator, research-focused, and pioneer studies are low. So, that limits the potential of innovative technologies and “state of art” solutions. That eventually effects the quality and originality of the AI works in Turkey as a fifth step. Sixthly and finally, the number of AI products that are implemented publicly are low compared to the developed projects. If the number of projects that are not implemented is 80% globally, this rate is increasing to around 95% in Turkey. According to participants, Turkey is fortunate in terms of human resource. Even though many of the participants state that the qualified human resource on AI migrate to abroad for better working conditions and to develop themselves more; they claim that the Turkish AI engineers and academics are very qualified, but they are not benefitted efficiently. Some of the participants claim that the number of Turkish online sources such as YouTube videos, courses, and blogs are

increased in recent years. So, it can have a positive impact on the development of AI in Turkey for the people who are not advance in English. Finally, the subject of ‘AI hype’ is mentioned again under this topic. Many of the participants state that there are AI products in the industry that are not developed by AI methodologies, but simple rule-based softwares. The individuals, startups, and companies try to benefit from this hype to get public attention and get investment. The naming of non-AI software as AI cause to enlargement of the “AI Hype” and paradoxically many individuals and startups again want to benefit from this hype. Therefore, there are many simple (by simple I mean non-AI) developments and products called AI in the Turkish tech industry. Actually, the number of studies on AI lower than it is perceived by the public.

The working models and job hierarchies in AI companies, startups, and teams are the another important aspect to understand the workplace culture where the latest innovative technologies are developed in Turkey. I tried to analyze the implementation of “startup culture” driven by the Silicon Valley tech startups’ rapid growth strategy with a workplace understanding which is the casual, flexible, away from hierarchy. In the study, 18% of the participants work at the corporate companies, 4% of them work at a global tech company, and 78% of them work at the startups. Most of the participants define their working models and hierarchical order with the comparison of startups and corporate companies. They describe the startup culture as efficient, flexible, task-focused, and result-oriented. While some of the startups are totally flexible in terms of the working hours as day or night, weekday or weekend; some of them state that they have determined working hours with a flexible working environment. According to almost all of the participants, working at a startup required employees to have an understanding of work above the working hours. Since there are less number of employees at startups, each employee have big responsibility with a busy workload. So, according to the participants’ narratives, if you work at a startup you must love your

job and see it as your hobby. All of the participants define that they enjoy their work and that's how they can work at weekends, after working hours, or research about their work-related issue at late night. This blurred balance between work and hobby causes a dense pace of work for them. The less number of employees causes to use the brain power efficiently inside of the startups. So, creating micro project groups and assign employees in different project groups with different extent of responsibility is a common methodology. Also, in relation with the less number of employees, there is an uncertainty of the roles in teams. So, the roles are not divided with sharp and precise distinctions compared to corporate companies. The participants who work at the AI teams of corporate companies define that their working model is similar to the startup culture different from the other departments in the company. One of the participants especially state that the R&D team implements the Silicon Valley structure to distinguish their working model. According to them, they benefit from the positive aspects of corporate culture such as the division of labour in terms of responsibilities of each employee. This situation reduces the responsibility of them by dividing the tasks to the related individuals and relieves them in terms of workload.

According to participants, the hierarchical models are not suitable for the technology companies and startups. The leadership-oriented structure comes to the forefront in the interviews as it allows employees to self-govern themselves. The feeling of "having a share in management" is important for the participants to be productive while working with any member of the company/startup directly and closely. Almost all of the participants define that they have a horizontal hierarchy in the working environment. Most of the participants who work at startups and companies explain that there is no hierarchy in the process of doing jobs, having meetings, or in social relation; there is only a hierarchy in the titles as a formality to have structured system. Only, a few of them states that the working environment requires an hierarchy to manage the projects.

GENDER DIVERSITY IN AI COMPANIES, STARTUPS, AND TEAMS: PERCEPTIONS ON WOMEN IN AI

A. Introduction

In this chapter, I aim to analyze the perceptions of participants on gender in AI from an employee distribution and discrimination at the workplaces perspective. So, I touched upon the concept of gender distribution in the startups and companies, the number of women in technical occupations, participants' perspectives on this distribution, perceptions on gender in AI and in relation with that perceptions on less number of women in AI, reasons and solutions to this issue. I would like to understand how participants evaluate the issue of gender in AI, do they see a problem related to this, and how do they define the gender disparity in the field.

Secondly, I aimed to comprehend the issue of gender discrimination and bias which is the core research area of this study. Even though I did not asked participants directly about this issue, I analyze their perceptions on gender discrimination with the examples of realized events. I asked participants about the gender discriminative practices that are experienced and publicly/globally known cases in global tech companies. Besides that, in the semi-structured interviews, the topic of gender discrimination and bias subject naturally in the flow of conversation. In the interviews, I also observed that gender stereotypes on the developers' mindsets (maybe subconsciously) are revealed themselves. They often use stereotypical assumptions and referrals while explaining their views on gender in AI or women in AI. In addition to that, I especially talked about their real-life experiences, perceptions, feelings, thoughts, and more importantly their stories with women participants. Because, their feelings and experiences tell more about the situations of women who work on AI. In this study, 5 of the 22 participants were women developers from the early career to mid career women which tell different stories, experiences, differentiated perspectives, but also

some similar feelings and stories in details. This is the part of the study where we listen about women in tech only from women developers.

At the final step of interrogating the gender distribution, discrimination, and bias; I analyzed the solutions perspective for the gender inequality in AI. Under this topic, I asked about how do participants perceive the activities of women networks in the technology industry. Women organizations in tech industry are focusing on the strengthening women's presence in the field of technology by bringing together the women developers in certain specific areas or technology in general. They often work to provide networking possibilities, ensuring the information flow between women, and undertake activities in scientific or industrial areas. I wonder whether if the participants are member of one of these organizations or do they follow any of their activities. I also tried to understand how they view these organizations in terms of their role of bringing and strengthening women's presence in the field. Following that, the topic of "positive discrimination" was opened by all of the participants even though I did not ask specifically about positive discrimination. Actually, when I was structuring my question & topic set, I did not include a question on positive discrimination. But, as I observed from the interviews, the positive discrimination is an important agenda in gender-related discussions in AI. So, this topic became an important part of the study as a part of the solutions perspective which positive discrimination refer to the "artificial" efforts of institutions, companies, or NGO's to equalize the number of women and men in AI. To sum up, this second chapter of the study focuses on gender distribution, gender inequality in numbers, gender discrimination and bias, reasons and solutions about these issues from a workplace dynamics perspective.

B. Gender Distribution in Companies, Startups, and Teams

In this part, I collected startup employee data via LinkedIn to discover the number of women and men working on this field and the number of women in technical occupations to enlighten the gender distribution in the industry. According to my analysis, the total number of employees working at the AI startups is 2083 and number of women working in these startups is 597. So, the ratio of the women working at the AI startups is %28,6. However, this ratio reflects the total number of women who work on both technical and non-technical occupations at the startups. The total number of women working in technical occupations at AI startups is 184, which brings us the ratio of %8,8. In addition to the employee statistics, I collected data from the Higher Education Information Management System website of YOK which is the Council of Higher Education in Turkey. I aimed to see the gender distribution in the college departments which are related with the computer science and have the potential to work on AI after graduation. According to the Higher Education Council in Turkey, the ratio of women students in the computer science related departments is 24% at Bachelor's degree, 26,4% at Master's degree, and 25,7% at PhD.

I asked participants about the gender distribution in their companies, startups, and teams to understand the proportion of women and men working in technical occupations. As the participants of the study whom I interviewed with are 22 people, I wonder that this sample represents what kind of a gender distribution and how they evaluate this distribution in terms of numerical equality in the numbers of men and women employees. However, the proportion of gender distribution is based on participants' statements and I did not reconsider this information with any verification mechanism. So, the numbers are according to the participants' perceptions and expressions. When I asked about the size of the startup or team that they are working and the gender distribution in there, two of the participants prefer not to directly answer the question. One of them, Participant

21, doesn't prefer to share, since their startup is a brand-new initiative with no formalized processes yet. He says that there are approximately 4 employees for now, but he prefer not to share information about gender distribution. The other participant, Participant 6, also doesn't want to share the numeric data. But, he states that there are women colleagues whom they work at the same department. He continues his sentences as "At this point, there is a balance. It is not 50% - 50% of course, but it is also not a ratio like 1 to 10. So there is a more balanced environment. At least I think it has a more balanced ratio than the Turkish National Assembly". The participants who don't want to share the numerical data of the company claim that there is a balanced distribution between men and women employees. A participant, Participant 5, support his argument with these sentences, "In fact, we are a company with a high number of female employees, especially in the development team. Normally, you can see a 10-man development team in companies on the market. But in our startup, the female-male distribution is not bad at all". Although, since they prefer not to share the data, I cannot verify their statements about the ratio.

I asked each participant about their AI teams numerical size and gender distribution inside of the team. Besides of the participants who does not want to share numerical data about their company, the number of employees in the AI teams that participants share approximately 130 people and 27 of them are women. This rate is based on the statements of the participants, so I give the numbers without any verification mechanism. According to these numbers, the rate of women employees who work at the technical occupations in participants' teams is 9,7%. Some of the participants also mention the total number of employees working at the startups. According to this information, there are also women employees working at a non-technical occupations such as marketing, customer relations, or sales. Three of the participants state that there are no women working their company in a technical or non-technical occupations while the size of their startups are consisted

of 5, 5, and 10 people. In addition to this, the eight of the participants claim that there are 1 women working in their team with a technical occupations. And five of the participants state that there are 2 or more women employees in the startups that they are working.

While answering this question, some participants made a statement by mentioning the reasons, advantages and disadvantages of the ratio of women and men, while some participants found it sufficient to share only numerical data. Even though I did not ask for the reasons or their opinions on the issue, some participants point out the issue of the gender equality, the importance of merit in job application processes at the companies, human resource limitations in the AI field, and disadvantages of having women employees. In addition to that, some of the participants emphasize the women presence in this field with concrete examples from their lives. One of the participants, Participant 6, asserts that these are the male-dominant sectors and it takes time to equalize. He continues his statements as “There is no need to create gender equality just for ‘gender equality’. If the woman is already good, she will come and get that job”. Another participant, Participant 7, explain the low number of women in the companies by referring the limited opportunities in hiring processes. According to him, there are obstacles in the human resource of this field and companies cannot find candidates who can fulfill all the expectations. Therefore, there is no discrimination between men and women in his opinions. One of the respondents states that the number of women in their team is low as they are a very new initiative and this may be effect the gender distribution. One of the participant, Participant 2, who is the only women in an R&D department which is a team of 25 male colleagues recommends on the issue as “We are a team of 25 people, as the R&D center, I am the only girl. Did they do this on purpose? I think they didn't do it on purpose, otherwise they wouldn't really hire me either”. These answers enlighten the perceptions of

participants about the gender distribution in their teams and their understanding of the reasons behind of the low number of women working on AI.

Following the numerical data about gender distribution in AI development teams, I asked participants about how do they perceive the gender equality and gender diversity in their teams or startups regarding the numbers that they shared. Most of the participants claim that the rate of women and men in the teams are not reflecting an equality. Almost all of them claim that these numbers show the male dominance in the sector and it needs to be developed. Although, they are separated in terms of the reasons of this problem in their explanations and approaches. Some of the participants emphasize that their companies offer a tolerant atmosphere to all of the genders, races, or any other kind of differences.

As I mentioned before, many of the participants claim that the low number of women in the companies are not determined purposely and consciously just to increase the numbers of men and decrease the numbers of women. In many narratives, the reason for this situation is seen as the number of applications of women to the technical occupations or to startups are low. Since men apply for technical, AI-related job postings more often, male candidates are mostly hired. One of the participants relate this issue with the obstacles of human resource in this field. He, Participant 7, emphasizes these obstacles at the different times of the meeting as “Frankly, we look at our needs when we are recruiting staff. For example, we look for a staff who has done the following requirements about NLP. Whoever comes is recruited, there is no specific evaluation of gender”. Another participant relates this issue with the company’s legal obligation on discrimination, and he emphasizes the probability of low applications of women. In his statement “The company I work for is actually an ‘equal opportunity employer’ by law. Here, they are directly responsible for the law on discrimination issues such as race, gender, ethnic origin, sexual orientation”.

Some of the participants state that the ratio of female employees close to men is also important in terms of outsider perception about the company and communication and order within the company. For many of them, the corporate image and the perception when a person looks at the company as an outsider is an important factor to create a welcoming atmosphere. One participant explain this in their startup as “Especially, recently, there was a period when there were no women in the team, and we gave priority to female candidates a little during the recruitment process because we thought we might draw reaction at this point and on the other hand, we really thought that the team was moving away from professionalism. Because it is also valuable for us to ensure equality between women and men, but I can say that we are still in a deficiency”. This narrative also points out the two of the important effects of having female colleagues at the workplace: outsider perception on the company and order within the company. Another participant especially mentions that women employees bring order, discipline and decency in the workplaces. He, Participant 7, states that “I mean, the fact that there is a woman in the team gives everything in order. In general, a more disciplined environment is formed by that. This is reflected in the speeches of the staff, they do not speak too loudly or slang”. Another participant, Participant 2, points out this issue with her existence in the team as the only woman “The company we work with is very comfortable, there is actually an offhand culture among men. Since I was the only woman in the team, there was often the situation ‘Participant 2 is here now, I can't tell’. But in their way of speaking I see them limiting themselves for their kindness to me”. But, in her narrative, this situation gives her both a pleasure and a discomfort. These kind of self-limiting actions and attitudes of male colleagues are felt like “she is breaking their dynamics”. While she is appreciating their attitudes for her, she also feels like an outsider who disturbs them.

As a result, according to participants' statements, the rate of women employees who work at the technical occupations in participants' teams is 9,7% . Most of the participants define that the proportion of women do not represent a gender equality in terms of numerical distribution. Many of the participants see the main reason for this as low applications of women to the technical occupations. So, for them, there is no gender discrimination in the hiring practices and this proportion is not done in purpose. Some of the participants state that having women employees in the company is important in terms of company image and order within the company.

C. Perceptions on Gender in AI: The Situation, Reasons, and the Solutions

After examining the perceptions of participants about gender distribution and diversity in their workplaces, I asked about their perceptions on gender in AI generally in order to understand whether there are any problems of gender in AI according to them and to discuss both the reasons and the solutions. Most of the participants respond this question broadly by examining the social, individual, and cultural explanations around the issue. Totally, 11 of the 22 respondents which means %50 of the respondents assert that there is no problematic situation about gender in Artificial Intelligence (AI) generally. 4 of them claim that there is a numerical inequality between men and women working in this field, however there is no discrimination or any problem related to gender in the field. 3 of the respondents state that there is no problem particularly in tech or AI, but there is social and cultural problem in the stereotypical assumptions for each occupation. According to these narratives, participants tell the importance of family and society to shape the children's lives and career paths. But, it is not specifically in AI or tech, it is applied in many occupations. I will broadly analyze the effect of society in terms of heading to an occupation. The other participants who also claim there is no problematic situation about gender in AI emphasize the dependence of individual success to proceed in this field. In these narratives, AI and technology

sector are totally dependent on the personal skills of individuals. According to a participant's explanation, Participant 18, if we compare one woman and one man who have completed the same schools, courses, internships; they both have the same opportunities in professional life. 4 of the total participants make more uncertain statements about the problematic situations regarding gender in AI. They assert that they are not sure about the gender-related problems in AI. One of them claims that the situation of women working in this field is getting better and already good at academia. Two of them say that there can be a problem or not, they are not sure. The other participant tells that even if there is a problem in Turkey, according to his personal opinions and observations the situation between men and women is equal in the USA or Europe. Finally 7 of the participants which means 31,8% of all participants clearly state that there is a problem in gender distribution and diversity in the field of AI generally. While according to their narratives, the number of women in AI is less than men; respondents are differentiated in their responses on reasons and outcomes of the issue. One of the participants, Participant 8, defines the "problem" in reference to struggles that women academics face in this field, but she emphasizes the importance of not equalizing people just because of equalizing them. According to her, personal success of individuals is more important than ensuring the numerical equality between men and women. And she defines that she has an uncomfortable feeling of getting the royal treatment just because being a woman. She states that "I don't like being emphasized that I am a woman. I do not work there because I am a woman. That's bad if I'm chosen because of that. I do not like to use my being a woman or to emphasize that I come from a certain social segment in my applications. However, I see the inequality in the ratio of men and women". Another participant, Participant 9, defines the problem in relation to the algorithmic fairness and bias. He states that the gender imbalance in the workforce is reflected in the algorithms and systems; and he emphasizes that he is working actively

to strengthen the presence of women in the field of AI. However he also defines that women are not exposed to inequality of opportunity about getting a job, learning software, or taking part in a project in the beginning levels of their careers. According to him, gender is considered at the advanced level of their business life, such as being promoted to a managerial position. While other participants also emphasize the numerical inequality between men and women, one of them, Participant 20, states that the imbalanced ratio between genders is not specific to AI, but broadly in technology and engineering fields. Most of the participants refer to the societal reasons and social construction of gender roles as the reasons of lack of women in AI. So, what are the underlying causes of gender inequality in this area, according to the participants? How do software developers evaluate the foundations of gender equality or inequality in artificial intelligence?

The Underlying Causes of Gender Inequality

a) The Societal Reasons and Nurturing Styles of Families

I asked about the participants' perceptions on the reasons behind of the numerical inequality between men and women workforce in AI. Half of the participants refer to the societal reasons such as gender roles on division of labour and nurturing styles of families on children as the common reason of the lack of women in this field.

Some of the participants see the primary reason behind of this as nurturing styles of families. So, it is very important for families to be conscious about not raising the children according to the gender roles in society. One of the participants, Participant 6, states that he cares to hire people merit based methodologies and according to him, the male candidates have higher technical capabilities than female candidates so far. He sees that the reason of higher success of males lie behind the different nurturing styles of parents to their daughters and sons. Accordingly, he states that "In Turkey, whenever a rubic cube is bought as a toy, lego or puzzle is bought for every child,

regardless of whether they are a boy or a girl, it can develop in that way. I mean, not a barbie doll for a girl, not a truck for a boy ... If I have a girl one day, I will buy a truck as a toy. It develops this way, it doesn't happen the other way around". According to his narrative, the nurturing styles of families to girls and boys and responsibilities that they are taking in the family are so different. "In other words, the girl starts looking after someone from an early age, looking after her siblings. The boy goes to plow the fields with his father from an early age. There is already a code that sits in childhood". According to another participant, Participant 18, the role of the families in the process of choosing a profession is really important. So, he defines that both of the reason and the solution lies behind of the families: "The responsibility for this lies with the family. I think positive discrimination should be widespread in the family. Unless we raise the awareness of families, neither inequality nor anything else will end. Let's give thousands of seminars in companies, this may not end, but I think this inequality will decrease when we work on families". Another participant, Participant 20, also gives importance to the families and the nurturing styles of them in the process of university preferences. Participants often refer to their personal experiences about these issues while evaluating the womens' presence in the field. One of them, Participant 21, also states that families have a huge role in the process of choosing a discipline at the university. He tells that "When I looked at the starting process to university myself, my girlfriends around me were always directed by their families to professions called "women's professions" such as medicine and pharmacy. For example, a friend of mine had a completely engineer mindset, she was a very successful, very intelligent friend, but she studied medicine at the insistence of her family."

Some of the participants state that the gender roles in division of labour gain importance in this inequal distribution of genders. According to that thought, the successfull women in the STEM

fields tend to choose professions like medicine or department of molecular biology and genetics. While some professions and departments at universities are seen as suitable for males, the other ones are seen suitable for women. One of the participants, Participant 6, gives an example of “teaching for girls and engineering for boys” while talking about the perception of society on gender roles. Other participants also support the idea that the perception of society determine the choice of certain occupations for genders. According to a participant, Participant 19, gender division of labour in daily life refer to the same differentiation such as “when the TV breaks down, man fixes it, not the woman”. In addition to the gender division of labor, one of the participants emphasizes the historical roots of this differentiation. In his opinion, Participant 7, the less number of women in AI is related to the associated with less participation of women in the labor force. So, if we would like to understand the reasons behind the unequal distribution of genders in AI, we should look at the reasons of less proportion of women in the labor force.

Another participant, Participant 8, refers to the gender stereotypes and prior experience as the reasons behind of this numerical inequality. Gender stereotypes such as “women cannot work at the construction sites” are the barriers in front of women in some occupations, although the computer engineering is not an occupation like that. She states that the prior experience and personal interest on computers can be a reason for women to stay away from this area. Because, according to her, generally boys are more interested in computers and computer games. So, people assume that they should have a prior knowledge or interest on computers to become a computer scientist. She emphasizes that the media also reinforces the gender stereotypes by characters. “I don't want to attribute it to this, but we always see black screens, green letters and male hackers as outliers in movies, actually, this may be a bit related to the media. I have never seen a woman in this character. Men are always played. I am actually one of them. At some point you feel like a

‘geek girl’ is a very rare thing”. The stereotypes regarding gender roles are also mentioned in another interview. One of the participants, Participant 2 says that the gender roles for each occupation have transferred through society. And she states that “However, it has not much to do with the fact that this (technology and artificial intelligence) is a man's job. But yes, that "nerd" character in my head is also a man.” The narrative of stereotypical assumptions and the role of the media reinforcing these stereotypes in society are mentioned some of the interviews. According to some of the participants, cultural products such as movies or TV shows reflect those stereotypes and therefore the perception in the public are shaped by those images and characters. One of the participants, Participant 5, states that “We have seen for years both in movies and as social culture is an imposed perception that things like engineering are done by men.”

b) Lack of Role Models

While most of the participants evaluate that the reason lies behind of the less number of women in the field as societal factors such as stereotypes, division of labour, and nurturing styles of families; correspondingly, some of them state that the reason may be the lack of role models for women. According to them, the lack of role models for women in the engineering areas becomes prominent factor as one of the reasons that women do not choose these areas as professions. One of the participants, Participant 9, emphasizes the lack of role models and motivation of women. As a result of the inequality of opportunity women suffered in the past, he sees that women do not have enough motivation because of the uncertainty of what to aim and where to reach. For him, even though there is not an inequality of opportunity for women in the beginning levels of business life, these two factors effect women to choose or proceed in these fields. He tells that “You may not set out on a road that you cannot see the end of. So, for example, you are walking on a road, if there is the sea at the end, you will walk to that side. But if there is a garbage dump at the end, you don't

walk in that direction. This situation is just like that. In other words, if we do not reveal situations such as women achieving very significant success, if these examples do not exist, unfortunately women will not be motivated for that job from the beginning. It is not enough just to create an opportunity.” According to his narrative, even though there are no barriers for women to enter or work in AI, the number of women is less because of lack of role models and motivation. Therefore, creating an opportunity for women such as offering free courses for them does not efficient by itself, you need to increase the number of succesful role models for them. Another participant, Participant 11, evaluate the role model issue from a different perspective. According to her, the role models of people’s lives are the important figures when growing up such as teachers. And their guidance has an important effect to determine the career paths and fields of interest. According to one of the participants, Participant 19, define the effects of lack of role models as “Again, as a vicious circle, the low number of women working in the sector prevents them from entering.”

c) Personal Field of Interest & Characteristic Features of Women

Some of the participants find the roots of the problem in sociobiological explanations regarding the characteristic features of women and their personal interests. The sociobiological roots for the sexual differences also exist in the literature. For example, a former Google software engineer wrote a ten pages manifesto called “Google’s Ideological Echo Chamber” which argues the reason of the less number of women in the technology field and leadership positions is because of differences of women’s abilities and preferences. The whole document included a resentment towards Google’s efforts on increasing the diversity (Gurchiek, 2017). As some of the participants refer to sociobiological reasons by explaining the low number of women in the field, some of other participants refer to these kind of stereotypical assumptions about women to evaluate gender-

related issues in general. According to their narratives, women tend to like areas such as designing or a field that they can add their “social skills” more than men. Therefore, women engineers prefer web or mobile design occupations or business-related jobs at the job market rather than developer jobs. Some of the participants claim that there are more women in academia working about computer science and/or AI just because the stability and assurance of the academic jobs rather than the industry. So, these participants state that gender diversity in academia is more balanced than the industry. One of the participants, Participant 19, states that finding a job on AI is more troublesome than other areas and also the working conditions of startups such as salary or working hours are worse or more difficult than corporate companies. So, according to her, maybe women may want to feel themselves safe more than others or work in a more comfortable working environment. That’s why they do not prefer to work on AI. In these narratives, we can see that a secure, safe, comfortable, and more stable job environments are often found suitable for the characteristics of women. Another participant claims that there may be a little less technology inclination in the nature of a woman, but she is not sure of the validity of this thought. According to her, the talkative, social aspects of women cause them to stay away from the technology-related areas which requires a more asocial human type.

One of the participants, Participant 20, states that the characteristic features of women may be not suitable for the field of technology, but she is uncertain about the validity of this assumption. She tells that “Maybe there may be a little less technology inclination in the nature of a woman. But I am not sure. I personally don't think it is, but maybe it could, I don't know. The social side of women is more dominant than men. Maybe we can make such a generalization. I can say that the woman is a more talkative, more social type of person, and therefore the job branches with more social environments may be attractive to teaching, medicine, nursing and so on. Because when you

enter the field of technology, you can shift towards a more asocial structure.” One of the participants, Participant 21, criticizes the thought of seeing women inferior in the field of technology and AI because of the natural aspects of women. He states that “Unfortunately, I had a colleague who argued that the number of women was low because of the innate failure of women in this area. And it is not unlikely that people with this kind of thinking will be encountered. This of course also has a domino effect. So when such people work, when these people become decision-makers and recruit, that brings along their prejudices.”

d) Technical Proficiency in the Field

When discussing about gender in AI, some of the participants state that AI is a field which only requires technical skills and proficiency of the developers, so the problematic situation with gender diversity is not caused by technology or AI. This is not a reason for the numerical inequality between genders, but I especially handle this topic under the reasons heading since I would like to show the perceptions of developers on gender and AI in total. The participants who emphasize the importance of technical side of AI are the ones who search the causes of less number of women in the historical development of division of labour, societal factors such as gendered identities of occupations, and nurturig styles of families toward their kids. So, this emphasis on technicality and objectivity is important to understand the perceptions of developers at the intersection of gender and AI, as a concept that are in relation with each other.

According to the statements of some participants, gender of the individuals is actually not an important factor to work on this field. When a person meets the technical and knowledge-based requirements of the job, gender of the candidates are not considered as a metric to hire them. For one of the participants, Participant 7, there are already obstacles in the human resource of this field, so companies or startups cannot evaluate or discriminate the people according to their genders who

apply for the job even though they want male employees. So, if you meet certain requirements you are more than welcome whatever your gender or race is. According to another participant, Participant 6, it is important to recruit employees on merit. He tells about his recruitment method which includes testing the technical competences of candidates to complete the recruitment process on merit independent from the characteristic aspects of them such as gender. He states that “For example, I prepared a system for the recruitment of interns and this system was very popular. First, I prepared a quiz for the selected candidates and sent it, I chose the candidates I would meet with the answers given to these questions. Whether the candidate is a man or a woman does not affect any of these questions. If the CV is strong, the CV is strong. But let me tell you what I noticed, unfortunately I did not do a video interview with any female candidate. Because the technical competencies of the female candidates who applied to us were lower than the male candidates. The reason I say unfortunately is that I really wanted to take the initiative to meet with female candidates, but at the end of the day, when we compared the answers, as a result of the mathematical realities, it was the male candidates who had the characteristics I wanted in terms of CV and technical proficiency.” The participant defines that he is familiar with preparing these kind of questions from his university, Bilkent University which is a well-known, successful, and prominent private university in Turkey. This kind of hiring method of the participant is really similar to the “whiteboard challenge” which is a popular hiring method for the Silicon Valley startups and classroom work at Ivy League institutions. There is a similar risk here as this recruitment method creates the illusion of bringing together people of similar gender, similar backgrounds, similar universities, and similar socio-economic status as in Silicon Valley. Although it is thought that such a recruitment method will produce objective results, it may cause unconscious biases to come into play. This entails the danger of eliminating people who are not

educated in leading schools and who are not habitual to solve such problems. This situation can bring about not only gender but also other types of exclusion as seen in the literature (Thompson, 2019). The familiarity between whiteboard challenge in Silicon Valley and the participant's quiz-based hiring method refers to the culture of coding and computer science. According to Thompson (2019), "women are not the only ones who are excluded but also everyone outside of this culture (Thompson, 2019). According to another participant, Participant 8, the technical aspect of the job annihilates the importance of gender. For her, gender does not create a difference in the process of working on AI, so it should not be forced to be numerically equal in any case. She states that the different kinds of genders do not enrich the quality of the work, therefore there should not be any artificial effort such as positive discrimination to increase the number of women. Accordingly, in her narrative, the most important factor is the technical capacity and quality of the person who is coding or working on AI.

In parallel with this thought, two of the participants suggest that there is no need for equality just to create the equality. They mean that the numerical gender equality in AI does not have an extra positive impact on the developments in AI and technology. One of the participants suggest that gender would not enrich the quality of the works on AI because of the technical structure of the field. The other participant suggest that there is a need for qualified developers in the field from any gender and race, and we cannot make a distinction for any of the genders.

D. Gender Discrimination, Bias, and Stereotypes About Women: Examples from Big Tech Companies

In this section, I aimed to understand the perspectives of developers on gender discrimination and bias comprehensively. I did not ask participants directly about what they think about gender discrimination. However, I tried to understand their views on gender discrimination with the real

cases from global tech companies. Besides that, in the semi-structured interviews, the topic of gender discrimination and bias subject naturally in the flow of conversation. These cases contain different kinds of discrimination and bias towards women engineers working at tech companies. I selected a few of the global examples that contain different kinds of discrimination in the leader companies in the tech industry such as Tesla, Uber, Google, Oracle, and Microsoft. There are also other discriminative, scandalous incidents experienced in other companies, but I wanted to select some of them to diversify the incidents from wage gap to discrimination and harassment since these are the pioneer and well-reputed companies in the tech industry. At 2013, AJ Vandermeijden filed a lawsuit against Tesla where she was working as an engineer because of the concrete, harmful outcomes of male dominated environment at the company such as pay gap between male and female employees, discrimination and harassment incidents towards women (Kolhatkar, 2017). At 2017, Susan Fowler, a former engineer at Uber, wrote a blog post about her experiences of sexism in the company towards women employees, gender bias, several inappropriate, sexual harassment cases that she and other women colleagues went through, and no actions that are taken after these cases are reported to high-level managers and HR (Fowler, 2017). At 2017, Google was accused of that a “systemic compensation disparities” between men and women employees by US Department of Labor (DoL). According to the statements of US Department of Labor (DoL), Google has a huge gender pay gap against women employees in almost any department at the company compared to men. Similar to Google, Oracle which is another big tech company, was accused of pay discrimination against women (Levin, 2017). At 2019, an e-mail chain which contains e-mails of dozens of women working at Microsoft was leaked about their experiences that includes gender discrimination, sexual harassment, and overlooking of HR to these incidents (Campbell, 2019). Besides their perceptions on the global discriminative

cases towards women, I also observed the gender stereotypes on developers' mindsets and perceptions by examining their explanations, their words that they used while talking on women in AI or the relationship of gender and AI.

When I asked about the gender discrimination, bias, and harassment cases in big tech companies, I wanted to understand whether the participants follow these kinds of social crisis in these companies, how do they approach to these events, and how do they evaluate the gender discrimination and bias in tech companies. Most of the participants claim that they are not following such events of the big tech companies, but they mention that there are already aware of inhumanitarian conditions at these companies in terms of working hours or employing low-cost employees such as immigrants in the USA. Some of them says that they are partially following these events and news.

While some of the participants interrogate the reasons behind of the gender wage gap, some of them automatically respond by emphasizing the impropriety of the situation. According to most of the participants, the reason behind of the wage gap is the disadvantageous positions of women because of their maternity leaves or the higher possibility of turn over of women than men. They state that since these companies are working with a capitalist system, they would like to decrease their costs and risks as much as they can. One of the participants, Participant 6, interprets these issues as "The value of the position should be evident so that the equality of men and women is equal in pay grade. As this is not the case, women are often at a disadvantage anyway. So there are companies that make contracts not to get pregnant with women. At the end of the day, in case of getting pregnant and leaving the job, companies pay low wages and reduce the risk. For example, one of the reasons is this very simple. Another reason is adaptation problems: in male-dominated sectors, women's adaptation is not necessarily same as men's adaptation. Therefore,

here they try to take a lower risk to see if it will be turnover due to adaptation problems.” Some of the participants touches upon the importance of seniority of titles and positions while evaluating the wage gap in big tech companies. According to them, the wage ratio of men and women can depend on their seniority and professions. If there are more males at the management level, this can effect the distribution of wages and make the difference. According to one of the participants, Participant 7, the wage distribution is related to the professions at the company. For him, we cannot determine whether women earn lower salaries because of they are women or because of they apply to occupations which have lower salaries is a hard question to answer. He states that “We need to look at what the professions of those low-salary employees were. Inevitably, there is this, it is not desirable to employ men in certain occupational groups because it is said that if we employ a man here, he will have a family to support, the wages we pay are not very high. That's why the man who will work here leaves after a while. If we hire a woman, it will be like an additional income. As a matter of fact, the social expectation is not above her at the point of supporting the family. This would be an extra income for the woman, and an extra income for the family. But when you look from the top, people in a department get less salary and employees are more women. Naturally, such a structure has been formed, but it has come to the point where women are paid less. I don't know, it is very difficult to measure such things frankly. In other words, whether they earned less salary because they were women, or because more women applied to a less salary department, women automatically reached the level of receiving less salary. We do not know this. In other words, it is a fact that female employees are paid less in Turkey, so automatically.” Some of the participants touches upon the negotiation skills of women at the job interviews. According to them, since women are less skilled in negotiations regarding the job conditions, they are more likely to be less paid. Participant, Participant 18, states that “Yes there is discrimination but I think

it is purely statistical. I saw a research about job application. For example, there is an advertisement, there are 10 criteria, men and women meet 3 criteria, but women do not apply for a job, men apply. Recruitment rates may also be related to this, that is, men may also be able to apply and enter a job they think they cannot get. Secondly, a person's negotiation skills are very important. At that point, there may be clearly discrimination in companies ... people need to learn to market themselves, HR interview is something that has very clear mathematics, if you are the dominant party and main factor in the HR interview, then you may be able to determine the price of that meeting.” In relation to the wage negotiation skills, participant Participant 2 emphasizes that women should criticize themselves for this wage gap. She states that “I think women should criticize themselves here, too. I have also observed this in myself. I woke up to this idea first thing, when I read Facebook's CEO book. He says that although the trend of feminism has increased, why does not the number of female managers increase? I think he says it very well, he criticizes women, so he finds the fault in us. Actually, he says, you don't sit down and do that bargain. In other words, we did not seek our rights or we were hesitant. We see that women actually have a tendency to say that I will have a child anyway, I have more responsibilities at home, should I take an additional responsibility. Here the thinking of women needs to change a little bit. They need to be more confident in themselves, sit at the table and ask for more. Perhaps because women were shy, the other side was also inclined to exploit. In other words, he actually pays 12,000 TL to a man who does the same job as you, but when I say my salary expectation is 10,000 TL there, he says that we will pay you 12,000 TL is very extreme with a business mindset. I mean, we actually created the problem a little bit. So it's actually due to the insecurity within women. If we become conscious here, this problem will not remain. We definitely have to self-criticize ourselves here.”

According to these evaluations, the companies try to hire people with the lowest cost, so these kind of events could be happen.

Some of the participants are irresolute between whether these big tech companies are applying discriminative attitudes and conditions for women employees or not and whether the whole company is responsible for these unpleasant events. Participant Participant 8 comments on the issue as “In such a situation, I do not know if the people at the top of the company are aware of this or whether everyone in the hierarchy is aware of each other. So I am confused about how to comment on the company's vision. I wonder whether the decision of a wrong manager should cost the company or not, or should there be a bias about that company based on such a wrong decision.” Another participant, Participant 14, tells about his indecision as “I don't follow these events privately, but of course I hear the news, I listen to what people think about these issues. But I don't follow very often. I also listen to people who are against it, there are people who say that this salary separation has very different reasons and that discrimination is not malicious. Complex problems, lots of people give very clever answers on both sides, both opponents and supporters. I am not sure because my own experience is very insufficient.”

Another participant, Participant 11 evaluates the issue with questions on the gender discrimination. She claims that the working conditions in big tech companies are not very humane, but these are not specifically for women. She says that “I follow these events less as they come to mind. But I know that working conditions in those big companies are not very humane anyway. They pay more based on performance and based on your manager's performance evaluation. And because the competition is so high, it takes minutes for them to throw at you and find someone else. I didn't know that there was a lot of discrimination against women, but in these companies, I don't think so. Could they be doing this kind of discrimination against women? I know that there were protests,

but I don't know how much trouble they have experienced.” She continues her comments with evaluating and comparing the women in tech and women who live in different bad conditions: “In the technology sector, women are relatively comfortable, I think when compared to a non-working woman, a woman in the East, a child bride. I think it stands out with a lot of success and work. I think gender is in the background too. I hope this is the case, especially now in Western societies.”

Some of the participants comment on these issues as a mere negative attitudes of the companies. According to that, the companies should evaluate the performance of employees or any other measureable, concrete parameters. And, gender is not one of them. They believe that gender pay gap is an unacceptable policy for any company. Participant 19 interprets on this topic as “So I'm just saying it's so sad that people experience these things because of their gender. We need to look at what people do. If they are doing that job as desired or better, their personal characteristics should not be very important to anyone. We have to pay them for their labor. Repaying their characteristics is not something companies are supposed to do. What I call characteristics is being woman, being black, being Muslim, these kinds of things...” Another participant Participant 22 mentions about his anger to these issues “In fact, I realize at times that these companies are not that big, I realize that people still carry their prejudices there. I'm very angry about these issues, I don't know what I can do, but if I ever come to a startup or a big company, I will pay attention to these issues. So that's the best thing I can do right now. So I am reactive.” One of the participants, Participant 13, suggests solution mechanisms for women while commenting on the issue negatively. He states that “I haven't heard of these events much. Maybe because I don't follow the agenda very much. Of course, if there are such things, it is very wrong. It is very wrong if they pay less just because they are women, independent from their performance. I think transparency may be the solution. Transparency of the company and employees to each other can solve this problem.

Or it can help employees to join unions and try to prevent this. Because if everyone is being wronged without knowing each other, everyone can think of themselves as being injustice individually. But if they know about each other, they can prevent it. Trade unions, communication and transparency can be important.”

Two of the participants mention the problems that women face at their professional lives and the effect of culture on these issues. These kind of wrong applications are not specific to the technology or AI, these can be seen in any industry and in the society itself. One of the participants, Participant 21 states that “The effect of this on technology may be through culture. In an environment where such practices exist, it is guaranteed that the culture within the company will also be harmed. In general, healthy products do not come out of an unhealthy environment. Since these companies are big companies, they give the opportunity to see the trouble that is happening in the general society. So I think this is neither specific to Google, nor Facebook or any other company. I think the repercussions of larger problems in those companies.” Another participant, Participant 3, emphasizes that this is not a specific topic for artificial intelligence. In general, he thinks that there are situations such as giving women less salary, less responsibility, less authority, not promoting higher positions in working life. But he highlights that these situations are getting better by time and we need to stay positive.

Only one of the participants, Participant 12, answers this question with a precise ignorance of discriminative attitudes and policies at companies. According to him, people determine the value that they work for and nobody force them to work on any sharp amount of salary. He states that “No, I do not follow. I've never seen it, frankly. But I can say that there is no such thing as discrimination. After all, they give you a value. Nobody makes you work by force. You can work or not work if you want. After you accept the offer, no one is responsible. If person A works for

this amount of salary and Person B works for this amount, this is not a matter of concern to anyone. The company can follow a salary policy as it wishes.”

As a brief conclusion, most of the participants do not follow these kinds of social events of the big tech companies, only a few of them share that they see some of these news. We can see from the narratives, many of the participants see the primary responsible for this wage gap as women. They state that the disadvantageous positions of women such as pregnancy, working in a male-dominant area, low negotiation skills, and characteristic aspects cause to happen this kind of wage policy of the companies. Some of the participants say that they are not sure if these cases are actually happening and should we blame the companies for some people’s or HR’s decision. Only a few of the participants comment on the issue as a mere negative and discriminative policy of the company.

E. The Stories of Women Developers: Perceptions and Experiences of Women on Gender Discriminations

In this research, interviewing women developers is especially important to understand the gender discrimination and bias in AI. Because, even though there are previous studies to demonstrate the difficulties for women in tech on payments, promotions, conscious or unconscious biases, and harrasment at the workplace; it is vital for my research to understand women’s experiences from the primary source. What are their experiences as women developers? How do they prefer to follow a career in AI? How do they perceive gender discrimination and bias in this field? What kinds of experiences do they go through?

I interviewed six women who actively work on AI. While one of them is working at a global technology company and one of them is working at an online media company; four of them works at AI startups. But, all of the participants are working at the AI, ML, or R&D departments of their companies and have technical professions there. When I asked about their personal stories to

choose to study on engineering at the university, most of them state that they choose this field because of a personal interest on mathematics, succesful education history on STEM fields, or an earlier interest on computers. Four of the participants mention that their previous experiences and interest on computers effected them to study on computer science. Two of them state that they did not think of preferring computer science even though they have a special, personal interest on computers. One of them tells about her process as “Although I was heavily interested in technology and computers, computer engineering had not crossed my mind during the university preference period. I also saw myself as someone really free from sexist thoughts. But perhaps it was such a fundamental societal bias that it never crossed my mind. After the exam, I noticed that ‘there is also a computer engineering department’. All of my friends and I suddenly thought, ‘Why don’t I really think of computer engineering?’ even though I was so interested. I still think about how it didn’t cross my mind.” From this narrative, we can see that the societal biases on gender division of labour may effect our perceptions consciously or unconsciously. Even though the participant defines herself as “conscious about sexism”, she says that she also “fall into this trap”. The societal biases and male-dominant aspect of the area can mislead women who are evaluating to study or work on that. Another participant, Participant 19, tells about her indecision period as the field of computer science is a male-dominant area. She states that “When I was at the process of entering college, I was asking the following questions like everyone else: ‘Is engineering a man’s job? Will I be able to be there? What is the ratio of men to women?’ The rate of men was 70 percent while I entered university, I think it still is. People inevitably think about these while choosing a profession and it seems to be a disadvantage in the eyes. I thought it was a disadvantage of this field that there were too many men. Unfortunately, I had questions such as should I not go or is it not suitable for me. Total unconsciousness.” Two of the participants tell that they prefer to study

on electrical and electronic engineering because of their success and interest on mathematics and to have multiple working area possibilities after the graduation. Following their university preferences, all of the participants state that they decided to move forward in AI, ML or DL as this area was interesting and fun for them and their personal interest about the field.

According to my interviews with them, most of the participants do not like to be emphasized as a “woman”. They are concerned of their gender to get in the way of their success. Furthermore, they are worried about excluding themselves from all developers and engineers by emphasizing the identity of “women” so much. Especially, two of the participants accentuate this fact. One of the participants, Participant 4, claims that the emphasis on being “a woman developer” has a negative effect more. She says that “I never wanted to stand out with my gender, to define myself as “oh, I am a woman software developer”. I always wanted to say I am a software developer. So, for example, when you create a grouping, you also exclude yourself even if you don't have it in mind. I do not like this kind of situations very much.” By ‘excluding yourself’, she means that excluding yourself from male software developers when you identify yourself as a female software developer. Another participant, Participant 8, also comments in a similar way. She claims that the emphasis on “being a woman developer” makes herself uncomfortable like she has achieved more than the male developers. But, she says that “They see it as if they actually glorify you. In fact, it seems to those people that even though the things you do are the same, you have accomplished something great because you are a woman.” She highlights the uncomfortable feeling of being defined like that.

At the previous section, I mentioned that some of the participants dwell on the technical structure and aspect of the AI and technology. Some of the male and female participants define that the gender does not change anything related to the quality of the job because of its a pure technical

process. So, as long as a person is a good developer, s/he will do the job well. In parallel with this, one of the participants, Participant 8, defines that gender does not have a positive impact or not create a difference on the development of AI which is a mere technical field. She adds that the different ethnic backgrounds may create a difference, bring something different to the table, although gender diversity cannot. In any case, an artificial effort to increase the gender or ethnic diversity should not be applied according to her. While explaining this, she gives the example of “a speaker group that is only consisted of male participants”. She states that “Some speeches are only consisted of men. It's ok for me to have only men in some of the events. In my opinion, if a speaker will be there just because she is a woman, then she should not be there at all. Perhaps the subject is really the area of expertise of those people. There are also some facts, women are not small in the development of AI. So I don't think it's right to put a woman there just because she is a woman. I think it is necessary not to be angry because a speech consists only of men.” Another participant, Participant 4, also evaluate the male domination in the field in the similar, positive direction. According to her, people who criticize discrimination against women discriminate more by emphasizing the women’s absence and male dominance so much. She says that “What really bothers me is that people attack this as a group of 7 people are all men. 7 is a small sample set, so it seems quite plausible that everyone is male. It can be like that. Or when they see a woman, they flabbergastingly say 'woman software developer', these anti-discriminatory people who actually discriminate. Sometimes it evolves into this, they involuntarily discriminate themselves. It bothers me. Of course, there are many people who are trying to achieve this very properly, but sometimes they are hindering instead of supporting. This situation bothers me.”

I also asked participants about their experiences on conscious or unconscious discriminatory attitudes and behaviors during their education and business lives. I especially asked them the

situations that could make them feel uncomfortable and a sense of 'not belonging there'. Because, as I see in the literature, these situations may not be overt discrimination all the time. These can be a look, an implication, a word, an attitude that can be felt them bothered. According to most of the participants, discriminatory or biased attitudes and behaviors are experienced more at the early years of education and at the younger ages. According to one of the participants, Participant 11, “At school, in a more inexperienced environment, in an environment where students are present, there is a different feeling. Well, there is such a prejudice, you feel it.” According to her, especially when the number of female students are very low, the social relationships at school become different and female students feel the prejudice against them. However, while the education level is increasing, the prejudiced attitudes, behaviors, and feelings decrease. She defines that especially at the Master’s and PhD level or at the working environment, there is a positive effort of male colleagues to “not be sexist”. Following that, even though the number of women is still low, men are so conscious about these social issues and they are trying to be sensitive. Another participant also points out the same situation that the level of consciousness depend on the age and education level of individuals. According to her, Participant 19, while she experienced discriminatory and biased situations at the Bachelor’s degree, she does not encounter such situation at her workplace. Most of the participants state that they do not encounter any biased or discriminatory attitudes and behaviors at their workplaces. Yet, they mention that they have experienced such behaviors at their schools or networks.

The first discriminatory behavior is consulting or asking to a man rather than woman who works at the same topic and has knowledge on that. Almost all of the participants have experience on this negative attitude at their university times. According to their narratives, female or male friends tend to ask a male friend even though they know that she has knowledge on the issue or people do

not care about the comment on a technical issue that she do. One of the participants, Participant 19, tells about a situation that she was dealing with her close friend at the university. According to her, even though she was the highest ranked student at the computer science department, her knowledge was taken for granted. She states that “When I was in college, my best friend would often ask another boyfriend about the point she stuck with in an assignment, instead of asking me, even though she knew I knew the subject. She thought men were better than me. She often expressed this openly as 'men are better in this area, they will be better. Because this is their hobby. For example, they develop coding techniques in their spare time. But when you're idle, you're walking around an online shopping application.' Okay, right, I'm doing this, but that doesn't mean I'm bad or that I haven't improved myself in another free time. It is very difficult to explain this.” According to her narrative, she did not only experience this situation with one friend, many of her friends at the college had the same attitude. She says that “I had a lot of friends who talked to me about ordinary issues and when the topic of homework was brought up, more talked to someone else than to me. Or, for example, fifty people are talking homework in the classroom, sometimes in the lecture hall, but your comments don't get stuck there.” Following that, she mentions that her degree of highest ranked student were often related with taking notes or memorizing the subjects, but not her intelligence. People had the perception that it was an easy thing if she did it, rather than thinking it was a difficult thing that they should appreciate. The participant also claim that she has experienced a similar situation at the Telegram group of a networking organization which works on AI. She tells that people in the Telegram group asks some technical questions and others who know the subject answers. And, according to her observations, people tend to discuss and ask more about the subject when a man answers the question; oppositely when the respondent is woman they tend to close the topic and just thank to person who respond. They are more open to talk about

if there is something they do not understand in the response when the respondent is man. But, she accentuate that this is only an observation of herself, it is not something that she directly experience. One of the participants, Participant 20, tells about experiences that she has got through in her working life. Since she has working in a big tech and consulting companies, she has had a lot of transnational meetings with clients in her job. She says that she was the only woman at most of the meetings. So, when she started the meeting, the body languages, looks, and attitudes of men seemed like they are not taking attention to her at the beginning, but they were getting used to her and started talking and discussing after awhile at the meeting. She states that she always faced a resistance at the beginning and she tried to proof herself everytime throughout her working life. But in time, she says that she has tried to see them as challenge, something to overcome.

Another discriminatory attitude and behavior is to perceiving women as a sexual being, interpreting their attitudes, behaviors, and closeness as different such as a sexual or emotional intimacy, and treating them differently from men in the position. Most of the participants tell their experiences of being treated differently by men and their discomfort about these situations. Participant 8 states that she was uncomfortable with the different understanding of her behavior and that her teachers might behave differently to female students and male students because of afraid of people's inappropriate comments. In her opinion, this situation is disturbing that people can think that way. She states that "I am a person who asks a lot of questions and I always ask questions to the professors. I was pressured not by the teachers, but with the thought that other people would get it wrong when they went too often. I felt as if they were going to interpret that habit of mine differently. Sometimes there were glances like that, as if a student couldn't come every week. This may be my complete conspiracy theory, but I wouldn't like it to be interpreted differently. For example, I often attend our problem sessions. A friend of mine said, 'Are you

going because the teacher is so handsome?’. It is an excessive comment, but in general I do not like having such silly comments.” This kind of experiences of the participant cause her to limit herself and act in a controlled manner always. This is such an exhausting habit that she defines that she sometimes concerned about that her cheerful and humorist characteristics may be misunderstood by her colleagues at the workplace. Two of the participants tell about their experiences with men who are willing to have an emotional or sexual relationship with themselves. Participant 11 states that she experienced inappropriate experience such as that the assistants at the lab courses helped her in coding and other things, but not looked the other students. She says that she felt uncomfortable with this situation. Another participant, Participant 20, tells about the proposals of marriage from her colleagues to her at the beginning of her career. She states that “For example, when I first started my job, I was very young and just out of college, I was single. I was getting proposals from a lot of people like getting married. That situation was disturbing. But this was not a discomfort in the work environment, my colleagues were also people I socialized with. I was the only woman in the environment and therefore all the demands were directed at me in that age group. There was a time when I felt this discomfort.”

Other than that, participants also claim that they feel like they are disturbing their male friends or colleagues since there is a male-dominant environment. As all of the participants are working in male-dominant teams and maybe one woman at there or studied in such an environment, they are more likely to socialize with men at work or school. One of the participant, Participant 11, says that “You are becoming friends with men, but maybe they are not comfortable with you.” Another participant who is the only woman at her workplace tells about her experiences with male colleagues as “In fact, there is an unbuttoned culture where men are among themselves. Since I was the only woman in the place where I worked, the situation was generally “I can't say now

because Participant 2 is here”. But I see that they corrected their way of speaking for me because of their kindness. I mean, the men have a very sincere conversation inside, no lies. It saddens me that they don't live it because of me. But they have an extra sensitivity to me. Seeing that sensitivity too, I don't know, it's strange. Sometimes I feel like I'm breaking their dynamics.”

According to a participant, Participant 2, the discrimination against women is not specific for the technology sector or AI. According to her, there are less number of women in AI and technology, but if there are discriminatory attitudes and behaviors, these are existent in all industries, in the society. She states that there is a negative view on women due to factors such as pregnancy, getting more leave and marriage and that the state should protect women in these areas. However, this is not unique to the technology industry. She says that “As the number of women in this field increases, the numerical imbalance may improve. The era we live in right now is not a system and period that will reject you when you say 'look, I can do these things, if you hire me I can do these' Especially in Silicon Valley logic...”

F. Solutions or Not: Women Networks and Positive Discrimination

Women organizations in tech industry are focusing on the strengthening women's presence in the field of technology by bringing together the women developers in certain specific areas or technology in general. They often work to provide networking possibilities, ensuring the information flow between women, and undertake activities in scientific or industrial areas. There are global organizations in this field such as Women in Tech, Anita Borg Institute, Black Girls Code, Girls in Tech, Girls Who Code, Women Techmakers, Women in Technology International (WITI), Women Who Tech and many more (*Top Ten Women in Tech Organizations*, n.d.). There are also women networks, organizations, and projects in Turkey to increase the number of women in the area of AI and technology and create an awareness about the issue. Some of them are

TechnoLadies, Kadın Yazılımcı (*Women Developers*), Sisters Lab, Bilim ve Teknolojide Kız Çocukları Projesi (Girls Can STEM Project), Kadın için Teknoloji Projesi (Technology for Women / Habitat Association) and Teknolojide Kadın Derneği (*Wtech*). And some of the AI, technology, and coding organizations work to create a positive impact on women's presence in AI and technology such as Global AI Hub and Kodluyoruz (We Are Coding).

In the context of women in AI discussions, I asked participants about their perceptions on women in AI or women in tech networks in terms of their functions, necessities, and memberships of participants to these networks. Almost all of the participants claim that they are not a member of these communities nationally or internationally. Only, one of the participants claim that he is a member of the "Women in Tech" platform to support and attend their events. Besides that he states that he has supported these kind of women developers groups since the college both by attending their events or following their activities.

Most of the participants interpret these platforms as positive initiatives to support and strengthen women's presence in tech. They emphasize that if a social group is an underrepresented group in an industry, they should be supported by these kind of initiatives to increase the awareness and their visibility. Some of the participants claim that they wish it would not be necessary to create these kind of initiatives for women such as that there is not a network called "Men in Tech". So, these are important and necessary for now to ensure equality between men and women. According to one of the participants, Participant 10, the networking function of these initiatives is really important to convey the knowledge and experience to the future generations and to diminish the male dominance in the field that is provided by transferring the social relationships of men to the promotion and hiring possibilities at work. He states that "I think that if a person comes to a position, s/he does not come with only technical skills. If only technical skill was important, you

would expect approximately the same number of men and women to come if you taught 100 men and 100 women something and finally passed an exam and only looked at technical skill. If a person is rising to a position or hired by a company which has gate keeping, there is politics, there is a networking effect, there is everything. Men hang out with men outside of work, so men may be more close with men, go drinking together, go golfing together, etc. And when it comes to nominate a position, he will most likely tell the nearest. In other words, the fact that this area is a male-dominant area and there are fewer women is also a socialization problem. So if a man and woman are not socializing together, man chooses their closer boyfriend when someone is going to be promoted. So the network is an important thing. Today, it is not the society of the 60s, 70s, 80s, and certain effects may be broken in that respect, but it is still not at the ideal level. Therefore, since the network is so important and certain groups are totally negatively affected by this network effect, they cannot benefit historically, it is important that they come together and get them to the place they deserve with networking. Apart from this, there may be a transfer of various knowledge and skills when people are out of business and not doing business. For example, if college professors are mostly men and they are more comfortable working with male students, when they look past a generation, men may have learned more on average. Because they may have spent more time with their teachers. There is a historical baggage, although this effect continues to diminish. Therefore, I think it is important that a person who has knowledge skills in a group communicates with those people in her/his own group or underrepresented group and conveys her/his knowledge, skills, experience, as well as networking effects. For example, there is a group called R Ladies all over the world. There were events every week at our university. The boys also attend their activities, so they don't have anything like we are a girl group anyway. They can give that socialization effect, you can see their peers and gain experience from them, as well as technical

knowledge, etc. Therefore, they can break the effect of situations such as men having easier access to certain things, which still continue due to historical effects, and at least they are working to balance them over time.” Another participant Participant 16 touches upon the importance of the equality between women and men in this field. He states that “I think this solidarity is very important because there is a fact in the world that for centuries there was a world society in which women were more held back than men. Maybe this has changed in the last fifty years, but there is still this shortcoming. Perhaps this is now ingrained in the genes of humans, and the whole world has to work together to change that. And I think these kinds of communities are doing very well and I think they need to be supported even more. Because we can never make a distinction between a woman and a man in this area. This equality should be achieved.” Another participant, Participant 19, also mentions the importance of women networks and initiatives to encourage women to prefer these fields. She says that “I follow such communities. I find this solidarity nice. Because, as I said, the low number of women in this field is something that discourages people who will enter this field. The more we show this as something positive and make women feel that they are not alone, the more positive it will be. So these are really nice things that encourage people. These platforms should exist, so I support them.” Another participant emphasizes the positive effects of these networks as creating role models for younger women and bringing education to girls who live in financially inadequate regions. He tells that “I think such platforms are very valuable in terms of showing women what is possible. You know, there have always been such inspirational people for us. To show that something is possible, prejudices in the minds of younger people are more easily broken down. That's why these kinds of platforms are very meaningful and valuable to me. At the same time, it forces companies to act as if they do, even if they do not care much about it. In other words, it is not a very important issue in practice, but as such a consciousness is

formed, companies inevitably have to pay attention here. This totally turns out to be a plus from our pragmatist point of view. That's why I find it valuable. There are some non-governmental organizations that provide coding training, especially in Anatolia and other regions that are financially inadequate. These are very good, I think very positive.” The participant, Participant 2, states that the women networks in tech are important to support each other, however according to her, it would be better not to need them. She says that “I wish there were no such networks. But it should be right now, in a transitional phase. That's why I say I support, but when I look at the point I aim to reach, I wish they didn't exist, of course. They only exist right now to achieve that balance, because of need. They wanted to support each other so that it occurred.”

One of them, Participant 7, emphasizes that these initiatives helps people to cooperate and create in common, so they bring a value to develop AI besides that their aspect of bringing women together and strenghtening their presence in AI. He states that “Any structure that will support cooperation is necessarily beneficial, they are consisted of women or not.” He claims that he supports these kinds of iniatives by participating in their events as speaker or providing job opportunities for them. Another participant, Participant 17, also emphasizes the cooperation function of networks besides the women focus and he focuses that these iniatives should produce a social benefit if they are getting together as women developers. He states that “In my eyes, there is no difference between the network of game-loving software developers and the network of female engineers. I see it as platforms where people with common ground meet. Especially being a woman has no effect. But if women contribute to the education of girls, if they provide a social benefit, I think it must be. The part they benefit from as an output is important. This is the part that stands out for me. Other than that, I see it as a normal group.” Another participant, Participant 18, takes attention to that these groups should act according to their establishment purposes “These

solidarity groups are supposed to exist, but I don't think each group is suitable for its purpose. Some groups are just for show, some are very political, there are some associations that do not support the things that should be supported, I think some of them like inflation. But there are also groups that work properly. I would like to make the following suggestion for those who work properly: if they want to solve the problem radically, they should go to the families, they should go to Anatolia, they should go to the people, to their homes. Otherwise, you cannot give people awareness.”

Some of the participants state that the women networks in AI and Tech may have problematic sides and negative effects towards women. Two of the female participants claim that these networks have negative effect on women developers. According to one of them, Participant 8, the “sisterhood” movement is not suitable for the technology field, it can be applied to sports to encourage women. But, anyone who has financial or educational opportunities can work on AI and technology. She says that “Everyone's opinion is different, but I saw a slogan saying 'if he did it, you can do it too' and the word ‘sister’ and it sounded very terrible to me. I think the mentality of 'if he did it, you can do it too' is not about technology. Maybe getting on the same level with a man in sports etc can be very difficult in terms of muscular structure, but if your economic situation or place of birth is good, you can already do it here. Since the women networking there are doing well, I think these kinds of things will cause full positive discrimination.” Another women participant, Participant 4, stands out the exclusion effect of these networks as “women developer” from the males. She states that “Of course, there are good things about these networks. But there is also the effect of self-alienation and exclusion. I never wanted to stand out with my gender and define myself as a female software developer. So, I think when you create a grouping, you also exclude yourself.” Some of the participants interprets the topic of women in AI or gender in AI as

a disimportant factor for developing technology because of its technical structure. So, when they approach the technology as a mere technical process and development, they tend to evaluate the social topics as unnecessary. Another participant, Participant 15, emphasizes that the efforts of women to emphasize they are disadvantaged group or discriminated are not right. He states that women's work in this field in Turkey is a proud thing, but he says that anyone who wants can achieve their goals and succeed without using gender issues. He states that “When I see an initiative or a platform, it is not something that I pay much attention to whether they are women or men. Frankly, I do not find it right that these are expressed too much everywhere. In other words, I do not find it right to write articles on LinkedIn every time they are not hired or to state that they are a disadvantaged group. So everyone creates their advantage. Why do they not get somewhere if everyone does their work right? There are such situations, of course, but there are also in the world. I mean, it's not just specific in a certain place. These situations exist, but I think they can achieve something without any excuse.” The participant, Participant 6 interprets the women networking groups from a different perspective. He states that the formations that bring such women together can have the effect of excluding men and radicalizing women. He says that “At the end of the day, it makes sense, but I'll look at it from another angle: Bauman has a concept called an echo chamber. The echo chamber says that the people you follow on social media will be people with similar tastes after a while, so you start to radicalize each other in similar views. Radicalization of views can come very quickly or reach to unpredictable points. Therefore, we start to radicalize each other out of nowhere in the echo chamber, we may produce problems that do not exist, we may lose the objectivity in our perspective. Because we always hear the same point of views. In this case there may be a similar problem. For example, the fact that feminist

organizations are found too radical by some people in society, even I sometimes find it too radical. Maybe it might be related to that.”

From the solutions perspective, another important topic is positive discrimination towards women in tech. Actually, the positive discrimination topic was not belong to my semi-structured question set before the interviews. However, I realized that this topic was mentioned by the participants when we talked about discrimination and bias against women and women networks/organizations working in the tech industry. While in some of the interviews the participants opened this subject by themselves, I consciously asked to others as well. Almost all of the participants define that they are either experienced or heard different positive discrimination cases towards women such as favoring women at the college application processes or internship opportunities of companies only for women. One of the participants, Participant 13, gives the example of university application period “We have observed that among my friends who applied to universities in America, the chances of those whose gender was female increased more. But, I'm not sure if this is true.” Another participant, Participant 8, exemplifies that one of her friends advises her to emphasize her gender in university applications. Positive discrimination are discussed around the efforts of companies and universities to increase the number of women in AI and balance the unequal numerical distribution of genders. Most of the participants interpret these positive discrimination cases and efforts as negative activities, while a few of them claim that these applications are necessary for now to intrigue women to the field.

Most of the participants state that they are irresolute while thinking about positive discrimination. According to that, positive discrimination is necessary to increase the number of women in technology and to provide a balance between genders; on the other hand, it is important to be fair to all genders and positive discrimination should not be applied. According to them, if there is an

unbalanced situation, the necessary steps should be taken by the actors to balance it. But, it should be done in a fair way. Another participant, Participant 12, also claims that encouraging women to proceed in these fields is important, but other than that the practices in the industry should be equal for both genders. One of the participants, Participant 14, also define that he is not sure that the positive discrimination is an ethical thing to do or not; but he is sure that especially the big companies apply these. He states that “Especially large companies care a lot about how the company looks to the outside, and of course they are right to do so. If we think it's a company that is all about making money, and if we think that people are bringing in money, they might be doing things like this. After all, this company should appeal to people somehow.” He emphasizes that the companies do these kinds of positive discrimination against minority groups to promote themselves well. Another participant also touches on this subject. According to her, the companies are taking advantage of the social responsibility issues to promote themselves as responsible employer.

Some of the participants approach positive discrimination as a useless implementation or it has negative effects towards women who are willing to come forward with their success, not by their gender. According to them, people should search for the solution at the problem. Positively discriminating women is not the solution for increasing the women’s presence in AI. Instead of it, people should turn their faces to education, children, young girls to attract them into the STEM fields. According to one of the participants, Participant 22, the positive discrimination cause insecurity among women. The participant, Participant 6, claims that the positive discrimination implementations are useless because of the historical examples of situations where the right is given from above. He emphasizes the women’s demand on the issue and mature societal conditions for the effectivity of the artificial solutions. He states that “As far as we have learned from history,

there is a situation like this: rights are not granted, rights are taken. Although women's access to the freedom to vote and be elected in Turkey is not something that happens with the women's movement, there are important female figures. There is also freedom from the top, but at the end of the day, have women been able to use their right to be elected effectively? Therefore, we can draw a serious difference between effective implementation when the right is granted from above and effective implementation in case the right is taken, right? In a situation where the right is given from above, the conditions do not mature yet, maybe it takes some time for people to digest it. In the case where the right is taken, we can talk about a more mature situation. In other words, it is necessary to demand the right.” In other words, he possess that an incentive may be required to create an opportunity for people who are good, but the continuation of the system does not happen with positive discrimination. Because, for him, the system is profit oriented. And if the company do not get efficient performance from the person that they hire, the system becomes unsustainable. Another participant, Participant 8, defines that she is very uncomfortable with the positive discrimination against women. She states that if she achieves something good, it is really bad to think other people that she accomplish that because of being a woman. She says that “A friend of mine went to MIT, for example, she told me to emphasize that I am a woman when I am applying to schools, and I was shocked. I didn't like it being said to emphasize that I am a female engineer.” Another participant, Participant 2, also emphasizes the uncomfortable feeling of herself because the positive discrimination. She claims that the positive discrimination should be applied to even the unequal distribution between genders at this transition phase, however it is not comfortable or a good feeling to be in it. She states that “No woman wants positive discrimination against us. There is a humiliating side of it somewhere, if you ask me, I feel the frustration. I wish that we

didn't have to and it happened organically. But I see that in order to break that imbalance, it is necessary to make positive discrimination in that transition phase.”

The participant Participant 18 defines that people should be careful about what they are calling as positive discrimination or not. Because, according to him, just increasing the number of women in the company cannot be positive discrimination. The women who are hired should be working in the management board or production to make a difference with the positive discrimination that they are applied. “So there should be more women in management, production. In other words, I am trying to say that we would not make positive discrimination by assigning women to more passive roles. If there is positive discrimination in the part that really gets her hands dirty, keeps her hands in the middle of production and adds value, that’s okay. For example, I heard about a company, all of the call center employees were women and therefore the number of female employees was high. So would you say that this company positively discriminates? You don't say.”

One of the participants emphasize the positive effects of positive discrimination. Participant 19, claims that she does not approve of any kind of positive discrimination towards her in her daily life, but the situation with AI and technology is different. According to her, if the positive discrimination leads girls to prefer computer science or work in this area, these should be applied. She states that “Because what matters here is not about me or my pride or my right, but whether we can win people at that time. I feel like we've won them if even one girl prefer computer science.” She emphasizes the importance of bringing more women to the fields of AI, computer science, and technology. She states that girls who make a university choice have question marks about the gender distribution in the field and they are not sure whether this area is suitable for them because it is a male-dominant field. For this reason, she thinks that the more female figures appear

in conferences, classrooms and workplaces, albeit through positive discrimination, will enable more women to focus on this field.

Only one of the participants claim that there is no positive discrimination applied to women. Because, according to him, there are problems in the human resources of this industry. Companies or teams that work on AI need qualified human resources from any gender. So, those companies do not have any gender filter which is positive or negative discrimination when evaluating the candidates. When they find a candidate who meets all the expectations related to technical capabilities, gender is not even a parameter. But, he tells about their special applications for women employees in terms of the job conditions, working hours, and facilities. He says that “Let's not say that we give priority, we tolerate more their special situations. For example, a female friend leaves her job at 3:30 every day to pick up her child from school. Normally, nobody is allowed to leave early every day and continue their remaining work from home. Or we give a female friend who is a graduate student two days off a week, although normally the postgraduate leave period for other employees is one day. We had a friend who gave birth, for example, during the pregnancy process and we took care not to extend her work hours, and we ensured that she could go without any extra leave when there were doctor appointments, and we did not cause any difficulties. After her pregnancy was over, we allowed her to work from home. So let's not call it priority, but we treat women employees more tolerantly.”

G. Subconclusion

This chapter focuses on gender distribution, gender inequality in numbers, gender discrimination and bias, reasons and solutions about these issues from a workplace dynamics perspective. In the gender distribution subsection, I collected numerical data about employees' gender distribution in AI startups and the proportion of women students in related departments with computer science

which reflect the roots of AI gender gap. In addition to these statistics, I asked participants about the ratio of men and women employees in their teams, startups, or companies; and I tried to understand how they evaluate this proportion in terms of gender equality.

According to the student statistics collected from the Higher Education Council in Turkey the ratio of women students in the computer science related departments is 24% at Bachelor's degree, 26,4% at Master's degree, and 25,7% at PhD. According to LinkedIn data, the ratio of the women working at the AI startups is %28,6 and the ratio of women working at a technical occupation at the AI startups is %8,8. According to participants' narratives, the rate of women employees who work at the technical occupations in their teams and companies is 9,7%. While some of the participants prefer to share number of employees in their team, the others say about the total number of employees. So, there are also women employees working at a non-technical occupations such as marketing, customer relations, or sales. Three of the participants state that there are no women working their company in a technical or non-technical occupations. In addition to this, the eight of the participants claim that there are 1 women working in their team with a technical occupation. And five of the participants state that there are 2 or more women employees in the startups that they are working. These different kinds of numerical data enables us to trace the roots of gender diversity problem in different stages. At the first stage, we can observe that there is more diversity in college education with 24% of women at the Bachelor's Degree, 26,4% at Master's degree, and 25,7% at PhD. However, this rate decreases to 9% in average when we look at the startup employee data on LinkedIn and participants' explanations on gender distribution in their companies. Before examining the reasons behind of the less number of women in AI workforce, we can say that there is a more diverse population and more number of women at the universities when we compared to current employee population (Rangarajan, 2018).

Following that, I asked participants about their perceptions on gender equality based on the numerical gender distribution at their companies and startups. Most of the participants claim that the rate of women and men in the teams are not reflecting an equality. Almost all of them claim that these numbers show the male dominance in the sector and it needs to be developed. However, the statements of the employees about the reasons of the low ratio of women in their workplaces are differentiated. Many of the participants claim that the low number of women in the companies are not determined purposely and consciously. According to them, the reason for this situation is that because of the number of applications of women to the technical occupations or to startups are low. Since men apply for technical, AI-related job postings more often, male candidates are mostly hired. While the participants of the study evaluate the low number of women in their teams as low application of women to these occupations; they define two important effects of having women employees as outsider perception on the company and order within the company. According to them, if there is no women in the company or startup, it creates a non-welcoming atmosphere for the outsiders. And this creates a negative perception about the company, so having women employees is important in terms of this effect. Secondly, according to some of the narratives, it is nice to have women employees in the company to provide the order, have professionalism, and decent workin environment within the company.

After examining the perceptions of participants about gender distribution and diversity in their workplaces, I asked about their perceptions on gender in AI generally. I tried to understand whether there are any problems of gender in AI according to them and to discuss both the reasons and the solutions. Totally, 11 of the 22 respondents which means %50 of the respondents assert that there is no problematic situation about gender in Artificial Intelligence (AI) generally. They claim that there is no problematic situation about gender in AI by emphasizing the dependence of individual

success to proceed in this field. 4 of them claim that there is a numerical inequality between men and women working in this field, however there is no discrimination or any problem related to gender in the field. 7 of the participants which means 31,8% of all participants clearly state that there is a problem in gender distribution and diversity in the field of AI generally. Respondents are differentiated in their responses on reasons and outcomes of the issue.

Half of the participants refer to the societal reasons such as gender roles on division of labour and nurturing styles of families on children as the common reason of the less number of women in this field. According to the participants, gender stereotypes in the society have an important role in gender division of labour. They state that there is a division in the society such as “man’s job” and “woman’s job”. So, this division effects the gender distributions in the occupations. For them, the gender stereotypes are also reinforced by the media and cultural products. They give the example of that the “nerd” character in movies and series are always men. One of the participants, Participant 19, states that even though she is a woman developer who works on AI, she also has the picture of “male nerd character” in her mind. In parallel with the gender division of labour imposed by society with common sense and media effect, families also have a big role in maintaining this inequality inside of the home everyday. According to them, families treat their sons and daughters differently at the early age such as buying cars or legos for boys and barbies for girls. At the older ages, the responsibilities of daughters and sons are still kept differentiated such as giving the caring of others responsibility for girls and letting boys to work with their fathers. So, this kind of differentiation inevitably effect the division of labour in genders. In addition to that, one participant refer to the lack of prior experince of women with computers can have an impact on preferring these fields as profession. As I see in the literature, this is also in relation with the different treatment of families to their children. The impact of families and their

treatments towards kids is studied by Jane Margolis and Alan Fisher (1995) in their book called *Unlocking the Clubhouse* (2002) to understand the underlying reasons for underrepresentation of women in the computer science. They have found out that the male first-year computer science students in Carnegie Mellon has significant pre-experience in computers. According to their study, parents tend to buy a computer as a gift to boys and they prefer to put the computer into son's room, not daughter's. In addition to that, fathers are often more inclined to teach the technical tasks to boys and encourage them in these kind of works with an "internship" relationship (Thompson, 2019). Similar to the narratives in my interviews with participants, these stereotypical attitudes towards boys and girls are structured and reinforced by even in the first games of childhood: cars and constructive toys for boys and dolls for girls. These separation implicitly show who belongs to where.

The importance of role models and mentors are discussed in the literature on the lack of gender diversity in the STEM fields and digital / technical skills of women (First Round State of Startups 2016 ; *I'd Blush If I Could*). In parallel with the literature, some of the participants claim that the lack of role models in AI and computer science has an important impact on the less number of women preferring these fields. According to the participants narratives, lack of role models create a lack of motivation in women, and so they are more likely to aim a profession that they cannot see a future, a goal, a role model who accomplished inspiring things. According to participants, as a result of the inequality of opportunity women suffered in the past, women do not have enough motivation because of the uncertainty of what to aim and where to reach. So, the achievement stories of women and increasing the number of successful role models in AI or technology would take the attention of women to these fields and more women prefer to pursue a career in technology. One of the participants, Participant 19, defines the paradoxical relationship of lack of

role models and less number of women in the field as **“Again, as a vicious circle, the low number of women working in the sector prevents them from entering.”**

Another important and prominent explanation made by participants is the sociobiological explanations regarding the roots of the problem as characteristics of women and their personal interests. Briefly, sociobiology handles the reasons for social behaviours as evolutionary developments and eventually biological aspects in different sexes. The participants made sociobiological explanations both in the reasons for lack of women in the field and their statements about gender issues in general unconsciously. They emphasize the “social skills” of women and they claim that women are more likely to do jobs that they can use their social skills such as designing or teaching. The software development occupations necessity a more asocial character since that the developers spend almost all of their times in front of the computers, alone. Therefore, even though women study computer science or a related department to it at the college, they pursue a career in design, business, or academia. Some of the participants claim that there are more women in academia working about computer science and/or AI just because the stability and assurance of the academic jobs rather than the industry. In the narratives, we can see that a secure, safe, comfortable, and more stable job environments are often finded suitable for the characteristics of women.

As the final step of reasons for numerical inequality between genders in AI workforce, the technical aspect of the AI and technology become prominent in participants’ narratives as not a reason for lack of women, but to understand how they evaluate the intersection of gender and AI. Some of the participants state that AI is a field which only requires technical skills and proficiency of the developers, so the problematic situation with gender diversity is not caused by technology or AI. Some of the participants of this study emphasize that this is a technical-based area, and so

there are no limitations or boundaries that may cause gender discrimination for any of the genders. According to them, if people are strong with their technical knowledge and proficiency in the field, they can proceed and be successful in AI / technology. One of the participants, Participant 6, states that he applies a recruitment method which tests the technical competences of candidates with quizzes before the face-to-face interviews. He believes that he complete the recruitment process on merit independent from the characteristic aspects of them such as gender. According to him, this kind of recruitment process enables to work with technically strong engineers. However, he also shares that no woman candidate can pass through the quiz stage as he observes that the male candidates who applies for them are technically stronger than the female candidates. The participant defines that he knows how to prepare a well quiz to test the technical competences of the candidates from his university, Bilkent University which is a prominent private university in Turkey. This kind of hiring method of the participant is really similar to the “whiteboard challenge” which is a popular hiring method for the Silicon Valley startups and classroom work at Ivy League institutions. There is a similar risk here as this recruitment method creates the illusion of bringing together people of similar gender, similar backgrounds, similar universities, and similar socio-economic status as in Silicon Valley. Although it is thought that such a recruitment method will produce objective results, it may cause unconscious biases to come into play. This entails the danger of eliminating people who are not educated in leading schools and who are not habitual to solve such problems. This situation can bring about not only gender but also other types of exclusion as seen in the literature (Thompson, 2019) . The familiarity between whiteboard challenge in Silicon Valley and the participant’s quiz-based hiring method refers to the culture of coding and computer science. According to Thompson (2019), “women are not the only ones who are excluded but also everyone outside of this culture (Thompson, 2019). The other participants

who claim the technical aspect of the job annihilates the importance of gender believe that there should not be created an equality just to create an equality. Since gender is not a parameter to effect the quality or content of the job, they state that there should not be an artificial effort to provide this.

Under the topic of gender distribution, diversity, discrimination, and bias in AI, I also analyze the perceptions of developers on gender discrimination in AI. In the literature, gender discrimination and bias towards women are studied around the topics of unequal payment and promotion for women, sexual harassment of women in the tech industry, discriminative and biased attitudes and behaviors at the workplaces, and gendered practices (Acker, 1990; Carter & Kirkup, 1990; *Employed Persons by Detailed Occupation, Sex, Race, and Hispanic or Latino Ethnicity*, 2019; “Life as a Female Techie,” 2018; *The Global Gender Gap Report 2018*, 2018; “Uber Investigated over Gender Discrimination,” 2018; Gershgorn, 2019; Gurchiek, 2017; Kiesler et al., 1985; Kiser & Mantha, 2019; Kolhatkar, 2017; Massachusetts Institute of Technology, Laboratory for Computer Science, 1983; Matthews, 2003; McIlwee & Robinson, 1992; Molla, 2017; Prokos & Padavic, 2005; Rangarajan, 2018; Ranson & Reeves, 1996; Shih, 2006; Spertus, 1991; Statt, 2018; Thompson, 2019; Tiku, 2019; Vassallo et al., 2017; Walby, 2011; M. West et al., 2019; Yancey Martin, 2003). I tried to understand developers’ perceptions on gender discrimination and bias according to the global gender discrimination, bias, and harassment cases of big tech companies such as Tesla, Uber, Google, Oracle, and Microsoft. I aimed to understand whether the participants follow these kinds of social events in these companies and how do they evaluate the gender discrimination and bias in these companies. First of all, most of the participants state that they are not following these kinds of social events about the big tech companies, and some of them says that they partially follow these news as they come across online. But, many of them mention the

inhumanitarian conditions at these companies in terms of dense working hours. Some of the participants both are surprised and do not regard as possible that these kind of cases can occur at these big companies. While some of the participants interrogate the reasons behind of the gender wage gap, some of them automatically respond by emphasizing the impropriety of the situation. According to most of the participants, the reason behind of the wage gap is the disadvantageous positions of women because of their maternity leaves or the higher possibility of turn over of women than men. Therefore, the companies apply a strategy of reducing the risks as much as they can such as minimizing the cost of women employees and paying them the minimum wage as they can. As the maternity leaves and turnover rates of women are disadvantageous for women in terms of wages, the male-dominance of the area is another aspect that may cause adaptation problems for them and turnover. In relation with the high turnover rates of women, one of the participants also emphasizes the disadvantageous positions of women in the working life as the social expectations from women. According to him, women work at the jobs which have less salaries since they are not the primary responsible for the house income. He sees that the wage of the woman is an additional and extra income for the family, because man is the “breadwinner, head of household”. These opinions are similar to the concerns of the nineteenth century: as women entered the labor force in the nineteenth century, men are threatened with the women’s entrance into the labor force. Because, first of all, women left their homes (where they supposed to be) to work and they worked for low salaries. This thought, again, bears the trace of the argument about women’s primary place is home (De Beauvoir, 2010). Some of the participants make stereotypical assumptions about women such as low negotiation skills on job conditions and wage of women compared to men. Similar to this argument, one of the women participants state that “We did not seek our rights or we were hesitant. Here the thinking of women needs to change a little bit... They

need to be more confident in themselves, sit at the table and ask for more. Perhaps because women were shy, the other side was also inclined to exploit.” Here, we can see that mostly women are perceived as the responsible of these kind of discriminative and sexist attitudes of the companies. The explanations of participants about this issue shows that women are not only seen as bad at negotiation, but also shy, diffident, insecure, and cannot asking for their rights and demands. Some of the participants state that they are not sure that global tech companies apply discriminative attitudes and applications for women. One of the participants ignore the cases that I shared while asking the question, and he states that he does not believe that these kinds of events can happen. According to him, there is no such thing as discrimination and nobody makes that women to work by force. He sees that the company can follow any salary policy as it wants. Some of the participants comment on these issues as a mere negative attitudes of the companies. According to that, the companies should evaluate the performance of employees or any other measurable, concrete parameters. And, gender is not one of them. They believe that gender pay gap is an unacceptable policy for any company. One of the participants recommend that transparency in the wages and unions inside of the company can prevent these kinds of problems to occur. Another participant emphasize that these kinds of events may effect the company culture totally and eventually culture in the society.

I interviewed with six women participants who are actively in a technical role in startups and companies. One of the women participants works at a global tech company, one of them works at a online media company, and other four of them work at the different startups on AI. First of all, I asked them about their personal stories of preferring to proceed in computer science and AI. Most of them state that they choose this field because of their personal interest on mathematics, STEM fields, and computers. Four of the participants state that their previous experience and interest on

computers have an impact on choosing computer science. Two of them state that they did not think of preferring computer science even though they have a special, personal interest on computers; but later they preferred this field with the support of their family and friends. They mentioned that the societal biases and male-dominance in the field might effect their perception on the area unconsciously. Following the college, all of the participants state that they decided to move forward in AI as their personal interest about the field. Most of the participants do not like to be emphasized as a “woman” developer. They are concerned of their gender to get in the way of their success. Furthermore, they are worried about excluding themselves from all developers and engineers by emphasizing the identity of “women” so much. They state that they do not achieve something greater than the male developers just because of their gender is “female”, and so this emphasis is unnecessary. They claim that the male dominance in the field is not something to be angry about. According to them, AI and technology is a field that necessities a technical proficiency of developers, so the personal success is more important rather than the gender. Some of the participants gave the example of all male speech groups/participants at conferences or events, and they state that these men are there because of their success, so just bringing a woman there just for adding a “woman” is not fair for the succesful people. One of the participants interprets the issue as “These anti-discriminatory people who actually discriminate. Sometimes it evolves into this, they involuntarily discriminate themselves.” In addition to that, I another important sub-topic for me is their experiences on conscious or unconscious discriminatory attitudes and behaviors during their education and business lives. I especially asked them the situations that could make them feel uncomfortable and a sense of 'not belonging there'; a look, an implication, a word, an attitude that can be felt them bothered. Most of the participants state that they do not encounter any biased or discriminatory situation at their workplaces. Yet, they mention

that they have experienced such attitudes and behaviors at their schools or networks. According to the narratives of women participants, women face two common biased and discriminatory attitude in this field: perception on the superiority of men such as asking questions to men more rather than women who are expert or working the same field and interpreting women colleagues or classmates as sexual beings rather than establishing a professional relationship. Almost all of the participants have experience about that their friends often asks their questions to men colleagues or classmates rather than women who has knowledge on that. According to their narratives, female or male friends tend to ask a male friend even though they know that she has knowledge on the issue or people do not care about the comment on a technical issue that she do. Another discriminatory attitude and behavior is to perceiving women as a sexual being, interpreting their attitudes, behaviors, and closeness as different such as a sexual or emotional intimacy, and treating them differently from men in the position. Most of the participants tell their experiences of being treated differently by men and their discomfort about these situations. Other than that, participants also claim that they feel like they are disturbing their male friends or colleagues since there is a male-dominant environment. As all of the participants are working in male-dominant teams and maybe one woman at there or studied in such an environment, they are more likely to socialize with men at work or school.

After analyzing the perceptions of developers on gender distribution, reasons for the diversity problems, gender discrimination and women's experiences; I aimed to look from the solutions perspective at the final subsection of this chapter. So, I asked about how do participants perceive the role of the women organizations in the tech industry which are focusing on the strengthening women's presence in the field of technology by bringing together the women developers in certain specific areas or technology in general. They often work to provide networking possibilities,

ensuring the information flow between women, and undertake activities in scientific or industrial areas. I wonder whether if the participants are member of one of these organizations or do they follow any of their activities. Following that, the topic of “positive discrimination” was opened by all of the participants even though I did not ask specifically about positive discrimination. I observed that positive discrimination is an important issue for participants when discussing about gender in AI and tech in general. In that part, I tried to understand their perceptions on positive discrimination towards women to equalize the number of women and men in AI.

The women organizations in AI or tech are beneficial to convey the knowledge and experiences to different women working in this field, to balance the gender diversity, educate and give trainings to younger women, enhance the impact of women and strength the presence and place of the women in AI. There are local and global organizations in this field such as Women in Tech, Anita Borg Institute, Black Girls Code, Girls in Tech, Girls Who Code, Women in Technology International (WITI), Women Who Tech and many more (*Top Ten Women in Tech Organizations*, n.d.). According to my interviews with developers, almost all of the participants state that they are not a member of a women’s organization nationally or internationally. Only one of the participants claim that he is a member of a community and he works for these kinds of organizations since college. Most of the participants evaluate these organizations as positive initiatives to support the women’s presence in the industry. They believe that these kind of activities and organizations provide a visibility and awareness for the underrepresented groups. Some of the participants state that they wish it would not be necessary to establish such kind of networks and organizations, but they add that it is necessary for now. Many of the participants state that the women networks in AI and Tech may have problematic sides and negative effects towards women. They claim that these networks have negative effect on women developers. They mention that these organization cause a self-

alienation and exclusion of women from men developers and AI is not an area that is dependent on gender, but the technical proficiency. And also, some of them state that these kind of organizations have the risks of radicalizing the inner group as feminists and cause to come forefront with their genders.

Positive discrimination are discussed around the efforts of companies and universities to increase the number of women in AI and balance the unequal numerical distribution of genders. Participants define that they are either experienced or heard different positive discrimination cases towards women such as favoring women at the college application processes or internship opportunities of companies only for women. The participants interpret these positive discrimination cases and efforts as negative activities, while a few of them claim that these applications are necessary for now to intrigue women to the field. Most of the participants state that they are irresolute while thinking about positive discrimination. According to that, positive discrimination is necessary to increase the number of women in technology and to provide a balance between genders; on the other hand, it is important to be fair to all genders and positive discrimination should not be applied. Some of the participants approach positive discrimination as a useless implementation or it has negative effects towards women who are willing to come forward with their success, not by their gender. According to them, people should search for the solution at the problem. Positively discriminating women is not the solution for increasing the women's presence in AI. Instead of it, people should turn their faces to education, children, young girls to attract them into the STEM fields. Only one of the participants emphasize the positive effects of positive discrimination. Participant 19, claims that she does not approve of any kind of positive discrimination towards her in her daily life, but the situation with AI and technology is different. According to her, if the

positive discrimination leads girls to prefer computer science or work in this area, these should be applied.

As a conclusion, we can say that there is no consensus about the perceptions on women networks. While some of the participants perceive the activities of women organizations as their positive impacts to society, to underrepresentation of women; the others believe that these kind of organizations reinforce the discrimination in the society by applying positive discrimination. However, almost all of the participants express that they are not a member of any kinds of women networks and organizations. The participants' opinions are also differentiated in the topic of positive discrimination towards women in AI. While some of them are not sure if they should evaluate the positive discrimination as a positive thing or a negative thing; most of them state that these kinds of artificial efforts are useless or not fair to the successful people in the field. According to their opinions, people should reach at some points and succeed things by fair methods and roads and positive discrimination is not a positive thing for both men and women in the field. Only one of the participants emphasize the positive impacts of positive discrimination to diminish the stereotypes and perception on gender division of labour, and to increase the number of women in the field.

ALGORITHMIC BIAS: REASONS AND SOLUTIONS

A. Introduction

In the final chapter of Findings & Analysis part, I analyze gender diversity, discrimination, and bias topic from the angle of algorithmic bias, by moving from the workplace dynamics & relations to the machines, codes, systems, and algorithms. Because, the gender discrimination in the workplaces, humans, and societies and gender bias in algorithms are the two sides of the same problem in AI. They are the cause and effect of each other in a loop. As West et al. pointed out

“many researchers have shown that bias in AI systems reflects historical patterns of discrimination. These are two manifestations of the same problem, and they must be addressed together” (S. M. West et al., 2019).” So, driven from that thought, after I analyzed the perceptions of developers on gender distribution, diversity, and bias in the real world, in their workplaces, in their personal stories, in the big tech companies, in the society; I moved to start analyzing their perceptions of what can be the relation of real-life discrimination with algorithmic bias. I wonder how they evaluate and relate these seemingly different topics in what contexts and to what extent or more importantly do they relate these two different kinds of discrimination and bias. First of all, I tried to understand or search the underlying causes for algorithmic discrimination by taking the participants’ attention to the workplaces where these systems are developed and to the humans who code, develop, and create those technologies. Therefore, I interrogate the role and the impact of the identities of developers into the systems. Following that, I aimed to see their perceptions on algorithmic bias from the reasons and solutions perspectives. I gave the examples that some of the global AI systems create biased outcomes for different genders, ethnic groups, races, skin colours, or social groups and asked the participants about how they see the reasons behind of these biased outcomes, how do they distribute the responsibility for these kinds of discriminative incidents, and finally and more importantly what can be the solutions for them.

B. Searching for the Underlying Cause: The Effects of Identities of Developers

After examining the perceptions of participants on gender diversity, gender discrimination, and bias in the workplaces such as companies, startups, and teams that work to develop AI systems and software; I tried to understand their views on algorithmic bias. As the first step of this subject, I wanted to analyze how do participants perceive the transition of human biases and discriminative thoughts/attitudes to algorithmic, computational systems and I asked participants about the

importance of developers' identities for the system that they are developing. I wondered if gender, religious belief, ideological point of view, age, ethnicity, or any other personal characteristics of developers or data scientists have any importance in the AI systems such as leaking the personal biases into systems. I aimed to understand how do human biases and thoughts leak to the AI systems and how do developers evaluate these cases. Six of the 22 participants claim that any kind of identity of individuals does not directly effect the algorithm or AI system. They mention that the important thing with the AI softwares is technical and computational structure of the model and technical capacity of the developers. If someone is a qualified developer, than nothing else matters. One participant, Participant 7, highlights the importance of technical skill set and knowledge rather than identities of developers. He states that “In fact, it has a structure that has a predominant mathematical side in general. In this area, as an advantage of open source in general, it has an infrastructure that enables people to work together all over the world. If you look at Facebook today, it is like the United Nations. You will see different developers of all nationalities, all kinds of ethnicities. Enough to have a certain perception level, a certain skill set, a certain level of intelligence. In this case, no one cares about where you are from, how you are and maybe it is one of the areas where racism and so on are the least. Because there is no such thing as a stranger anyway. Everyone is a stranger. So if you look at a team, let's say 10 people on Google, one of them is Indian, you will occasionally come across Turks like that. There are Americans, there are Germans and so on. Since it is such a very mixed group, there is no problem with ethnicity. The better you perceive that mathematical model while developing applications, the better things come out. So it is completely based on knowledge level. I can say that it has almost no effect.” Another participant, Participant 8 also support this idea as “I believe it has no effect as it is a technical issue. Because the operations we do are not open to interpretation of the person in mathematics and

mathematics. You can prove it or you cannot prove it. Since it is zero or one, the person has no probability of making it 0.75.” One of the participants, Participant 11, emphasize the important technical steps while answering the question as the identity of the developer does not effect the system. She says that “I don't think the gender, ethnicity etc. of the algorithm developer will have an impact. Important points when developing an algorithm: What type of data is your data? Are you working with sound or image? Second, how much data do you work with? Do you have three samples from each class? Do you have 3 million samples? The algorithm to be chosen depends on that. Third, on what will this performance be measured, on which platforms will it be used and for what purpose? So is it to produce an advertisement, to detect an object, or to make sense of a scene? After completing the problem, it becomes very important how much data you have. It matters how complex this data is and how many resources you have. Resource is very important because, for example, when you have 10 computers, you can try 10 different algorithms. So if you try endless things, you can actually find the best. Other than that, does the people's ethnicity, gender or something has an effect? No, I don't think.” Another participant, Participant 19, says that the identities of individuals do not affect the system directly. However, she mentions the value of differences while developing AI systems. She states that “Actually, my direct answer is no. I don't think this will have any effect. Frankly, I don't think it will make a difference. But I always think about people's language, religion, ethnicity, gender has this effect: when I look at a system, the shortcomings and the beauties I see are different from what you see. That's why every person adds another change, a beauty to a system, which I see with the culture I got until the age of 22. You too, evaluate it according to the culture you have taken, and find negative or positive aspects.”

Some of the participants are irresolute in determining whether the identity has an effect on the system or not while answering this question. Most of them start their answers by declaring that

these aspects would not affect the systems, although, in the continuation of their explanations, they could not decide that it has or not. The participants who were undecided in their answers and some of the other participants state that they had never thought about this issue before. While answering the question, participant Participant 3 could not decide about the effect of developers' identities. He states that "So I guess not. I think things like ethnicity, age, gender and so on are not important. Frankly, I do not know if it affects something in this perspective. I don't think people of different ethnic groups, genders, and ages think differently when developing an artificial intelligence algorithm. But I didn't think about it. Maybe it's having an effect, but I'm not so sure." Another participant, Participant 2, claims that the developers may let their gender or ethnicity effect the system that they are developing, although it cannot effect unconsciously. She says that "So it's not something I ever thought about, but it didn't seem like something that could have a lot of impact to me. So motivation is important there, if you set out with the intention of promoting ethnic identity, of course it can be. So why not. But you must be doing this on purpose. It can be consciously, if that is the motivation, but I don't think it can happen unconsciously." In addition to that, the participants who state that they are undecided and not sure about the issue tend to separate the identity of individuals and the identity of the data. According to their statements, the identity of data which is used in AI systems is important in terms of bias in AI system, although they are not sure what can be the relation between the identity of individuals and identity of data. For them, when you select, clean, and train the data well, the systems should work well, without any problems or errors. One of the participants, Participant 20, define the relationship of data and model and the role of the developer in this balance as "When creating the model flow, what kind of data you provide to that model is more important than what kind of history or features you have. Actually, I personally do not have any importance ... The data I give as an input to that algorithm that makes

the model a model. The selection of that data is very important. It is important how responsible the software or data scientist acts in the selection of that data or how much importance he attaches to the details ... Maybe your past may lead you to different choices while taking those actions. But the model is directly affected by the data. So you get what you give. If you give something biased, you get a biased model. For example, if you are giving data that discriminates ethnically, you get it. That's why it depends a lot on data.” Another participant, Participant 22, supports this idea as “Here, the identity of the data is more important than the identity of the developer. So the developer is actually the person who connects it. The software developer doesn't usually add anything of his own there. So if the developer adds something from himself, it will be obvious, it will appear immediately.” Another participant, Participant 4, also points out the importance of data in AI systems rather than the identity of developers “Although the identity of the developer has no effect, the data s/he collects may be in that respect. For example, if s/he collects data from her/his environment or if s/he collects data from a very specific group, it would be collecting wrong data anyway. This can have an effect.”

There are also participants who claim that the ethnic, gender, or any kind of background identity of developers can have an affect on the AI systems, because they are the actors who process all the steps while developing it such as training the data, developing the model, and setting up the correlations that model takes attention to. Only four of the participants clearly states that the identities of developers affect the systems except for those who are indecisive and who don't think there is an effect. According to one of the participants, Participant 21, the identity of developers affect the models, but it is a problem-specific area. He states that “The way of approaching the problem actually affects the solution of the problem a lot. In other words, these qualities you mentioned will also affect the solution as they will affect the way of approaching the problem. So

it will definitely have an effect, but of course problem-specific. In other words, it is not very effective for a racist person to be racist while developing a model that makes cat-dog classification, but his approach can be effective when developing a system that predicts people's characteristics. It depends very much on the problem.” Another participant, Participant 15 emphasize the importance of social statuses and point of views of people while developing an algorithm. He says that “Of course, when developing a model, it will be important to what position a person is in social terms and how s/he approaches the problem. Because when people deal with a problem, they develop algorithms by thinking from their own world. For this reason, diversity and people's command of the field are important.” The participant, Participant 13, highlights the role of the developer while determining the hyper-parameters in AI. He relates the position and approach of the developer with data and system directly. He claims that “Because there are things called hyper parameters in artificial intelligence. These hyper parameters are; normally you have a mathematical model, besides you have data. You need to learn this data to this model, but there are parameters that the programmer has to select manually while teaching this. These are the parameters chosen by trial and error, which are chosen a little more by eye. The identity of software developer plays a big role at these points.” Another participant, Participant 10, also touches on the correlation between data and outputs of the system, and the role of the developer in this relation. He explains that the identities of developers especially gain importance if they are coming from a minority group, because they are more likely to experience discriminative attitudes in their life stories, and so they are more likely to realize these kind of biased or errored outputs in the AI systems. He states that “The developer's identity is clearly reflected in the results of the algorithm he developed, that is, what the algorithm predict. When developing a face detection model, for example, a black female goes and tries it, the model works with 70% accuracy on herself, while a

white male works with 98% accuracy. In that case, of course, it is easier for a person from the minority group to notice such things. Because it is easier to think from that point of view. Because she has encountered this type of prejudice and discrimination many times in her life story. For example, a model has been developed in China that allegedly determines the future crime rate of people. So what happens when you put a little bit of technical details aside and look at what this model is actually doing is actually, they make certain features from the photo, and the most important feature is the angle on the right and left sides of the lip. Because this shows whether a person laughs or not in the photograph. For example, the problem there is; They need to collect data, they have taken photos of people who have committed crimes, and they have taken photos of random people from the internet. The photos taken from the internet have a more relaxed facial expression, some of them are smiling. But otherwise the man has committed a crime and he's on the record so you know he'll look sulking or angry, etc. The model actually only sees it. If you give the model a photo that you look angry as an input, it guesses you will commit a crime. So it's impossible to predict such a thing because you're actually only learning a certain correlation in the data there. But if you label people who have never committed a crime as criminal, for example, he would learn him as criminal as well. Or if you label all the men as guilty and the women as not guilty and give a male photo, he will probably say guilty. Maybe he will look at his hair or something, and if he sees a woman with short hair, maybe he will call her a criminal. While interpreting this, of course, people's positions, backgrounds, and consciousness are very important. So ultimately this is not magic, artificial intelligence models ultimately learn certain correlations. In the US, the rate of calling black people guilty while not guilty is much higher than white because the data they train is biased, so the model learns it. Therefore, when evaluating the results of the model or deciding whether to use the model in a serious decision, of course, people's social

characteristics are important. Those who notice these things are usually minority groups because they are exposed to it.”

C. Perceptions on Algorithmic Bias: Reasons and Solutions

In relation with the previous topic, I asked participants about their perceptions on the global cases that AI systems give biased or discriminative results for different genders and/or ethnicities. As I mentioned at the literature review, there are several examples that AI systems produce biased outputs towards women such as offering high status jobs to men at online ads, aspiring men to occupations like doctor or engineer and women to housewife in translation tools; and there are also AI systems that give discriminative results for different races, ethnicities, and skin colours (Barr, 2015; Bolukbasi et al., 2016; Buolamwini & Gebru, 2018; Garg et al., 2018; Hamidi et al., 2018; Ingold & Soper, 2016; Kay et al., 2015; Keyes, 2018; Leavy, 2018; Lee, 2009; Obermeyer et al., 2019; Sweeney, 2013; The Artificial Intelligence Channel, 2017; Urbi, 2018). As the last step of my semi-structured question set, I asked participants about their perceptions on global cases like these to understand do they aware of and follow these kinds of societal harms that AI systems created, how do they evaluate these incidents in terms of the role of the developers, company, and algorithm itself, and how do they approach the reasons and solutions of these biased outcomes.

Reasons

When I asked about their perceptions on biased and discriminative results of AI system, most of the participants tend to answer this question by referring to the technical, computational, and non-humane aspects of AI systems and algorithms. They claim that these systems do not have any biases or inner thoughts about certain genders, races, ethnicities, or any other disadvantaged groups in the society like humans have. However, the results of these systems are the reflections of society. Whatever you put in to the system, you get the same. As one of the participant refers to a machine

learning terminology “garbage in, garbage out”. The participant Participant 10 defines this phrase as “If something garbage comes from the data, you cannot extract anything meaningful, valuable from it. In fact, the model does not learn anything that it does not see in the data. As a result, nothing comes from nothing. If those models give an output, they have either seen it in the data or it has been taught with certain templates. Therefore, it is necessary to consider it and develop some things in a controlled manner.” According to many of the narratives, we cannot blame the machines and AI systems for these outputs, we should turn to ourselves, our societies for these biases and discriminative attitudes to prevent it from the beginning. So, for them, if we would like to solve these societal issues, we should work on our minds, our people, our society, and our culture. So, the reflection of the society to data and the reflection of data to the system is the common answer while participants explain the reasons behind of the biased systems. While some of them limit their answers with data, others make the correlation with society. In addition to all of this, some of the participants also emphasize the false perception and misinformation that media has created with fake or distorted news about AI. They state that the media misunderstand and misrepresent developments about artificial intelligence.

One participant, Participant 8, also emphasizes the importance of unbalanced data in these biased AI systems. According to her, it is not something that someone do it on purpose to impose such discriminative thoughts. While training the data, some of the features dominate the model and these kinds of results can originate. To solve these kinds of unbalanced situations, developers can manipulate the data by data tagging or eliminating a feature that cause an error in the system. In the explanation of biased results of AI systems, the participants also refer to a metaphor of “a little child”. Therefore, they can take the responsibilities from machines such as you cannot lay a burden on a child. She states that by referring to the case of gender bias in Translation tool “The reason

for this is data. Because for example, there is a child and if s/he sees one of the 10 doctors as a woman, he will actually do the same.” Another participant, Participant 11, also explains the reason behind of the biased systems as unbalanced data. She states that “Actually, there is a very simple explanation. When you train models, you have certain data sets, for example a system to distinguish between cats and dogs. You also have 200 dog data, and three cat data. Then you give a cat or a dog that this system doesn't see, for example, the system is more likely to call it dog. Because he saw more dogs. Mathematically, it is a situation with a very high probability. But when you give equal data, it will fit into another feature. We cannot expect the machine to gain such common sense. It gives what you feed. An error caused by unbalanced data.” Two of the participants also consider the biased results of AI systems as mere technical “bugs”. One participant, Participant 16 states that these problems can be easily fixed by data after figuring out there is this kind of problem. However, according to him, the actual important and challenging step is noticing these problems. Another participant, Participant 17, says that the model can discover distinguishing aspects at different races or genders, therefore it can give these kinds of results.

Some of the participants define that these problems are originated from the inner biases and discriminative thoughts of societies when we look behind the data. One of the participants, Participant 6, defines that the biased outcomes of AI systems are originated because of data, so we cannot say that the machines are sexist or racist. He states that “For example, something happened about gender, you write “s/he is a doctor” in a gender neutral language to Google Translate. And it automatically translates it as “he is doctor” in English. There is a data problem here, and there is no concept of equality that you can explain to machine learning. For example, the word doctor has the suffix "le" in French, meaning women do not become doctors, for example they do not

have an article. There is such a problem in data. The machine also accepts it as true as it sees it. Then we call it machine sexist. Similar problem arises with the thing, like California crime dataset came out. It detects the next crime location. For example, the algorithm has a bias for black people. Is the algorithm racist, no. The data is racist, so data is like this.” According to another participant, Participant 7, these biased results are originated from the inner biases and discriminations that are already established in the society. And these biases leak to systems via datasets. He mentions that “Now, for example, an artificial intelligence that tweets with racist rhetoric actually stems from the data set. Or if there are very few black people in the face recognition system, he comments that ‘the faces I saw were all white, this is black so it is not a face’. It’s all about the data set. You can think like a mirror. Whatever exists in our subconscious, in general, exists as cases but that people do not accept, they actually come out.” Similar to him, another participant, Participant 13, evaluate this issue from the point that these systems are the reflections of reality. He states that “So at that point, a sampling is done while creating the data. And I think it’s actually a fair sampling. If there are more male pilots in that data, I can say that there are more male pilots in the world. Or, the crime rate of blacks may be higher than that of whites (the non-overlap is related to the backwardness of the people who developed that model anyway). So I think those data reflect the truth, I don’t see any problem with it, but we can prevent it from affecting artificial intelligence. In other words, because artificial intelligence will further reinforce a fact that was taught to him, for example, if blacks are more guilty in the data, the AI can learn this and find blacks more guilty, even if they are not. I have seen that there have been studies on this in recent years so that these data do not affect the AI.” Another participant, Participant 12, comments on the issue as “I think this data will be a little difficult to fix unless people fix themselves first. This is a situation caused by the disorder of people.” A participant also emphasizes the role of the developers and society as

the reason of biased and discriminative AI systems. He states that “In fact, in which part of the world this algorithm is being developed, it means that the people there look at social issues actually has a great effect on the algorithm, which creates such problems. We see that it is reflected in the algorithm in different segments of the society, for example, even if it is a software developer. In other words, whatever problems there are in the countries and regions where the algorithm developers, teams, companies are located, are reflected in the work. And I think this is a problem for the world of course, that people should not be offended in terms of human rights and these are problematic things.” Another participant, Participant 18, also points out that human’s ethical values reflect to the datasets and models. He states that “There is of course a statistical explanation for this at this point. So statistically, you've hired more white men in the past, you've already favored the men, and you're teaching this to the model. At this point, the model will naturally make an erroneous, unethical inference in the future. If you feed the model with incorrect data, you will encounter unethical consequences, in which again the source of unethical results are the people themselves.” Another participants, Participant 19 comments the issue as “You need data for artificial intelligence systems and this data is now being produced by humans. In other words, it is produced by people who have prejudices, act prejudiced and discriminate. Inevitably, the data created by these people is necessarily the data carrying this information. I think it's not surprising that the machines where you teach this data are also doing this. This can be prevented by correcting the data, but when you correct the data, you run away from naturalness, which is not true, it is not natural. I guess Amazon had an HR system that discriminated against women, if I'm not mistaken. It chose women less when choosing which to get hired. If HR is already doing this, it is natural for a machine that uses HR data to do so.” Other participant Participant 21 also claims that the reasons behind of the biased systems are the biases and discriminative thoughts of humans, so we cannot

blame machines for these results. He says that “When a person is biased, you can blame them. But you have no chance to blame the model that way. Because the model is a human creation that tries to reach the result from the data you provide and wants to do it in the easiest way. That's why we see people's own values, people's own prejudices, completely infiltrating artificial intelligence or models. Here, action and reaction are intertwined.” Another participant, Participant 5 lays stress on the mathematical structure of algorithms which cannot contain any kind of biases like humans have. He states that “Algorithms cannot be biased. Mathematics is not biased, after all what we call an algorithm is a sequence of mathematical operations in a row. People are prejudiced. When you give the data to the neural network or any artificial intelligence algorithm, it will learn it. The purpose of the artificial intelligence algorithm is to try to bring a function closer to a function you are looking for. So most artificial neural network algorithms work as a universal function approximation. So it's not the algorithm's fault, it's actually a bit of people's perspective. It is a problem we have been dealing with for thousands of years already. So ultimately these algorithms work like this, because this guy did it, not a different person.”

Solutions

The participants have different approaches and opinions on how to solve the problem of biased and discriminative results of AI systems. While some of them recommends that we should turn back to our society and culture to solve the problems with fairness and discrimination, others make suggestion of fixing the dataset to balance the unbalanced data. Only a few of the participants emphasize the importance of role of the developers and engineers who develop these systems, behind the computational, statistical structure of algorithms.

According to a participant, Participant 6 claims that people are expecting from machines to be fair, to not discriminate. However, for him, machines do not have any understanding of fairness, it is

all about what you give to it and what kind of output you would like to have from it. He states that “Machine learning has a fairness problem when making decisions. This fair treatment is to ensure that the system does not discriminate against different disadvantaged groups. Now what can you do to create this? You can set a fairness metric, right? You say this is the criterion for being fair. As far as I have observed, the most fair distribution method is random distribution. At the end of the day, it is about what you attribute to these concepts and what kind of data you use. What is the criterion for what is fair? While people have not been able to make these decisions, the machine is expected to resolve these decisions.” For him, these decisions like fairness or discrimination should be resolved by humans, by the society. Machines are prone to make errors, they are dependent on the data and knowledge that you upload to it. Therefore, AI systems should be used as decision support systems, not as the direct decision mechanism. It can help doctor to diagnose a disease and it would be very effective, but it cannot be used to diagnose cancer to a patient directly. He states that “Therefore, at the point where even our own mathematics was confused, waiting for the machine to make the decision maybe because of the movies and series like Terminator and Person of Interest ... So, for example, what we call deep learning detects the image through pixels. The researchers only change one pixel in a dog picture and the algorithm that can detect the dog can't detect the dog after one pixel change, it detects it as a plane. But the human eye still sees the dog picture. Therefore, we can understand that what we call a machine is biased, overfitted, that is, it memorizes data from time to time and cannot generalize. The conclusion we draw from here is that you use it as a decision support system, you can iteratively improve the system over time, discuss the decisions it makes for you later.” So, as a solution, the participant suggests to use the AI systems in decision support, not as an authority to call the final decision.

Another participant, Participant 7, divides the problems in two categories as ethical concern and functional problem while discussing the solutions to mitigate bias in the systems. According to him, the ethical interventions to AI systems can cause to disrupt reality, so it has its own risks. However, functional or modelling problems such as not recognizing darker-skinned faces well is a problem that has roots in data, again. He states that “There are actually two sides to solving these problems. First, it might be focusing on producing ethical output, such as not making racist discourse. You have to guess this from the beginning and remove them from the data set. But when the model cannot recognize black faces, this is actually a functional disorder. Here, the model does not deliberately and willingly reject them by saying 'are you human? This shows that you cannot model the problem you want to solve very well. That is, it shows that the data was not collected correctly. But if you look at the ethical outcomes, if you think that Amazon's human resources robot marks female employees less positively, this is a complete reflection of reality. That is why the system produces such an output because reality is. In other words, Amazon's human resources female employees did not evaluate very positively. It is very difficult to observe them and take precautions. You have to think and eliminate everything one by one. And if there is such a thing, that is, if Amazon's human resources do not want female employees, then the AI that you have developed does not do this, which disrupts the reality. Whether it is right or wrong is another matter, but if Amazon has such a policy and the AI you developed treats everyone equally, then it broke your policy. So there will also be a modeling problem, you intervene in reality. Because when you say that you should treat women equally, you will disrupt other functions of the model.” Similar to the definition of the “functional problem” in Participant 7, another participant Participant 19 emphasizes that balancing or correcting the data can denaturalize the natural aspects of data in which this denaturalization may ruin another aspect of it. She states that

“Balancing/equalizing training dataset can eliminate biased situations. But then the training data ceases to be natural and can create a margin of error elsewhere.”

While discussing the reasons and solutions against biased systems, some of the participants tend to answer by emphasizing that these developments in AI are technical developments. So, these kind of errored cases can occur. Many of the participants propose technical approaches such as balancing the data, manipulating the data, or determining the features of dataset well to avoid from these kind of biased results. One participant, Participant 21 emphasizes that people cannot blame the machines for bias or discriminative outcome since the reasons behind of these problems are humans themselves. He suggests that “If we are naturally going to be dissatisfied with a decision based on race or gender, as we will, then this should not be included in the dataset as a feature. It should not be used when defining a data sample. Therefore, this is actually a process that starts with the design and collection of data at the beginning.” One of the participant suggest that the developments in technology have always proceeded by trial and error method. He states that “There are too many cases in real life. It is actually very difficult to predict all of these. I think people should be able to make these improvements, reveal them, then make corrections on them.” Another participant Participant 2 also refers to the trial and error method with emphasizing the technical and passive aspects of AI systems and human biases. She states that “There is no case where you can blame the machine. Because you give it the data that people generate, it learns through it. But there are solutions such as the tasks of identifying the problem and de-gendering, and such studies can be done. But of course you always find solutions to problems as you encounter them. There will always be problems that you cannot foresee. So it seems like we will always try to find a defect of artificial intelligence, but this is because of us. The fault is in us and we are trying to correct our fault there.” In relation to that, another participant, Participant 11 defines that

people should evaluate the developments in AI independently as tools to make our lives easier in different areas, apart from the social implications. Developers can solve these kinds of errors that are originated from data with different techniques. However, these errors should not be pulled to different places with a sociological point of view. She states that “The easiest, if available, to sync the data. What can we do when "unbalanced data" is one of the most studied subjects in the field of artificial intelligence in the academy? If you do not have data other than that, there are different methods. Whichever functions the algorithm optimizes, sometimes it can be manipulated on the optimized function. There is a method called Augmentation. You take the data, enlarge it, crop it, increase it artificially, and such data can be added. So these situations are somehow the responsibility of those who developed the algorithm. But it also seems to me that these social events are being pulled somewhat differently than artificial intelligence studies are sometimes. So you shouldn't do too much. I think it's a good method in engineering, it's a very powerful method. It is very enjoyable, very interesting and also requires creativity. It will definitely enter our lives. Because it makes things much easier. But on the other hand, it is very different to make a sociological inference... So I don't know, it sounds very strange to me. I think AI developments should be viewed independently of social implications.”

While talking about the biased AI systems, the subject comes to role of the developer in terms of reasons behind it and how the biases can be mitigated in the systems. One of the participants, Participant 10, takes the attention to the free will and ethical stand points of the engineers. According to him, engineers and developers should have some ethical boundaries in terms of what they develop, whom they develop, and what are the possible impacts of the system that they develop even though the company they work with demands non-ethical or discriminative systems. He states that “Everyone is familiar with the concept of a doctor's Hippocratic oath, so as a result,

the ethical boundaries of the work of healing a human being were established in Ancient Greece, and a doctor takes this oath before doing it. This is something that happens all over the world and in all cultures, so how many ideas have there been in the world? They take this oath and do their profession after that, and it can become a legal responsibility for them to break a rule throughout their profession. Here I think engineers also need to realize that their work is a responsibility. I mean, 'My employer wanted it and I did it' statement is not something you can take shelter behind. For example, Google has asked China to censor certain things against China in exchange for certain services to be allowed in China. But at the end of the day, these technical improvements have to be made by engineers, and when this situation spreads internally at Google, employees gather among themselves and oppose it. After all, there is something called freedom of speech and China is trying to prevent it, you support it for the sake of financial gain and they say that if you do this, we will quit and Google is taking a step back ... It means that people have a leverage in bargaining here. The company may not back down, but then if you do not find ethical, you can leave that company. As we see now, it is not very difficult for a person working as an AI engineer to find another job after leaving a place. Therefore, people should have limits on this issue. In the context of ethical considerations, there should be words that every person should give to himself. For example, there is a face detection system in the security cameras on the street, they are all gathered in one place and every step of everybody is followed. But here's the engineer who developed it. Because when you tell the man to develop a face detection algorithm, he develops a face detection algorithm, so he doesn't care much for what and why he developed it." Another participant also focuses on the ethical principles of developers. According to his narrative, there are two kinds of developers or companies while developing AI systems: responsible ones and the promoter ones. The responsible developers think about the segments in society and develop products coherent

with the society's values considering the social issues within the society. The promoter developers/companies consider that there is no such thing as bad publicity. So, for him, it is important to look what does the company or developer want to become prominent with. He states that "Money isn't everything. Before financial gain, there should be principles, human virtues should be created in common, and people should be respected." Also, he states that it may be beneficial for countries to develop certain protocols on these issues. One participant also emphasizes the role of the developer while developing AI systems, although according to him a team work with diverse backgrounds and profession would also be helpful in creating solutions that are coherent with real life. He states that "Now, first of all, the thing is very important, data is very important, but it is very important to make a risk assessment rather than data. It is very important to observe real life... In fact, you should not only be in front of the computer, but also in life. I want to come to that. So, for example, if you are an engineer developing an autonomous vehicle, you need to observe driving and the factors that you may encounter while driving, and find out what difficulties there are in their lives. The risks and the accuracy of the data set actually come from real life, the more we dive into real life, the more successful we will be on a computer. I think it is necessary to develop a model with real life. So the most important thing is to be in real life and to know the data." Another participant, Participant 3 also defines that developing the AI models with a crowded team with diverse backgrounds under the supervision of them can help to solve these kind of problems.

D. Subconclusion

In this study, I tried to focus on tracing the road between discrimination and bias among humans and algorithmic bias of AI systems. So, after analyzing the perceptions of developers on gender diversity, discrimination, and bias in relation with the AI systems from a workplace and society

angle; I tried to understand their views on algorithmic bias about the reasons behind it and the solutions for it. As a first step, I asked participants about how do they evaluate the importance and role of the identities of developers, coders, engineers for the AI systems that they develop. Six of the 22 participants state that any kind of identity of individuals does not directly effect the algorithm or AI system. According to their narratives, the algorithms and AI software are technical and computational structures that cannot contain any kind of interpretation and humanlike aspects. So, the technical proficiency and knowledge about the issue of the developers are important while developing AI systems, not the identities. They emphasize the mathematical aspects of algorithmic systems that cannot bear the trace of the identities of developers. Some of the participants are indetermined whether the identities of developers would have any effects in AI systems or not. Some of them emphasize that they had never think about this issue, so while they were thinking at the same time they were answering. Most of them start their answers by declaring that these aspects would not affect the systems, although, in the continuation of their explanations, they could not decide that it has or not. One of the participants states that maybe the identities can effect the algorithmic systems unconsciously. Only four of the participants say that the ethnic, gender, or any kind of identity of developers can have impacts on the AI systems. Since the main actor for AI systems is the developer who create the system; their perspectives, social situations, gender, ethnic backgrounds are important when developing the systems. One of the participants especially emphasized that if the developer comes from an underrepresented group, they are more likely to find out the biases in AI systems. He explains that the identities of developers especially gain importance if they are coming from a minority group, because they are more likely to experience discriminative attitudes in their life stories, and so they are more likely to realize these kind of biased or errored outputs in the AI systems.

Following that, I asked participants about their evaluations on the examples of global discriminative and biased AI systems. As mentioned in the Literature Review chapter, there are AI systems such as facial recognition algorithms, AI-powered translation systems, online ad algorithms, and many more which contain gender, racial, and ethnic biases and discriminative outcomes. So, I wonder about the perspectives of AI developers about these societal impacts and harms to underrepresented groups. Do they follow these kinds of incidents that focus on the societal impacts of AI systems, how do they interpret these biased outputs, and how do they see the role of the companies, developers, and the algorithms themselves? Finally, how do they evaluate the reasons of these undesired outputs and solutions for them?

Most of the participants evaluate these cases by referring to the technical, computational, and non-humane aspects of AI systems and algorithms. According to them, these systems cannot contain any kind of humane aspects such as inner beliefs, biases, or thoughts about genders, ethnicities, and races. So, they state that machines or algorithms cannot be blamed for these kinds of undesired outputs since they cannot produce such a result with a purpose, an intention. They emphasize that these problems occur because of the societal biases, discriminative thoughts, stereotypes, and prejudices of humans. For them, we should turn to people, societies, and culture to solve these kinds of problems, because the problems do not belong to the AI systems. While some of the participants find responsible the society and culture behind of these systems, some of the participants limit their answers by referring the data. According to them, these problems are originated from the unbalanced data. While training the data, some of the features dominate the model and these kinds of results can originate. As one of the participant refers to a machine learning terminology “garbage in, garbage out”. Some of the participants emphasize the false perception and misinformation that media has created with fake or distorted news about AI. They

state that the media misunderstand and misrepresent developments about artificial intelligence. So, the news that subject about the harms of AI systems may contain misinformation and panic the society for no reason.

After exploring the reasons behind of the biased AI systems, the participants comment about the issue on how to solve these kinds of problems. They have different approaches and opinions in terms of extent of the problem. In relation with their explanations about the reasons, most of the participants suggest that we should turn back to our societies, cultures, our inner discriminative thoughts, and our prejudices to solve these kinds of problems. Since the society is biased, these biases can reflect to the systems inevitably. If an AI-powered hiring system is discriminating women, then we can be sure that the HR department which do the hiring tasks manually before does the same thing at all. Other participants evaluate the issue from a more technical, and limited perspective by only considering the data. They suggest that fixing the dataset or manipulating the system by modifying the dataset can be the solution to prevent these kinds of undesired incidents. Only a few of the participants emphasize the importance of role of the developers and engineers who develop these systems, behind the computational, statistical structure of algorithms. However, we can say that there is a consensus among the participants of the research about the technical, mathematical structures of AI systems that cannot contain any biases consciously by itself.

CONCLUSION

In this study, I aimed to demonstrate the perceptions of AI developers on gender distribution, discrimination, and bias in AI at Turkey with the focus of workplace dynamics and algorithmic systems. While gender in AI is discussed both from the perspectives on workplace diversity, discrimination, bias and algorithmic bias; I aimed to comprehend and analyze these two sides of gender problems in AI which are intertwined in each other to draw a comprehensive framework about perspectives of AI developers. I conducted semi-structured interviews with 22 participants who are AI developers in different startups and companies. 6 of the participants were women and 16 of them were men which both of the genders enriched my analysis with their narratives. I structured the findings of the research into three main categories as: a) Introduction to AI in Turkey: The Definitions, Working Models, and Job Hierarchies, b) Gender Diversity in AI Companies, Startups, and Teams: Perceptions on Women in AI, c) Algorithmic Bias: Reasons and Solutions.

In the first section, I elaborated the non-technical definition of AI, state of AI in Turkey according to participants' perceptions, and working models & hierarchical orders of the startups and companies that they are working. The participants referred to the human-like aspects of AI while defining the concept of AI in a non-technical perspective. They tended to compare the capacities of AI algorithms & machines with humans such as in strategical decisions AI can be more successful since it can work on big amount of data, however humans are more successful in physical movements compared to robots. Some of the participants refer to the technical aspects of Artificial Intelligence (AI) such as certain methodologies, working mechanisms, and current state of capabilities in AI. The participants emphasize the enabling functions of AI systems such as "making people's lives easier". In the definition of AI, many participants shared their two main

concerns regarding what is AI and what is not such as misperception about AI by cultural products and the startups, companies, and people that want to benefit from AI hype. I will open these topics in the following paragraph while analyzing the perceptions of participants on the state of AI in Turkey.

On the topic of the state of AI in Turkey, the participants shared different obstacles that are faced in the AI industry and academia in Turkey. They also mentioned positive aspects of AI in Turkey, but the obstacles are challenging and outnumbered compared to the strengths. The challenges that are mentioned in the interviews are the lack of financial source, high rate of brain drain, language barrier, industry-focused simple solutions, quality and originality of the works, and low ratio of implementation of AI projects into products and services. According to the participants, the insufficient financial sources and investments prevent to conduct research-focused works on AI in Turkey and cause a high rate of brain drain of qualified human resource in this field. They claim that most of the qualified human resource in the country tend to migrate abroad for better job conditions, conduct research-focused works on AI, and work at the top companies and institutions. They evaluate that the country cannot benefit from the qualified human resource in AI efficiently. For the participants, the language is a compelling barrier for Turkish students and employees who want to work in this field since an advanced English is a necessity to proceed in the field well. In relation with all these previous challenges, some of the participants express that the quality and originality of the works and studies on AI in Turkey are low. Some of the participants mention the positive aspects of the state of AI in Turkey as increasing number of Turkish sources such as YouTube videos, courses, and blogs and qualified human resource of the country. However, the participants emphasize that there are many companies and startups which promote their products and services as AI-powered to benefit from the AI Hype even though they are developing softwares

without AI. According to participants, the AI Hype helps them to get investment more and quickly, and take public attention to their products and services.

Another dimension in the first section of Findings is working models and job hierarchies of the workplaces where the participants work. In the study, 18% of the participants work at the corporate companies, 4% of them work at a global tech company, and 78% of them work at the startups. The comparison of startups and corporate companies commonly take place in the narratives. The participants define the model of startups as efficient, flexible, task-focused, and result-oriented. But the flexibility of the startup depends on the startup, so we cannot make a generalized analysis on that issue. While some of the startups are flexible in terms of the working hours as day or night, weekday or weekend; some of them state that they have determined working hours with a flexible working environment. The participants emphasize the busy workloads at startups since there are less number of employees and have a more fluid work definition for each employee. All of the participants state that they do not see their jobs as just a work, they are enjoying to work on AI as a hobby and an area that they are personally interested in. Many of the participants say that there is an uncertainty of the roles at the startups. The participants who work at the AI teams of corporate companies define that their working model is similar to the startup culture different from the other departments in the company. However, they also emphasize that the corporate structure provide them a more specific work definition and set of responsibilities compared to startups which is a positive thing according to the participants who work at corporate companies. According to all of the participants, the hierarchical models are not suitable for the technology companies and startups. They care about the feeling of “having a share in management” and no-hierarchy in terms of the process of doing jobs, meetings, or in social relations. While some of the participants state

that they have horizontal hierarchy, only a few of the participants mention that the working environment requires an hierarchy to manage the projects.

The second part of Findings of the research focuses on the gender diversity, gender discrimination and bias, reasons and solutions about these issues from a workplace dynamics perspective. In this part, I evaluated the gender distribution in AI startups and in college departments in Turkey, gender distribution in the participants' workplaces, perceptions of developers on generally gender in AI and gender discrimination/bias in AI, stories and experiences of women developers as they are main and direct encounters of gender problems in the industry, and finally women networks and positive discrimination as a solution or not. I analyzed the quantitative data about gender distributions in two dimensions as student statistics of college education and employee statistics of AI startups in Turkey. According to the student statistics collected from the Higher Education Council in Turkey the ratio of women students in the computer science related departments is 24% at Bachelor's degree, 26,4% at Master's degree, and 25,7% at PhD. To enlighten the gender distribution in the industry, I collected startup employee data via LinkedIn to discover the number of women and men working on this field and the number of women in technical occupations. According to my analysis, the ratio of the women working at the AI startups is %28,6 and the ratio of women working at a technical occupation at the AI startups is %8,8. It can be seen from the statistics that the number of women in technical, technological and engineering departments were higher during the education. However, the ratio dropped to 8,8% in the analysis of the ratio of women in technical occupation. When we came to the gender distribution numbers that are shared by the participants during the interviews, the rate of women employees who work at their teams or startups 9,7%. Some of the participants share the numbers in AI teams with technical occupations, some of them prefer to share the total number of women in their startup or company.

So, this rate includes women employees with no technical occupation. Three of the participants state that there are no women working their company in a technical or non-technical occupations. In addition to this, the eight of the participants claim that there are 1 women working in their team with a technical occupation. And five of the participants state that there are 2 or more women employees in the startups that they are working. Following this topic, the participants interpret that this ratio is not reflecting a numerical equality between genders and it show the male dominance in the area. The narratives of participants are differentiated in terms of the reasons behind of this low number of women in AI workforce. Many participants claim that the number of women employees were low, because the number of applications of women to these occupations are low. So, it is not a systemic or consciously exclusionary attitude of companies.

%50 of the respondents assert that there is no problematic situation about gender in Artificial Intelligence (AI) generally by emphasizing the dependence of individual success to proceed in this field. 4 of them claim that there is a numerical inequality between men and women working in this field, however there is no discrimination or bias related to gender in the field. 7 of the participants which means 31,8% of all participants clearly state that there is a problem in gender distribution and diversity in the field of AI generally. Half of the participants refer to the societal reasons such as gender roles on division of labour and nurturing styles of families on children as the common reason of the less number of women in this field. According to the participants, the society have an important role to distinguish and determine the gender division of labour by reinforcing the gender stereotypes through families, media, and cultural products. The nurturing styles of families have an important place in the narratives of participants. According to them, families treat their sons and daughters differently at the early age such as selecting different kinds of toys at the early ages and directing them to different responsibilities inside of the home. Some

of the participants claim that the lack of role models in AI and computer science has an important impact on the less number of women preferring these fields and the lack of role models create a lack of motivation in women. Another important and prominent explanation made by participants is the sociobiological explanations by defining the roots of the problem as characteristics and interests of women. According to them, the asocial structure of the job computer engineering may not be suitable for the “social” character of woman. Some of the participants claim that there are more women in academia working about computer science and/or AI just because the stability and assurance of the academic jobs rather than the industry. In the narratives, we can see that a secure, safe, comfortable, and more stable job environments are often found suitable for the characteristics of women. Finally, the technical aspect of the AI and technology become prominent in participants’ narratives to understand how they evaluate the intersection of gender and AI. Some of the participants state that AI is a field which only requires technical skills and proficiency of the developers, so the problematic situation with gender diversity is not caused by technology or AI. To sum up, participants tend to find the root causes of the gender diversity problem by looking at the societal and cultural impacts outside of and independent from the AI or technology industry. However, they miss that the societal impacts are not independently affect women besides of the technology industry, the industry itself has its own societal dynamics, division of labour, stereotypical assumptions, and working environment with full of social relationships.

I also analyze the perceptions of participants on gender discrimination and bias according to the global gender discrimination, bias, and harassment cases of big tech companies such as Tesla, Uber, Google, Oracle, and Microsoft. Most of the participants state that they are not following these kinds of social events about the big tech companies, and some of them says that they partially follow these news as they come across online. Participants state that the reason behind of the wage

gap is the disadvantageous positions of women because of their maternity leaves or the higher possibility of turn over of women than men for the companies. Some of the participants make stereotypical assumptions about women such as low negotiation skills on job conditions and wage of women compared to men. The explanations of participants about this issue shows that women are not only seen as bad at negotiation, but also shy, diffident, insecure, and cannot asking for their rights and demands. Some of the participants state that they are not sure that global tech companies apply discriminative attitudes and applications for women. One of the participants ignore that there can be discriminative attitudes and behaviours in the industry.

The women participants state that they do not like to be emphasized as “woman” developer. They are concerned about excluding themselves from all developers by emphasizing their identity of “women” and also worried about diminishing the importance of their success with the emphasis on gender. Most of them do not find uncomfortable of the male dominance in the area. They focus on the technical aspects of AI and technology, and claim that personal success and technical competence is more important than the gender. In addition to that, another important sub-topic for me is their experiences on conscious or unconscious discriminatory attitudes and behaviors during their education and business lives. Most of the women participants state that they do not encounter any biased or discriminatory attitude at their workplaces. Yet, they mention that they have experienced such attitudes and behaviors at their schools or networks. According to the narratives, men in the field are perceived superior in terms of the technical knowledge and competences by classmates or friends such as asking questions more to men. Another discriminatory behavior is interpreting women colleagues or classmates as sexual beings rather than establishing a professional relationship. Participants also claim that they feel like they are disturbing their male friends or colleagues since there is a male-dominant environment at schools or workplaces.

At the final stage of the second part, I asked participants about their perceptions on women organizations that are working to strengthen women in the technology sector from a solutions perspective. Except one of the participants, almost all of the participants state that they are not a member of a women's organization nationally or internationally. Most of the participants evaluate these organizations with their positive impacts on supporting the women's presence, increasing the visibility and raising an awareness. Many of the participants mention about that the women networks in technology sector may have problematic sides and negative effects towards women. They state that these organizations may cause a self-alienation and exclusion of women. And also, some of them state that these kind of organizations have the risks of radicalizing the inner group and cause to come forefront with their genders.

Under the topic of gender diversity and discrimination in AI, all of the participants express their thoughts on positive discrimination even though it does not belong to my semi-structured question set. I observed that positive discrimination is an important issue for participants when discussing about gender in AI. Participants state that they are either experienced or heard different positive discrimination cases towards women in school applications, job applications, or internship opportunities that are offered only for women. While some of the participants evaluate the issue as a negative, non-fair and useless application; the others state that these kinds of artificial efforts are necessary for now to equalize the proportion of women and men. However, most of the participants are irresolute while thinking about positive discrimination. According to that, positive discrimination is necessary to increase the number of women in technology and to provide a balance between genders; on the other hand, it is important to be fair to all genders and positive discrimination should not be applied. Only one of the participants emphasize the positive impacts

of positive discrimination to diminish the stereotypes and perception on gender division of labour, and to increase the number of women in the field.

At the final stage of Findings, I analyze the perceptions of participants on algorithmic bias from the reasons behind it and solutions for it. Before asking directly about the algorithmic bias, I wonder how they evaluate the relation between the identities of AI developers or teams with algorithms and AI systems. About this topic, most of the participants state that they are indetermined about the effects of identities over AI systems. Six of the 22 participants state that the identities of individuals does not directly effect the AI systems since AI softwares are technical and computational structures that cannot contain any kind of interpretation and humanlike aspects. Only four of the participants claim that any kind of identity of developers can have impacts on the AI systems.

Therefore, I asked participants about their evaluations on the cases of global discriminative and biased AI systems. Most of the participants claim that these systems cannot contain any kind of humane aspects such as inner beliefs, biases, or thoughts about any social identity or situation. So, they state that machines or algorithms cannot be blamed for these kinds of undesired outputs since they cannot produce such a result with a purpose, an intention. They emphasize that these problems occur because of the societal biases, discriminative thoughts, stereotypes, and prejudices of humans. For them, we should turn to people, societies, and culture to solve these kinds of problems, because the problems do not belong to the AI systems. While some of the participants find responsible the society and culture behind of these systems, some of the participants limit their answers by referring the data. According to them, these problems are originated from the unbalanced data. Other participants evaluate the issue from a more technical, and limited perspective by only considering the data. They suggest that fixing the dataset or manipulating the

system by modifying the dataset can be the solution to prevent these kinds of undesired incidents. Some of the participants emphasize the false perception and misinformation that media has created with fake or distorted news about AI. They state that the media misunderstand and misrepresent developments about artificial intelligence. So, the news that subject about the harms of AI systems may contain misinformation and panic the society for no reason. In terms of the solutions perspective, only a few of the participants emphasize the importance of role of the developers and engineers who develop these systems, behind the computational, statistical structure of algorithms. However, we can say that there is a consensus among the participants of the research about the technical, mathematical structures of AI systems that cannot contain any biases consciously by itself.

In light of the research findings, I can suggest that the AI developers who are the participants of this research have a tendency to divide the technical and societal from each other. According to their narratives, the AI systems, algorithms, and models are belonging to the “technical” world which cannot contain any kind of biases, discriminative attitudes and behaviors, inner thoughts. And so most of them claim that there is not a concrete common ground for gender and AI to think about them commonly to examine neither the problems nor the solutions. They tend to divide the social one from the technical one; and gender is belonging to the social world in where the societal problems about it should be solved within the culture, families, people, and the society. Since AI is a technical, computational, and mathematical area, they define the area with its technical borders such as quantitative aspects of “realities”, “mathematics”, “personal success”, “knowledge-focused”. Women participants also approach to the problems of this research same as men. They also think that the emphasis on women have the risk of diminishing the impact of personal success.

As a conclusion, I aimed to draw a comprehensive framework about gender diversity, discrimination, and bias on AI in Turkey with this more than a year long research. This research aims to fill the gap and contribute in the literature with its focus on perspectives of AI developers in Turkey. I selected the participants of this research as AI developers, because they are the everyday creators of AI systems. And if we would like to understand the algorithmic biases in AI systems, I believe that we should trace back these biases and discriminations till reaching out the workplaces where these technologies are developed and developers who create & develop the AI systems. That's why it is very vital to center the perceptions of developers into the findings and analysis of this research. To give a broader spectrum about gender diversity on AI in Turkey, I also added the statistical rates of men and women studying and working in this field. Also, I added the perceptions of developers on fundamental concepts in AI such as definition, state of AI in Turkey, working models, and hierchical orders to enrich the framework about AI in Turkey. Further research is needed to evaluate and analyze each aspect of this study more deeply and enlighten the other spaces that are not mentioned in this research at the intersection of gender and AI.

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APPENDIX A: TABLE OF STUDENT STATISTICS BY EDUCATIONAL LEVELS AND DEPARTMENTS, 2019 – 2020

TABLE 1. NUMBER OF STUDENTS BY EDUCATIONAL LEVELS AND DEPARTMENTS, 2019 - 2020									
DEPARTMENTS	BACHELOR'S			MASTER'S			PhD		
	M	F	T	M	F	T	M	F	T
Computer Science	310	67	377	83	53	136	50	22	72
Computer Science and Engineering	459	160	619	98	33	131	63	16	79
Computer Engineering	36269	11729	47998	3193	1165	4358	1461	512	1973
Computer Technology and Information Systems	1012	160	1172	11	3	14	0	0	0
Computer and Information Engineering	0	0	0	72	21	93	70	11	81
Computer and Software Engineering	86	27	113	0	0	0	0	0	0
Computer Software	0	0	0	2	1	3	5	1	6
Information Systems Engineering	1109	451	1560	87	38	125	0	0	0
Information Technologies Engineering	0	0	0	26	6	32	15	3	18
Electrical and Computer Engineering	0	0	0	497	137	634	122	50	172
Electrical, Electronical and Computer Engineering	0	0	0	61	10	71	54	11	65
Electronical and Computer Engineering	0	0	0	25	15	40	19	4	23
Artificial Intelligence	0	0	0	1	0	1	0	0	0
Artificial Intelligence Engineering	33	7	40	0	0	0	0	0	0
Artificial Intelligence and Robotics	0	0	0	11	6	17	0	0	0
Artificial Intelligence and Data Science	0	0	0	8	4	12	0	0	0
Software Development	21	1	22	0	0	0	0	0	0
Software Engineering	5098	1452	6550	94	43	137	40	27	67
TOTAL	44397	14054	58451	4269	1535	5804	1899	657	2556

APPENDIX B: STARTUPS MAP IN TURKEY (FEBRUARY 2021)



Türkiye Yapay Zeka İnişiyatifi Girişimler Haritası

Makine Öğrenmesi



Optimizasyon



Öngörü ve Veri Analitiği



Doğal Dil İşleme



Otonom Araçlar



Arama Motoru ve Arama Asistanı



Chatbot ve Diyalogsal Yapay Zeka



RPA



Akıllı Platformlar



Görüntü İşleme



<https://turkiye.ai/girisimler>
info@turkiye.ai
Şubat 2021

Source: Türkiye Yapay Zeka İnişiyatifi (The Initiative of Artificial Intelligence in Turkey)