EXAMINING THE ROLE OF GENDER IN REACTIONS TO AI-AUGMENTATION IN NEGOTIATION

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ABSTRACT

Recent years have seen rapid growth in the development and organizational use of artificial intelligence (AI), including in negotiation training, preparation, and decision support. This dissertation explores the unintended social consequences of AI awareness in negotiation. Specifically, how knowing that a negotiation partner has used AI systems influences negotiators' behaviour and outcomes in gendered ways. Drawing on research on stereotype threat and masculinity effects in negotiation, I theorize that awareness of a partner's AI augmentation serves as a socially meaningful signal that alters evaluative dynamics, leading women and men to respond differently and achieve different outcomes. Across two experimental studies, I investigated these ideas by manipulating whether negotiators are informed that their opponent has used AI systems for negotiation training or assistance. Study 1 involved human–human negotiations in a controlled laboratory setting, and Study 2 expanded the design to a larger online sample negotiating against standardized AI confederates while believing they were interacting with human partners. The results showed partial support for interaction effects between gender and AI awareness as independent variables and negotiation outcomes as the dependent variable. The simple effects revealed mixed results such that women tended to achieve lower results when a partner's AI use was made salient, while men's outcomes remained relatively stable, with some directional increases. No main effects of AI awareness or gender were observed. Contrary to theoretical expectations, the proposed mediating mechanisms, stereotype threat and masculinity threat, were not supported. Overall, this research contributes to scholarship on negotiation, gender, and AI by demonstrating that AI impacts social interaction not only through what it enables people to do but also through what its presence signals to others, with significant implications for fairness and transparency in technology-augmented work.

Keywords

Negotiation; Artificial Intelligence; AI Augmentation; Gender; Stereotype Threat; Masculinity Threat

DEDICATION

To my parents, maman Afsaneh and baba Mahdi

And in memory of my brave Iranian brothers and sisters who sacrificed in defiance of tyranny

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CHAPTER 1: INTRODUCTION

The Rise of AI in Interdependent Work

In the past decade, there has been significant growth in the development and application of new artificial intelligence (AI) systems at work. These systems are machines that perform cognitive functions usually associated with human minds, such as learning, interacting, and problem-solving (Raisch & Krakowski, 2021). Due to this rapid proliferation of AI systems in the workplace, 86% of firms now report they expect AI to revolutionize their operations within the next five years, and 21% of U.S. workers say at least some of their work is done with the use of AI (Lin, 2025; World Economic Forum, 2025). As a result, AI is not only automating routine and repetitive tasks but also supporting complex activities such as strategic planning, customer service interactions, and predictive analytics (Raisch & Krakowski, 2021; Salesforce, 2023).

As AI advances into higher-order domains of social capability, it increasingly intersects with work that relies on social interdependence in professional tasks. With the advent of AI systems capable of negotiating with individuals, negotiations can now occur between humans and AI systems or between humans and AI agents. As decision-support tools, AI can assist human negotiators with real-time data analysis, scenario simulations, and recommendations that enhance preparation and strategic thinking (Boothby et al., 2023; Gans, 2024). Human users can also train with AI systems, as many negotiation students are currently doing in dozens of North American business classes (see iDecisionGames.com). Across experimental and classroom settings, studies show that users who engage with AI-supported negotiation platforms tend to achieve higher joint gains, make more strategically sound concessions, and demonstrate stronger preparation compared to those relying solely on traditional methods (Dinnar et al., 2021; Gratch et al., 2016), thus significantly enhancing the performance in negotiation for the users.

As AI systems become more integrated into negotiation training, preparation, and real-time decision support, they increasingly appear in interactions where outcomes rely on relative advantage, perceived competence, and strategic behaviour. Therefore, understanding how AI affects negotiation requires attention not only to what AI systems are capable of but also to how their presence is perceived within interconnected social exchanges.

Negotiation as a Socially Interdependent and Status-Sensitive Context

Negotiation is a key process in which individuals and organizations allocate resources, resolve conflicts, and coordinate interests that depend on one another (Thompson et al., 2010). Unlike many personal decision-making tasks, negotiation results are created together: what one party gains depends directly on the other party's behaviour, perceptions, and responses. Therefore, negotiators must constantly pay attention not only to their own strategies but also to signals about their partner’s skills, intentions, and relative power. These signals influence expectations about the bargaining range, shape concession patterns, and determine whether negotiators act more aggressively or cooperatively.

A key aspect of negotiation is its comparative and evaluative nature (Lewicki et al., 2020). Success is seldom judged solely on absolute measures; instead, negotiators assess their performance relative to their counterpart’s outcomes, goals, and perceived skill. This evaluative framework makes negotiation particularly responsive to signals indicating disparities in preparation, information, or ability. Even subtle cues, such as reputation, credentials, or perceived expertise, can influence how negotiators interpret the power dynamics and modify their strategies accordingly (Tasa & Chadha, 2023).

I posit that the increasing use of AI in negotiation settings creates a new category of signals. When negotiators assume that their counterpart is supported by advanced analytical tools, predictive models, or AI-based training systems, they might think the opponent is better prepared, more strategically skilled, or less likely to make mistakes. These assumptions can influence behaviour even before any real interaction takes place. Therefore, AI can affect negotiation dynamics not only through its direct impact on decisions but also by shaping how others perceive the situation at the table.

From AI Capability to AI Awareness

The interdependent nature of negotiation, and the rapidly evolving shifts towards AI adoption, raise an important question: how do people respond when they know that others are using AI? In socially interdependent scenarios like negotiation, the effects of AI may come not only from its actual use but also from awareness of its deployment by a counterpart. This dissertation focuses on AI awareness as a unique and meaningful concept. AI awareness is a negotiator's understanding or belief that their counterpart has used AI systems for training, preparation, or decision support, regardless of whether this actually changes their behaviour. Unlike actual AI use, which directly impacts the user's thinking and choices, AI awareness functions as a social cue, potentially indicating greater competence, technological edge, or strategic sophistication. A related notion is AI augmentation, which refers to the practice of using AI to assist in preparing or negotiating (Brynjolfsson & Mitchell, 2017).

Distinguishing AI awareness from AI augmentation is particularly important in negotiation. Since negotiators often form expectations and strategies before interaction (Jang et al, 2018; Tasa & Behmani, 2023), beliefs about a counterpart's preparation or tools can influence behaviour even if no visible differences exist. Knowing that a counterpart has access to AI may increase perceived stakes, raise uncertainty about one's relative position, or change assumptions about how aggressively the counterpart will bargain. These effects can occur before any offers are exchanged and may continue regardless of whether the AI actually provides an objective advantage.

By separating AI awareness from actual AI use, this dissertation explores how AI acts as a symbolic and relational signal in negotiation. This method clarifies how technology influences interpersonal dynamics through perception, expectation, and interpretation, rather than solely through direct algorithmic action. In doing so, I shift focus from what AI enables individuals to do, to how the presence of AI, whether real or perceived, alters how people respond to one another in interdependent decision-making situations.

Gender and Negotiation: Inequality in Evaluative and Interdependent Contexts

Gender inequality has been a longstanding focus in research on negotiation and organizational behaviour (Bowles et al., 2022; Mazei et al., 2021). In various professional fields, negotiations determine access to vital resources, such as pay, promotions, job tasks, and strategic chances. Since negotiation outcomes accumulate over time, even small differences can have significant long-term effects on career paths and financial stability (Thompson, 2020). Consequently, researchers have continuously examined when, why, and how gender disparities appear in negotiation behaviour and results.

Extensive research indicates that negotiation is not gender-neutral (e.g., Kray et al., 2001). Women and men often face different expectations about appropriate behaviour, competence, and assertiveness, especially in ambiguous evaluation situations (Bowles et al., 2025). Negotiation often involves traits linked to agency, dominance, and competitiveness, qualities that are generally expected of men more than women. Consequently, women may face structural and interpersonal barriers that affect their approach to negotiations and how others perceive their behaviour. These barriers do not signal a lack of ability; rather, they reflect societal meanings tied to gender in evaluative interactions (Bowles & McGinn, 2008; Spencer et al., 2016).

Negotiation is especially sensitive to such barriers because it is both interdependent and evaluative. Negotiators must advocate for themselves while also managing impressions, relationships, and legitimacy concerns. For women, this dual demand can be particularly impactful. Previous research shows that women might expect social or relational costs when engaging in assertive bargaining, especially in mixed-gender interactions or male-typed domains (Babcock & Laschever, 2021). Concerns about being judged through gender stereotypes can affect their aspirations, risk-taking, and strategic decisions. These dynamics demonstrate that gender inequality in negotiation can stem not only from others' reactions but also from the psychological and social pressures inherent in the situation itself.

The growing integration of AI into negotiation introduces a new and potentially powerful context cue. AI systems are often linked to analytical rigor, optimization, and technical skill, qualities culturally associated with competence and expertise. Awareness that a negotiation partner has access to these tools may influence existing gendered expectations regarding ability, preparedness, and legitimacy. Instead of reducing gender inequality, AI-related cues may become part of the same social structures that shape how negotiation performance is viewed and practiced.

Critically, this interaction does not require AI to actually change a counterpart's behaviour. Since negotiation is forward-looking and expectation-driven, beliefs about a counterpart's abilities can influence strategic actions even before any real exchange takes place. If AI awareness signals increased competence or advantage, it might heighten evaluative pressure on some negotiators while encouraging competitive responses in others. Based on what is known about gender and negotiation, these responses could systematically differ for women and men.

Theoretical Perspectives and Expectations

Understanding how awareness of a counterpart's AI use influences negotiation outcomes requires a theoretical perspective that considers both the social significance of technological cues and the psychological processes they may trigger. Since AI awareness acts as a signal rather than a direct behavioural intervention, its effects are likely to manifest through how negotiators interpret and evaluate the situation they face. Therefore, this dissertation draws on theoretical frameworks that highlight evaluation and appraisal in social interaction, while remaining open to the possibility that no single mechanism fully explains the observed effects.

One influential framework for understanding responses to evaluative cues is stereotype threat theory (Spencer et al., 2016), which examines how situational reminders of group-based stereotypes can impair performance in domains where individuals fear negative evaluation.

Extensive research demonstrates that stereotype threat can be triggered by subtle contextual signals that heighten performance scrutiny or comparative evaluation, even in the absence of explicit prejudice (e.g., Kim et al., 2022). In negotiation, a domain often culturally associated with analytical skill, assertiveness, and strategic dominance, such cues may be especially salient. Awareness that a counterpart is supported by advanced AI systems could increase the perceived sophistication and evaluative intensity of the interaction, thereby amplifying concerns about performance for individuals whose competence has historically been stereotyped in this domain. From this perspective, AI awareness may function as a situational cue that heightens evaluative pressure and alters behaviour, particularly for women.

A complementary line of theory focuses on masculinity concerns in negotiation. The Masculinity Effects in Negotiations (MEN) model (Mazei et al., 2021) emphasizes how men may respond to cues that signal challenges to competence or dominance. Research on the effects of masculinity in negotiation suggests that bargaining contexts often serve as arenas for demonstrating agency and status, especially for men. When men perceive that their relative standing is threatened, whether by a highly capable counterpart or by signals of superior preparation, they may respond by increasing competitive effort, asserting control, or intensifying value-claiming strategies. Awareness that a counterpart uses AI may therefore be interpreted as a challenge cue that motivates compensatory behaviour aimed at preserving status or demonstrating competence. Importantly, such responses need not produce large or uniform gains; they may instead stabilize outcomes or lead to modest improvements relative to baseline performance.

Beyond these gender-based perspectives, cognitive appraisal theories provide a broader framework for understanding how individuals interpret situational demands and respond accordingly. For example, the cognitive appraisal framework of Folkman and colleagues (1986) states that individuals evaluate situations along dimensions such as threat versus challenge, perceived demands, and available coping resources. Awareness that a counterpart is technologically augmented may increase perceived task demands, but negotiators may differ in whether they interpret this situation as a threat that exceeds their resources or as a challenge that motivates engagement. These appraisals can shape attention, effort, and strategic flexibility, influencing outcomes even when observable behaviour changes are subtle. From this viewpoint, gender differences in responses to AI awareness may reflect systematic differences in appraisal patterns shaped by socialization and prior experience, rather than discrete psychological mechanisms alone.

While each of these perspectives offers plausible predictions, an important implication of prior research is that the presence of an effect does not guarantee the operation of a specific mechanism. Negotiation outcomes can be influenced by multiple overlapping processes, including shifts in aspiration levels, risk tolerance, concession strategies, or strategic posture, without necessarily producing strong or measurable changes in self-reported psychological states. Additionally, gendered responses to contextual cues need not be symmetrical: women's and men's outcomes may differ in magnitude, consistency, or stability, even when exposed to the same signal.

Therefore, this dissertation uses a theory-testing and theory-refining approach. Instead of assuming that AI awareness operates solely through stereotype threat, masculinity threat, or a single appraisal process, the current research examines whether these well-known views explain the gender differences observed in negotiation outcomes. At the same time, it considers that AI awareness might serve as a broader social signal that alters expectations and strategic behaviour in ways that existing threat-based measures might not fully capture.

By placing AI awareness within these theoretical perspectives and subjecting them to empirical analysis, this dissertation aims not only to evaluate existing theories but also to enhance understanding of how emerging technologies intersect with gender and evaluation in interdependent decision-making contexts.

Overview of the Empirical Approach

To explore how awareness of a counterpart's AI use affects negotiation outcomes, and whether these effects vary systematically by gender, this dissertation uses a multi-study experimental approach. The empirical strategy aims to isolate AI awareness as a perceptual cue rather than as a source of actual behavioural enhancement, while enabling rigorous tests of theoretically driven predictions across different negotiation settings and participant groups.

Across two experimental studies, the central manipulation involves whether negotiators are informed that their counterpart has used AI systems for negotiation training or assistance. Importantly, this information is provided without altering the counterpart's objective behaviour. By holding actual negotiation conduct constant, the design enables a clean test of whether beliefs about AI use, rather than AI use itself, are sufficient to shape negotiation behaviour and outcomes. This approach reflects the dissertation's theoretical emphasis on AI awareness as a social signal operating through perception, expectation, and appraisal.

Both studies employ multi-issue negotiation tasks that allow for a combination of cooperative and competitive strategies. These tasks are well suited for examining how negotiators balance value creation and value claiming under conditions of interdependence. Objective negotiation outcomes serve as the primary dependent variables, capturing the economic consequences of strategic adjustment. In addition, behavioural indicators such as first offers are examined to provide insight into how awareness of AI use may influence negotiators' strategic posture early in the interaction.

The empirical design also allows for systematic examination of gender differences in responses to AI awareness. Gender is treated as a theoretically grounded moderator rather than as a simple control variable, reflecting extensive prior research demonstrating that negotiation behaviour and outcomes are shaped by gendered expectations and evaluative dynamics. By testing for interaction effects between AI awareness and negotiator gender, the studies assess whether the same informational cue produces different outcome patterns for women and men.

To evaluate proposed explanations for these effects, the studies incorporate measures of psychological processes suggested by existing theory, including perceived threat and appraisal-related constructs. These measures enable tests of whether established frameworks, such as stereotype-based evaluative pressure or masculinity-related concerns, account for observed outcome differences. At the same time, the empirical approach remains open to the possibility that AI awareness influences negotiation outcomes through indirect, diffuse, or only partially captured pathways. This dual focus allows the research to both test and refine prevailing theoretical accounts.

The two studies are intentionally complementary. The first examines human–human negotiations in a controlled experimental setting, providing a baseline test of how AI awareness affects interpersonal bargaining dynamics. The second extends this logic to a more standardized negotiation environment using AI-based confederates as counterparts, allowing for greater experimental control and increased statistical power. Together, these studies strengthen the robustness and generalizability of the findings by demonstrating whether observed patterns replicate across different samples, interaction formats, and levels of contextual realism.

Chapter Overview

The rest of this dissertation is organized as follows. Chapter 2 reviews the literature that underpins the current research. It begins by surveying key theories and findings in negotiation research, with special attention to interdependence, evaluative dynamics, and outcome determination. The chapter then covers emerging work on AI in negotiation, focusing on AI augmentation, training, and assistance, and emphasizing the difference between technological capability and social perception. Finally, it explores previous research on gender inequality in negotiation, identifying the conditions that lead to gender differences and the influence of contextual cues on negotiation behaviour and outcomes.

Chapter 3 develops the theoretical framework and hypotheses guiding the empirical studies. Drawing on research on stereotype-based evaluation, masculinity and status concerns, and cognitive appraisal, this chapter articulates competing expectations about how awareness of a counterpart's AI use may influence negotiation outcomes for women and men. Instead of assuming a single explanatory mechanism, the chapter presents these perspectives as testable accounts of how AI awareness serves as a social signal in negotiation settings.

Chapter 4 presents the empirical tests of these ideas through two experimental studies. The chapter starts by describing the research design, participants, materials, and procedures for each study. It then shares the results of hypothesis tests examining the interaction between AI awareness and negotiator gender, as well as analyses evaluating proposed psychological mechanisms and exploratory pathways. Together, the studies provide converging evidence about when AI awareness affects negotiation outcomes.

Chapter 5 examines the findings in relation to existing theory and research. It interprets the results with particular focus on the implications of strong interaction effects alongside weak or absent mediation, and explores what these patterns reveal about the social and psychological impacts of AI in interdependent work. The chapter ends with a discussion of theoretical contributions, practical implications for organizations and negotiators, limitations of the current research, and suggestions for future research. Through this structure, the dissertation advances a coherent argument: that AI influences negotiation not only through its technical capabilities, but also through the social meanings attached to its use, and that these meanings can shape outcomes in gendered ways.

CHAPTER 2: LITERATURE REVIEW

This chapter situates the study within multiple interconnected research areas. It begins by reviewing foundational scholarship on negotiation to identify key processes, outcomes, and behavioural dynamics relevant to bargaining. The review then shifts to growing research on AI in negotiation, focusing on AI augmentation of human decision-making, AI for negotiation training, and AI systems providing real-time negotiation support. Building on this, it discusses the idea that AI augmentation is not only a productivity tool but also a potential threat in professional and decision-making settings, setting the stage for why gender matters in this context. Finally, the review examines gender inequality in negotiation, covering the negotiation gender gap, gender backlash in negotiation behaviour, and recent research on how AI augmentation may interact with gender dynamics. These sections together outline the empirical and conceptual landscape relevant to this dissertation. Importantly, this chapter summarizes existing research without developing the critical theoretical framework that underpins the study's hypotheses, which is presented separately in the third chapter.

Negotiation

Negotiation is a vital process in both professional and personal settings, where individuals or groups engage in dialogue to reach a mutually acceptable agreement (Boothby et al., 2023). It takes place in situations ranging from salary negotiations, business contracts, and procurement agreements to family decisions, academic collaborations, and interpersonal conflicts. Whenever individuals are mutually dependent and have partly conflicting interests, negotiation is the primary way to coordinate actions and resolve disagreements. Scholars have long recognized negotiation as a key element of conflict resolution, resource distribution, and organizational decision-making processes (Bazerman et al., 1990).

In its general form, negotiation can be defined as a communicative process between two or more parties seeking to reach a consensus on an issue or set of issues where their interests are initially divergent (Thompson, 1990). The process involves exchanges of offers, counteroffers, concessions, and, occasionally, threats or commitments, with the aim of reconciling these differences and arriving at an outcome acceptable to all parties. Although negotiations differ in structure, duration, and stakes, they share the defining characteristic of voluntary agreement under conditions of mutual dependence.

Negotiation is not merely about exchanging offers but also about uncovering and understanding the underlying interests, priorities, and constraints of the negotiating parties (Tasa & Chadha, 2023). A critical distinction in negotiation theory is that between positions and interests. Positions represent explicit demands or stated preferences, whereas interests reflect the deeper motivations, needs, or concerns that give rise to those demands (Boothby et al., 2023). Skilled negotiators attempt to move beyond rigid positions and explore underlying interests, as this often reveals opportunities for creative trade-offs and integrative solutions (Lax & Sebenius, 1986). For example, two parties may disagree on price but differ in their sensitivity to delivery timelines or risk allocation, thereby enabling mutually beneficial exchanges across multiple issues. This process requires not only analytical thinking but also interpersonal sensitivity and effective communication (Lewicki et al., 2020).

The negotiation process involves a strategic interplay between cognitive, emotional, and behavioural elements. Negotiators must assess their alternatives, estimate the counterpart's reservation point, and determine their own target and aspiration levels. At the same time, they must manage impressions, interpret social cues, and regulate emotions such as frustration or overconfidence. Psychological factors, including anchoring effects, framing biases, overoptimism, and fairness concerns, can significantly influence both strategy and outcomes (Bazerman et al., 1990). Moreover, trust and relational dynamics shape the willingness of parties to share information and engage in joint problem-solving (Thompson et al., 2010). As a result, negotiation is best understood as a complex social interaction that combines rational calculation with social perception and emotional regulation.

Negotiation requires cooperation because agreement is only possible if parties are willing to engage constructively with one another. The cooperative dimension involves building rapport, establishing credibility, and demonstrating a willingness to consider the other party's perspective (Fisher et al., 2011). Through open communication and information exchange, negotiators can identify compatible interests and create value by expanding the range of possible agreements. This integrative approach is particularly relevant in long-term relationships, such as partnerships or employment relationships, where maintaining trust and mutual satisfaction is crucial (Lewicki et al., 2020). Cooperation fosters value creation by encouraging flexibility, perspective-taking, and collaborative problem-solving.

At the same time, negotiation also entails competition, as each party typically seeks to maximize its own outcomes. When resources are fixed or perceived as scarce, gains for one party may directly reduce gains for the other. Under such conditions, negotiators may adopt competitive tactics such as making ambitious opening offers, withholding information, strategically timing concessions, or leveraging power asymmetries (Walton & McKersie, 1965). Competitive behaviour can be advantageous when claiming value is paramount; however, excessive competitiveness may erode trust, reduce information sharing, and jeopardize agreement altogether (Lax & Sebenius, 1986). Thus, negotiators must continuously evaluate how assertive or accommodating to be, depending on their objectives and the nature of the relationship.

The dual nature of negotiation is captured by the concept of the “negotiator’s dilemma” (Lax & Sebenius, 1986). This dilemma reflects the inherent tension between creating value through cooperation and claiming value through competition. Cooperative strategies are necessary to uncover integrative potential and expand the overall pie, whereas competitive strategies are often required to secure a favorable share of that pie. Overemphasizing one dimension at the expense of the other can lead to suboptimal outcomes, either by leaving value unclaimed or by preventing value creation in the first place. Effective negotiation therefore requires strategic adaptability: the ability to balance openness with assertiveness and collaboration with self-advocacy (Lewicki et al., 2020).

The distinction between distributive and integrative negotiations further elucidates the interplay of cooperation and competition in negotiation. These two types of negotiation represent different approaches to handling the parties' conflicting interests. Distributive negotiation, also known as zero-sum or competitive negotiation, is characterized by parties focusing primarily on dividing a fixed pool of resources (Lewicki et al., 2020). The critical characteristic of distributive negotiation is that one party's gain is perceived as the other party's loss. This approach is commonly used in situations where a single issue is at stake, such as price, and the parties' interests are directly opposed. A negotiator’s goal in distributive negotiation is to claim as much value as possible, often at the other party's expense (Thompson et al., 2010). Distributive negotiation typically involves competitive behaviours such as making high initial demands, using hardball tactics, bluffing, and giving minimal concessions (Lewicki et al., 2020). For instance, a classic example of distributive negotiation occurs in salary negotiations, where an employer and an employee negotiate the employee's salary. The employer may start with a low offer, while the employee may counter with a higher demand, leading to a series of concessions until an agreement is reached (Pinkley et al., 1994).

In contrast, integrative negotiation, also known as win-win or cooperative negotiation, involves a collaborative approach in which the parties seek solutions that satisfy the interests of all parties (Fisher et al., 1991). Rather than viewing negotiation as a zero-sum game, integrative negotiation focuses on creating value by exploring mutual interests and generating creative options that benefit both sides (Brett & Thompson, 2016). This approach is particularly effective when multiple issues are on the table, enabling trade-offs and package deals that can satisfy the parties' different priorities. Integrative negotiation is characterized by cooperative behaviours such as information sharing, joint problem-solving, active listening, and the exploration of mutual interests (Thompson, 1990). For example, in a business partnership negotiation, the parties might focus on combining their resources and expertise to achieve greater market success rather than simply dividing profits. By adopting a cooperative mindset, negotiators can uncover hidden interests, generate new ideas, and reach more satisfying, sustainable agreements for both parties.

In this research, the focus is on integrative negotiation scenarios in order to capture the full range of cooperative and competitive behaviours that negotiators may display. By examining interactions in contexts where parties have opportunities to create value as well as to claim it, this study aims to observe how individuals balance collaboration with self-interest. Through systematic analysis of negotiation processes and outcomes, I assess how different behavioural patterns, such as information sharing, concession strategies, and problem-solving approaches, lead to changes in the resulting individual and joint gains achieved at the conclusion of each negotiation, when negotiators are aware that their counterpart is using AI systems in negotiation.

As scholars have emphasized over decades of research in this area, negotiation is a dynamic, context-dependent process shaped by structural factors, interpersonal dynamics, and individual differences. Power asymmetries, cultural norms, communication styles, and technological developments can all influence how negotiations unfold (Boothby et al., 2023). As negotiation increasingly occurs in digital and technology-mediated environments, understanding these foundational principles becomes even more important. By appreciating its cooperative and competitive dimensions, as well as the psychological processes underlying decision-making, scholars can better navigate the complexities of negotiation and help practitioners achieve outcomes that are both economically efficient and relationally sustainable.

AI in Negotiation

After the release of ChatGPT in late 2022 and the rapid success of large language model (LLM)-based AI systems in performing tasks previously considered uniquely human, a new wave of technological integration in the workplace began (Captain, 2023). Organizations across industries began experimenting with and adopting AI tools to streamline operations, improve efficiency, and enhance decision-making. From drafting reports and analyzing data to generating creative content and supporting customer interactions, these systems quickly demonstrated their potential to augment human capabilities (World Economic Forum, 2025). Research increasingly shows that employees who utilize such technologies gain a remarkable performance advantage over those who do not. For instance, at Boston Consulting Group, consultants using AI technology (ChatGPT 4.0) were significantly more productive, achieving a 12.2% increase in task completion and a 25.1% increase in speed. Moreover, they produced output rated 40% higher in quality than consultants who did not use AI (Dell'Acqua et al., 2023). These findings suggest that AI systems, when properly integrated into workflows, can substantially enhance both efficiency and effectiveness.

The growing influence of AI extends beyond traditional knowledge work tasks. Recently, these technologies have begun affecting more complex interpersonal areas, including negotiation. Historically, negotiations followed a familiar pattern: two or more people engaged in direct interaction through offers, counteroffers, arguments, concessions, and trade-offs, ultimately ending with either an agreement or a deadlock (Jang et al., 2018). This process depended heavily on human judgment, emotional regulation, strategic thinking, and communication skills. However, with the rise of AI systems, negotiation is no longer limited to just human-to-human exchanges. AI technologies now assume roles ranging from fully automated bargaining agents to supportive systems that help human negotiators.

AI Augmentation

While some organizations have experimented with automating negotiations entirely, such as Walmart's Pactum AI, which autonomously negotiates supplier contracts (Sirtori-Cortina & Case, 2023), there is growing interest in approaches that do not replace human negotiators but instead support them. Scholars refer to this approach as AI augmentation (Brynjolfsson & Mitchell, 2017). Augmentation emphasizes collaboration between humans and AI systems, rather than substitution. Instead of removing humans from the negotiation process, AI systems are designed to enhance human decision-making, strategic thinking, and performance (Raisch & Krakowski, 2021).

Augmentation refers to the process through which humans are assisted by AI systems rather than being entirely replaced by automation (Brynjolfsson & Mitchell, 2017). In augmented systems, the human remains central, retaining ultimate authority and responsibility, while the AI provides analysis, feedback, suggestions, or insights that extend human cognitive capacities. Augmentation can enhance a human user's capabilities for performing tasks, and it can occur through a variety of mechanisms and system designs, depending on the nature of the task. For example, JP Morgan Chase adopted an augmentation approach to assess job candidates by combining the expertise of experienced HR managers with an AI-based solution that identified reliable, firm-specific predictors of candidates' future job performance (Raisch & Krakowski, 2021). Rather than replacing human judgment, the AI system complemented it by analyzing patterns in data that might otherwise go unnoticed.

Similarly, AI virtual agents have been incorporated into educational and training contexts to help individuals develop complex interpersonal skills. These systems have been used to improve public speaking skills (Chollet et al., 2014), collaborative problem-solving abilities (Graesser et al., 2018), and social communication skills (Tanaka et al., 2016). In these settings, AI agents simulate realistic interactions, provide feedback, and allow learners to practice repeatedly in low-risk environments. Such examples illustrate the broad applicability of augmentation strategies, especially in domains that require nuanced human behaviour.

Now, imagine a human–human negotiation enhanced by AI systems. This enhancement can happen in at least two main ways: pre-negotiation training and real-time support during the negotiation. In the first case, a human negotiator trains by interacting with an AI negotiation bot instead of, or alongside, practicing with another human (Dinnar et al., 2021). These AI systems might be LLM-based generative AI (GenAI) models, such as versions of ChatGPT trained specifically on negotiation exercises (e.g., platforms like iDecisionGames.com), or non-GenAI chatbots with visual, human-like avatars that simulate realistic negotiation partners (Mell & Gratch, 2016; Schweitzer et al., 2023). Negotiation students can access these systems anytime and anywhere, practice various scenarios repeatedly, and get structured feedback on their strategies and results.

The flexibility of AI-based training systems addresses many limitations of traditional negotiation education. Human role-play exercises require coordination, scheduling, and the presence of equally motivated partners. In contrast, AI systems can provide unlimited practice opportunities, immediate feedback, and exposure to a wide range of negotiation styles (Dinnar et al., 2021). Furthermore, AI systems can be programmed to simulate different personality types, cultural backgrounds, or strategic tendencies, thereby preparing negotiators for diverse real-world interactions. By repeatedly engaging with these systems, learners can experiment with different tactics, such as anchoring, information sharing, concession timing, and integrative trade-offs, and observe the consequences of their choices (Johnson et al., 2019; Johnson et al., 2023).

Although negotiations offer opportunities for significant individual and joint gains, negotiators often fail to achieve optimal outcomes (Brett & Thompson, 2016). Suboptimal results may occur when negotiators depend on unsuitable tactics, misinterpret the situation, or focus too much on a single issue at the expense of broader trade-offs. At best, subpar agreements leave value on the table, missing chances for mutual benefit. At worst, such outcomes can lead to inefficient agreements, strained relationships, and long-term mistrust (Thompson et al., 2010). A common barrier to reaching the best agreements is the inability to accurately understand a counterpart's needs, preferences, and priorities (Thompson & Hastie, 1990). Misaligned assumptions and poor information sharing can prevent parties from finding integrative solutions. For these reasons, AI enhancement shows great promise as a way to improve both negotiator behaviour and negotiation results.

AI Training in Negotiation

AI negotiation systems have the potential to address these challenges by helping users develop both analytical and interpersonal competencies. Through structured exercises, feedback, and simulations, these systems can teach individuals how to gather information effectively, recognize compatible interests, design creative trade-offs, and manage competitive tactics strategically (Dinnar et al., 2021; Gratch et al., 2016). By analyzing patterns in user behaviour, AI systems can highlight tendencies such as excessive competitiveness, premature concessions, or insufficient information sharing, and suggest alternative approaches (Johnson et al., 2019; Johnson et al., 2023).

Empirical research supports the effectiveness of AI-based negotiation training. Studies have shown that individuals who engage with such systems demonstrate significant improvements in negotiation performance (Dinnar et al., 2021). In one study, participants who received pedagogical feedback from an AI negotiation system invested more effort in the exercise. They spent more time negotiating, reported trying harder, and recognized areas for potential improvement (Gratch et al., 2016). The presence of feedback appeared to increase engagement and motivation, encouraging deeper reflection on strategy.

In another study, students who participated in AI-supported training improved their value-claiming abilities, and this benefit was amplified when the system provided feedback on both tactics and outcomes (Johnson et al., 2019). By analyzing specific behaviours, such as initial offers, concession patterns, and information disclosure, the AI system helped users refine their strategies in a targeted manner. Importantly, these benefits are not limited to competitive tactics. More recent research indicates that participants who receive instruction and feedback from AI systems become more adept at value creation as well. Specifically, they learn to identify opportunities for joint gains by shifting their focus from improving outcomes on a single issue to making trade-offs across multiple issues (Johnson et al., 2023). This shift reflects a deeper understanding of integrative negotiation principles.

Beyond skill acquisition, working with AI systems may also enhance negotiators' psychological readiness. According to Bandura's (1997) theory of self-efficacy, individuals' beliefs in their ability to perform a task influence their motivation, persistence, and performance. AI-supported negotiation training can strengthen self-efficacy through two key mechanisms: mastery experiences and verbal persuasion. By successfully navigating simulated negotiations, users accumulate mastery experiences that reinforce their sense of competence. Additionally, positive and constructive feedback from the AI system serves as verbal persuasion, further bolstering confidence. Increased self-efficacy can translate into improved real-world performance, as negotiators approach interactions with greater assurance and strategic clarity.

AI Assistance in Negotiation

In addition to pre-negotiation training, AI systems can provide real-time assistance during active negotiations. In this augmentation model, the AI functions as a continuous advisor rather than a training partner. For example, an AI system may offer recommendations on what settlement offers to propose in complex negotiations (Gans, 2024). It may analyze prior exchanges, estimate the preferences of the counterpart, or simulate potential responses to proposed concessions. Such support can reduce cognitive load and help negotiators make more informed decisions under time pressure.

The capabilities of AI assistants extend beyond strategic suggestions. AI systems can translate messages across languages, detect emotional cues in text or voice, recommend adjustments in tone, or even modify a user's digital appearance and speaking style in virtual environments (Baten & Hoque, 2021; Johnson et al., 2017; Johnson et al., 2019; Dinnar et al., 2021). These features can be particularly valuable in cross-social group negotiations, where misunderstandings may arise from linguistic or emotional misinterpretations. By highlighting potential misalignments or suggesting more constructive phrasing, AI systems can facilitate smoother communication.

Furthermore, research suggests that AI-powered assistants can influence human reasoning processes in collaborative decision-making contexts. In one study, a ChatGPT-powered assistant provided decision recommendations, introduced new perspectives, and articulated novel rationales, leading users to adjust their reasoning, language, and argumentative stance in ambiguous situations (Ferguson et al., 2023). Such findings imply that AI systems do not merely provide information; they can shape cognitive processes and strategic framing. In negotiation contexts, this influence could encourage users to consider integrative solutions they might otherwise overlook.

Through these applications, AI augmentation moves beyond preparatory training and becomes embedded in the negotiation process itself. Instead of restricting AI support to the period before negotiations begin, human negotiators can benefit from real-time analysis, feedback, and strategic guidance (Shonk, 2026). This continuous partnership between human and machine has the potential to reshape how negotiations are conducted, blending human intuition and relational concerns with computational analysis and pattern recognition.

While AI augmentation shows great promise for negotiator learning, skill acquisition, and performance, integrating AI into negotiation raises important questions about inequality, fairness, trust, and dependency. Different social groups may not have the same levels of access to AI systems, do not benefit equally from using them, nor do they use them in a similar way (Chatterji et al., 2025; Kochhar, 2023; McClain et al., 2025). Overreliance on AI recommendations could undermine human judgment or reduce authentic interpersonal engagement. Negotiators may also need to consider transparency: should parties disclose the use of AI assistance? How might perceptions of manipulation or fairness be affected? As organizations increasingly adopt AI augmentation strategies, these considerations will become central to responsible implementation.

In sum, the rapid advancement of LLM-based AI systems has transformed not only routine workplace tasks but also complex interpersonal processes. From pre-negotiation training platforms to real-time advisory tools, AI augmentation offers promising avenues for enhancing negotiation performance. By improving skill acquisition, fostering self-efficacy, supporting strategic decision-making, and facilitating communication, AI systems can help negotiators achieve higher individual and joint gains (Dinnar et al., 2021; Johnson et al., 2023). As research in this area continues to evolve, understanding how best to design and integrate these systems will be crucial for maximizing their benefits while mitigating potential risks.

AI Augmentation as Threat

Relatively little attention has been given to the potential downsides of using AI in inherently interpersonal settings, such as negotiations. Negotiation is not just an analytical task. It is a highly social process that involves exchanging values, managing relationships, and sharing resources (Boothby et al., 2023). The interdependence between parties means that each side's outcomes depend on the other's actions and decisions. Unlike purely technical problem-solving, negotiations rely on perception, trust, impression management, and emotional cues (Bazerman et al., 1990). These factors create vulnerabilities that can be worsened when one party uses AI support while the other does not.

If one party gains an advantage through AI assistance, it might disrupt the delicate balance that the non-augmented side expected. Negotiators usually start discussions with assumptions about their relative skills, access to information, and bargaining power. These assumptions influence their strategies, openness, and pattern of concessions (Brett & Thompson, 2016; Thompson et al., 2010). The introduction of AI can alter these expectations even before any meaningful interaction takes place. The mere belief that the other side has superior analytical tools can be seen as an imbalance in preparedness or sophistication, which can affect perceptions of ability, status, or fairness.

This perceived disruption becomes particularly concerning when the AI-augmented party's improved performance is viewed as a threat (situations that contain the possibility of harm or loss (Folkman et al., 1986)). For instance, a negotiator who learns that the other side is using AI tools may become more guarded, suspicious, or even adversarial. Instead of engaging collaboratively to create joint value, they may assume that the augmented party possesses hidden information or optimized strategies that are difficult to counter.

Drawing on the cognitive appraisal framework (Folkman et al., 1986), the appraisal and perception of augmentation itself, regardless of its actual effects, may be sufficient to alter negotiation dynamics. Negotiation outcomes are inherently relative, and success is often evaluated in comparison to the counterpart's outcome (Curhan et al., 2006). Even the suggestion that a counterpart is equipped with a virtual agent can be construed as an unequal advantage, heightening concerns about distributive imbalance and decreased status. Such stressful encounters involve a process of primary appraisal, in which individuals evaluate whether a situation poses a threat or challenge, and then a secondary appraisal, where they assess their available coping options (Folkman et al., 1986).

Research has shown that negotiators often respond negatively when they perceive gender-related threats, particularly in contexts where stereotypes about competence or dominance are salient, like for women in negotiation contexts (Spencer et al., 2016). Upon the primary appraisal of AI use by the counterpart as a threat, women can feel the stereotype threat for being evaluated on their performance against a capable, assisted counterpart, thus lead them to react with increased anxiety upon their secondary appraisal.

Men, on the other hand, may react to perceived AI-based advantages with increased competitiveness, especially in situations like negotiation (Mazei et al., 2021). If AI is seen as a tool that boosts dominance or strategic power, men who feel their position is threatened might become more assertive or even confrontational to regain control. These reactions are not necessarily driven by hostility toward technology itself but are influenced by broader gender concerns and masculinity defense.

Understanding the psychological and social consequences of AI augmentation is essential for both scholars and practitioners (Karunakaran et al., 2025). Organizations integrating AI into negotiation training or real-world bargaining contexts must consider not only how AI improves analytical capability, but also how its presence is perceived by others. Transparency about AI use, norms around technological assistance, and mutual access to similar tools may mitigate some of the asymmetries that give rise to threat perceptions (International Monetary Fund, 2024; Joyce et al., 2021).

In the upcoming sections, I explore in greater detail how the sense of threat caused by awareness of a counterpart's AI use may influence women's and men's reactions in negotiation differently. By analyzing these gendered responses, I seek to shed light on the complex relationship between technological enhancement and interpersonal dynamics. Only by considering both the instrumental and relational aspects of AI can we fully grasp its effect on negotiation processes and results.

Negotiation and Gender Inequality

Gender inequality has been one of the most widely studied topics in the social sciences, spanning economics, psychology, sociology, and management (Bowles & McGinn, 2008; Bowles et al., 2022). Despite decades of legal reforms, diversity initiatives, and changing cultural norms, disparities between women and men persist across nearly every work domain (Kricheli-Katz, 2021). These inequalities affect hiring decisions, pay, promotion rates, access to high-profile assignments, leadership roles, and everyday interactions (Goldin, 2021). Previous research has extensively documented and examined gender inequality and the underlying factors that cause it, including issues like the gender pay gap, gender stereotypes, biases, and gender role expectations.

A widely documented form of gender inequality is the persistent gap in earnings between women and men, which has its roots in gender inequality in negotiations. Research shows that women earn less on average, even after accounting for factors such as education, work experience, occupation, and hours worked. For example, Blau and Kahn (2017) find that although the gender wage gap has narrowed over time, a substantial unexplained portion remains after controlling for observable characteristics, which may reflect discrimination, differences in negotiation outcomes, and organizational practices that disadvantage women. These pay differences also accumulate over time: small disparities in starting salaries can expand through percentage-based raises, bonuses, and retirement contributions, producing significant lifetime income differences (Blau & Kahn, 2017; Goldin, 2021). As a result, gender pay inequality is not only a short-term disparity but a long-term process shaping economic security, wealth accumulation, and career trajectories (Goldin, 2021).

Many such gender disparities are rooted in stereotypes about appropriate behaviour for women and men. Social role theory suggests that gender stereotypes develop from historically divided labor roles, shaping expectations about personality traits and competencies (Eagly & Karau, 2002; Ellemers, 2018). Women are typically associated with communal qualities such as warmth, empathy, and cooperation, whereas men are linked with agentic traits such as assertiveness, independence, and competitiveness (Bowles et al., 2022). Role congruity theory argues that prejudice occurs when these stereotypes conflict with the perceived requirements of leadership roles, which are often culturally associated with agentic traits (Eagly & Karau, 2002).

Consequently, women aspiring to leadership may face a “double bind”: assertive women may be viewed as competent but less likable, while women who conform to communal expectations may be perceived as likable but lacking leadership potential (Bowles et al., 2025; Davies et al., 2005; Ridgeway, 2001; Rudman et al., 2012). In addition, prescriptive gender norms can trigger social penalties when violated, influencing hiring, evaluations, and promotion decisions and reinforcing systemic advantages for men in environments that prioritize agentic behaviours (Rudman & Phelan, 2008; Cortes & Pan, 2018; Cotter et al., 2001).

Against this broader backdrop of structural and cultural inequality, negotiation emerges as a critical micro-level process through which disparities are both enacted and potentially challenged (Bowles & McGinn, 2008). Negotiation shapes starting salaries, raises, promotions, resource allocations, job responsibilities, and access to opportunities. It is not merely a discrete event, but an ongoing process embedded in everyday organizational life.

Negotiation scholars have long demonstrated that individuals are imperfect decision-makers. Foundational work by Bazerman and colleagues (1990) highlights how negotiators are susceptible to cognitive biases, including anchoring, overconfidence, fixed-pie perceptions, and egocentric interpretations of fairness. Negotiators often assume that gains for one party necessarily imply losses for the other, even when integrative solutions are possible.

When gender differences are prominent, these cognitive biases intersect with social stereotypes (Bowles et al., 2022). Expectations regarding how women and men *should* behave can influence initial offers, concessions, responses to assertiveness, and final outcomes. Therefore, negotiation is not gender-neutral but is embedded in social meaning systems that shape behaviour and evaluation. Scholars like Bowles and McGinn (2008) argue that negotiation is a crucial mechanism in both creating and reducing inequality. On one side, differences in negotiation behaviour and treatment can worsen wage gaps and career disparities. On the other side, effective negotiation strategies and structural reforms (e.g., transparency, standardized pay scales) can help reduce these inequalities.

Negotiation Gender Gap

A significant amount of research has explored whether and how women and men differ in negotiation outcomes. Early studies indicated that women tend to achieve less favorable economic results than men in distributive bargaining situations. Meta-analyses by Stuhlmacher and Walters (1999), as well as Mazei and colleagues (2015), confirmed that a small but consistent gender gap exists in certain negotiation environments.

Importantly, these differences are context-dependent. The gender gap is more pronounced in situations characterized by ambiguity about bargaining norms, lack of clear standards, and mixed-gender interactions (Bowles et al., 2025). When negotiation norms are explicit and information is transparent, gender differences often diminish. This suggests that structural clarity can buffer against bias-driven disparities.

Research by Kray and colleagues (2002) further demonstrated that gender stereotypes can shape expectations and self-perceptions in negotiation contexts. For example, when negotiation tasks are framed as requiring traits stereotypically associated with men (e.g., competitiveness), women may perform differently than when tasks are framed in more neutral or communal terms. Such framing effects underscore how subtle contextual cues can activate gendered expectations.

Gender Backlash in Negotiation

One particularly influential line of research examines gender differences in negotiation initiation. Studies have found that women are less likely than men to initiate salary negotiations, especially when norms are ambiguous (Babcock & Laschever, 2021). However, focusing solely on women's initiation rates risks oversimplifying the issue. The social context surrounding negotiation attempts is equally important.

Research has revealed that women who initiate negotiations for higher compensation may experience social backlash (Bowles et al., 2007). Evaluators perceived female negotiators as more demanding and less pleasant than male negotiators making identical requests. This negative shift in interpersonal evaluations translated into less favorable outcomes. Similarly, Amanatullah and Tinsley (2013) have shown that women who advocate strongly for their own interests may face relational penalties because their behaviour conflicts with prescriptive gender norms. This backlash creates a dilemma: failing to negotiate may perpetuate inequality, but negotiating assertively may incur social and professional costs.

Interestingly, research suggests that women may experience more positive results when negotiating for others rather than themselves. Previous studies have shown that women advocating for others are less likely to face backlash and sometimes achieve better outcomes (Amanatullah & Morris, 2010). Similarly, Bowles and colleagues (2005) found that aligning negotiation behaviour with communal roles can reduce negative perceptions. These findings support the communal–agentic framework and broader theories about gendered role expectations (Bowles et al., 2022). Women are generally expected to focus on relationships and group welfare, while men are expected to focus on individual gain and competition. Deviating from these norms can lead to evaluative penalties, affecting both perceived impressions and actual negotiation results.

Gender disparities are especially pronounced in mixed-gender negotiations. Research suggests that men may perceive themselves as more naturally suited to negotiation tasks and may enter negotiations with higher expectations of success. Mazei and colleagues (2021) highlight how self-perceptions of competence and entitlement can influence aspiration levels, first offers, and persistence. Moreover, evaluators' biases can shape how identical behaviours are interpreted depending on the negotiator's gender. Assertiveness from a male negotiator may be seen as appropriate and strategic, while the same behaviour from a female negotiator may be interpreted as abrasive (Bowles et al., 2022). Such differential interpretations reinforce outcome disparities.

Gender and AI Augmentation

With the advent of AI, a new frontier for research has opened for analyzing gender dynamics in the workplace, beyond previously studied issues such as gender stereotypes, biases, and negotiation gaps in human–human interactions. AI systems are increasingly embedded in organizational decision-making, productivity tools, and communication processes, creating new forms of human–AI collaboration (Bankins et al., 2024). This transformation has prompted scholars to examine how gendered patterns of behaviour and inequality may persist, change, or even be amplified when workers rely on AI tools for decision support and task augmentation. Rather than eliminating social biases, early research suggests that AI often reproduces existing social structures, raising important questions about how gender dynamics evolve when technology mediates work interactions (Joyce et al., 2021).

A substantial amount of research explores how algorithmic systems can reproduce or amplify gender bias in workplace settings. Because AI models are trained on historical data that reflect existing social inequalities, they can inherit and reinforce those patterns in automated decisions. Studies have demonstrated that AI systems used for recruitment, evaluations, and other decision-making processes can put women at a disadvantage when biased training data influence the model's outputs (Mehrabi et al., 2021). For example, research has shown how AI systems may reproduce stereotypes or unequal outcomes in areas such as hiring or career evaluation, mirroring broader societal gender biases embedded in the training data (Dastin, 2022). These findings underscore a key concern in the literature: AI does not operate in a neutral social environment but interacts with and potentially magnifies existing inequalities within organizations (Karunakaran et al., 2025).

Another emerging stream of research focuses on gender differences in the adoption and use of AI tools in the workplace. Evidence suggests that women may adopt generative AI tools at lower rates than men, partly due to concerns about the ethical implications of using AI or fear of negative judgment for relying on such technologies. One study found that women adopt AI tools roughly 25 percent less frequently than men on average, even though the productivity benefits appear similar across genders (Otis et al., 2024). This adoption gap may have long-term consequences if AI augmentation becomes a key source of productivity and career advancement. Additionally, social perceptions surrounding AI use can be gendered. Experimental evidence indicates that women who rely on AI assistance may be judged as less competent compared with men producing the same AI-assisted work, illustrating how gender stereotypes can shape evaluations of technologically augmented performance (Gai et al., 2025).

Scholars have also begun examining how gender biases manifest in interactions between humans and AI systems. Research on human–AI cooperation suggests that people often project gender stereotypes onto artificial agents. For example, experiments in which AI systems are assigned gender labels show that participants interact with them differently depending on whether the AI is presented as male or female, reflecting biases similar to those observed in human–human interactions (Tu et al., 2025). In one experimental study, participants were more likely to rate AI partners labeled as female more warm and less competent than those labeled as male, demonstrating that gender stereotypes can shape behaviour even when interacting with non-human agents (Tu et al., 2025). These findings suggest that AI-mediated interactions may reproduce gendered expectations and power dynamics, especially when AI systems are anthropomorphized or embedded in collaborative decision-making processes.

Research on gender and negotiation provides another important lens for examining AI augmentation at work. Decades of negotiation research document systematic gender differences in negotiation behaviour and outcomes, including disparities in salary negotiations and first offer behaviour (Bowles et al., 2022). As AI tools increasingly support decision-making in tasks such as salary benchmarking, career advice, and negotiation preparation, scholars have begun exploring how these technologies interact with gendered negotiation dynamics. Experimental research using virtual agents and AI-mediated environments has demonstrated that gender cues and interaction design can influence participants' negotiation perceptions and strategies, suggesting that AI systems may shape how individuals approach bargaining situations (Hale et al., 2026; Kokić et al., 2024).

Despite the increasing research on gender bias in AI systems, gender differences in AI adoption, and AI-supported negotiation advice, current studies still have an important gap. Most research focuses either on algorithmic bias or on behavioural responses to AI tools, but it rarely explores the strategic implications of AI use in interpersonal negotiations. Specifically, prior work has not looked at the unintended effects that can occur when individuals use AI to assist in negotiations, nor how knowing that a negotiation partner is using AI might create gendered dynamics in bargaining interactions. These dynamics are fundamentally different from previously studied gender effects, such as biases and backlash effects. These unexplored mechanisms highlight a significant gap in the literature, which the next chapter will address by building a theoretical framework on how AI use in negotiations could influence gendered interaction patterns.

CHAPTER 3: THEORY AND HYPOTHESES

This research explores how people react when they discover their negotiation partner is using AI, and how these reactions vary by the gender of the negotiator. Importantly, the theoretical framework I develop in this chapter does not assume that all women or men respond in exactly the same way. Instead, it suggests that systematic patterns are likely to emerge on average when AI is used as an augmentation cue in negotiation settings. The framework also does not require a single psychological mechanism to operate the same across genders. Instead, it allows for the possibility that women's and men's responses are shaped by different combinations of cognitive, emotional, and behavioural processes, all influenced by gendered interpretations of status and competence cues.

I move beyond the communal–agentic lens and other previously discussed theoretical frameworks on gender inequality to focus on two perspectives centered on the idea of threat. As I mentioned earlier, I expect negotiators to perceive threat when they become aware of their counterpart's use of AI, and I aim to analyze how they respond to such threat. First, *stereotype threat theory* is used to understand how women might react when AI increases concerns about being judged based on negative stereotypes related to competence or technical skills. Second, research on *masculinity effects in negotiation* is included to explore how men might react when AI alters perceptions of dominance, autonomy, or status during bargaining. By combining these two frameworks, I aim to provide a more detailed understanding of how awareness of AI interacts with gendered psychological processes to influence negotiation behaviour and outcomes.

Stereotype Threat for Women

Stereotype threat, the situational pressure that occurs when individuals fear confirming a negative stereotype about their social group, has long been shown to impair performance by increasing anxiety, cognitive load, and self-monitoring (Spencer et al., 2016). Instead of reflecting a lack of ability, stereotype threat works through subtle psychological mechanisms that interfere with otherwise intact competence. When people realize their performance might be viewed through the lens of a negative stereotype, they often experience heightened physiological arousal, intrusive thoughts, and worries about how they are perceived (Pennington et al., 2016; Kim et al., 2022). These processes drain valuable cognitive resources, especially working memory capacity, and shift focus away from task-relevant information toward self-monitoring. Consequently, performance declines not because of diminished skill but because mental bandwidth is diverted to managing threat-related concerns (Spencer et al., 2016; Pennington et al., 2016).

In negotiation settings, these psychological mechanisms are especially important. Successful negotiation requires sustained concentration, flexible thinking, emotional regulation, and the ability to process multiple pieces of information quickly (Bazerman et al., 1990). Negotiators need to monitor offers and counteroffers, understand their counterpart's motives, and adjust their strategies rapidly. When stereotype threat increases anxiety and cognitive load, negotiators may struggle to stay engaged strategically (Lewicki et al., 2020). Worry and rumination can overload working memory, reducing the ability to evaluate trade-offs or develop creative solutions. Self-monitoring might also rise, causing individuals to second-guess their proposals or shy away from assertive tactics that could strengthen their position. Therefore, stereotype threat weakens not just confidence but also the mental skills essential for effective bargaining.

For women, these challenges can become more intense in negotiation settings. Negotiation has often been connected with traits culturally seen as masculine, such as assertiveness, dominance, competitiveness, and decisiveness (Bowles et al., 2022; Mazei et al., 2021). Because common gender stereotypes depict women as communal, accommodating, and relationship-oriented rather than agentic and competitive, negotiation environments can emphasize gendered expectations. When women participate in negotiations with conditions that heighten awareness of these stereotypes, like direct references to performance comparisons, evaluative scrutiny, or male-dominated settings, they may experience stereotype threat more acutely (Kray et al., 2001; Kray et al., 2002). The very field in which they operate is implicitly viewed as one in which their social group is assumed to be less competent or less naturally suited.

Research on negotiation specifically shows that gender-related beliefs significantly influence bargaining behaviour and outcomes. Bowles and colleagues (2022) emphasize that women's negotiation performance is particularly affected by contextual cues related to evaluation and gender norms. For instance, subtle reminders of gender differences or signals that performance will be judged comparatively can impact how assertively women advocate for themselves. Kray and colleagues (2001) demonstrate that stereotype activation can cause women either to conform to prescriptive gender expectations, by acting more cooperatively or less aggressively, or to experience reactance, a motivational pushback against the stereotype that can still disrupt strategic focus. In both cases, activating stereotypes changes cognitive and motivational processes during the negotiation.

Beyond internal cognitive effects, women must also navigate external social penalties. Backlash concerns, as documented by Rudman and Phelan (2008), further limit women's negotiation assertiveness when they anticipate being penalized for violating feminine stereotypes. Women who negotiate strongly for higher pay or better terms risk being seen as abrasive, selfish, or unlikable, evaluations that can have real professional consequences. Anticipating such backlash can create a double bind: not negotiating assertively may limit economic outcomes, but negotiating assertively may threaten social standing. The mere expectation of this trade-off can increase anxiety and self-regulation efforts, further draining cognitive resources during the interaction. Together, these studies suggest that when external cues increase the importance of gender stereotypes, women may start negotiations with higher anxiety, greater concern about social judgment, and less cognitive capacity, ultimately lowering their negotiated results.

Introducing AI-assisted negotiation counterparts presents a novel but potent cue that can trigger stereotype threat in women. Although AI systems are ostensibly neutral, perceptions of technological superiority or computational precision can reshape the psychological landscape of negotiation. Being informed that one's counterpart is supported by an AI agent may signal that the interaction will be analytically demanding, performance-focused, and subject to objective optimization. For many individuals, this may increase pressure; for women negotiating in domains already linked to stereotypes about analytical or competitive deficits (Schmader, 2023), the effect may be particularly pronounced.

Moreover, AI assistance may amplify perceived evaluative scrutiny. Negotiating against a human counterpart already involves concerns about social judgment, but the presence of AI may introduce an additional layer of perceived objectivity and precision. Women may worry that their concessions, offers, or reasoning will be systematically analyzed and compared against optimal benchmarks. This perception can intensify self-monitoring, as negotiators become preoccupied with avoiding errors or appearing irrational. Heightened self-monitoring, in turn, reduces spontaneity and strategic flexibility, key components of successful negotiation (Lewicki et al., 2020).

Importantly, these effects do not necessarily indicate actual performance inferiority compared to AI-supported counterparts. Instead, they reflect the psychological impact of stereotype-relevant cues present in the negotiation setting. The AI acts not just as a tool but as a contextual signal that triggers broader cultural stories about gender, competence, and technology. In this way, AI-supported negotiations might unintentionally recreate the very conditions in which stereotype threat is most likely to impair performance, such as heightened evaluative pressure, clear group-based expectations, and perceived competence gaps (Spencer et al., 2016; Pennington et al., 2016).

Taken together, the literature on stereotype threat, gender and negotiation, and backlash concerns provides a compelling framework for understanding how AI integration could differentially affect women's negotiation experiences. By increasing anxiety, cognitive load, and self-monitoring, stereotype threat undermines the cognitive and emotional processes essential for effective bargaining. When gendered expectations are made salient, whether through explicit stereotypes, evaluative cues, or the symbolic presence of advanced technology, women may face compounded psychological pressures. As AI becomes more prevalent in professional decision-making contexts, understanding these subtle yet consequential dynamics will be critical to designing negotiation environments that promote equity rather than inadvertently reinforce existing disparities.

Masculinity Effects in Negotiations

According to the MEN model (Mazei et al., 2021), men often see negotiation as a domain closely linked to masculine identity. The model suggests that men are especially responsive to situations where gender norms emphasize agency, competitiveness, and dominance. Negotiation, particularly in distributive or high-stakes contexts, strongly aligns with these traditionally masculine traits. As a result, men may view negotiation as a testing ground—an arena where they are expected to display competence, strength, and strategic superiority. Success in negotiation can thus serve not only as a practical achievement (e.g., securing better financial terms) but also as a symbolic affirmation of masculinity and social status (Mazei et al., 2021).

However, the MEN model also reveals a paradox within this perception. While men may feel entitled to or confident in negotiation settings, they are also vulnerable to status threats. In cross-gender negotiations, not outperforming a female counterpart can be seen as a loss of gender status, especially in contexts where men are culturally expected to dominate competitive interactions (Bowles et al., 2022; Mazei et al., 2021). Even in same-gender negotiations, men might fear losing social status if they are outperformed by another man. Since masculinity is often defined in comparative and hierarchical terms, not winning or even appearing less assertive can threaten a man's identity and position within both gender and social hierarchies (Mazei et al., 2021).

This dual dynamic can evoke both enthusiasm and anxiety. On one hand, viewing negotiation as "their domain" can energize men, boosting engagement, motivation, and competitive spirit. On the other hand, the risk of failure creates psychological pressure. The threat of losing status may provoke anxiety, especially when the negotiation is prominent, evaluative, or public. In this context, anxiety is not just about financial loss but about symbolic defeat and damage to reputation. As Mazei et al. (2021) note, men might respond to this perceived threat by engaging in behaviours that protect and highlight their masculinity.

One way men may handle status threats is by increasing aggressive negotiation behaviours. Studies show that when masculinity feels challenged, men tend to make bolder first offers, concede less often and less generously, and exchange less information (Kray et al., 2001; Mazei et al., 2021; Walters et al., 1998). These actions serve both strategic and symbolic roles. Strategically, bold offers and fewer concessions help set negotiations in their favor and boost personal gains. Symbolically, such behaviours show toughness, dominance, and a reluctance to back down — qualities linked to masculinity. By emphasizing competitiveness, men can reaffirm their gender identity and demonstrate resilience when threatened (Mazei et al., 2021).

These defensive strategies may have relational and distributive consequences. Lower levels of information exchange can reduce opportunities for integrative agreements, in which both parties create value through mutual problem-solving (Boothby et al., 2023). Fewer concessions and rigid stances may escalate conflict or prolong negotiations (Thompson et al., 2010). Moreover, defensive evaluations, such as perceiving the counterpart as overly aggressive or untrustworthy, can arise when men interpret the interaction through a status-threat lens. These reactions may hinder the counterpart's success, not necessarily because the counterpart lacks skill, but because the male negotiator's defensive competitiveness shapes the interaction in adversarial ways. Thus, the MEN model helps explain how identity concerns can transform negotiation from a problem-solving exercise into a status-protection contest.

Building on this framework, the introduction of AI-assisted negotiation counterparts adds a novel dimension to gender status dynamics. As previously discussed, AI technologies can enhance negotiation skills by offering data-driven insights, predictive analytics, structured training, and real-time strategic recommendations. Studies such as Gratch et al. (2016), Johnson et al. (2019; 2023), and Ferguson et al. (2023) suggest that AI-supported negotiators may achieve better outcomes compared to those who rely solely on unaided human judgment. AI can improve the quality of preparation, optimize offer strategies, and help users avoid common cognitive biases. In short, AI augmentation can increase a negotiator's objective and perceived capabilities.

From the perspective of the MEN model, this technological enhancement may be perceived as a direct challenge to male status in negotiation. If negotiation is seen as a domain where men must demonstrate inherent competence and dominance, learning that a counterpart is leveraging advanced AI to gain an advantage can destabilize that expectation. The AI becomes more than a neutral tool, symbolizing amplified analytical power, preparation, and strategic sophistication. For a male negotiator who prides himself on being naturally skilled or superior in competitive bargaining, this signal may trigger concerns about being outmatched (Mazei et al., 2021).

This perceived threat can operate in multiple ways. In same-gender negotiations, knowing that another man is augmented by AI may challenge one's image as a strong negotiator in general. Losing to an AI-supported counterpart may feel like a reputational setback, especially if the outcome suggests inferior analytical capability or preparation. In cross-gender negotiations, the dynamic may be even more psychologically charged. Traditional gender norms often position men as dominant in competitive settings (Bowles et al., 2022). If a female counterpart is supported by AI and achieves superior performance, this could undermine expectations of male dominance and challenge traditional gender hierarchies. The presence of AI may therefore intensify perceived status threats, both socially and symbolically.

Importantly, the heightened competitiveness induced by AI augmentation may not depend on the actual magnitude of the AI's advantage. Even the perception that the counterpart has access to superior technology can activate defensive responses. Consistent with the MEN model, men who perceive their status as threatened may respond by increasing their competitiveness: raising their initial offers, reducing concession size and frequency, and restricting information sharing (Mazei et al., 2021). These adjustments are aimed at securing a larger share of the final pie and preventing status loss. Acting more competitively allows the male negotiator to reassert agency and demonstrate resilience in the face of a perceived technological edge. This way, they can increase their individual gain and reassert dominance and victory over the counterpart.

Overall, integrating the MEN model with the emergence of AI-assisted negotiation suggests that technology can reshape not only capabilities but also status dynamics. For men who perceive negotiation as central to masculine competence, the introduction of AI on the opposing side may represent a potent status cue. In response, they may intensify competitive behaviours to defend their social and gender standing. Consequently, AI does not merely alter the technical aspects of negotiation; it also transforms the psychological landscape, activating status-based motivations that shape offers, concessions, and information exchange. Understanding these dynamics is crucial for anticipating how AI integration may differentially influence negotiation behaviour across genders and contexts.

The logic discussed in the last two sections supports the hypothesis that there is a crossover interaction effect on the final negotiation outcome, driven by two factors: the gender of the negotiators and whether they are aware of their opponent's use of AI. Therefore, no main effects of either participant's gender or awareness are expected. Based on the crossover interaction, I expect to see simple effects for men and women, such that awareness of AI use will positively influence negotiation outcomes for men but negatively for women (hypotheses 2a–b). Furthermore, the mechanisms behind these interaction effects are different threat perceptions for each side, with stereotype threat being heightened for women and masculinity threat triggered for men. This leads to two moderated mediation hypotheses (hypotheses 3a–b), so I include the mediation hypotheses for each group below.

Hypothesis 1. There will be a significant interaction between AI use awareness and participants' gender on negotiation outcomes, such that of AI use will improve negotiation outcomes for men but reduce them for women.

Hypothesis 2a. Women who are made aware of the counterpart's AI use will achieve lower negotiation outcomes than those who are told nothing about AI use.

Hypothesis 2b. Men who are made aware of the counterpart's AI use will achieve higher negotiation outcomes than men who are told nothing about AI use.

Hypothesis 3a. The negative relationship between AI awareness and negotiation outcomes for women is mediated by stereotype threat: greater AI awareness increases perceived stereotype threat, leading to lower negotiation performance.

Hypothesis 3b. The positive relationship between AI awareness and negotiation outcomes for men is mediated by masculinity threat: AI awareness increases perceived masculinity threat, thereby leading to higher negotiation performance.

Counterpart's Gender and Sexist Beliefs

As mentioned earlier in the introduction, this research also explores whether the effect of a negotiator's gender on their response to awareness of their counterparts' AI usage varies depending on the gender of the counterpart. Specifically, it examines whether men's tendency to achieve better negotiation outcomes or women's tendency to experience lower outcomes in response to AI-augmentation information is influenced by whether they are negotiating with a man or a woman. More precisely, I seek to determine whether men see even greater improvements in outcomes when negotiating against women, and whether women experience a more significant decline when facing men. This approach considers the possibility that interacting with a counterpart of the opposite gender may reinforce masculinity norms or gender stereotypes, thereby intensifying the observed effects.

On one hand, while I hypothesize that there is always an adjustment in the level of competitiveness on the male side upon realizing the counterpart is using AI, I believe the extent of this adjustment would differ for the female counterpart. In a mixed-gender negotiation, if the female side uses an AI system and her capabilities and performance improve, the male counterpart may end up with a smaller performance gain. Even when the female negotiator cooperates effectively and helps expand the total pool of resources to divide, the male counterpart may still worry about securing a larger share of the expanded pool relative to the female negotiator, in order to maintain his upper hand not only in that specific negotiation but also in the gender hierarchy.

This different assessment arises because a mixed-gender negotiation is not just between a male and a female counterpart but also affects the status quo of gender hierarchy (Mazei et al., 2021). A male negotiator is concerned with achieving a satisfactory outcome in that mixed-gender negotiation by demonstrating his higher status and maintaining his position in the gender hierarchy (Mazei et al., 2021). Hence, a female negotiator's performance improvement from using the AI system can serve as a resource for challenging the status quo in a mixed-gender negotiation (Mazei et al., 2021).

The extent to which male negotiators believe in the gender hierarchy can influence how they perceive threats and respond accordingly. Therefore, an explicit or implicit sexist belief can act as a moderator. Sexist beliefs, especially hostile sexism (Glick & Fiske, 1996), can significantly influence the backlash effects women face when using AI systems in mixed-gender negotiations. Hostile sexism, which involves overtly negative attitudes and hostility toward women who challenge traditional gender roles, can worsen backlash when women employ AI tools. Men with hostile sexist views may see AI-augmented women as even more threatening to their perceived status and authority, leading to more intense and aggressive reactions. These men might view AI use as a challenge to their dominance, further boosting their competitive behaviour and resistance.

In contrast, benevolent sexism, which involves patronizing attitudes that regard women as needing protection and support, may lead to undermining evaluation of female negotiators using AI systems, but not necessarily leading to backlash against them. Men with benevolent sexist beliefs react less aggressively while still holding discriminatory beliefs regarding women (Hideg & Ferris, 2016). Male negotiators who hold benevolent sexist beliefs may feel uncomfortable or conflicted when facing a female negotiator using AI, as this behaviour contradicts their expectations of women as cooperative, communal, and non-competitive. They believe negotiation is not the domain of women and undermines the female negotiator’s competence and autonomy. They may view AI as a tool women need to compensate for perceived inadequacies rather than as an enhancement of their negotiation skills. However, these issues do not lead men to respond with a similar type of overt competitiveness or aggression as those high in hostile sexism. Thus, although we expect that benevolent sexism can still affect the extent to which a male negotiator would evaluate the AI-augmented female negotiator negatively and undermine her capabilities, the backlash effect would not be expected as with hostile sexism. Thus, I state the last pair of hypotheses as follows.

On the other hand, I expect women will be more affected by AI-use awareness when their counterpart is male. This expectation is based on research on stereotype threat and evaluative situations, which suggests women are more conscious of the risk of negative judgment regarding their skills when interacting with men in traditionally male-dominated areas like negotiation (Kray et al., 2001; Bowls et al., 2022). Due to gender stereotypes discussed earlier, female negotiators may feel increased pressure to demonstrate competence when bargaining with men, as they might anticipate their abilities will be closely scrutinized or dismissed. Conversely, when negotiating with another woman, the evaluative pressure associated with gender stereotypes might be weaker, making awareness of AI use less likely to influence negotiation behaviour .

Furthermore, similar to the situation discussed earlier regarding men and sexist beliefs, women who endorse high levels of hostile sexism and support a traditional gender hierarchy are more vulnerable to the negative effects of stereotype threat. This is because they hold an internalized framework that justifies male dominance in competitive settings (Glick & Fiske, 1996). When facing a male opponent, especially one perceived as enhanced by AI, these women may experience increased evaluation anxiety. They might interpret the man's success not as a challenge to be overcome but as a natural outcome of a societal order they believe in. This connection between their personal beliefs and negative stereotypes can lead to greater negotiation anxiety and a higher likelihood of psychological withdrawal. As a result, instead of resisting the threat, they might subconsciously submit to the male partner's perceived authority, leading to lower goals, more concessions, and significantly poorer negotiation outcomes than in interactions with other women.

Overall, I can state the hypotheses below as the last hypotheses regarding the effects of the counterpart's gender on negotiation outcomes and the moderating role of sexist beliefs (particularly hostile beliefs) for those effects.

Hypothesis 4a. Male participants who are aware of their counterparts' AI usage will achieve higher negotiation outcomes against female counterparts than against male counterparts.

Hypothesis 4b. Female participants who are aware of their counterparts' AI use will achieve lower negotiation outcomes against male counterparts than against female counterparts.

Hypothesis 5. Sexist beliefs (hostile) moderate the relationship between the participant's gender, the counterpart's gender and negotiation outcomes.

CHAPTER 4: METHODOLOGY AND RESULTS

Transparency and Overview of Studies

To test my hypotheses, I conducted a series of pre-registered experiments (registered on AsPredicted; see Study 1 at https://aspredicted.org/s7xn47.pdf and Study 2 at https://aspredicted.org/vt992n.pdf). These studies were reviewed and approved by the Office of Research Ethics at York University in spring 2025 (with Certificate #: STU 2025-015). Across both main studies, a between-subjects factorial design was employed. The two main independent variables were AI use awareness (control vs. AI use awareness condition) and participant gender (man vs. woman).

In all studies, I used multi-issue negotiation scenarios specifically designed to allow both competitive and cooperative dynamics to emerge naturally during the interaction. Multi-issue negotiations offer a richer and more realistic context than single-issue bargaining because they enable integrative trade-offs, value creation, and distributive claiming behaviours to happen simultaneously (Thompson et al., 2010; Boothby et al., 2023). This design let negotiators demonstrate both competitive and cooperative adjustments that can occur when individuals know AI tools are being used in the negotiation process.

The primary target population included individuals who may realistically interact with AI-supported negotiation systems in educational or professional contexts. Accordingly, I tested my hypotheses across different participant populations to enhance the robustness and generalizability of the findings. One sample consisted of undergraduate students, who are frequent users of educational negotiation simulations and emerging AI tools in academic environments (see iDecisionGames.com). The second sample comprised members of the general working population, representing individuals more likely to encounter AI-assisted decision systems in professional negotiation contexts. By drawing from different types of samples, I sought to strengthen the external validity of the results, ensuring that observed effects were not limited to a single demographic or experiential category (Brewer, 2000; Campbell, 2017). At the same time, the controlled experimental structure and standardized negotiation protocols supported strong internal validity by minimizing confounding influences (Brewer, 2000; Campbell, 2017).

Before my two full-scale studies, an initial small pilot test was conducted. The pilot study was conducted with a small sample to ensure clarity of instructions and to intercept any flaws in the data collection process. Based on insights from the pilot, minor adjustments were made to the survey design on Qualtrics, the wording of the awareness manipulation, and the payoff structure of the negotiation issues to ensure balance and realism in both main studies.

In Study 1, I examined human–human negotiations to establish a baseline understanding of how AI use awareness influences interpersonal bargaining behaviour when both parties are human decision makers. This study enabled me to track differences in first offers, perceptual patterns, and outcome distributions across varying awareness conditions.

In Study 2, I extended the design to human–AI bot negotiations, in which participants negotiated with an AI-driven confederate programmed to follow consistent strategic rules. This innovative methodological approach aligns with recent experimental research demonstrating the effectiveness of AI bots as standardized interaction partners in behavioural studies (Anthis et al., 2025; Charness et al., 2025). Using AI bots as confederates allowed me to maintain tight control over counterpart behaviour while substantially increasing sample size efficiency. Because AI agents can interact simultaneously with multiple participants at low marginal cost, this approach nearly doubled my achievable sample size within the same budget constraints. Together, the two studies provide complementary evidence regarding the behavioural and psychological effects of AI use awareness across both interpersonal and human–AI negotiation contexts.

Research Philosophy and Paradigm

This research adopts a post-positivist research paradigm, grounded in the assumption that social phenomena can be examined through systematic observation, experimental manipulation, and statistical inference (Creswell & Creswell, 2018; Phillips & Burbules, 2000). Post-positivism acknowledges that while absolute objectivity is unattainable, rigorous experimental design, control of extraneous variables, and statistical testing allow researchers to approximate causal relationships with reasonable confidence (Phillips & Burbules, 2000).

Ontologically, this research assumes that psychological constructs such as threat perception and negotiation performance are measurable and can be operationalized through validated instruments (Flake et al., 2022). Epistemologically, knowledge is generated through hypothesis testing, empirical observation, and statistical modeling (Phillips & Burbules, 2000). The use of a 2 × 2 factorial experimental design reflects a post-positivist commitment to testing theory-driven hypotheses, establishing causal inference through manipulation and control, using statistical modeling to estimate direct and indirect effects, and replicating findings across samples (Creswell & Creswell, 2018; Trochim & Donnelly, 2008).

The experimental methodology allows for the isolation of independent variables (gender and AI awareness condition) while holding other factors constant (Levine et al., 2023). Random assignment to the AI awareness manipulation condition strengthens internal validity and supports causal claims regarding the treatment effect (Shadish et al., 2002). Moreover, the inclusion of two studies with different populations (college students in Study 1 and a general working population in Study 2) reflects a commitment to external validity and robustness (Campbell, 2017; Trochim & Donnelly, 2008). Study 1 provides a controlled test of theoretical predictions in a student sample, while Study 2 examines the generalizability of findings in a more ecologically valid workforce population. Overall, the methodological approach aligns with a theory-testing, quantitative, experimental research tradition aimed at identifying causal mechanisms underlying negotiation dynamics in AI-awareness contexts.

Pilot Study

Method

The pilot test was carried out solely to confirm that the experimental procedures worked as planned and that there were no technical or procedural errors in setting up the research. Specifically, the goal was to verify that the Qualtrics survey functioned correctly and that the Zoom-based negotiation interaction could be smoothly implemented and recorded in accordance with the study protocol. The pilot was not meant to produce results that could be analyzed. Due to a small sample size and a flaw in the data collection process, participants were not distributed evenly across conditions, leaving no female participants in the AI awareness condition. The data collected during the pilot were ultimately unusable for statistical analysis. Therefore, no formal data analysis was performed. Instead, this section provides a brief, high-level overview of the study design and procedures used during the pilot phase.

Participants. 51 undergraduate students enrolled at a large Canadian business school in spring 2025 participated in dyadic negotiations. Participants ranged in age from 19 to 23 years.

The gender distribution was 54.9% men and 45.1% women. The racial distribution reflected: 47.0% South Asian, 13.7% East Asian or Southeast Asian, 11.8% White/European, 3.9% Black or African, and 23.4% identifying as other. Participants' prior work experience varied, with 25.5% reporting 0–1 year, 51.0% reporting 1–3 years, and 23.5% reporting more than 3 years.

Participants were recruited through course announcements and received course credit in exchange for their participation. Random assignment was implemented using Qualtrics' randomization function, ensuring approximately equal distribution across conditions. Demographic characteristics were examined across conditions to confirm successful randomization and to assess whether any systematic differences emerged.

Materials and Procedure. All participants engaged in a full version of the Deep Space negotiation case developed by the Dispute Resolution Research Center (DRRC; see Appendix A). The case involves a multi-issue negotiation between two technology firms: a start-up chip vendor and an established mobile phone manufacturer seeking to commercialize cutting-edge technology through an existing distribution network. In the pilot test, I used the full version with 5 issues, but based on feedback about respondents' timing, I decided to shorten the case to 3 issues for the main studies, after consultation with my advisor. The detailed description of the case is in the Study 1 section.

The negotiations took place online via Zoom, with participants joining from their own devices regardless of location. Pre- and post-negotiation surveys were administered through Qualtrics. During the negotiations, video and audio were kept on, and participants were instructed to record and send their audio to ensure full completion and reliable data. The pre-negotiation survey included basic demographic questions used to assign participants to different condition groups based on gender, while the post-negotiation survey contained questions on threat perception and AI awareness manipulation check.

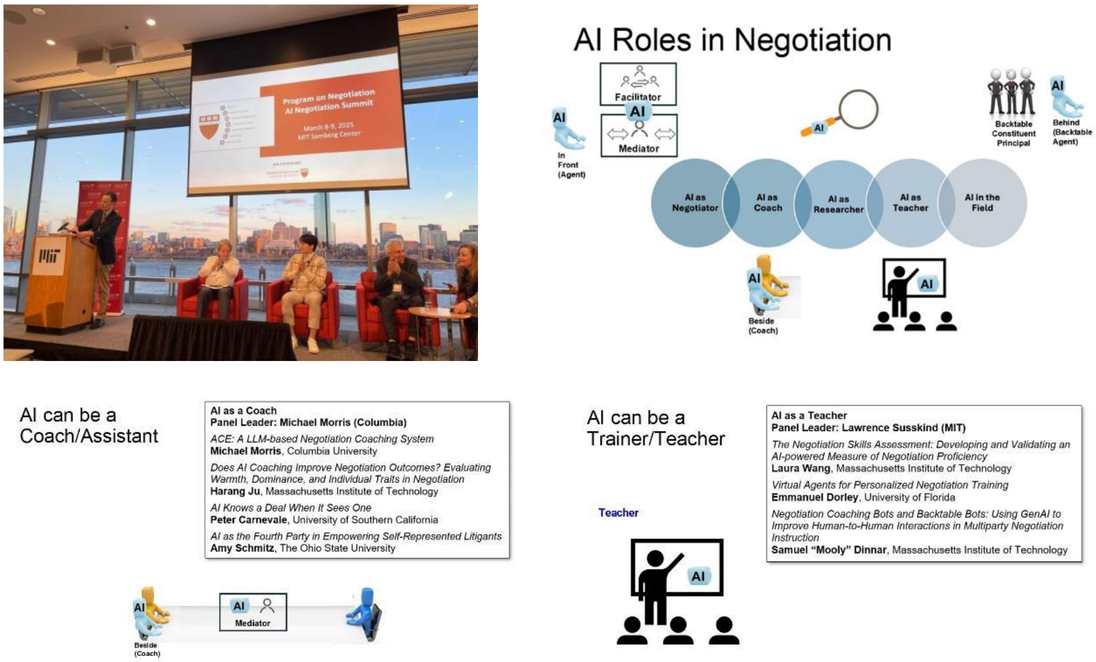
Measures. After the negotiation, participants' *final agreement* score was computed, and their intended *first offer* was recorded prior to the live negotiation. Also, *perceived threat* was measured using the public discomfort scale, which has been used in past research to assess threat perception (e.g., Dahl et al., 2015; Weaver & Vescio, 2015). The details about these measures are discussed in the next sections on Study 1 and Study 2.

Manipulation of AI-Use Awareness. The experimental manipulation was designed to induce awareness that the counterpart used AI-based negotiation support systems, without altering the counterpart's actual behaviour. Prior to negotiation, focal participants in the AI-use awareness condition were presented with infographic-style material describing AI augmentation in negotiation contexts. The content introduced both AI-assisted training and real-time support tools, framed as legitimate and increasingly common professional practices.

To enhance realism, participants were told a hypothetical narrative about a friend named Alex who had attended a "PON AI in Negotiation Summit" at MIT in March 2025. The materials summarized key insights from that summit, including how AI systems can analyze bargaining zones, predict counterpart concessions, and improve the quality of preparation. They were shown some simple information about the use of AI in negotiation from that summit's presentations (see Figure 1).

Figure 1

Content for AI Awareness Manipulation based for Studies 1 and 2



Subsequently, participants were informed, during the standard pre-negotiation briefing, that their counterpart had experience using AI systems for training and preparation. This addition was embedded alongside neutral biographical information, including the counterpart's gender. The purpose was to embed the information in a manner consistent with a process in which negotiators gather information about the other party and their reputation during the planning and preparation phase (Jang et al., 2018; Elfenbein, 2015; Tasa & Bahmani, 2023). Hence, a sentence was added[1] to the information given to the participant in Appendix A about the other party's use of AI systems in training and assistance in their role as their company's representative (along with their gender being revealed in their description). The control group received identical materials except for the AI-use information.

At the end of the experiment, a manipulation check was conducted by asking participants a brief set of questions about the effects of AI use in negotiation and whether they believed AI augmentation helped their counterparts (Fiedler et al., 2021). The details of the questions and the results for each main study is discussed in their respective sections.

Adjustments to the Research Protocol After Pilot Study

The pilot study led to several improvements. It helped me realize that I need to shorten the negotiation case from 5 issues to 3 to prevent cognitive exhaustion among participants. Additionally, there was a minor glitch in the Qualtrics survey process that rendered the data unusable for this study, but it allowed me to fix it and prevent similar issues in the main studies.

[1] That sentence was "You have heard from your friend Alex who knows your counterpart that they have been recently provided some negotiation training with AI bots. Also, he may even have access to online AI coaching or assistance bots."

Finally, I discovered which method would be more effective and time-saving for randomly pairing participants for the Zoom negotiation.

Study 1

Method

Study 1 employed a between-subjects factorial experimental design to examine how awareness of a counterpart's AI augmentation influences negotiation outcomes. Specifically, focal negotiators were randomly assigned to one of two conditions: (1) control, in which no mention of AI use by the counterpart was provided, and (2) AI-use awareness, in which participants were informed that their counterpart had received AI-based negotiation training and assistance. Importantly, no counterpart actually used AI, and the manipulation affected only the focal participants' beliefs.

The primary dependent variable was the objective negotiation outcome (individual agreement scores). The design also allowed analysis of whether perceived stereotype or masculinity threat mediates the relationship between AI-use awareness and negotiation behaviour. Additionally, I examined whether any increase in first offers (as an indicator of competitive behaviour) can be observed. This exploratory analysis aimed to shed light on possible ways negotiators changed their behaviour that led to different negotiation outcomes.

Participants. A total of 242 undergraduate students enrolled at the Schulich School of Business in spring 2025 took part in dyadic negotiations. Their ages ranged from 17 to 23. The gender breakdown was 57.9% men, 40.9% women, and 1.2% identifying as other. The racial composition was quite diverse: 34.8% South Asian, 26.5% White/European, 17.8% East Asian or Southeast Asian, 6.1% West Asian, 0.4% Black or African, and 14.3% identifying as other.

Participants' previous work experience varied, with 40.9% reporting 0–1 year, 36.8% reporting 1–3 years, and 22.3% reporting more than 3 years.

After excluding 6 participants due to incomplete responses or inattention (based on failed attention checks and missing data), the final sample of focal participants consisted of 115 individuals. These focal negotiators were randomly assigned to either the control or the AI-use awareness condition. Each focal negotiator was paired with a counterpart drawn from the same participant pool, but only the focal negotiator was the subject of this study, was exposed to the experimental manipulation, and their data was analyzed.

Participants were recruited through course announcements and received course credit in exchange for their participation. Using undergraduate business students is common in negotiation research because they are usually familiar with business scenarios and motivated to perform well in negotiation simulations. Although student samples may limit generalizability to experienced managers, prior research shows that negotiation processes observed in laboratory settings often yield reliable results (Buelens et al., 2008; Minson et al., 2023).

Random assignment was carried out using Qualtrics' randomization feature, ensuring roughly equal distribution across conditions based on participants' reported gender, as reported early in the demographic questions.

A power analysis was also performed using G*Power to determine the smallest detectable effect size with the current sample. With a total of $N = 115$ participants in a 2×2 factorial ANOVA, assuming $\alpha = .05$ and power $(1 - \beta) = .80$, the design was adequately powered to detect effects around Cohen's $f = 0.26$ (roughly $\eta p^2 \approx .065$), which represents a medium effect size based on standard benchmarks.

Materials. All participants engaged in a shortened version of the Deep Space negotiation case developed by the Dispute Resolution Research Center (DRRC; see Appendix A). The case involves a multi-issue negotiation between two technology firms: a start-up chip vendor and an established mobile phone manufacturer seeking to commercialize cutting-edge technology through an existing distribution network.

As mentioned in the Pilot Study section, the original case included five issues. For this study, it was simplified to three issues to lessen cognitive overload and fatigue during online participation. Each issue provided multiple options with different point values for each party. The payoff structure was integrative, meaning that although some options caused distributive tension, the overall setup allowed for mutually beneficial trade-offs through information sharing and cooperation.

Participants received confidential role instructions outlining their priorities and payoff structure. The maximum achievable individual score across all issues was 160 points. Joint gains were maximized when negotiators effectively exchanged information and made logrolling concessions.

To prevent priming unintended constructs, cross-cultural framing elements from the original case were removed. No power imbalances, gender-related advantages, or cultural distinctions were included in the materials. This ensured that any observed differences could be more confidently attributed to the AI-use awareness manipulation rather than to extraneous contextual cues.

Manipulation of AI-Use Awareness. The experimental manipulation was carried out exactly as in the Pilot Study.

Manipulation Check. At the end of the experiment, a manipulation check was conducted by asking participants a brief set of questions about the effects of AI use in negotiation and whether they believed AI augmentation helped their counterparts (Fiedler et al., 2021). This check consisted of four questions based on the four criteria of the Subjective Value Inventory (SVI), which measures 1) how negotiators evaluate their outcomes, 2) feel about themselves, 3) assess the negotiation process, and 4) view the relationship they might build with their counterpart (Curhan et al., 2006).

Accordingly, I asked four questions regarding these criteria, each inquiring how much the participant thought AI use impacted one of those four aspects. The questions were: ‘‘How much do you think the use of an AI negotiation system by your counterpart affected _____ in the negotiation?’’ (negotiation outcomes, feelings about yourself, negotiation process, your relationship with the counterpart), answered on a 7-point scale (1 = not at all; 7 = a lot). Reliability analysis indicated an α of .921 for this scale. The responses to all four questions showed normal distributions with means of 3.73, 3.55, 4.04, and 3.62, and standard deviations of 1.49, 1.70, 1.51, and 1.69, respectively. When respondents who answered 1 to 3 were removed, the main effects results remained unchanged.

To avoid priming participants in the control group, the content about AI use awareness was not shown to them at all. If they had been tipped off about anything related to AI at this point, they would have changed their behaviour, even without being explicitly told that their counterpart was using AI. Therefore, the only option was to rely on actual changes in how participants in each condition negotiated and the results they achieved (Hauser et al., 2018), along with asking those in the treatment condition how much they believed AI affected the negotiation. Then, I checked if the results still held among those who self-reported that the AI effect was small in their judgment. While I acknowledge a limitation in that the data for the control group was not recorded for comparison with the manipulation group, the findings that the results do not change when I remove the higher scorers suggest the manipulation was effective. Most participants believed that AI-assisted or trained agents on the other side had an impact, and that belief influenced how they negotiated.

Measures. In this study, final agreement scores (as objective outcomes), first offers, perceived threat, and sexist beliefs were measured as follows.

Final Agreement. After the negotiation, each party's *final agreement* score was calculated based on the outcomes they agreed on for each issue in the final agreement and the payoff table provided to participants, which assigned scores to each option. As shown in Appendix A, each issue offers five options, each with a specific score for each party as displayed in their payoff tables. By summing the scores received for each issue, the total score could be determined. Each participant could earn a maximum of 160 points across all issues combined.

First Offer. Participants were also required to record their intended *first offer* before engaging in the live negotiation. First offers are widely recognized in negotiation research as indicators of competitiveness and anchoring strategies. More extreme first offers indicate stronger value-claiming intentions and distributive positioning.

Perceived (Stereotype and Masculinity) Threat. To examine the role of stereotype and masculinity threat perception, *perceived stereotype and masculinity threat* were measured using the public discomfort scale, which has been used in the literature to measure gender-related threats (e.g., Dahl et al., 2015; Weaver & Vescio, 2015). This scale assesses how people feel when their performance is publicly known, aligning with our focus on performance-related stereotypes and masculinity threat in negotiation. Participants were asked to imagine their negotiation outcomes (including their counterpart's results and mentioning her/his gender) being made public. Using a 7- point scale (1 = not at all; 7 = a lot), participants responded to the question for each of eight emotions: ‘‘When you think about your name and score being published, how _____ do you feel?’’ (anxious, nervous, defensive, depressed, calm, joyful, happy, and confident).

I included specific items of anxiousness, nervousness, and confidence (reversed) for stereotype threat, and anxiousness, defensiveness, and calmness (reversed) for masculinity threat. The decision to use these specific measures is theory-driven and based on how each threat uniquely disrupts a negotiator's internal state. While both involve psychological discomfort, they trigger different coping responses (Folkman et al., 1986). Stereotype threat creates a burden of suspicion, where negotiators fear confirming the negative stereotype that they are less capable (Spencer et al., 2016). I included anxiousness, nervousness, and lack of confidence because this construct focuses on the pressure to disprove a baseline incompetence, leading to a depletion of cognitive resources through heightened physiological arousal and a direct impact on one’s perceived self-efficacy in the task. Conversely, masculinity threat is less about general ability and more about a perceived loss of manhood through an inability to prove oneself as a capable male negotiator (Mazei et al., 2021). I included anxiousness, defensiveness, and decreased calmness because this threat triggers restorative responses. When masculinity is challenged, the response is not just nerves; it is a masculinity- protective stance. Defensiveness captures the reactive nature of trying to reclaim lost dominance, while a lack of calmness reflects a volatile state of being on guard against further loss. Overall, the reliability analysis indicated α =. .829 for this scale.

Sexist Beliefs. The Ambivalent Sexism Inventory (ASI), developed by Glick and Fiske (1996; see Appendix B), was used to assess the *sexist beliefs* of negotiators to determine whether the effects I hypothesized depended on the gender of the opponent and the underlying sexist attitudes. The ASI includes 22 items that measure two subscales: hostile sexism (e.g., negative stereotypes and beliefs about women) and benevolent sexism (e.g., seemingly positive yet patronizing beliefs about women). Participants rated their agreement with each statement on a Likert scale from 0 (strongly disagree) to 5 (strongly agree). Higher scores on the subscales indicate stronger endorsement of hostile or benevolent sexist attitudes. I combined all hostile items to create a single score for hostile sexist beliefs. The reliability analysis showed $\alpha = .823$ for this scale.

Procedure. The procedure was exactly like the Pilot Study, with the minor adjustments mentioned in that section (reducing negotiation issues to three and correcting the condition assignment process on Qualtrics).

Data Analysis Plan. Data analysis involved several organized stages for both Study 1 and Study 2. The analyses aimed to examine the main effects of participants' gender and AI awareness condition, the interaction effects between gender and AI awareness, the mediating role of threat perception, the moderating effect of sexist beliefs on how the counterpart's gender influences the main effects, and the consistency and robustness across different samples. All analyses were performed using statistical software (e.g., SPSS), with bootstrapped confidence intervals where appropriate.

Before conducting hypothesis testing, some preliminary steps were taken, such as screening data for missing values and outliers, assessing the reliability of multi-item scales (e.g., Cronbach's alpha), and calculating descriptive statistics and zero-order correlations.

To test the primary effects of gender and AI awareness condition on negotiation outcomes, a 2×2 factorial ANOVA was conducted separately for each study. This analysis examined the main effect of the participant's gender, the main effect of AI awareness condition, and the interaction effect (Gender × AI Awareness). A significant interaction would indicate that the effect of AI awareness varies by gender. Effect sizes (e.g., partial η^2) will be reported alongside p-values. Following the ANOVA, I conducted subsequent simple-effect tests to determine whether the hypothesized effects for each man and woman group are observed.

To test whether threat perception mediates the relationship between AI awareness condition and negotiation outcome, a mediation analysis was conducted using regression-based bootstrapping. Because gender is also an independent variable in the factorial design, moderated mediation was tested to examine whether the indirect effect of AI awareness on negotiation outcome via threat perception differs by gender. This was tested using bootstrapped confidence intervals. An indirect effect was considered significant if the 95% confidence interval does not include zero.

Finally, in Study 1, further analyses were conducted to explore whether effects differ by counterpart's gender, meaning that negotiation outcomes for male participants varied depending on whether their counterpart was a man or a woman, and whether sexist beliefs moderated this relationship.

Study 1: Results

Descriptive statistics are shown in Tables 1 and 2. Participants in the AI use awareness condition exhibited lower final agreements and first offers than those in the control condition for women (94.375 and 119.688 compared to 112.188 and 137.500, respectively), but the opposite trend was observed for men, who made higher first offers and achieved higher final agreements when AI use was made salient (108.590 and 137.949 compared to 105.227 and 130.795, respectively). Stereotype threat perception got slightly higher for women when they were made aware of AI use, but not different for men (3.375 compared to 3.083 and 2.863 compared to 2.894, respectively), while masculinity threat perception showed a similar pattern and got slightly higher for women only when they were made aware of AI use, but not different for men (3.333 compared to 2.917 and 2.795 compared to 2.924, respectively). Also, final agreement was positively correlated with the first offer ($r = .319$, $p < .01$) and stereotype threat was positively correlated with the participant's gender ($r = .131$, $p < .05$; meaning it was significantly higher for women), whereas stereotype and masculinity threat perception, AI manipulation condition, and participant gender showed no significant correlations with the main negotiation outcomes.

Table 1

Means and Standard Deviations of Final Agreements, First Offers, and Threat Perception by Levels of Condition and Gender for Study 1

Manipulation Condition	Gender	Final Agreement M (SD)	First Offer M (SD)	Stereotype Threat Perception M (SD)	Masculinity Threat Perception M (SD)
AI Use Awareness	Women	94.375 (6.284)	119.688 (7.248)	3.375 (.423)	3.333 (.474)
	Men	108.590 (4.025)	137.949 (4.643)	2.863 (.181)	2.795 (.203)
Control	Women	112.188 (6.284)	137.500 (7.248)	3.083 (.241)	2.917 (.308)
	Men	105.227 (3.790)	130.795 (4.371)	2.894 (.214)	2.924 (.236)

Note. N = 115

Table 2

Descriptive Statistics and Bivariate Correlations for Study 1

	M	SD	1	2	3	4	5	6
1. Final Agreement	105.830	25.339						
2. First Offer	132.610	29.262	.319**					
3. Stereotype threat Perception	3.077	1.246	.010	-.047				
4. Masculinity threat Perception	2.928	1.441	.063	-.087	.885**			
5. AI Manipulation Condition (0 = control, 1 = AI use awareness)	0.48	.502	-.052	.001	.026	.010		
6. Participant's Gender (1 = male, 2 = female)	1.42	.495	-.063	-.086	.131*	.046	.027	

Note. N = 115

* $p < .05$.

** $p < .01$.

Hypotheses Tests. To examine hypothesized relationships, I first test the main and interaction effects using a two-way ANOVA, followed by simple effects tests to analyze each effect. Results are shown in Table 3. In Hypothesis 1, it was proposed that there would be significant interaction between AI use awareness and participants' gender on the negotiation outcome, such that the awareness of AI use will improve negotiation outcomes for men but reduce negotiation outcomes for women. A two-way ANOVA was performed with manipulation condition (AI use awareness vs. control) and participant gender (male vs. female) as factors predicting negotiation outcomes. For Final Agreement, no main effects of condition, $F(1, 111) = 1.91$, $p = .170$, $\eta^2 = .017$, or gender, $F(1, 111) = 0.48$, $p = .490$, $\eta^2 = .004$, were observed. However, the interaction between condition and gender was significant, $F(1, 111) = 4.09$, $p = .045$, $\eta^2 = .036$. These ANOVA results provide initial support for the predicted interaction between AI use awareness and participant gender (Hypothesis 1), depending on the significance of simple effects tested in the subsequent section.

Table 3

ANOVA Results for Study 1

Source	Sum of Squares	df	Mean Square	F	p	η^2
DV: Final Agreement						
Manipulation Condition	1204.392	1	1204.392	1.906	.170	.017
Gender	303.562	1	303.562	.480	.490	.004
Manipulation Condition x Gender	2586.282	1	2586.282	4.093	.045	.036
Error	70137.351	111	631.868			
Total	1361100.000	115				
DV: First Offer						
Manipulation Condition	655.364	1	655.364	.780	.379	.007
Gender	770.364	1	770.364	.916	.340	.008
Manipulation Condition x Gender	3595.175	1	3595.175	4.277	.041	.037
Error	93306.494	111	840.599			
Total	2119900.000	115				

To follow up on the significant interaction between manipulation condition and gender, simple effects analyses were conducted to examine the effect of manipulation condition within each gender, using Bonferroni-adjusted comparisons (see Table 4). For men, the manipulation condition did not significantly influence final agreement scores, $F(1, 111) = 0.37$, $p = .544$. Men in the control condition (M = 105.23, SE = 3.79, 95% CI [97.72, 112.74]) reported similar levels of agreement to men in the AI-use awareness condition (M = 108.59, SE = 4.03, 95% CI [100.61, 116.57]). The pairwise comparison confirmed that the difference between conditions was not significant (Mdiff = −3.36, SE = 5.53, $p = .544$).

Table 4

Simple Effects of Manipulation Condition on Final Agreement by Gender in Study 1

Gender	Condition	M	SE	95% CI	F(1,111)	p
Men	Control	105.23	3.79	[97.72, 112.74]	0.37	.544
Men	AI-use awareness	108.59	4.03	[100.61, 116.57]		
Women	Control	112.19	6.28	[99.74, 124.64]	4.02	.047
Women	AI-use awareness	94.38	6.28	[81.92, 106.83]		

In contrast, for women, the manipulation condition significantly influenced final agreement scores, $F(1, 111) = 4.02$, $p = .047$. Women in the control condition reported significantly higher agreement (M = 112.19, SE = 6.28, 95% CI [99.74, 124.64]) than women in the AI-use awareness condition (M = 94.38, SE = 6.28, 95% CI [81.92, 106.83]). The pairwise comparison showed that this difference was significant after Bonferroni correction (Mdiff = 17.81, SE = 8.89, $p = .047$). Therefore, examining the group means further clarifies the interaction in line with Hypothesis 1. Regarding Hypothesis 2a, I suggested that women made aware of the AI use by their counterparts would achieve lower negotiation outcomes than women who were not informed about AI use, whereas in Hypothesis 2b, I predicted that men who were aware of the AI use would achieve higher negotiation outcomes than men who were not informed. Consistent with Hypothesis 2a, women in the AI awareness condition reached lower final agreements than women in the control group. However, men who were aware of the AI use did not achieve significantly higher final agreements than men in the control condition. Consequently, the findings do not support Hypothesis 2b.

Furthermore, no significant effects were observed for threat perception (masculinity or stereotype threat) as measured by the public discomfort scale, offering no support for Hypotheses 3a and 3b. These hypotheses proposed that the negative relationship between AI awareness and negotiation outcomes for women is mediated by stereotype threat, where AI awareness increases perceived stereotype threat, resulting in lower negotiation performance, while the positive relationship between AI awareness and negotiation outcomes for men is mediated by masculinity threat, with AI awareness increasing perceived masculinity threat, leading to higher negotiation performance.

Two moderated mediation analyses were conducted (PROCESS macro Model 7; Hayes, 2022) to examine whether stereotype or masculinity threat mediated the relationship between AI awareness condition and final agreement scores, and whether the AI awareness → stereotype or masculinity threat path was moderated by gender. The analysis was based on a sample of N = 115 with 5,000 bootstrap samples used to estimate confidence intervals.

For stereotype threat as a mediator, the regression model predicting stereotype threat from AI awareness, gender, and their interaction was not significant, $F(3,111) = 0.68$, $p = .566$, $R^2 = .018$. The interaction between AI awareness and gender was also not significant ($b = 0.32$, $SE = 0.55$, $t = 0.59$, $p = .557$), indicating that gender did not significantly moderate the relationship between AI awareness and stereotype threat. Additionally, the regression model predicting final agreement score from AI awareness and stereotype threat was not significant, $F(2,112) = 0.15$, $p = .858$, $R^2 = .003$. Neither AI awareness ($b = -2.63$, $SE = 4.77$, $t = -0.55$, $p = .582$) nor stereotype threat ($b = 0.09$, $SE = 1.83$, $t = 0.05$, $p = .961$) significantly predicted the final agreement. Furthermore, the direct effect of AI awareness on the final agreement was also not significant ($b = -2.63$, $SE = 4.77$, $t = -0.55$, $p = .582$, 95% CI [−12.08, 6.81]).

Bootstrapped conditional indirect effects of AI awareness on final agreement score via stereotype threat were analyzed at each gender level. For men, the indirect effect was not significant ($b = -0.003$, BootSE = 0.63, 95% CI [−1.46, 1.29]). Similarly, for women, the effect was not significant ($b = 0.026$, BootSE = 1.23, 95% CI [−3.57, 1.83]). Since both confidence intervals included zero, the mediation was not supported at either gender level. Additionally, the index of moderated mediation was not significant (index = 0.03, BootSE = 1.42, 95% CI [−3.90, 2.27]), indicating that the indirect effect of AI awareness on final agreement through stereotype threat did not differ significantly across genders. Overall, the results showed no evidence of mediation or moderated mediation, providing no support for Hypothesis 3a.

For masculinity threat as the mediator, the regression model predicting masculinity threat from AI awareness condition, gender, and their interaction was not significant, $F(3,111) = 0.50$, $p = .680$, $R^2 = .013$. The interaction between AI awareness and gender was not significant (b = 0.55, $SE = 0.62$, $t = 0.89$, $p = .378$), indicating that gender did not significantly moderate the effect of AI awareness on masculinity threat. Additionally, neither AI awareness condition (b = −0.68, $SE = 0.84$, $t = -0.81$, $p = .421$) nor gender ($b = -0.01$, $SE = 0.43$, $t = -0.02$, $p = .986$) significantly predicted masculinity threat. Moreover, the regression model predicting final agreement from AI awareness and masculinity threat was also not significant, $F(2,112) = 0.38$, p = .685, $R^2 = .007$. Neither AI awareness condition ($b = -2.66$, $SE = 4.76$, $t = -0.56$, $p = .577$) nor masculinity threat ($b = 1.09$, $SE = 1.62$, $t = 0.67$, $p = .501$) significantly predicted final agreement scores. Additionally, the direct effect of AI awareness on final agreement was not significant (b = −2.66, $SE = 4.76$, $t = -0.56$, $p = .577$, 95% CI [−12.09, 6.76])

Bootstrapped conditional indirect effects of the AI awareness condition on the final agreement score through masculinity threat were examined for each gender category. For men, the indirect effect was not significant ($b = -0.14$, BootSE = 0.70, 95% CI [−1.83, 1.26]). Similarly, for women, the indirect effect was also not significant ($b = 0.46$, BootSE = 1.32, 95% CI [−2.62, 3.07]). Since both confidence intervals included zero, there was no evidence of mediation at either gender level. Additionally, the index of moderated mediation was not significant (index = 0.60, BootSE = 1.57, 95% CI [−3.02, 3.83]), indicating that the indirect effect of AI awareness condition on the final agreement score via masculinity threat did not significantly differ by gender. Overall, the results show no evidence of mediation or moderated mediation, offering no support for Hypothesis 3b.

As stated in Hypotheses 4a-b, it was expected that the gender of a participant's counterpart would also influence their behaviour and outcomes. Hypothesis 4a suggested that male participants who are aware of their counterparts' AI use will achieve higher negotiation outcomes against female counterparts than against male counterparts, while Hypothesis 4b indicated that female participants aware of their counterparts' AI use will achieve lower negotiation outcomes against male counterparts than against female counterparts.

However, no significant effects were found regarding the gender of the counterpart, indicating that the effects observed above were not dependent on the counterpart's gender. Additionally, there were no relationships between the participants' gender and the awareness condition and sexist beliefs (Hostile and Benevolent Sexism), except for the overall finding that female participants reported significantly lower hostile sexism, aligning with previous research on the topic. Overall, the interaction and simple effects being significant only for the participant's gender, regardless of the gender of the counterpart, are consistent with prior research on gender in negotiation, as no power differences or gender cues in the negotiation case used in the experiment were included (Bowles et al., 2025).

Furthermore, Hypothesis 5 suggested that hostile sexist beliefs moderate the relationship between the participant's gender, the other person's gender, and negotiation outcomes. A moderation analysis using PROCESS Model 1 (Hayes, 2022) tested whether hostile sexism moderated the link between the manipulation condition and final agreement for men. The overall model was not significant, $F(3,79) = 0.16$, $p = .924$, accounting for less than 1% of the variance in final agreement. Neither the manipulation condition (b = 3.91, p = .893) nor hostile sexism (b = -1.42, p = .816) significantly predicted final agreement. Importantly, the interaction between the manipulation condition and hostile sexism was also not significant (b = -0.21, p = .982), indicating that hostile sexism did not influence the effect of the manipulation on final agreement. Therefore, the data did not support Hypothesis 5.

Exploratory or Supplemental Analyses. An ANOVA for First Offer was also performed, which showed no main effects of condition, $F(1, 111) = 0.78$, $p = .379$, $\eta^2 = .007$, or gender, $F(1, 111) = 0.92$, $p = .340$, $\eta^2 = .008$. Although there was no main effect for First Offer, the interaction between condition and gender was significant, $F(1, 111) = 4.28$, $p = .041$, $\eta^2 = .037$. Therefore, an exploratory two-way ANOVA on First Offer found no significant main effects of manipulation condition or participant gender, indicating that neither AI use awareness nor gender alone influenced the size of participants' initial offers. However, the significant interaction between condition and gender, F(1, 111) = 4.28, p = .041, suggests that the impact of AI use awareness on first offers varied between men and women.

Inspection of the means shows a pattern similar to that seen in the final agreement: women in the AI use awareness condition made lower first offers than women in the control condition, while men in the AI awareness condition made higher first offers than men in the control condition. Although this analysis was exploratory, the interaction suggests that awareness of a peer's AI use may influence initial negotiation behaviour differently for men and women, echoing the gender-reversing pattern observed in the final agreement outcome.

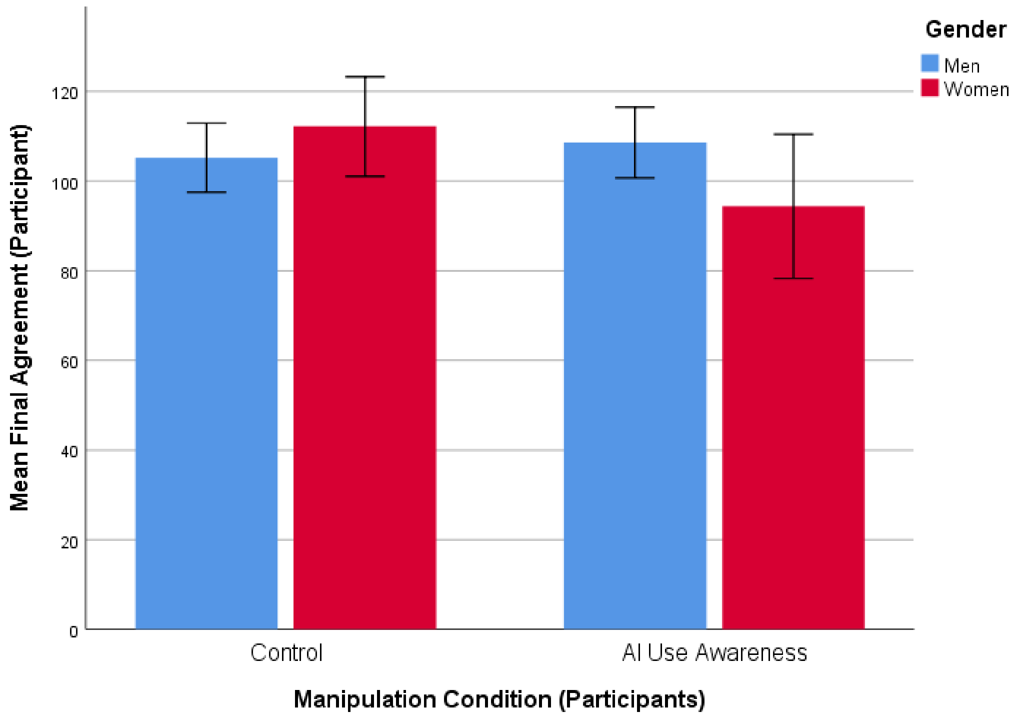
Discussion

In summary, the findings from Study 1 show that the impact of AI-use awareness on outcomes varied by gender. Specifically, awareness of AI use significantly lowered outcomes among women, while men's outcome levels were not notably affected by the manipulation. Women who were unaware of AI involvement had the highest agreement scores, but when AI use was made explicit, their agreement decreased considerably. This indicates that women may be more sensitive to revealing AI involvement in the task. In contrast, men's outcomes stayed relatively consistent across conditions, suggesting that awareness of AI use did not greatly influence their responses.

Overall, these results emphasize a gender-specific response to AI disclosure, indicating that transparency about AI involvement may have different psychological or evaluative effects depending on participant gender, as shown in Figure 2. Additionally, further analysis of first offers suggests a possible behavioural mechanism through which final agreement scores are influenced: the different effects of AI use awareness on first offers, based on participant gender, impact the final agreement reached. However, no significant mediation or moderated mediation was found between our IVs and DV, which will be discussed further in the general discussion.

Figure 2

Effects of AI Use Awareness on Female and Male Negotiators' Final Scores in Study 1



Study 2

Study 2 was designed to replicate and extend the Study 1 methodology in several ways. First, I attempted to strengthen external validity and methodological control by using AI bots as counterparts to double the sample size to ensure low statistical power is not the issue in not observing significant effects. Whereas Study 1 used a student dyadic negotiation design, Study 2 employed a controlled, text-based negotiation paradigm with AI confederates. Second, the sample in study 2 was more diverse in age, levels of education, or work experience, as it was drawn from the working adult population through Prolific. This design allowed me to examine whether the effects observed in Study 1 generalize to a broader population with substantial professional experience. Finally, participants received a participation bonus that depended on their performance in the negotiation simulation, potentially incentivizing them to increase task-specific energy and attention.

The study used a between-subjects experimental design in which participants were randomly assigned to either a control condition or an AI-use awareness condition. As in Study 1, the manipulation centered on whether participants were informed that their counterpart used AI-based training and assistance systems in negotiation preparation. However, unlike Study 1, in which the counterpart was another human participant, Study 2 used standardized AI confederates (prompted and trained ChatGPT API to negotiate as one side against the human participant on the other side) as counterparts.

The primary dependent, mediation, and exploratory variables remained consistent with Study 1 with a few modifications: 1) subjective outcomes were also measured using Curhan and colleagues' scale (2006; see Appendix C) to see if similar effects occurred on subjective valuation, and 2) "fixed sum perception," assessed with procedures by Kern and colleagues (2020; see Appendix D), was included to determine if this variable could be a potential mediator for the main effect.

The subjective outcome measure was included to examine whether gender differences exist in how participants assess the psychological experience they had during the negotiation, alongside the objective, economic results. Since this scale evaluates subjective perceptions across four categories, self, process, relationship, and outcomes in a negotiation, it is valuable to explore whether there are any gender-based differences in how participants perceive the impact of having an AI assistant on the other side within each of these categories.

Additionally, after realizing that the mediation mechanism and measure tested in the previous study did not yield significant results, I decided to include the fixed-sum perception measure to see if I could identify another potential mechanism as a mediator. In a negotiation context, fixed-sum perception (the belief that one party's gain is strictly the other's loss (Kern et al., 2020)) can serve as a key psychological mediator that translates gender and AI awareness into specific economic outcomes. When participants learn that their counterpart is using AI, it often triggers gendered schemas about how an AI-assisted opponent should be dealt with. For women, AI awareness may reinforce their socialized tendency to lean into accommodation to preserve the relationship or avoid deadlock with an apparently AI-augmented opponent, leading to lower individual scores at the end. Conversely, men may interpret AI as a challenge to their skills, viewing the fixed-sum nature of the task as an invitation to assert dominance and become more competitive. As a result, fixed-sum perception captures the mental shift where AI awareness prompts women to concede and men to compete, ultimately influencing the variation in final negotiation outcomes.

Method

Participants. A sample of 301 participants was recruited on Prolific in fall 2025. The age range was 21 to 80 years old, with a mean of 40.66 and a standard deviation of 11.76. The gender distribution was 49.2% men, 50.5% women, and 0.3% others. Racially, 3.0% were South or Central Asian, 68.8% White/European, 8.6% East Asian or Southeast Asian, 2.0% West Asian, 3.0% Native American or Indigenous, 13.3% Black or African, and 2.3% others. Education levels included 8.0% primary and high school graduates, 7.6% vocational degree recipients, 14.3% with some university experience (no degree), 48.8% college degree holders, and 20.6% with postgraduate degrees. Work experience was 4.3% with 1-3 years, 26.9% with 3-10 years, and 68.8% with more than 10 years. Participants were compensated between $3 and $4.50 for a 20-minute study that included a negotiation task and a subsequent survey. Their bonus, ranging from $0 to $1.50 above their $3 participation fee, depended on the outcome of their negotiations.

After excluding participants with incomplete data or failed attention checks, the final sample consisted of 290 individuals. Exclusion criteria included missing agreement data, implausibly fast completion times (less than 5 minutes), and failure on embedded attention checks, which asked participants to choose option 2 in a question embedded within the subjective valuation scale (Trochim et al., 2008). Random assignment to condition was implemented via Qualtrics randomization, resulting in approximately equal distribution across conditions. Demographic equivalence across conditions was assessed and confirmed.

Since the effect sizes in studies on gender differences in negotiation are mainly medium to small (Mazei et al., 2015), I increased the sample size in this study to prevent being underpowered to detect the effects I am interested in. A sensitivity power analysis was performed using G*Power to identify the smallest detectable effect size for the current sample. With a total sample of $N = 290$ in a 2×2 factorial ANOVA, assuming $\alpha = .05$ and a power $(1 - \beta) = .80$, the design was adequately powered to detect effects of about Cohen's $f = 0.17$ (roughly $\eta p^2 \approx .026$). This represents a small-to-medium effect size based on standard benchmarks.

Materials. As in the previous study, I used the shortened version of the case Deep Space from DRRC, with 3 issues, and scored options for each issue (see Appendix A).

Measures. Some of the scales and measurement processes were the same as in study 1, including final agreement, first offer, and threat perception. In this study, I also measured two additional variables: subjective outcomes and fixed-sum perception.

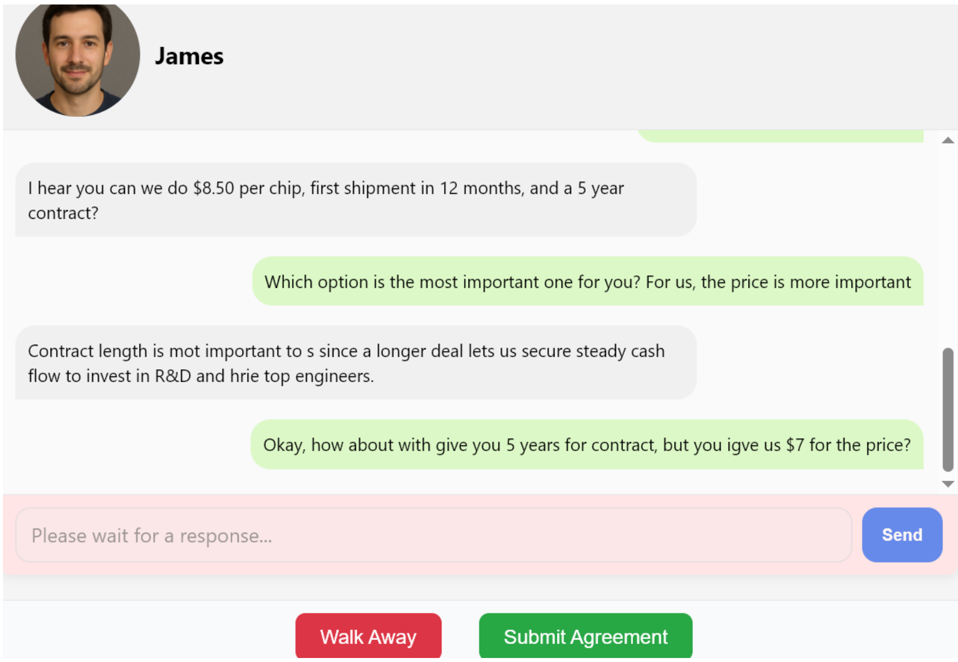
Subjective Outcome. For measuring *subjective outcomes,* I used Curhan and colleagues' Subjective Value Inventory (SVI) (2006), which is a 16-item scale asking respondents about their perceptions of four aspects in the negotiation they experienced: their feelings about the objective payoff, their feelings about themselves, their relationship with the counterpart, and their feelings about the negotiation process. You can find the scale and its items in Appendix C. The reliability analyses showed $\alpha = .832$ for this scale.

Fixed Sum Perception. To measure *fixed-sum perception,* I used the method by Kern and colleagues (2020), which asks participants to rate how much they believe their counterpart values each option for each issue in the negotiation, given their own payoff values for each option. This way, we can measure the extent to which they believe the negotiation is a fixed sum by deducting the values they have ascribed to their counterparts from the values they have in their own payoff table to see how much they see room for trade-off between themselves and their counterparts over each issue. You can find the details of the procedure in Appendix D. The reliability analyses showed α =.947, for this measure.

Procedure. In this study, negotiations were conducted via a chatbot with AI confederates as counterparts, each represented by an avatar (see Figure 3 for the platform interface). Some pre- and post-task questions were answered on Qualtrics. The AI confederates were prompted to negotiate as 5X's representatives (see Appendix A). In collaboration with the developers of the experimental platform (where the negotiations took place), I implemented a waiting lobby with a 15-second delay for participants who matched, and added a delay for random typos in chat responses. This prompted the bot to use simple language, making it appear more human. Participants were given two buttons: Walk Away and Submit Agreement. The Walk Away button could be used after at least ten messages were sent, while the Submit Agreement button was only available after the bot had determined that an agreement had been reached.

Figure 3

Platform Interface for Negotiating with AI Confederates in Study 2



After the end of the negotiation, participants were given a completion code to paste when they returned to Qualtrics.

AI Confederate as Human Counterpart Manipulation Check. I asked three questions (with 7-point Likert answers, 1 = Not at all, 7 = Extremely) after the manipulation debrief about the extent to which the participants doubted they were negotiating with a bot in the negotiation, how much their doubt was confirmed during the negotiation by what they saw from the other side, and how much they doubted at the end of negotiation, respectively. The answers to all three questions represented normal distributions with means of 3.39, 3.61, and 4.73, and standard deviations of 1.89, 1.95, and 2.20, respectively. After removing respondents who chose 5 to 7 in their answers, the results for the main effects did not change. Thus, these results indicate that the design has worked successfully, as when they entered the negotiation or during the negotiation they believed they were negotiating with a human counterpart.

Results

This study examined the impact of participants' gender and AI use awareness manipulation on negotiation offers and outcomes. A 2 (Participant Gender: male, female) × 2 (AI Awareness: aware, control) between-subjects factorial design was employed. The primary dependent variable was the final agreement score.

The descriptive statistics and bivariate correlations are shown in Table 5 and 6. Within the AI use awareness condition, men reported higher final agreement scores (M = 93.12, SD = 2.72) than women (M = 83.87, SD = 2.68), while women made higher first offers (M = 153.09, SD = 4.78) than men (M = 144.63, SD = 4.92). In the control condition, women had slightly higher final agreements (M = 90.58, SD = 2.57) than men (M = 86.80, SD = 2.64), whereas men made somewhat higher first offers (M = 153.97, SD = 4.64) than women (M = 147.24, SD = 4.55).

Table 5

Means and Standard Deviations of Final Agreements, First Offers, and Threat Perception by Levels of Condition and Gender for Study 2

Manipulation Condition	Gender	Final Agreement M (SD)	First Offer M (SD)	Stereotype Threat Perception M (SD)	Masculinity Threat Perception M (SD)
AI Use Awareness	Women	83.873 (2.680)	153.087 (4.775)	2.986 (.144)	2.498 (.163)
	Men	93.116 (2.718)	144.631 (4.919)	2.500 (.133)	2.231 (.148)
Control	Women	90.584 (2.573)	147.237 (4.549)	2.730 (.131)	2.363 (.132)
	Men	86.795 (2.643)	153.973 (4.642)	2.588 (.120)	2.158 (.145)

Note. N = 290

Table 6

Descriptive Statistics and Bivariate Correlations for Study 2

	M	SD	1	2	3	4	5	6
1. Final Agreement	88.900	22.125						
2. First Offer	150.270	39.902	.179**					
3. Stereotype Threat Perception	2.703	1.151	-.028	.019				
4. Masculinity Threat Perception	2.313	1.270	-.008	.011				
5. AI Manipulation Condition (0 = control, 1 = AI use awareness)	0.49	.501	-.052	-.019	.039	.041		
6. Participant's Gender (1 = male, 2 = female)	1.51	.501	-.063	.006	.134*	.092	-.006	

Note. N = 290

* *p* < .05.

** *p* < .01.

Stereotype threat perception increased slightly for women when they were aware of AI use, but there was no difference for men (2.986 compared to 2.730 and 2.500 compared to 2.588, respectively). Similarly, masculinity threat perception showed the same pattern—it was slightly higher for women only when they were aware of AI use, with no difference for men (2.498 compared to 2.363 and 2.231 compared to 2.158, respectively). Final agreement was positively correlated with the first offer ($r = .179$, $p < .01$), and stereotype threat was positively correlated with participant gender ($r = .134$, $p < .05$), indicating it was significantly higher for women. Conversely, stereotype and masculinity threat perceptions, AI manipulation condition, and participant gender showed no significant correlations with the main negotiation outcomes.

Hypotheses Test Analyses. Similar to Study 1, to examine causal relationships, I first analyze the main and interaction effects using a two-way ANOVA, then test each effect with subsequent simple effect analyses. The ANOVA results are shown in Table 7. In Hypothesis 1, it was proposed that there would be a significant interaction between AI use awareness and participants' gender on the negotiation outcome, such that awareness of AI use would improve negotiation results for men but decrease results for women. A 2 × 2 ANOVA on final agreement found no significant main effects of AI use awareness ($F(1, 286) = 0.036$, $p = .850$, $\eta^2 = .000$) or gender ($F(1, 286) = 745$, $p = .188$, $\eta^2 = .006$). However, the interaction between gender and AI use awareness was significant, $F(1, 286) = 7.777$, $p = .006$, $\eta^2 = .027$. Similar to Study 1, I conducted an ANOVA for First Offer and found no significant main or interaction effects this time (interaction effect non-significance at $F(1, 272) = 2.586$, $p = .109$, $\eta^2 = .009$). Overall, these ANOVA results provide initial support for the predicted interaction between AI use awareness and participant gender (Hypothesis 1), depending on the results of subsequent simple tests.

Table 7

ANOVA Results for Study 2

Source	Sum of Squares	df	Mean Square	F	p	η²
DV: Final Agreement						
Manipulation Condition	2.749	1	2.749	.005	.942	.000
Gender	538.030	1	538.030	1.055	.305	.001
Manipulation Condition x Gender	3073.465	1	3073.465	6.028	.015	.021
Error	145809.551	286	509.824			
Total	2425301.000	290				
DV: First Offer						
Manipulation Condition	214.900	1	214.900	.137	.712	.000
Gender	52.171	1	52.171	.033	.856	.000
Manipulation Condition x Gender	4068.032	1	4068.032	2.586	.109	.009
Error	438858.799	279	1572.971			
Total	6793822.500	283				

To follow up on the interaction between condition and gender, simple effects analyses were conducted to examine the effect of condition within each gender, with Bonferroni adjustments for multiple comparisons (see Table 8). In Hypothesis 2a, I stated women who were made aware of the counterpart's AI use would achieve lower negotiation outcome than women who were told nothing about any AI use, while in Hypothesis 2b we had men who were made aware of the counterpart's AI use would achieve higher negotiation outcome than men who were told nothing about any AI use.

Table 8

Simple Effects of Condition on Final Agreement by Gender in Study 2

Gender	Condition	M	SE	95% CI	F(1, 286)	p
Men	Control	86.80	2.64	[81.59, 92.00]	2.78	.097
Men	AI-use awareness	93.12	2.72	[87.77, 98.47]		
Women	Control	90.58	2.57	[85.52, 95.65]	3.26	.072
Women	AI-use awareness	83.87	2.68	[78.60, 89.15]		

For men, the effect of condition on final agreement was not statistically significant, $F(1, 286) = 2.78$, $p = .097$. Men in the AI-use awareness condition (M = 93.12, SE = 2.72, 95% CI [87.77, 98.47]) reported slightly higher agreement than men in the control condition (M = 86.80, SE = 2.64, 95% CI [81.59, 92.00]), but the difference was not statistically significant after adjusting for multiple comparisons (Mdiff = 6.32, SE = 3.79, $p = .097$).

For women, the effect of the condition was not statistically significant, $F(1, 286) = 3.26$, $p = .072$. Women in the control group (M = 90.58, SE = 2.57, 95% CI [85.52, 95.65]) showed slightly higher agreement than women in the AI-use awareness group (M = 83.87, SE = 2.68, 95% CI [78.60, 89.15]). However, the pairwise comparison did not become significant after Bonferroni correction (Mdiff = 6.71, SE = 3.72, $p = .072$). Therefore, unlike Study 1, Hypothesis 2a is not supported, as women in the AI use awareness group had lower final agreement scores than women in the control group, but this difference was not statistically significant. Similarly, as in Study 1, men aware of their partner's AI use tended to have higher final agreement scores than men in the control group, but again, this effect was not statistically significant. Consequently, the results do not support Hypothesis 2b.

Moreover, no significant effects were found for threat perception (masculinity or stereotype threat) as measured by the public discomfort scale, thus providing no support for Hypotheses 3a and 3b, which stated, respectively, that the negative relationship between AI awareness and negotiation outcomes for women is mediated by stereotype threat, such that AI awareness increases perceived stereotype threat, leading to lower negotiation performance, while the positive relationship between AI awareness and negotiation outcomes for men is mediated by masculinity threat, such that AI awareness increases perceived masculinity threat, leading to higher negotiation performance.

Two moderated mediation analyses were conducted (PROCESS macro Model 7; Hayes, 2022) to examine whether stereotype or masculinity threat mediated the relationship between AI awareness condition and final agreement scores, and whether the AI awareness → stereotype or masculinity threat path was moderated by gender. The analysis included N = 290 participants, and 5,000 bootstrap samples were used to estimate 95% confidence intervals. Overall, the results provide no evidence for mediation or moderated mediation, not providing any support for Hypothesis 3a.

For stereotype threat as the mediator, the regression model predicting stereotype threat from AI awareness condition, gender, and their interaction was not statistically significant, $F(3,286) = 2.27$, $p = .080$, $R^2 = .023$. The interaction between AI awareness and gender was not significant ($b = 0.28$, $SE = 0.27$, $t = 1.04$, $p = .301$), indicating that gender did not significantly moderate the relationship between AI awareness condition and stereotype threat. Additionally, neither AI awareness condition ($b = -0.32$, $SE = 0.43$, $t = -0.73$, $p = .463$) nor gender ($b = 0.17$, $SE = 0.19$, $t = 0.91$, $p = .364$) significantly predicted stereotype threat. Moreover, the regression model predicting final agreement score from AI awareness condition and stereotype threat was not significant, $F(2,287) = 0.12$, $p = .886$, $R^2 = .001$. Neither AI awareness ($b = -0.25$, $SE = 2.68$, $t = -0.09$, $p = .925$) nor stereotype threat ($b = -0.56$, $SE = 1.16$, $t = -0.48$, $p = .633$) significantly predicted final agreement scores. Also, the direct effect of AI awareness condition on final agreement score was not significant ($b = -0.25$, $SE = 2.68$, $t = -0.09$, $p = .925$, 95% CI [−5.53, 5.03]).

Bootstrapped conditional indirect effects of AI awareness condition on final agreement score through stereotype threat were examined at each level of gender. For men, the indirect effect was not significant ($b = 0.02$, BootSE = 0.24, 95% CI [−0.45, 0.55]). For women, the indirect effect was also not significant (*b* = −0.14, BootSE = 0.37, 95% CI [−1.01, 0.57]). Because both confidence intervals included zero, there was no evidence that stereotype threat mediated the relationship between AI awareness condition and final agreement scores for either gender. Furthermore, the index of moderated mediation was not significant (index = −0.16, BootSE = 0.47, 95% CI [−1.25, 0.72]), indicating that the indirect effect of AI awareness condition on final agreement score through stereotype threat did not significantly differ by gender.

For masculinity threat as the mediator, the regression model predicting masculinity threat from AI awareness condition, gender, and their interaction was not significant, $F(3,286) = 0.95$, $p = .418$, $R^2 = .010$. The interaction between AI awareness condition and gender was not significant ($b = 0.05$, $SE = 0.30$, $t = 0.17$, $p = .862$), indicating that gender did not significantly moderate the relationship between AI awareness condition and masculinity threat. Additionally, neither AI awareness condition ($b = 0.03$, $SE = 0.47$, $t = 0.06$, $p = .951$) nor gender ($b = 0.20$, $SE = 0.21$, $t = 0.97$, $p = .332$) significantly predicted masculinity threat. Moreover, the regression model predicting final agreement score from AI awareness condition and masculinity threat was also not significant, $F(2,287) = 0.02$, $p = .984$, $R^2 < .001$. Neither AI awareness condition ($b = -0.30$, $SE = 2.68$, $t = -0.11$, $p = .912$) nor masculinity threat ($b = -0.15$, $SE = 1.06$, $t = -0.14$, $p = .892$) significantly predicted final agreement scores. Also, the direct effect of AI awareness on final agreement was not significant ($b = -0.30$, $SE = 2.68$, $t = -0.11$, $p = .912$, 95% CI [−5.58, 4.98]).

Bootstrapped conditional indirect effects of AI awareness condition on final agreement **score** through masculinity threat were examined at each level of gender. For men, the indirect effect was not significant ($b = -0.01$, BootSE = 0.27, 95% CI [−0.68, 0.47]). For women, the indirect effect was also not significant (b = −0.02, BootSE = 0.28, 95% CI [−0.63, 0.61]). Because both confidence intervals included zero, the mediation effect was not supported at either level of gender. Furthermore, the index of moderated mediation was not significant (index = −0.01, BootSE = 0.35, 95% CI [−0.68, 0.86]), indicating that the indirect effect of AI awareness condition on final agreement score through masculinity threat did not differ significantly across gender. Overall, the results provide no evidence for mediation or moderated mediation, not providing any support for Hypothesis 3b.

Exploratory or Supplemental Analyses. Subjective outcomes were assessed using the SVI scale (Curhan et al., 2006), and fixed-pie perception was evaluated using the method from Kern et al. (2020). However, neither measure produced statistically significant results. Specifically, no significant relationships emerged between participants' gender and the AI-use awareness condition regarding subjective outcomes. A two-way multivariate analysis of variance (MANOVA) was performed to analyze the effects of AI awareness condition and participants' gender on five subjective outcome measures: subjective valuation of self, relationship, process, outcome, and the overall subjective valuation total. Using Pillai's Trace, the multivariate results showed no significant main effect of AI awareness condition, V = .008, F(4, 293) = 0.593, p = .668, and no significant main effect of gender, V = .014, F(4, 293) = 1.012, p = .401. The interaction between AI awareness condition and gender was also not significant, V = .015, F(4, 293) = 1.098, p = .358.

Follow-up univariate ANOVAs also showed no significant effects of AI awareness condition, gender, or their interaction on any of the subjective outcome variables. Specifically, AI awareness condition did not significantly impact subjective valuation of self, $F(1, 296)$ = 1.142, p = .286; relationship, $F(1, 296)$ = 0.000, p = .991; process, $F(1, 296)$ = 0.128, p = .721;

outcome, $F(1, 296) = 0.003$, $p = .954$; or the overall subjective valuation total, $F(1, 296) = 0.122$, $p = .727$. Similarly, gender showed no significant effects on self, $F(1, 296) = 1.284$, $p = .258$; relationship, $F(1, 296) = 0.468$, $p = .494$; process, $F(1, 296) = 1.013$, $p = .315$; outcome, $F(1, 296) = 0.001$, $p = .979$; or the overall subjective valuation total, $F(1, 296) = 0.603$, $p = .438$. The interaction between condition and gender was also not significant across outcomes (all *p*s > .05), although the interaction for subjective valuation of relationship came close to significance, $F(1, 296) = 3.286$, $p = .071$.

Additionally, fixed-pie perception did not mediate the primary effect between participants' gender and the AI-use awareness condition on objective outcomes. Two mediation analyses using PROCESS Model 4 (Hayes, 2022) were performed to assess whether fixed sum perception mediates the relationship between AI awareness condition and final outcomes separately for men and women. For men, results showed that the manipulation condition did not significantly predict fixed sum perception, $b = -27.73$, SE = 38.15, t = -0.73, $p = .469$, and the model explained very little variance in the mediator, $R^2 = .004$. When predicting final agreement, the overall model was not statistically significant, $F(2,139) = 2.19$, $p = .116$, $R^2 = .031$. Neither manipulation condition ($b = 6.64$, SE = 3.93, $p = .093$) nor fixed sum perception ($b = 0.012$, SE = 0.009, $p = .185$) significantly predicted the final agreement score. The direct effect of manipulation condition on final agreement was not significant, and the indirect effect through fixed sum perception was also non-significant, as the bootstrapped 95% confidence interval included zero ($b = -0.32$, *BootSE* = 0.59, 95% CI [-1.66, 1.66,0.72]).

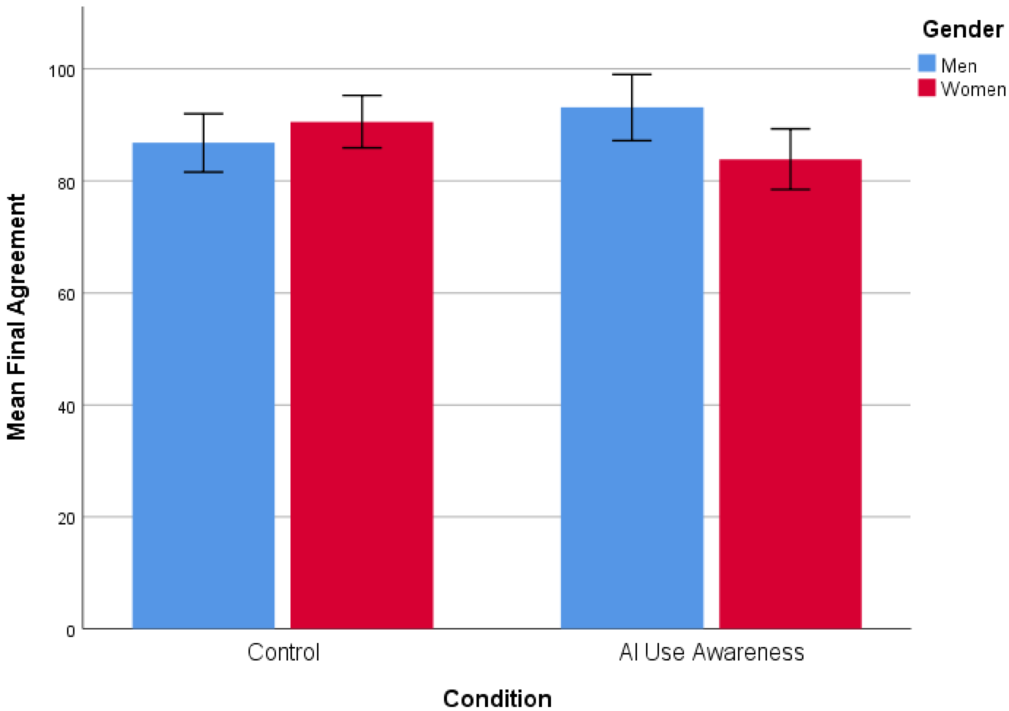
For women, results indicated that manipulation condition did not significantly predict fixed sum perception ($b = -46.92$, SE = 37.76, t = -1.24, $p = .216$), and the model explained a small proportion of variance in the mediator ($R^2 = .010$). When predicting the final agreement score, the overall model was statistically significant ($F(2,146) = 5.55$, $p = .005$, $R^2 = .071$). Within this model, fixed sum perception significantly predicted the final agreement score ($b = 0.021$, SE = 0.008, t = 2.74, $p = .007$), indicating that higher fixed sum perception was associated with higher final agreement scores. However, manipulation condition did not significantly predict the final agreement ($b = -5.65$, SE = 3.50, t = -1.62, $p = .108$). The direct effect of manipulation condition on the final agreement was therefore not significant. Additionally, the indirect effect of manipulation condition on the final agreement through fixed sum perception was not significant, as the bootstrapped 95% confidence interval included zero ($b = -0.98$, *BootSE* = 0.92, 95% CI [-3.05, 0.66]). Overall, these results indicate that fixed sum perception does not mediate the relationship between manipulation condition and final agreement score for either men or women.

Discussion

In summary, the simple effects analyses indicated that condition did not significantly influence participants' final agreement within either gender, although the pattern of means suggested a potential gender-specific trend. Among men, agreement scores were somewhat higher when participants were aware of AI use compared to the control condition. In contrast, women showed the opposite pattern, with slightly higher agreement in the control condition than in the AI-awareness condition. Although these differences did not reach conventional levels of statistical significance, the pattern suggests that awareness of AI involvement may influence men and women in different directions. Specifically, AI awareness appeared to slightly increase agreement among men while slightly decreasing agreement among women (as seen in Figure 4), while the results were not proven to be statistically significant. Future research with greater statistical power may help determine whether these trends represent meaningful gender differences in responses to AI disclosure.

Figure 4

Effects of AI Use Awareness on Female and Male Negotiators' Final Scores in Study 2



CHAPTER 5: DISCUSSION AND CONCLUSION

Discussion and Overview of Findings

This dissertation explored how awareness of a counterpart's use of AI influences negotiation outcomes in gendered ways. Instead of viewing AI solely as a technical tool that enhances decision quality or bargaining success, the primary theoretical focus was to understand AI awareness as a socially meaningful cue. This cue can change expectations, strategic behaviour, and evaluative dynamics in interdependent interactions. Through two experimental studies, the results showed that discovering a counterpart has used AI can affect negotiation outcomes, in particular for women.

The core empirical result across both studies was a reliable interaction between negotiator gender and AI awareness, specifically for women. Awareness of AI use did not produce uniform effects across participants. Instead, the same informational cue shifted outcomes in different directions for women and men. Women tended to achieve statistically significant lower outcomes when AI awareness was made salient (though inconsistent across studies), whereas men's outcomes were comparatively stable, with some directional increases but without statistical significance. Importantly, there were no main effects of AI awareness or gender alone. This pattern indicates that AI awareness's influence in negotiation is conditional and relational rather than additive, and highlights the importance of understanding how technological cues are interpreted within social contexts.

A second important finding is what the studies did not reveal. In both experiments, none of the hypothesized psychological mechanisms, stereotype threat or masculinity threat, or even exploratory mechanism of fixed-sum perception, mediated the link between AI awareness and negotiation outcomes. Although women reported higher levels of stereotype threat than men, these self-reported feelings did not explain outcome differences.

Theoretical Contributions

This research makes several theoretical contributions to the literatures on negotiation, gender, and AI by reframing how emerging technologies influence interpersonal and interdependent decision-making. A central contribution of this dissertation is the conceptual distinction between AI capability and AI awareness. Prior research on AI in organizations has largely focused on what AI systems enable users to do, such as improving efficiency, accuracy, or learning. For instance, prior studies have looked at how AI tools improve task efficiency, support knowledge workers, and enhance problem-solving quality (e.g., Brynjolfsson et al., 2025; Dell'Acqua et al., 2023; Dell'Acqua et al., 2025; Vaccaro et al., 2024). Others have viewed technology as a shared contextual factor that influences communication patterns between individuals or teams (Geiger, 2020). While these approaches are useful, they often miss the deeper psychological and relational processes that develop when AI systems are integrated into social interactions. By contrast, this research demonstrates that beliefs about a counterpart's use of AI can influence outcomes independently of whether AI actually changes behaviour.

A second contribution involves expanding negotiation theory beyond a narrow focus on observable tactics to include how contextual cues reshape the meaning of the bargaining situation itself (Jang et al., 2018). Traditional negotiation models highlight behaviours such as anchoring, concession patterns, and information exchange. While these behaviours remain important, the current findings suggest that changes in outcomes can happen before or independently of these tactics, through shifts in how negotiators interpret the interaction they face.

This research also advances theory on gender in negotiation by demonstrating that technological cues can serve as gendered signals even when formally neutral. Negotiation research has long documented gender gaps in outcomes and evaluations, often attributing these differences to variations in behaviour, expectations, and social penalties (Bowles et al., 2022; Bowles & McGinn, 2008). However, the role of technology, especially AI systems, as a mediator of gendered dynamics has largely gone unexplored. By analyzing how AI use interacts with gender stereotypes, I widen the analytical perspective to include the impact of technological artifacts on social bias. Women's outcomes were more significantly affected by AI awareness than men's, suggesting greater sensitivity to contextual cues that heighten evaluation in domains historically associated with masculine competence.

This perspective builds on previous research on gender in negotiation by showing that negative gendered effects can happen even without assertive or dominant behaviour. Past studies have mainly focused on how women are penalized when they use assertive negotiation strategies that conflict with traditional gender norms (Bowles et al., 2022). Those findings point to the double bind women face, failing to assert themselves can lead to worse outcomes, but asserting themselves can cause backlash. This study, however, aimed to shift the focus from behavioural assertiveness to technological mediation. I argued that similar negative reactions can occur not because of what women do interpersonally, but because of the tools used. The introduction of a non-human agent, such as an AI system, may disrupt gendered expectations and elicit responses similar to those seen in cases of assertive behaviour. Therefore, this mechanism demonstrates that technological mediation itself can act as a trigger for gender gaps, regardless of individual behaviour.

Finally, this research refines theories of stereotype threat and masculinity threat by clarifying their boundaries. Although these frameworks motivated the initial hypotheses, the consistent absence of mediation suggests that AI awareness does not exert its influence primarily through consciously experienced threat. Instead, the findings point to a potentially broader class of status-relevant and evaluative signals that shape behaviour without necessarily generating reportable emotional states. Rather than rejecting threat-based theories, this work specifies when they may be less likely to apply. In fast-moving, strategic interactions like negotiation, individuals may adjust behaviour in anticipation of evaluation or relative disadvantage without labeling their experience as threatening. This insight has implications for research on identity, status, and evaluation beyond AI-mediated contexts.

In summary, this research advances both technology and gender studies by incorporating insights from organizational behaviour, social psychology, and STEM fields. It demonstrates that the behavioural and cognitive impacts of AI use can significantly affect social interactions within organizations. At the same time, the examination of gender in negotiation was broadened by recognizing technological mediation as a distinct source of bias. Overall, these contributions emphasize the importance of viewing AI not just as a technical innovation but also as a socially embedded resource that interacts with identity, power, and inequality. By applying interdisciplinary research and focusing on relational dynamics, scholars and practitioners can better anticipate unintended consequences and create strategies that promote both technological advancement and social equity.

Limitations and Future Research

Several limitations qualify the conclusions of this research and suggest directions for future work. First, although the interaction between gender and AI awareness replicated across two studies, simple effects were not uniformly significant across samples. Specifically, I observed mixed results for women and null findings for men across both studies. As one possibility, these patterns may reflect small effect sizes typical of contextual social cues rather than methodological weakness. Future research with larger samples and higher powered designs may help estimate the magnitude of these effects more precisely.

Additionally, the absence of observable effects among men may stem from differing baseline assumptions about AI use in professional contexts. Given that men, on average, tend to report higher rates of AI system usage in the workplace (Chatterji et al., 2025), they may be more likely to assume that others are also benefiting from such tools. As a result, explicit AI awareness cues may be less salient or influential for men, since these cues align with their existing expectations rather than introducing new or contrasting information.

Second, the absence of mediation suggests that self-report measures may have limits in capturing the processes through which AI awareness operates. Future research should incorporate alternative approaches, such as behavioural process tracing, linguistic analysis, physiological indicators, or time-based measures of strategic adjustment, to better capture anticipatory and situational mechanisms. Additionally, incorporating behavioural measures, such as concession patterns, time to agreement, and communication tone, could help identify the mechanisms underlying the observed outcome differences. By strengthening methodological rigor, future work can clarify whether the small effect sizes observed here represent stable social patterns or context-dependent fluctuations. For instance, parallel dynamics may be at play, such as perceptions of female competence in working with AI systems, which could shape expectations and responses during interaction. If participants hold implicit beliefs about women being less or more proficient with AI, these perceptions may interact with AI awareness cues in ways not captured by the current design. Exploring how perceived technological competence intersects with gender and AI awareness represents an important avenue for future research.

Third, it is important to consider that perceptions of AI usage and its implications for negotiation are likely evolving rapidly. Over the past two years, the widespread diffusion of generative AI tools such as ChatGPT has increased both familiarity with and expectations about AI-assisted performance in professional contexts (Chatterji et al., 2025; Kochhar, 2023). As a result, individuals may now be more likely to assume that counterparts are using AI, to view such use as normative, or to strategically adjust their behaviour in anticipation of AI-augmented capabilities. These shifting perceptions could attenuate or amplify the effects of AI awareness observed in the present studies, depending on whether AI use is seen as a baseline expectation or a competitive advantage. Future research should explicitly account for this temporal dynamic by measuring participants' prior exposure to AI, their beliefs about its prevalence in negotiation settings, and how these beliefs evolve over time, in order to better capture the context-dependent nature of AI-related social inferences.

Fourth, this research focused deliberately on AI awareness rather than actual AI use. While this design isolates the social signaling effects of AI, perception and capability often co-occur in real-world settings. When a negotiator uses AI, two things happen at the same time: first, the other party develops beliefs and expectations about the AI-enhanced negotiator; second, the AI-supported negotiator might actually change their behaviour, preparation, confidence, or strategic approach. These behavioural changes can either reinforce or reduce the initial response. For instance, if AI support leads to more collaborative strategies or better preparation, it could counteract defensive reactions to perceived competition. Conversely, if AI support increases assertiveness or enhances value-claiming tactics, it might provoke more backlash. Since current studies have only examined perception, we cannot determine how these two processes interact in real life. Future research should include experimental designs where both negotiators actively use AI tools, so researchers can observe how perception-based threats and actual behavioural changes together affect outcomes. Long-term studies could also examine how repeated exposure to AI-supported counterparts influences expectations over time.

Fifth, both studies were conducted in online negotiation environments. While these settings offer strong experimental control, they may attenuate or alter social cues present in face-to-face negotiations. Replicating these findings in laboratory or field settings would help clarify the role of embodiment and nonverbal evaluation. It would also be advantageous to somehow heighten the degree to which participants were meaningfully impacted by the negotiation outcomes.

Finally, beyond these methodological considerations, the findings open several new avenues for research. One promising path involves exploring AI use in other socially interconnected settings characterized by fixed-sum or competitive resource allocation. Negotiation is just one example of such environments. Similar dynamics may occur in leader–follower relationships, peer competition, team-based incentive systems, or performance evaluation situations. In contexts where resources, recognition, or authority are limited, introducing AI assistance could change perceived status hierarchies and provoke defensive reactions among those who feel relatively disadvantaged.

Particularly important is the issue of backlash effects on individuals in lower-status positions. If AI tools allow members of traditionally lower-status groups to improve their performance or competitiveness, higher-status counterparts may see this as a threat to existing hierarchies. This dynamic is not limited to gender differences. Similar patterns can occur in cross-racial, cross-cultural, or cross-class interactions or negotiations. For example, when members of marginalized racial or socioeconomic groups use AI to address informational inequalities, opponents from historically dominant groups may feel threatened based on status or identity. Also, future research could explore how transparency about AI use affects these perceptions. Does openly acknowledging AI support decrease suspicion, or does it increase perceptions of unfair advantage? Additionally, cultural norms about technology adoption and authority may affect whether AI augmentation is viewed as legitimate or disruptive. Theories from social dominance theory (Sidanius et al., 2012), status characteristics theory (Berger et al., 1972), and intergroup relations (Mackie & Smith, 1998) can be combined with AI adoption research to examine these issues.

Another significant limitation of the present study, which opens up avenues for future research, is that I did not distinguish between AI systems used for training and those used for real-time assistance during negotiation. These two applications may have different psychological and behavioural effects. AI used for training purposes, such as simulation platforms or feedback systems, mainly improves skill development before the negotiation begins (Dinnar, 2021). In contrast, AI used for live assistance might influence decision-making in real time by suggesting offers, identifying leverage points, or predicting how the counterpart will react (Shonk, 2026).

Future research should separate these conditions to determine whether backlash effects vary based on when and how AI is used. For instance, negotiators who use AI solely for preparation against a male counterpart might seem more competent without explicitly signaling technological support, potentially decreasing backlash. Conversely, visible reliance on AI during live negotiations could amplify perceptions of artificial enhancement or unfair advantage. Moreover, exploring whether similar gender-related effects occur during the training phase itself is crucial. Educational environments often involve lower stakes, but social comparison processes still take place. If female students experience subtle backlash for using AI training tools in negotiation classes, educators need to proactively address these issues.

In conclusion, while this research helps explain how AI augmentation interacts with gender-based dynamics in negotiation, several limitations highlight the need for further investigation. Future studies should include perception and usage effects, replicate results in face-to-face settings, increase statistical power, explore other mediating mechanisms, and expand the framework to broader interdependent contexts. By addressing these points, scholars can develop a more complete understanding of how AI technologies influence social hierarchies, competitive behaviour, and perceptions of legitimacy in changing organizational environments.

Practical Implications

Finally, this research provides important practical implications by enhancing the understanding of how the adoption of AI technologies might unintentionally reinforce or worsen existing inequalities. Recent reports from the International Monetary Fund (IMF) warn that rapid advances in AI development and use could widen income and opportunity gaps within and between societies if access to these technologies remains unequal (Milmo et al., 2024). These concerns are especially relevant in professional settings where access to AI tools can boost productivity, preparation, and strategic performance. If certain social groups, such as men, senior employees, or those in higher socioeconomic positions, have disproportionate access to AI systems, the advantages of technological growth may unevenly accumulate, reinforcing preexisting privileges.

Current findings suggest that even with equal access, perceptions of AI use can trigger negative social dynamics. Specifically, when negotiators use AI systems, their counterparts might see increased threats, influencing their strategic behaviour. In gendered environments, this can cause backlash effects, where female negotiators using AI encounter more competitiveness or resistance from male counterparts. Therefore, AI technologies do not operate in a social vacuum; their effects are shaped by existing social hierarchies and expectations. Policymakers and organizational leaders should therefore move beyond viewing AI solely as a productivity tool and consider its broader social consequences.

A key point is the need to ensure fair access to AI systems for all demographic groups. Organizations can take proactive measures to make access more equal by offering training programs, subsidized tools, and structured support for employees across genders, departments, and levels. Instead of letting AI adoption happen naturally, where early adopters with more resources benefit first, leaders can establish formal policies that promote inclusive sharing. These efforts might include organization-wide AI literacy workshops, mentorship programs focused on developing tech skills, and clear guidelines on how to use AI ethically and effectively in negotiations and decision-making. By making AI use common across groups, organizations can help lessen the idea that some individuals are gaining unfair advantages.

In addition, transparency is essential. When AI use is unclear or selectively revealed, it can increase suspicion and competitive risks. Creating shared standards around AI help, such as defining when it is suitable to use AI for preparation versus real-time decision support, can reduce uncertainty and build trust. Policymakers at larger societal levels can also help by promoting inclusive digital education efforts and supporting regulations that promote fair technological spread. If AI becomes a common professional resource rather than a selective enhancement, its potential to boost inequality may be lessened.

Beyond organizational policy, this research also provides practical insights for negotiators themselves. Male negotiators, in particular, may benefit from greater awareness of potential implicit biases when interacting with counterparts who use AI systems. If perceptions of threat or unfair advantage unconsciously lead to more aggressive opening offers or fewer concessions, outcomes can be skewed by bias rather than an objective assessment of the negotiation situation. By consciously reflecting on their motivations and decision-making processes, negotiators can prevent overreacting or becoming unnecessarily competitive. Simple reflective practices, like pausing to assess whether their response is proportionate to the actual situation, can help reduce bias-driven escalation.

Conversely, negotiators who use AI systems, especially women in settings where gender dynamics are prominent, should recognize the risk of underperformance under stress. Recognition does not mean self-limitation. Instead, it allows for strategic adjustment. For example, AI-enhanced negotiators might highlight collaboration, transparency, or shared problem-solving early in the process to minimize perceptions of hostility. They might also present AI as a tool for efficiency or mutual benefit rather than a means of dominance. Such framing can help shift AI's role from a symbol of power to a facilitator of joint value creation.

Importantly, these recommendations should not unfairly burden those who use AI tools with managing bias. The broader responsibility falls on institutions and leaders to create systems that reduce inequitable outcomes. However, giving individuals knowledge about these issues helps them navigate negotiations more effectively for now.

In summary, as AI technologies become more integrated into professional settings, their social effects should be considered alongside their technical abilities. This research shows that AI adoption can alter how people perceive each other and influence competitive dynamics, sometimes reinforcing inequality. By ensuring fair access, clear norms, and awareness of bias, policymakers, organizations, and negotiators can work toward making sure AI promotes inclusive growth instead of widening existing divides.

Conclusion

This dissertation demonstrates that AI influences negotiation not only through what it enables people to do, but through what its presence signals to others. Across two studies, we saw partial empirical support that the awareness of a counterpart's AI use systematically altered negotiation outcomes in gender-contingent ways, even when no objective advantage was present and no mediating psychological mechanism was observed.

By conceptualizing AI awareness as a socially embedded signal rather than a technical capability, this research advances understanding of how emerging technologies intersect with interdependence, evaluation, and inequality. The findings show that technology can reshape outcomes through perception and interpretation alone, highlighting a pathway through which AI may subtly reinforce or disrupt existing social dynamics.

As AI becomes increasingly integrated into professional decision-making, its social meanings will matter as much as its technical capabilities. Understanding how AI awareness reshapes evaluative contexts is therefore essential for leveraging technological innovation while promoting fairness and effective collaboration in interdependent work.

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APPENDICES

Appendix A: Deep Space Negotiation Case

Deep Space Negotiation Case (DRRC) – Deep Space Representative Role

General Information

You are entering a negotiation between two corporations: A modern chip maker, 5X, and Deep Space, a mobile phone producer.

Deep Space is looking for a partnership with a cutting-edge chip developer. If Deep Space can grab hold, the company would be well-positioned to secure market supremacy with the next generation technology inside its phones. 5X also wants a larger stage for its cutting-edge system, and they believe their company could take over the global market if only it had a far-reaching partner.

Deep Space read about 5X in the latest issue of Inc. magazine and contacted them. The parties agreed to meet face-to-face to discuss establishing a partnership.

Confidential Information

You are the negotiator on behalf of Deep Space. You believe that 5X has the technology needed to fuel your growth throughout Region B in your market; you just have to get your hands on the best-in-class chip.

You believe you are the largest corporation courting 5X, which they need in order to establish themselves as a major player.

You and 5X agreed that there were three issues to discuss and would need to come to an agreement in order to proceed with a deal.

These are your key interests for each of the issues.

1. **Price License for the Chip:** You have been warned by your investors and stockholders to keep costs low; thus, you want to keep the licensing price low. The typical rate for chip licensing in the industry ranges between 7 and 9 $ per chip.

2. **Shipment Date:** Deep Space and 5X must agree upon when 5X will deliver the first shipment. It is customary for orders to ship six to fourteen months after a contract is finalized. The faster you get the new chip in your phone, the better. After all, this new technology won't stay ahead of the competition forever.

3. **Length of Contract:** It would be more advantageous to have a shorter contract until trust and confidence is established with this young company. While 5X has a good reputation in the Region A markets, they have no track record in the Region B markets yet. You also worry that 5X's technology might become obsolete if they don't continue to innovate.

You and 5X will need to come to an agreement on these three issues in order to proceed with a deal.

On the next page, you will be given a score table for the points you get for each option you have in each issue above.

Please feel free to take notes, screenshots, or photos from this page and next page to keep with yourself during the negotiation.

Just please do not share them with your counterpart as they are confidential.

The scoring system below contains the point values you have assigned to each option.

SCORING SYSTEM FOR DEEP SPACE

Issue	Options	Value
Price License for the Chip	$7.00	80
	$7.50	60
	$8.00	40
	$8.50	20
	$9.00	0
Shipment Date	6 months	50
	8 months	40
	10 months	30
	12 months	20
	14 months	10
Length of Contract	2 years	30
	3 years	25
	4 years	20
	5 years	15
	6 years	10

Deep Space Negotiation Case (DRRC) – 5X Representative Role

General Information

You are entering a negotiation between **two corporations**: A modern chip maker, **5X**, and **Deep Space**, a mobile phone producer.

Deep Space is looking for a partnership with a cutting-edge chip developer. If Deep Space can grab hold, the company would be well-positioned to secure market supremacy with the next generation technology inside its phones. 5X also wants a larger stage for its cutting-edge system, and they believe their company could take over the global market if only it had a far-reaching partner.

Deep Space read about 5X in the latest issue of Inc. magazine and contacted them. The parties agreed to meet face-to-face to discuss establishing a partnership.

Confidential Information

You are the negotiator **on behalf of 5X**. You are excited about the possibility of a partnership with the Region B behemoth Deep Space and feel it could be the liftoff you need to achieve your dream of global reach for your company.

You believe your chip quality is top class and it could elevate the performance of Deep Space phones.

You and 5X agreed that there were **three issues** to discuss and would need to come to an agreement in order to proceed with a deal.

These are your key interests for each of the issues.

1. **Price License for the Chip:** You know that the Deep Space phone might become the hottest

in their markets if it were paired with your chip, the sharpest of the cutting edge. You believe you are in a strong position to demand a higher rate among the customary range of 7-9 $. This will bring in the money you need to ensure you can hire the best engineers and scientists to help you stay ahead of the curve.

2. **Shipment Date**: Deep Space and 5X must agree upon when 5X will deliver the first shipment. It is customary for orders to ship six to fourteen months after a contract is finalized. As you want your current storage of chips to be taken out soon to have enough space for further production, you prefer the chips to be shipped faster.

3. **Length of Contract**: The general length of these contracts last between two to six years. You prefer a longer contract. You want to be able to focus your attention on what you do best: research, development, and engineering. A longer contract will help with cash flow to hire the cream of the crop.

You and Deep Space will need to come to an agreement on these three issues in order to proceed with a deal.

The **scoring system** below contains the point values you have assigned **to each option**.

Your **final performance** in this negotiation will be assessed by the **sum of scores you get from each issue** in this negotiation.

For instance, if you reach an agreement with your counterpart which includes 8 $ for price of license per chip, 10 months for shipment date, and 4 years for the length of contract, you will earn the combined score of 90 (40 + 30 + 20).

You want to have a good performance in this negotiation and achieve a high score for yourself and your corporation.

The scoring system below contains the point values you have assigned to each option.

SCORING SYSTEM FOR 5X

Issue	Options	Value
Price License for the Chip	$7.00	10
	$7.50	15
	$8.00	20
	$8.50	25
	$9.00	30
Shipment Date	6 months	10
	8 months	20
	10 months	30
	12 months	40
	14 months	50
Length of Contract	2 years	0
	3 years	20
	4 years	40
	5 years	60
	6 years	80

Appendix B: Ambivalent Sexism Inventory

Ambivalent Sexism Inventory (Based on Glick & Fiske, 1996)

Below is a series of statements concerning men and women and their relationships in contemporary society. Please indicate the degree to which you agree or disagree with each statement using the following scale: 0 = disagree strongly; 1 = disagree somewhat; 2 = disagree slightly; 3 = agree slightly; 4 = agree somewhat; 5 = agree strongly.

B(1) 1. No matter how accomplished be is, a man is not truly complete as a person unless he has the love of a woman.

H 2. Many women are actually seeking special favors, such as hiring policies that favor them over men, under the guise of asking for "equality."

B(P)* 3. In a disaster, women ought not necessarily to be rescued before men.

H 4. Most women interpret innocent remarks or acts as being sexist.

H 5. Women are too easily offended.

B(I)* 6. People are often truly happy in life without being romantically involved with a member of the other sex.

H* 7. Feminists are not seeking for women to have more power than men.

B (G) 8. Many women have a quality of purity that few men possess.

B(P) 9. Women should be cherished and protected by men.

H 10. Most women fail to appreciate fully all that men do for them.

H 11. Women seek to gain power by getting control over men.

B(I) 12. Every man ought to have a woman whom he adores.

B(I)* 13. Men are complete without women.

H 14. Women exaggerate problems they have at work.

H 15. Once a woman gets a man to commit to her, she usually tries to put him on a tight leash.

H 16. When women lose to men in a fair competition, they typically complain about being discriminated against.

B(P) 17. A good woman should be set on a pedestal by her man.

H* 18. There are actually very few women who get a kick out of teasing men by seeming sexually available and then refusing male advances.

B(G) 19. Women, compared to men, tend to have a superior moral sensibility.

B(P) 20. Men should be willing to sacrifice their own well-being in order to provide financially for the women in their lives.

H* 21. Feminists are making entirely reasonable demands of men.

B(G) 22. Women, as compared to men, tend to have a more refined sense of culture and good taste.

Note. H = Hostile Sexism, B = Benevolent Sexism, (P) = Protective Paternalism, (G) = Complementary Gender Differentiation, (I) = Heterosexual Intimacy, * = reverse-scored item.

Appendix C: Subjective Value Inventory for AI Negotiations

(Based on Subjective Value Inventory (SVI; Curhan et al., 2006)

Please answer to the items below with the degree to which you agree with the question asked.

1. How satisfied are you with your own outcome (the extent to which the terms of your agreement (or lack of agreement) benefit you)?
2. How satisfied are you with the balance between your own outcome and your counterpart(s)'s outcome(s)?
3. Did you feel like you forfeited or "lost" in this negotiation?
4. Do you think the terms of your agreement are consistent with principles of legitimacy or objective criteria (like common standards of fairness, precedent, industry practice, legality, etc.)?
5. Did you "lose face" (damage your sense of pride) in the negotiation?
6. Did you behave according to your own principles and values?
7. Do you feel your counterpart(s) listened to your concerns?
8. Would you characterize the negotiation process as fair?
9. Did your counterpart(s) consider your wishes, opinions, or needs?
10. How satisfied are you with your relationship with your counterpart(s) as a result of this negotiation?
11. Did the negotiation make you trust your counterpart(s)?
12. Did the negotiation build a good foundation for a future relationship with your counterpart(s)?
13. Did this negotiation make you feel more or less competent as a negotiator?

14. Did this negotiation positively or negatively impact your self-image or your impression of yourself?
15. How satisfied are you with the ease (or difficulty) of reaching an agreement?
16. What kind of "overall" impression did your counterpart(s) make on you?

Appendix D: Fixed Sum Perception Measure

For each issue in negotiation (like price of license or shipment date), your counterpart has a payoff table with scores assigned to each option as well, similar to the one you saw for yourself but with different scores.

Suppose the options in each issue has a score from 0 to 100 in that hypothetical payoff table for your counterpart. Please choose in the questions below how much you think each option is scored for your counterpart.

Reminder that your counterpart is the representative for the corporation 5X that produces the chips you want to buy.

1. For the issue of price license for the chip, please choose a number between 0 to 100 as the score you think is assigned to each option for your counterpart.

   As a reminder, your own payoff score for each option is mentioned beside each option.

   a. $7 (your own score: 80)
   b. $7.5 (your own score: 60)
   c. $8 (your own score: 40)
   d. $8.5 (your own score: 20)
   e. $9 (your own score: 0)

2. For the issue of shipment date, please choose a number between 0 to 100 as the score you think is assigned to each option for your counterpart.

   As a reminder, your own payoff score for each option is mentioned beside each option.

   a. 6 months (your own score: 50)
   b. 8 months (your own score: 40)

c. 10 months (your own score: 30)

d. 12 months (your own score: 20)

e. 14 months (your own score: 10)

3. For the issue of length of contract, please choose a number between 0 to 100 as the score you think is assigned to each option for your counterpart.

   As a reminder, your own payoff score for each option is mentioned beside each option.

   a. 2 years (your own score: 30)

   b. 3 years (your own score: 25)

   c. 4 years (your own score: 20)

   d. 5 years (your own score: 15)

   e. 6 years (your own score: 10)