

Building Better Negotiators? Experimental Evidence from Entrepreneurship Training In Uganda *

Dana Carney, Laura Chioda, Paul Gertler, Joan J. Martínez (UC Berkeley)

December 2025

Preliminary and Incomplete

[Click here for the most updated version](#)

Abstract

We study the impacts of an entrepreneurship business training on negotiation skills. The Skills for Effective Entrepreneurship Development (SEED) program is 3-week mini-MBA for youth who just graduated secondary school in Uganda. SEED was implemented as an at scale Randomized Controlled Trial (RCT) and presented two separate curricula. The hard skills MBA featured a mix of approximately 75% hard-skills and 25% soft-skills; the soft-skills curriculum had the reverse mix. Only youth in the Soft SEED arm received explicit training in communication, negotiation, and persuasion. Four years after the intervention, we conducted a lab-in-the-field experiment and collected speech-to-text data as youth engaged in incentivized negotiation involving financing and start dates for a possible sale agreement. Study participants in the soft SEED group struck better deals than the control and hard SEED groups. Leveraging large language model (LLM) annotation, we investigate how negotiation strategies profiles differ across experimental groups. Preliminary results suggest that youth in the soft SEED group adopted more aggressive stances in their initial offers; their communication style was more assertive, but they were also more able to manage disagreement, avoiding communication breakdowns.

Keywords: C93, D83, J24, M53

JEL Classification: Negotiation Skills, Human Capital Development, Business Education, Negotiation Strategies

*Corresponding author: lchioda@berkeley.edu. We thank the excellent research assistance of Piero Zanicco and Lisha Zhai. First version: December, 2025.

1 Introduction

Negotiation skills create systematic differences in economic outcomes and serve as a crucial mechanism for allocating value between parties. Recent studies show the prevalence of wage differentials between otherwise similar workers who have varying propensities to engage in negotiations (Cullen and Pakzad-Hurson, 2023, Cullen et al., 2025, Cullen, 2024). These negotiation-driven gaps extend to workplace promotion opportunities (Ramlall, 2004, Recalde and Vesterlund, 2023) and access to human capital resources (Ashraf et al., 2020). Moreover, the mechanics of effective negotiation processes remain largely understudied despite their documented economic importance. While current research indicates that interpersonal skills are foundational to successful negotiation strategies, it largely focuses on broad strategic approaches (such as split-the-difference strategies) rather than isolating the specific behavioral tactics through which these strategies are executed (Ambrus et al., 2018, Backus and Tadelis, 2020, Backus et al., 2020a, Kopelman et al., 2006, Mateen et al., 2020, Sullivan et al., 2006). The persistence of these disparities raise two empirical questions: whether negotiation effectiveness can be developed through targeted interventions and which specific negotiation tactics yield the highest economic returns.

We investigate these questions by examining the impact of a three-week, MBA-style training program on the negotiation skills of recent high school graduates ages 17 to 19 in Uganda. The *Skills for Effective Entrepreneurship Development* (SEED) program is a high-quality, in-residence training based on established U.S. and European MBA blueprints and tailored to the Ugandan context (see Chioda et al. (2021)). The program was offered to roughly 4,000 participants—a nationally representative sample of high school graduates—selected randomly from over 8,000 applicants. We isolate specific negotiation components by implementing and comparing two distinct curriculum through a randomized controlled trial. In the *Hard Skills* curricula, 75 percent of instructional time was dedicated to hard skills training, with the remaining 25 percent focused on soft skills. Conversely, the *Soft Skills* curricula allocated 75 percent of instructional time to soft skills development, reserving the other 25 percent for hard skills training. Critically, only participants in the Soft Skills curriculum received explicit training in communication, negotiation, and persuasion techniques. Four years after the program, we administered an incentivized negotiation exercise to assess the effects of participation in each curriculum track on the negotiation exercise outcomes.

We conduct a lab-in-the-field negotiation experiment to replicate as much as possible a real-world negotiation while holding fixed other elements that have been detected in the literature as introducing variation in negotiation outcomes and which are unrelated to negotiation skills (e.g. outside options, incentives) (Jäger et al., 2021, Lachowska et al., 2022, McClellan, 2024). The negotiation is also fully incentivized in a fair manner: those participants who win the negotiation have higher chances in the lottery for a monetary prize. The negotiation process is timed to replicate time limits in realistic negotiation settings.

We determine how the balance between hard and soft skills affects negotiation performance, particularly in securing favorable terms, reaching agreements, and employing effective negotiation strategies, as outlined in the outcomes above. The soft skills treatment fosters a more assertive negotiation style, enabling participants to take stronger initial positions while effectively managing disagreement and avoiding communication breakdowns—ultimately achieving more favorable outcomes without excessively increasing the number of words or rounds. Moreover, these participants perform better across various strategy indicators, significantly improving the overall strategies index. While improving specific aspects of deal quality for those who reach agreements, the hard skills treatment does not demonstrate the same robust improvements in negotiation dynamics or strategy usage, suggesting a more rigid and less flexible approach to negotiation.

These findings highlight the importance of integrating hard and soft skills into negotiation training. While hard skills help negotiators achieve more satisfactory outcomes in specific aspects, soft skills are critical in facilitating agreements and improving the overall negotiation process. Our results suggest that a balanced approach to skill development is essential for optimizing negotiation outcomes across various contexts.

The second part of the paper proposes a framework to unpack the nuanced actions: persuasion, emotional tone and conflict handling involved in managing and influencing the flow of one-on-one negotiations. We propose a taxonomy comprising three key tactic categories: Persuasion, Sentiment in Language, and Conflict Management. We design an annotation framework that relies on two types of independent annotations: an automated method and double-blind human annotations. The first approach consists of a zero-shot learning annotation process conducted by an open-sourced large language model (LLM). This classification approach allows us to obtain an initial classification that reduces the potential for biases and discretionary interpretation that can arise in human analysis of negotiation transcripts for a wide range of reasons

such as cultural differences between annotators that lead to varying interpretations of language (Geva et al., 2019), a lack of technical negotiation knowledge or introduction of subjective biases in the annotation process (Artstein and Poesio, 2008, Menzner and Leidner, 2024), and the challenge of interpreting context specific negotiation nuances (Pyatkin et al., 2023), among other sources of disagreements among classifications. As an alternative annotation from the automated method, we employed professional annotators, drawing on evidence of the critical role of human evaluators in refining and verifying the outputs of large language models (Bai et al., 2022). Together, these complementary approaches ensured both the efficiency and accuracy of our classification process.

This framework is applied to transcript data from negotiation exchanges gathered through the experiment, with text annotations conducted by a specialized team. Recent empirical studies have advanced more nuanced classifications of negotiation styles, identifying four distinct approaches: analytical, equitable, amicable, and aggressive (Kumar et al., 2009). These classifications acknowledge that negotiation effectiveness is contextually dependent, with different metrics of success beyond merely securing favorable terms. This multidimensional understanding of negotiation aligns with our approach of examining both hard and soft skills training effects on negotiation performance. We use a double annotation approach that parallels established methodologies in negotiation analysis. Similar to Pacella et al. (2017a), we employed both human annotation and automated classification to identify negotiation styles and tactics. This dual approach allowed us to leverage the nuanced understanding of human annotators while also utilizing the computational efficiency and consistency of large language models (LLMs) that are not subject to individual idiosyncrasies, fatigue or non-content related affecting the judgment on their classifications of negotiation tactics. The automated classification method applied zero-shot learning techniques to categorize negotiation rounds into tactics (persuasion, emotion conveyed in language, conflict management), consistent with the theoretical frameworks established in prior research on negotiation discourse (Sokolova et al., 2005).

Recent methodological advances have highlighted the importance of rigorous validation procedures when using large language models for causal inference on text-based outcomes. Modarressi et al. (2025) propose a framework that addresses key challenges in this domain, including the need for sample splitting to enable statistical validation of LLM outputs and human validation to substantiate claims about systematic differences in text across treatment groups. Our dual annotation approach builds on these insights while adapting them to the specific context

of negotiation analysis.

Our main contributions are to the literature that characterizes the impacts of the behaviors arising in empirically bilateral negotiation ([Backus et al., 2020b](#), [Bazerman et al., 2001](#), [Grennan, 2013](#)). For example, Rahim and Bonoma’s model identifies five negotiation styles: integrating, obliging, dominating, avoiding, and compromising ([Rahim, 1983](#)). Other frameworks distinguish between competitive versus cooperative strategies or examine contextual factors that influence negotiation effectiveness ([Bowles, 2013](#), [Mazei et al., 2015](#)). The literature increasingly recognizes that negotiation effectiveness is highly contextual, with environmental factors and individual characteristics jointly determining outcomes ([Recalde and Vesterlund, 2023](#)). This multidimensional understanding aligns with our approach of examining both hard and soft skills training effects on negotiation performance. We extend this body of work by demonstrating how different types of negotiation skills training can shape both the process and outcomes of negotiations. Unlike previous studies focusing primarily on theoretical or observational information on negotiations, our lab-in-the-field experiment provides causal evidence on how structured educational interventions shape negotiation strategies and success rates. In particular, we contribute to understanding how negotiation dynamics, such as sequential negotiation and split-the-difference strategies, are influenced by the development of interpersonal (soft) versus analytical (hard) skills. Negotiation research has identified various frameworks for classifying negotiation approaches.

We also contribute to the active research area of developing bundle skills that complement social interactions ([Ashraf et al., 2020](#), [Grennan, 2014](#)) which requires a disaggregation and identification of the elements that contribute to successful negotiation. A long-standing literature has theorized various negotiations strategies—such as sequential and cooperative approaches—and tactics like ultimatum offers to rationalize and predict negotiated outcomes ([Arnstein, 1969](#), [Coase, 1959](#), [Fisher et al., 1991](#), [McClellan, 2024](#), [Mcdonald and Solow, 1992](#), [Rubinstein, 1982](#), [Schelling, 1980](#), [Stiglitz, 2017](#), [von Neumann and Morgenstern, 2007](#), [Waltz, 1979](#)). However, negotiation is a complex bundle skill that requires interpersonal interaction, adaptability, and strategic thinking—akin to public speaking or leadership ([Lazear, 2012](#), [De Paola et al., 2021](#)) that changes depending on external conditions and information ([Hall and Milgrom, 2008](#), [Kuang and Moser, 2011](#), [Leduc and Liu, 2022](#)). The ability to teach negotiation skills in a structured environment has implications for policy design in education and workforce development, especially for youth entering competitive job markets or entrepreneurial endeavors.

Providing individuals with hard and soft skills through short, cost-effective, and scalable educational programs can help bridge gaps in workforce readiness and negotiation outcomes. This is particularly relevant for contexts where interpersonal relationships and negotiation strategies directly affect human capital accumulation, as demonstrated in recent empirical work by [Ashraf et al. \(2020\)](#), showing how targeted negotiation skills training enables adolescents to improve educational outcomes through better intergenerational bargaining with parents and guardians about investment decisions.

Lastly, our study contributes to the expanding literature on skill measurement in social interactions by advancing computational methods for modeling strategic behavior in dialogue. Although negotiation is conceptualized differently across disciplines, it is increasingly analyzed through diverse data sources, such as recorded speech and text transcripts ([Afantenos et al., 2012](#), [Boyle et al., 2012](#), [Conneau et al., 2017](#), [Traum and Larsson, 2003](#)). In economics, negotiation outcomes are typically quantified by measures such as deal values or allocative efficiency. In computational linguistics, negotiation is often assessed through algorithmic strategies designed to recognize different dialogue that mapped to different negotiation actions ([He et al., 2018](#), [Lewis et al., 2017](#)) or through the semantic analysis of message content ([Suleman et al., 2016](#), [Yang et al., 2019](#)). We contribute to this literature by applying a zero-shot classification approach using a pre-trained and fine-tuned large language model that is capable of producing scalable and consistent results for recognizing multidimensional feature of negotiations.

The paper is organized as follows. Section 2 introduces the intervention for the randomized controlled trial (RCT) and the lab-on-the-field task-based measures to study negotiation outcomes and strategies. Sections 4 and 5 describe the experimental design and the data, respectively. Section 6 presents the results of the two types of training on negotiation outcomes, and Section 7 introduces the results from the classification of negotiation strategies and tactics, examining their treatment effects for negotiation outcomes as mediators. Section 8 concludes.

2 Context: Educational Business Program

The Skills for Effective Entrepreneurship Development (SEED) program aimed to foster entrepreneurship among young Ugandan high school graduates by providing intensive, in-residence training based on U.S. and European MBA curricula. A predecessor study ([Chioda et al., 2021](#)) finds that earnings, business creation, business survival, and other entrepreneurial outcomes dis-

play considerable improvements among participants. This paper presents new evidence of the program’s ability to shape negotiation outcomes, assessed 3.5 years after the training. We examine the negotiation strategies used by participants who were randomly assigned to either a *Hard Business Skills Curricula* or a *Soft Business Skills Curricula*, with both groups additionally exposed to a shared *Business Plan Curricula*. We assess how these two distinct sets of skills influence negotiation outcomes on an incentivized interaction setting. Additional details on the SEED training program are provided in Online Appendix C.

In the context of the three and a half year follow-up, we gathered negotiation outcomes by implementing a structured negotiation task designed to mimic a real-world scenario. The incentivized lab-in-the-field experiment provides insights into negotiation strategies and styles of study participants. By measuring key negotiation metrics—such as agreement likelihood, deal terms, and the strategies employed—we aim to unpack how the SEED program influenced negotiation skills in a structured, measurable way.

The program comprised seventeen instructional days scheduled over three weeks between May 6 and May 24, 2013.¹ Three curriculum versions were designed for the program: (1) a *Hard Business Skills Curricula* that distinctly focuses on topics aimed at enhancing the knowledge of accounting, business creation, managing, and finance; (2) a *Soft Business Skills Curricula* that is differentially focused on developing intrapersonal and interpersonal skills such as leadership, team building, and communication; and (3) a *Business Plan Curricula* that is focused on business planning, which includes putting together a marketing strategy, financial planning, and pitching for fundraising. Depending on their treatment group, the students received a lesson about one of the first two curricula on each instructional day. Later in the day, they would receive a lesson about the business plan curriculum, which was shared by both treatment groups. The topics of each curriculum are outlined in Online Appendix Table C.1.

Both curricula covered negotiation-related concepts, although each one of them emphasized distinct skills pertinent to negotiation settings. While the hard skills training emphasized factual and quantitative knowledge of conducting business prone to be used as part of arguments in negotiation tactics (e.g., selecting a suitable market, identifying business opportunities), the soft skills training focused on making business knowledge *actionable* by developing collaboration, emotional tone, and persuasive techniques (e.g. win-win judgment, personal power, negotiation

¹To alleviate selection concerns affecting the students participation, the program was designed to be administered during the school break between the first and second terms of the 2012-2013 school year. This ensured that all students received boarding and accommodation. For additional details, please see (Chioda et al., 2021).

simulation). The following section presents a framework linking curriculum topics to the skills they develop, and in turn, to the negotiation tactics shaped by these skills.

3 Motivating Framework: Improving Negotiation Skills

In this section, we propose a conceptual framework defining the bundle comprising *negotiation skills* and explicitly describe how these skills shape negotiation processes.

3.1 Negotiation Rounds

Let us denote two agents as i and i' , engaging in a multi-stage interaction for negotiating an outcome. A negotiation consists of R rounds, where in each round $r \in \{1, 2, \dots, R\}$, agent i employs specific tactics $T_i(r)$ to communicate and implement their negotiation approach. The tactics $\{T_i(r)\}_{r=1}^R$ represent how negotiation moves are communicated and executed across all rounds, as represented in Figure 1.

$T_i(r)$ is an indicator variable that equals 1 when agent i successfully executes the corresponding tactic in round r , and 0 otherwise.

Negotiation Skills and Tactics. Tactics represent the manner in which negotiation positions are communicated and implemented. These include persuasion techniques, emotional expression, and conflict management approaches that affect how negotiation moves are received by the counterpart. On each round of interaction, the agent determines a specific tactic, $T_i(r)$, which depends on the agent’s skills, the opponent’s previous tactics, and the negotiation context. We consider tactics the effective communication approaches across the interactions that constitute a negotiation. Each tactic can leverage persuasion, sentiments conveyed in language, or conflict management. We model tactics, $T_i(r)$, as:

$$T_i(r) = t(S_i^h, S_i^s, T_{i'}(r-1), \epsilon_{ir})$$

where S_i^h represents agent i ’s hard skills, S_i^s represents agent i ’s soft skills, $T_{i'}(r-1)$ is the opponent’s tactic from the previous round, and ϵ_{ir} captures round-specific factors. The function $t(\cdot)$ is strictly increasing in both hard skills S_i^h and soft skills S_i^s , but we hypothesize that soft skills may have a larger marginal effect on tactical execution, reflecting that interpersonal and communication skills are particularly important for effective negotiation behavior. The

negotiation iterates until agreement or termination due to a disagreement.

3.2 Outcome of Negotiation

The negotiation outcome Y is a function of the round-level tactics employed by both agents, $\{T_i(r)\}_{r=1}^R$ and $\{T_{i'}(r)\}_{r=1}^R$, as well as external factors uncorrelated with the tactics, summarized in ϵ . This relationship can be expressed as,

$$Y_i = f(\{T_i(r)\}_{r=1}^R, \{T_{i'}(r)\}_{r=1}^R, \epsilon)$$

where Y_i represents the negotiation outcome achieved by agent i , and f is increasing in the effectiveness of agent i 's tactics, but may be decreasing in the effectiveness of the opponent's tactics. Each agent i aims to maximize their utility U_i derived from the negotiation outcome Y_i , subject to their own preferences, constraints, and beliefs. The optimization problem can be formulated as:

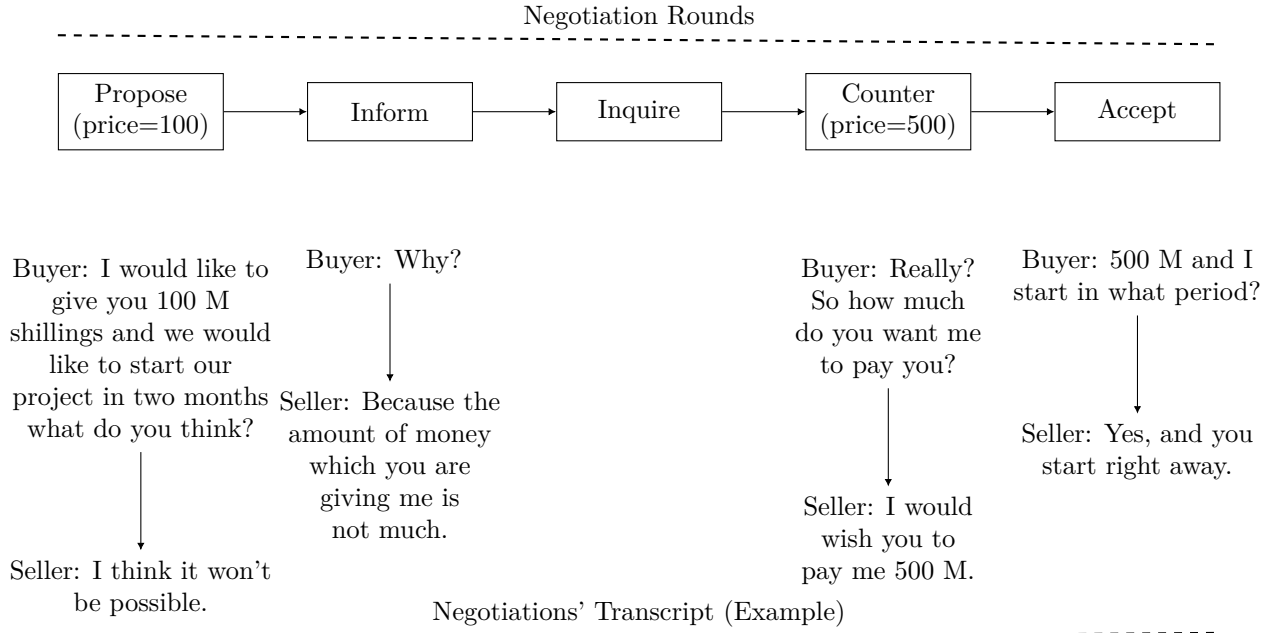
$$\max_{\{T_i(r)\}_{r=1}^R} U_i(Y_i) \quad \text{subject to skill constraints and strategic interactions}$$

In this framework, an agent's likelihood of achieving a higher negotiation outcome increases when tactics are successfully executed, which demands high levels of both soft and hard skills. However, it remains uncertain which skill type yields greater returns in enhancing outcomes: are better results driven by soft skills that improve tactical execution through enhanced interpersonal communication, or by hard skills that provide analytical foundations for tactical selection? We explore this question in the following sections.

4 Experiment Design

Our experiment is designed to evaluate the program's effects on negotiation outcomes by randomly assigning the instruction of students into curricula that emphasize different sets of skills relevant for negotiations in business settings. The experimental setting for measuring negotiation skills ensures that the effects we measure are attributable to the SEED program's participation in each treatment assigned.

Figure 1: Decodification of Language in Negotiation Sequence



Notes: This diagram is a schematic representation of the classification of tactics observed in a dataset of negotiation transcripts. The diagram takes as example an actual transcript, where each node represents a distinct stage in the negotiation process. We show the sequence of negotiation rounds, the content of negotiation and the responses between buyers and sellers.

4.1 Treatments

We want to compare the effects of a business and entrepreneurship education curriculum. We randomized the assignment into a *Hard Business Skills Curricula* that emphasizes factual and analytical business management and a *Soft Business Skills Curricula* that emphasizes inter- and intrapersonal management, which nurture negotiation skills differently (see Section 3). In particular, we aim to measure the differential effects of hard versus soft skills training on negotiation outcomes. See Appendix Table C.1 for a complete list of subjects and their accompanying skills.

1. *Hard Business Skills Curricula.* The first treatment focused on developing participants' strategic and analytical capabilities necessary for effective negotiation. The curriculum centered around essential business skills such as financial management, cost analysis, and legal aspects of business ownership. These contents were designed to provide participants with quantitative tools to assess trade-offs and make data-driven negotiation decisions. These sessions' technical focus aimed to improve participants' performance in negotiations that require financial precision and business sense. See Figure 2 for a list of topics and skills developed in each lesson of this curriculum.

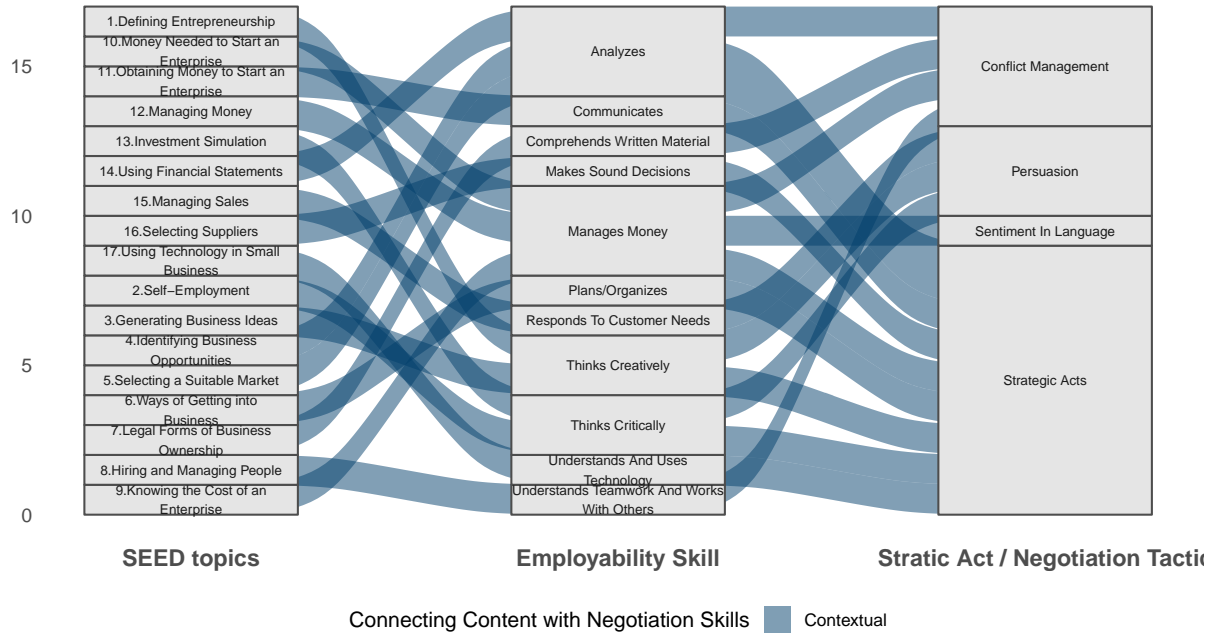
2. *Soft Business Skills Curricula.* This treatment emphasized socio-emotional competencies and targeted the interpersonal aspects of negotiation. The curriculum included communication, persuasion, and emotional intelligence modules to foster participants' ability to build rapport, influence others, and navigate complex interpersonal dynamics. Moreover, the curricula contained experiential learning activities like role-playing and negotiation simulations to teach participants and allow them to practice empathy, active listening, and conflict resolution skills, enhancing their capacity to achieve collaborative, relationship-focused negotiation outcomes. See Figure 3 for a list of topics developed on each lesson and their respective skills.
3. *Business Plan Curricula.* This curricula is focused on providing the foundational knowledge to create a business plan, combining practical knowledge and real-world applications through case studies. Appendix Figure C.1 establishes the correspondence of these topics with negotiation skills. The contents are focused on strategic planning tools encompassing marketing research, financial planning and fundraising. Moreover, the students are introduced to legal and financial responsibilities as business owners. The final sessions include a pitch preparation, concluding with persuasion-oriented exercises, executive summaries and delivering a business plan pitch.

4.2 Negotiation Game

We conduct a lab-in-the-field experiment with real monetary incentives for participants ([Charnes and Gneezy, 2009](#)). The experiment involves two parties: a *buyer*, who acts as the Commissioner of the Ministry of Lands and seeks to purchase farmland for a rail line project, and a *seller*, the owner of the farmland. The negotiation centers on whether the seller will agree to sell the land and under what terms. Both parties agree that the land is valued at UGX 600 million (approximately \$573,295.75, PPP adjusted).

The negotiation focuses on two critical aspects: (1) the financing terms, which determine the division between upfront payment and installment payments over the next 12 months, and (2) the start date for the project, which can be set anywhere between two and 12 months from the negotiation date. Both parties are aware that these terms will significantly influence their final payoffs. Different combinations of down payments and project start dates lead to varying

Figure 2: Hard Business Skill Curriculum —Correspondence of SEED Topics to Employability Skills and Negotiation Categories



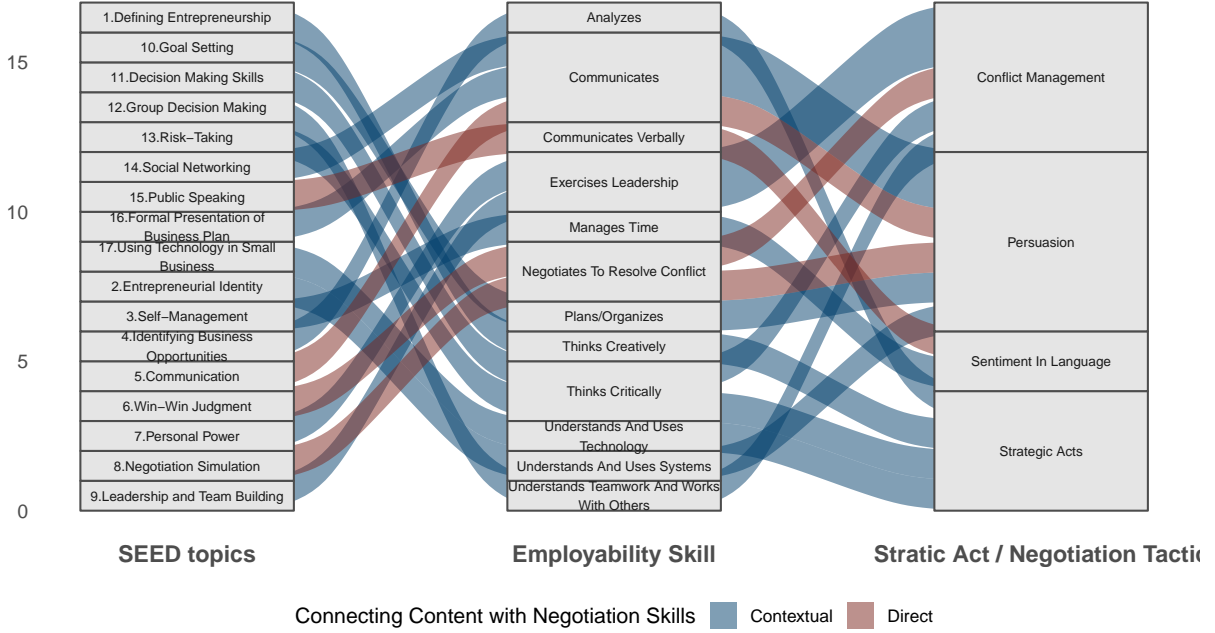
Notes: The figure shows the mapping between topics in the hard skills business curriculum, the Employability Skills compiled by the Office of Career, Technical, and Adult Education (OCTAE) at the U.S. Department of Education and Tactics (T_i). The Employability Skills taxonomy of skills is a comprehensive framework skills necessary for success in all sectors of the labor market.

payoffs, as outlined in Table 1.² The interactions are designed to motivate participants in a way that mimics the drive to win. Both parties know they will be entered into a lottery with a \$400 prize, with their chances of winning based on the points earned from the final agreement. They have four minutes to reach a deal, which is required to enter the lottery.

We designed a negotiation exercise that aligns closely with real-world scenarios because it does not involve simple single offer-level negotiations (Binmore et al., 1986, Kagel and Roth, eds, 2020). Participants must balance two goals, each with clearly defined payoffs contributing to overall success. Another feature of the experimental setting to measure negotiation skills is that we keep fixed two key determinants of negotiation outcomes: outside options and negotiation costs for both participants. The negotiation costs in the experiment are the same for all participants, avoiding any confounding influence on the treatment effects (Backus et al.,

²Table 1 also summarizes the Buyer's and Seller's preferred outcomes and strategies. The Buyer favors a smaller down payment and an earlier start date (in two months), placing more weight on the start date than on the financing terms. The Seller prefers full payment of UGX 600 million upfront and a start date in 12 months, prioritizing the financing arrangement over the start date.

Figure 3: Soft Business Skill Curriculum —Correspondence of SEED Topics to Employability Skills and Negotiation Categories



Notes: The figure shows the mapping between topics in the soft skills business curriculum, the Employability Skills compiled by the Office of Career, Technical, and Adult Education (OCTAE) at the U.S. Department of Education and Tactics (T_i). The Employability Skills taxonomy of skills is a comprehensive framework skills necessary for success in all sectors of the labor market.

2020a, Gneezy et al., 2000). Similarly, the outside options are fixed for all participants, eliminating concerns about differences in negotiation power within the treatment group and between the treatment and control groups (Binmore et al., 2002, Crawford, 1982). This also prevents differential treatment responses that could arise from varying outside options (Muthoo, 1999).

4.3 Implementation and Protocols

The experiment followed strict protocols to ensure consistency across sessions (Chioda et al., 2021). At the beginning of the negotiation interactions, participants were given a detailed explanation of the rules of the negotiation dynamics and an overview of the structure. In implementing the negotiation collection, we aimed to embed into the exercise as many characteristics as possible that emulated real-world negotiations.

First, participants were informed about the four-minute time limit, which was enforced to

Table 1: Negotiation Payoffs

Buyer (Enumerator)				Seller (Subject)			
Financing		Project Start		Financing		Project Start	
Paid Down Payment (UGX millions)	Points	Start Date	Points	Received Down Payment (UGX millions)	Points	Start Date	Points
100	500	2 months	1000	100	0	2 months	0
150	450	3 months	900	150	100	3 months	50
200	400	4 months	800	200	200	4 months	100
250	350	5 months	700	250	300	5 months	150
300	300	6 months	600	300	400	6 months	200
350	250	7 months	500	350	500	7 months	250
400	200	8 months	400	400	600	8 months	300
450	150	9 months	300	450	700	9 months	350
500	100	10 months	200	500	800	10 months	400
550	50	11 months	100	550	900	11 months	450
600	0	12 months	0	600	1000	12 months	500

Note: Buyer’s and Seller’s strategies: the Seller, the respondent, prefers a full payment, UGX 600 million,, up front and a delayed project start date; the Seller places relatively more weight on the financing arrangement than on the start date. The Buyer prefers a small down payment but an early start date, and assigns a higher weight to the start date than to the financing arrangements.

simulate time pressure, a common feature of real-world negotiations. They were informed that failing to reach an agreement would prevent them from entering the lottery. This provided a strong incentive to negotiate efficiently within the given timeframe. Second, we randomized the assignment of roles (i.e., buyer or seller) to avoid discretion by enumerators in picking a role for the participants or self-selection by the participants. An enumerator observed each interaction, ensuring that the negotiation followed the pre-established guidelines. All participants were briefed post-experiment to explain the outcomes of their negotiations and their lottery standings based on the final agreements reached.

5 Data

The outcomes are organized into two main categories. The first set captures negotiation results, including whether an agreement was reached and the negotiation dynamics that influenced the outcome. The second set looks at the deployment of various negotiation strategies, with particular attention to sequential negotiation and the split-the-difference method. We then shift our focus to the analysis of negotiation transcripts.

5.1 Estimation Sample and Negotiation Outcomes

Our estimation sample consists of 3,701 participants who completed the negotiation exercise, drawn from the original 4,000 program participants. Appendix Table B.2 shows baseline sum-

mary statistics for the group of students participating in the program baseline (N=4,402). At baseline, around a third of participants were female students who enrolled in the program. Around 2% of the participants had aspirations to attend university, and the SES of their families, proxied by their parents’ education being above median, is low. The work experience index of the students indicates that fewer than 2% of them had acquired any relevant on-the-job training experience at the moment of the baseline, and their entrepreneurial indicators are similar. Appendix Table B.1 describes in detail the outcomes variables of the negotiation.

5.2 Speech To Text Data: Transcripts and Annotations

We analyze speech data that has been transcribed, focusing on two levels of aggregation to uncover granular negotiation patterns that were introduced in Section 3. *Transcript-level* data encompasses dialogue from the entire negotiation between the seller and buyer, whereas *round-level* data comprises dialogue from each individual speaking turn. This section details the process of labeling tactics at the round level, which are subsequently aggregated for analysis at the transcript level.

Our annotation process implements a comprehensive classification framework and implementation protocol for negotiation interactions, systematically coding each round-level utterance across four theoretical dimensions

1. Persuasion
2. Sentiment in Language, and
3. Conflict Management

This multidimensional approach enables identification of tactical patterns throughout negotiation sequences, with higher-order meta-labels providing structured categorization of negotiation behaviors. To ensure validity in the assignment of these classifications, we employed specialized annotation teams with partial domain specialization, implemented double-blind verification procedures, and required comprehensive review of full transcripts to maintain proper contextual interpretation. The resulting classification system captures the nuanced dynamics of negotiation behavior beyond outcome measures, identifying patterns in tactical flexibility and emotional regulation that mediate negotiation effectiveness. Further details of the annotation protocol, including comprehensive category definitions, workflow implementation, and inter-annotator reliability procedures, are provided in the Appendix A.

Using the round-level data, we identify the tactics employed by participants during the conversation, interpreting them within the broader context of the negotiation process captured in the transcripts. Figure 1 illustrates the classification process of tactics, showing how buyer and seller dialogue is assigned values based on the semantic meaning, purpose, and intent of their speech. Additionally, we classify words and meanings into specific tactics, systematically organized at the round level within the negotiation transcripts.

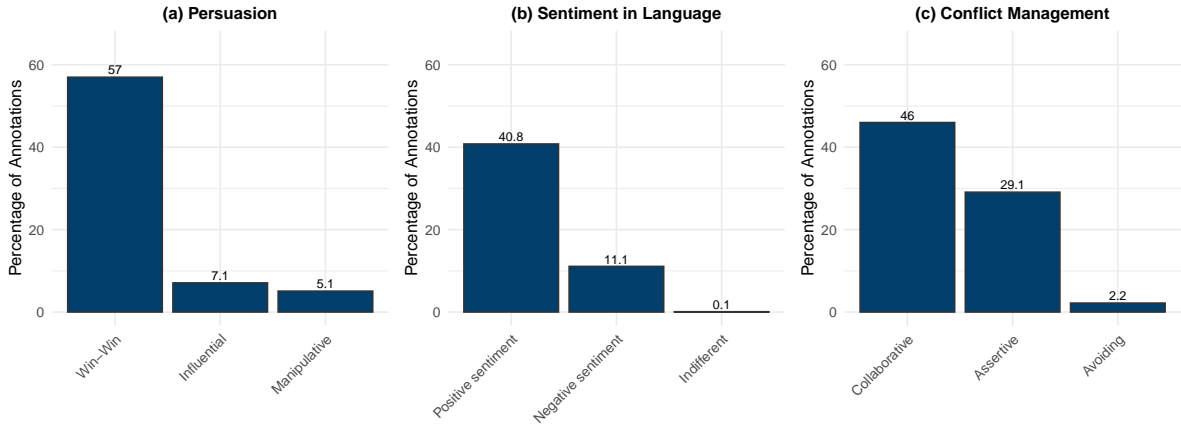
We employed two complementary approaches to conduct the classification which were performed independently.

Automated Annotation. We use a pre-trained and fine-tuned transformer-based model, LLaMA-2 (Llama), largely used and recognized for its performance, with parameter sizes ranging from 7 billion to 70 billion (Touvron et al., 2023). This approach enabled us to obtain a scalable and consistent framework of initial classifications, exploiting the capabilities of LLMs as zero-shot reasoner, as demonstrated in (Kojima et al., 2022, Meshkin et al., 2024).³ A key advantage of this approach is that the model parses the negotiation transcript text relying solely on its extensive pre-training on over 2 billion tokens (Touvron et al., 2023). This eliminates the need for task-specific fine-tuning or additional labeled training data, enabling efficient deployment without further customization. An additional advantage is that we did not provide a prompt, thus avoiding the sensibility of task conditioning to the language provided in the prompt (Li et al., 2023, Sclar et al., 2023).

We implemented a zero-shot learning routine that required minimal pre-processing of the transcribed speech data from the negotiations. The data was structured into rounds, representing the back-and-forth exchanges between participants. Notably, punctuation and other linguistic markers were retained, as LLaMA is proficient in interpreting such inputs without additional modifications (Brown et al., 2020, Frayling et al., 2024). Next, the LLaMA model provides a categorization solely based on the full set of categories and descriptions included in Appendix Table A.1, with the input consisting of the round-level negotiation speech, without the need to form a training sample. Figure 4 displays the frequency of classifications across tactics. This shows that the does not know category is the most frequently assigned by the automated annotation, followed by side offers and appeals to sympathy. The high prevalence

³The transformer model was downloaded and executed locally on UC Berkeley’s computer cluster within a partitioned and private computational environment for safeguarding the information provided by study participants.

Figure 4: Distribution of Annotation Categories Across Tactics Categories



Notes: This graph displays the distribution of annotation categories across negotiation tactics, including persuasion, sentiment in language, and conflict management. The meta-label “No tactic/Does not know” has been intentionally excluded from the visualization; however, when included, all categories sum to 100 percent. The analysis is based on 2,838 negotiation transcripts. Percentages are calculated as the proportion of annotations within each tactical classification relative to the total annotations in that classification.

of does not know annotation reflects the ambiguity of many round-level commentaries, which are often unclear in intent and unlikely to convey content related to a specific tactic. Regarding sentiment, contempt and distress are the most commonly identified emotions. Among conflict styles, accommodating is the most frequent, followed by competing and compromising as seen in the last two panels.

Human Annotation. Professional annotators were trained and responsible for assigning, to each round of negotiation, one of the sub-categories listed in Table A.2. In this approach, annotators annotated a subsample of the data which was used to train a supervised learning model that predicted the sub-categories corresponding to *tactics* categories in the remaining non-annotated sample. Using the semantic classification, we developed an annotation scheme, included in Online Appendix A. To provide further guidance to annotators, we included examples for each subcategory in the annotation scheme. We structured the annotation process with some considerations to increase the accuracy of their classifications and thus, the quality of the training data. The annotators specialized in one feature only, minimizing overlap in their judgments to ensure consistency and accuracy in the annotation process. We also collected demographic information of the annotation team to examine differences in their classifications based on demographic characteristics.

6 Results I: Negotiation Outcomes

To identify the causal impact of the SEED program’s hard and soft skills training on negotiation outcomes, we employ a randomized controlled trial (RCT) framework. Participants were randomly assigned to either the hard skills track, the soft skills track, or a control group with no additional negotiation training. Our analysis leverages the exogenous variation in program assignment to isolate the direct effects of the SEED training on negotiation behaviors, focusing on intent-to-treat (ITT) effects.

We estimate the treatment effects using the following baseline specification:

$$Y_i = g(T_i^h, T_i^s, X_i) + \epsilon_i \quad (1)$$

where Y_i denotes the negotiation outcome for individual i , such as whether an agreement was reached, the terms reached (e.g. date and financing) or the strategy used in the negotiation. Here, T_i^h and T_i^s are the hard and soft treatment indicators, and X_i is a vector of baseline characteristics included to increase precision. The function $g(\cdot)$ is an unknown nuisance parameter.

We report a refinement of the estimated treatment effects by implementing the Double/Debiased Machine Learning (DML) methodology proposed by Chernozhukov et al. (2019). The ITT estimator is then derived as follows:

$$ITT_j = \beta_j = E[g(T_i = 1, X) - g(T_i = 0, X)] \quad (2)$$

where $j \in \{h, s\}$ refers to the treatments for hard or soft skills. The coefficients of interest, denoted β_h and β_s capture the differential effects of the hard and soft skills training, respectively, on the negotiation outcomes relative to the control group. Standard errors are clustered at the individual level to account for repeated measures across negotiations.

DML allows us to flexibly control for the high-dimensional covariates X_i while ensuring our parameter estimates for the treatment effects remain unbiased.

6.1 Effects on Outcomes and Dynamics

Table 2 presents the estimated treatment effects on the primary negotiation outcomes. Column (1) shows that participants in the hard-skills treatment group exhibit a 2.8 percentage point decrease in the probability of reaching an agreement, although this effect is marginally significant

($p = 0.101$). Similarly, the soft-skills treatment group shows a 2.6 percentage point reduction in agreement likelihood, though this effect is not statistically significant. These findings suggest that both treatments may induce participants to be more selective or strategic about when to reach agreements, with the hard skills approach having a somewhat stronger effect on this dimension. Nevertheless, columns (2) and (3) further illustrate that the quality of agreements reached by the soft-skills treatment group is markedly superior as measured by the financing and start dates aspects of the negotiations. Specifically, the agreements by this group are 4.2 percent more advantageous in terms of the final down payment and about 7.7 percent more favorable regarding the second outcome, the agreement date. These results indicate that soft-skills training is particularly effective at improving the terms of agreements when they are reached, with consistent impacts across both negotiation dimensions.

The effectiveness of soft skills training in promoting collaborative negotiation aligns with findings from cross-cultural negotiation research ([Adair and Brett, 2005](#)) found that the reciprocation of priority information and affective persuasion sequences were positively associated with joint gains across cultural contexts. Similarly, our results indicate that soft skills training enhances these reciprocal behaviors, transcending potential cultural differences within our sample. The behavioral adaptability demonstrated by soft skills participants mirrors what [Kumar et al. \(2009\)](#) identified as a key characteristic of effective negotiators—the ability to adjust strategies based on context rather than adhering rigidly to a single approach.

Table 3 provides further insights into the treatment effects on negotiation dynamics and strategy indicators across treatment groups. Columns 1 and 2 indicate that the soft skills treatment group engages in more negotiation rounds without using more words. This suggests that soft-skills training induces more efficient communication strategies, with participants able to engage in more extensive negotiation without increased verbosity.

Columns 3 and 4 indicate that the soft-skills treatment significantly improves the quality of participants' first counteroffers for both financing (6.8 percentage points improvement) and start date (10.6 percentage points). The hard-skills treatment shows a marginally significant positive effect only on the financing counteroffer. These findings suggest that soft-skills training enables participants to establish more favorable initial positions in the negotiation, potentially contributing to better final outcomes.

Columns 5 and 6 show that the control group rarely employs the split-the-difference strategy, using it in only about one-third of negotiations regarding financing and start dates. We

Table 2: Hard and Soft Skills Training Effects: Negotiation Outcomes

		(1)	(2)	(3)
		Agreement on final offer	Down payment (USD PPP)	Start date (months)
Hard Skills	β	-0.028	0.021	0.037
	se	[0.017]	[0.019]	[0.033]
	p -value	0.101	0.256	0.261
Soft Skills	β	-0.026	0.042**	0.077**
	se	[0.017]	[0.018]	[0.032]
	p -value	0.126	0.022	0.016
Mean Control Group		0.813	375	4.674
p -value Hard skills = Soft skills		0.937	0.204	0.163
Observations		3,701	3,701	3,701

Notes. The coefficients in Column 1 are estimated using Double Machine Learning (DML) with 5-fold cross-validation and 100 sample splits, with point estimates and standard errors are computed using the median across splits, following the approach of Chernozhukov et al. (2018). Columns 2 and 3 are estimated using a cross-fit partialing-out lasso Poisson regression model. The outcome variables are the following: Column 1 reports a final agreement indicator; Column 2, financing terms (USD PPP); Column 3, project start date (months). In DML estimates we apply the Romano-Wolf step-down procedure to calculate p -values, using 1,000 bootstrap repetitions for accuracy. Standard errors are reported in parentheses. Significance levels: $p < 0.1(*)$, $p < 0.05(**)$, $p < 0.01(***)$.

interpret the minimal treatment effects on this negotiation style as indicative of a lack of its adoption. The second panel of Table 3 illustrates the impact of adopting sequential bargaining in approximately half of the negotiations. The hard-skills treatment group is more likely to engage in sequential bargaining for financing aspects. In contrast, the soft-skills treatment group adopts this approach for both financing and start date negotiations.

Column 7 shows an aggregate index that combines all strategy indicators presented in Table 2 and Table 3. The soft skills treatment yields a significant positive treatment effect of 0.079 standard deviations, while the hard skills treatment group shows no significant treatment effects. This comprehensive index reinforces the pattern that soft-skills training produces consistently superior negotiation strategies and outcomes compared to hard-skills training.

Table 3: Hard and Soft Skills Training Effects: Negotiation Dynamics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Number of rounds	Number of words	Financing (USD PPP)	Start Date (months)	Split the Difference	Sequential Negotiation	Aggregate Index
Hard Skills							
β	0.035	-0.074	0.033*	0.019	0.002	0.02	-0.014
se	[0.027]	[0.089]	[0.018]	[0.032]	[0.021]	[0.017]	[0.042]
p -value	0.202	0.402	0.069	0.56	0.931	0.24	0.738
Soft Skills							
β	0.083***	-0.025	0.068***	0.106***	0.015	0.063***	0.079*
se	[0.027]	[0.084]	[0.018]	[0.031]	[0.021]	[0.017]	[0.041]
p -value	0.002	0.77	0	0.001	0.469	0.000	0.057
Mean Control Group	4.516	391.628	435.663	5.853	0.473	0.776	0.000
p -value Hard skills = Soft skills	0.042	0.547	0.02	0.002	0.651	0.077	0.115
Observations	3,701	3,701	3,701	3,701	3,701	3,701	3,701

Notes. The coefficients in Panels A and B were estimated using Double Machine Learning (DML) with 5-fold cross-validation and 100 sample splits to estimate our models. Coefficients in Panels C and D were estimated using cross-fit partialing-out Poisson regression model. The point estimates and standard errors are computed using the median across splits, following the approach of [Chernozhukov et al. \(2018\)](#). The outcome variables are the following: Columns 1–2 report the number of rounds and words used in the negotiation; Column 3, the first counteroffer on financing terms (USD PPP), Column 4, the first counteroffer on the project start date (months); Column 5, a binary variable indicating the use of Sequential Negotiation on financing or start date, Column 6 is a binary variable indicating the use of Split the Difference on financing or start date, and Column 7 is an Anderson index computed from Columns 1–6 in addition to final agreement outcomes reported in Table 2. In DML estimates we apply the Romano-Wolf step-down procedure to calculate p -values, using 1,000 bootstrap repetitions for accuracy. Standard errors are reported in parentheses. Significance levels: $p < 0.1(*)$, $p < 0.05(**)$, $p < 0.01(***)$.

7 Results II: Unpacking Negotiation Skills

In this section, we propose a semantic classification framework, grounded in computational linguistics, for analyzing the language used in negotiations (He et al., 2018, Lewis et al., 2017) for analyzing the role of negotiation tactics and their causal treatment effects on the final negotiation outcomes. The classification is structured around the key components that capture the tactical aspects of negotiation rounds, as introduced in Section 3.

7.1 Semantic Classification of Negotiation Language

We propose a classification of the language used in negotiations into three main tactics:

1. Persuasion
2. Sentiment conveyed in language
3. Conflict management

Table A.1 summarizes the categories and respective sub-categories comprising this classification. To ensure the accuracy and validity of our automated annotation approach, we also classify basic speech forms that serve as calibration benchmarks. These speech forms capture fundamental negotiation dynamics that are classified based on the use of language, such as greetings, agreements, information sharing, proposals, and counteroffers. The speech forms classification, detailed in Appendix Table A.2, provides ground truth for validating our computational approach before applying it to the more nuanced tactical dimensions.

Our main focus is on the three tactical categories: Panel A lists the category involving *persuasion tactics*, which are conceptualized as methods used to influence others (Lewis et al., 2017, Yang et al., 2019). These include embellishments, casual conversations, side offers, appeals to sympathy, and references to shared knowledge. Panel B includes the category of *sentiment conveyed through language*, which reflect the emotional tone of the conversation (Buechel and Hahn, 2022, Keith Norambuena et al., 2019, Pang et al., 2008). Sentiments such as anger, contempt, distress, enjoyment, terror, excitement, humiliation, and surprise are identified and labeled. Panel C lists the category of *conflict management* which measures approaches and styles for handling disagreements between the involved parties (Friedman and Currall, 2003, Afzalur Rahim, 2002). The subcategories include collaborating, accommodating, competing,

avoiding, and compromising. Each style is labeled as positive or negative based on its approach to conflict resolution (Dong et al., 2024, Read et al., 2014).

7.2 Content Analysis of Negotiation Transcripts: Tactics

This section systematically analyzes the negotiation transcripts through computational linguistic classification methods and estimates the causal treatment effects of hard and soft skills training interventions on multidimensional negotiation behavior.

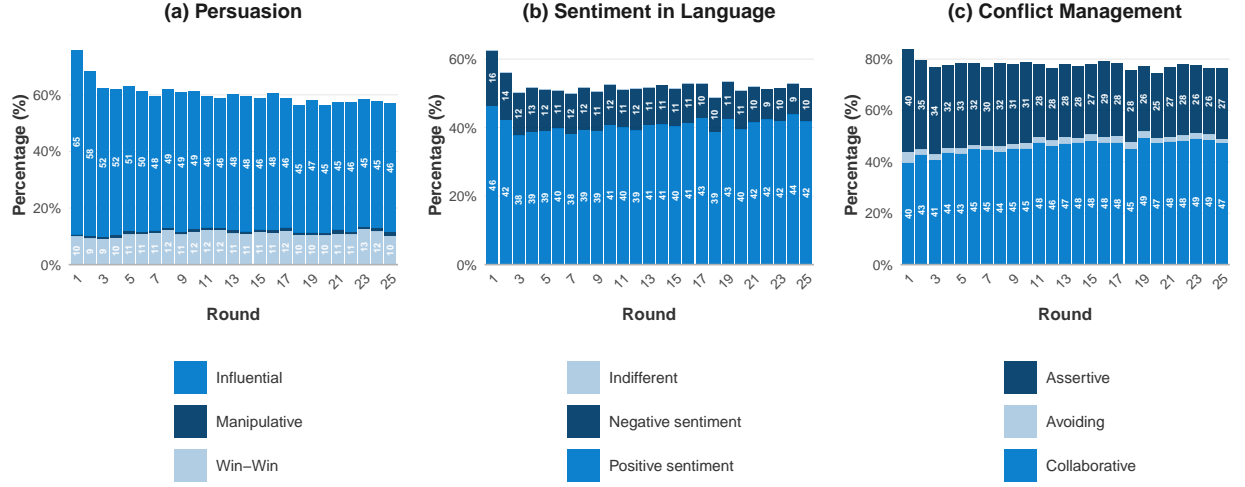
First, we present the distribution of tactics in persuasion, sentiment expression and conflict management derived from our semantic classification. Later, we estimate the differential treatment effects on these behavioral dimensions, examining both direct treatment effects on negotiation outcomes and indirect treatment effects through how skill acquisition influences tactical behavior in negotiation.

Figure 5 depicts the round evolution of negotiation *tactics*, illustrating how their prevalence changes across negotiation rounds. The results reveal notable trends across the three tactical dimensions. In the persuasion dimension, appeals to sympathy and side offers become more prominent in later rounds as participants seek to close deals. For sentiment expression, positive emotions like satisfaction increase toward the end of successful negotiations, while negative emotions like contempt decrease. In conflict management, accommodating and compromising behaviors increase in frequency as negotiations progress, while competing behaviors remain relatively stable. Conversely, annotations classified as “does not know” decline over time, indicating a refinement in participants’ tactical approaches as negotiations progress. Appendix Figure B.1 shows the prevalence of these categories per round.

Table 4 shows the treatment effects on a comprehensive taxonomy of negotiation behaviors, focusing on persuasion tactics, conflict management styles, and language sentiment. The coefficients expressed here are standardized effect sizes (standard deviation units) to facilitate comparisons across the aforementioned dimensions.

A striking asymmetry emerges between the two treatment arms. The hard-skills curriculum does not demonstrate any statistically significant treatment effects across all nine measured dimensions of negotiation tactics. In contrast, the soft-skills curriculum generates statistically significant treatment effects across multiple domains, with effect sizes ranging from 0.055 to 0.129 standard deviations. This suggests that the latter curriculum successfully modified participants tactical repertoire during actual negotiations. The null treatment effects observed for

Figure 5: Percentage of Negotiation Tactics by Round



Notes: The graph displays the distribution of negotiation *tactics* across three dimensions—persuasion, sentiment in language, and conflict management—used in the first thirty rounds. Percentages are calculated as the share of annotations attributed to each tactic category within a given round. The number of rounds in this illustration is truncated at twenty-five and only percentage values above 5% are shown for presentation purposes. The annotation categories of “Does not know” and “No tactics” are not shown in the figure. The total number of negotiation transcripts is 2,838.

Hard Skills training indicate that technical business knowledge alone may be insufficient to alter the interpersonal dynamics that characterize negotiation interactions.

Participating in the soft-skills treatment demonstrates a coherent pattern of treatment effects. In Table 4a, participants exhibit a marginally significant increase in influential persuasion tactics by 0.068 standard deviations, which represents an enhanced capacity to carry arguments aimed at changing counterparts beliefs or behavior through influence rather than manipulation. Participants trained in hard skills do not show detectable improvements in persuasion tactics.

To validate these automated classification results, we examine treatment effects using human-annotated negotiation transcripts in Table 5. This analysis leverages a larger sample from stacked double-annotations, with annotator fixed effects and clustered standard errors to account for annotator-level heterogeneity.

The human annotation results reveal substantially stronger treatment effects for soft-skills training compared to the automated classification. In Table 5a, column (1) shows that soft-skills participants demonstrate a highly significant increase in influential persuasion tactics, nearly double the magnitude observed in the automated classification. This effect is statistically distinguishable from the hard-skills treatment, providing strong evidence that soft-skills

Table 4: Hard and Soft Skills Training: Anderson Indexes Based on Number of Occurrences

(a) Persuasion Tactics							
		Persuasion Tactics					
		Influential	Manipulative	Win-Win			
		(1)	(2)	(3)			
Hard Skills	β	0.004	0.000	-0.010			
	se	[0.034]	[0.026]	[0.037]			
	p -value	0.911	0.995	0.788			
Soft Skills	β	0.067*	0.035	0.089**			
	se	[0.035]	[0.025]	[0.038]			
	p -value	0.052	0.163	0.018			
Mean Control Group		0.000	0.000	0.000			
p -value Hard skills = Soft skills		0.190	0.341	0.061			
Observations		2,835	2,835	2,835			

(b) Language Sentiment and Conflict Management Tactics							
		Conflict Management			Language Sentiment		
		Collaborative	Assertive	Avoiding	Positive	Negative	Indifferent
		(1)	(2)	(3)	(4)	(5)	(6)
Hard Skills	β	-0.042	0.041	0.010	-0.009	0.000	0.019
	se	[0.036]	[0.032]	[0.051]	[0.027]	[0.000]	[0.051]
	p -value	0.247	0.210	0.841	0.742	0.478	0.709
Soft Skills	β	0.039	0.085***	0.129**	0.055*	0.000	0.098*
	se	[0.036]	[0.032]	[0.054]	[0.029]	[0.000]	[0.056]
	p -value	0.279	0.008	0.016	0.064	0.817	0.082
Mean Control Group		0.000	0.000	0.000	0.000	0.000	0.000
p -value Hard skills = Soft skills		0.113	0.333	0.110	0.113	0.732	0.300
Observations		2,835	2,835	2,835	2,835	2,835	2,835

Notes. Observations at negotiation-round level. We report the coefficients β_j defined in Equation 2, that were estimated using Double Machine Learning (DML) with 5-fold cross-validation and 100 sample splits to estimate our models. Outcome variables are Anderson indexes computed using the number of occurrences indicators, assigned a value of one when the negotiation style listed in the column title is employed. Estimates and standard errors are median across splits, following Chernozhukov et al. (2018). We apply the Romano-Wolf step-down procedure to calculate p-values, using 1,000 bootstrap repetitions for accuracy. Standard errors are reported in parenthesis, p-values in brackets. Significance levels: $p < 0.1(*)$, $p < 0.05(**)$, $p < 0.01(***)$.

training specifically enhances participants’ capacity to employ influence-based persuasion strategies. Column (2) indicates that human annotators also detect a marginally significant increase in manipulative persuasion tactics among soft-skills trainees, an effect not captured by the automated system. Notably, column (3) reveals that both treatments show significant negative effects on Win-Win tactics, suggesting that trained participants may shift away from explicit mutual-benefit framing toward more sophisticated persuasion approaches.

The conflict management and sentiment results in Table 5b present a more nuanced picture than the automated classification. In column (2), soft-skills training produces highly significant increases in assertive conflict management, while column (1) shows a marginally significant increase in collaborative approaches. The treatment effects on these two dimensions differ significantly from hard-skills training, underscoring the differential impact of the two curricula on interpersonal negotiation dynamics. Interestingly, column (3) reveals that hard-skills training shows a significant positive effect on avoiding tactics that is not present among soft-skills trainees—a pattern that diverges from the automated classification results.

The language sentiment dimension reveals the most striking divergence between human and automated annotation. In column (5), human annotators identify a substantial increase in negative sentiment expression among soft-skills trainees, an effect significantly different from hard-skills participants. This counterintuitive finding suggests that soft-skills training may equip participants to strategically deploy negative emotional expressions—such as frustration or disappointment—as negotiation tools. Column (4) shows that the positive sentiment effects exhibit significant differentiation between treatments, with hard-skills training associated with decreased positive sentiment and soft-skills training showing no significant effect.

Table 4b results reveal that the most pronounced treatment effects are found in conflict management approaches: soft-skills trainees significantly increase assertive tactics by 0.085 standard deviations and avoiding tactics by 0.129 standard deviations, respectively. This simultaneous increase across these seemingly contradictory approaches suggest that participants of the soft-skills training develop greater tactical flexibility, knowing when to assert positions firmly and when strategic avoidance serves their negotiation objectives better. This behavioral adaptability represents a sophisticated negotiation capability that transcends rigid, one-dimensional approaches. In columns 4 to 6, we observe that the sentiments expressed in the language also show meaningful treatment effects under soft-skills treatment, increasing the positive sentiment expressions and indifferent sentiments expressed. This pattern indicates that Soft Skills training

Table 5: Hard and Soft Skills Training: Anderson Indexes Based on Number of Occurrences – Classification Based on Human Annotation

(a) Persuasion Tactics

	Persuasion Tactics		
	Influential (1)	Manipulative (2)	Win-Win (3)
Hard Skills			
β	0.036 (0.031)	0.001 (0.027)	-0.061*** (0.023)
Soft Skills			
β	0.132*** (0.030)	0.044* (0.027)	-0.071*** (0.024)
Mean Control Group	0.000	0.000	0.000
p-value Hard skills = Soft skills	0.028	0.256	0.769
Observations	4,548	4,548	4,548

(b) Language Sentiment and Conflict Management Tactics

	Conflict Management			Language Sentiment		
	Collaborative (1)	Assertive (2)	Avoiding (3)	Positive (4)	Negative (5)	Indifferent (6)
Hard Skills						
β	-0.044* (0.023)	0.045 (0.031)	0.060** (0.031)	-0.044* (0.024)	0.019 (0.035)	-0.002 (0.020)
Soft Skills						
β	0.048* (0.025)	0.131*** (0.033)	0.040 (0.031)	0.034 (0.025)	0.137*** (0.036)	0.038* (0.020)
Mean Control Group	0.000	0.000	0.000	0.000	0.000	0.000
p-value Hard skills = Soft skills	0.007	0.059	0.641	0.025	0.018	0.152
Observations	4,548	4,548	3,381	4,548	4,548	4,548

Notes. Observations at negotiation-round level including stacked double-annotations. The classification of each round level was performed by human annotators. We report the coefficients β_j defined in Equation 2, that were estimated using Double Machine Learning (DML) with 5-fold cross-validation and 100 sample splits to estimate our models. Outcome variables are Anderson indexes computed using the number of occurrences indicators, assigned a value of one when the negotiation style listed in the column title is employed. Estimates and standard errors are median across splits, following Chernozhukov et al. (2018). We apply the Romano-Wolf step-down procedure to calculate p-values, using 1,000 bootstrap repetitions for accuracy. We include annotator fixed effects. Standard errors are reported in parenthesis are clustered at the annotator level, p-values in brackets. Significance levels: $p < 0.1(*)$, $p < 0.05(**)$, $p < 0.01(***)$.

promotes affective regulation in negotiation contexts—participants can deploy positivity when advantageous while maintaining neutral emotional expression when strategic considerations demand it.

The results described provide an empirical validation of theoretical frameworks that aim to understand effectiveness in negotiation as contingent upon behavioral flexibility rather than domain-specific knowledge. The differential treatment effects between the two types of training received by participants align with contemporary negotiation theory that has emphasized the adaptive response capability over fixed tactical approaches that has been highlighted in recent studies in psychology (Boothby et al., 2023, Greer et al., 2018, Kong et al., 2014). In particular, the simultaneous increases in assertive and avoiding conflict management tactics represent a nuanced capability to modulate approach based on contextual demands—a hallmark of sophisticated negotiation behavior that conventional frameworks often fail to capture due to their tendency to position these tactics as mutually exclusive rather than complementary.

7.3 Human and Automated Annotations Agreement

To assess the validity of our annotation approach, we examine the consistency between human expert and automated annotations of negotiation tactics. We also examine agreement on speech forms classifications, which serve as calibration benchmarks for our automated system. The inter-rater reliability analysis reveals substantial heterogeneity in agreement across negotiation dimensions (Table 6), providing important context for interpreting our main results and highlighting which tactical classifications merit greater confidence.

For the speech forms used as calibration benchmarks, assertive acts demonstrate remarkably strong concordance across all three reliability metrics. The high correlation, substantial Cohen’s κ , and positive intraclass correlation coefficient indicate consistent classification of assertive behaviors by both human annotators and the automated system. This suggests that assertive negotiation language has distinctive linguistic markers that both humans and algorithms can reliably detect, providing confidence in our automated approach.

However, for cooperative acts, we observe statistically significant but modest agreement. The negative ICC indicates systematic differences in how humans and the automated system classify cooperative behaviors, suggesting potential threshold differences in identifying cooperation.

For the remaining categories—neutral acts, influential persuasion, and manipulative persuasion—agreement is notably poor. The negative correlations and negative ICC values

across these categories reveal systematic disagreement between human and automated classification approaches. This pattern suggests fundamentally different criteria are being applied to these more nuanced negotiation dimensions.

These findings have important implications for our measurement approach. The strong agreement on assertive strategies provides confidence in those particular estimates, while the weaker agreement in other categories necessitates additional robustness checks, such as the annotator fixed effects we employ in subsequent analyses. Our experience illustrates the practical challenges identified by [Modarressi et al. \(2025\)](#) in conducting causal inference on text-based outcomes. The mixed inter-rater reliability results underscore their argument that costly human validation is necessary to establish credible causal claims about treatment effects on text, particularly when LLM outputs reveal subtle patterns that may not align with human interpretation frameworks.

Table 6: Inter-rater Reliability Between Human and Automated Negotiation Strategy Annotations

Category	Feature	N	Correlation	Cohen’s κ	ICC
Strategic Acts	Strategy Cooperative	557	0.227***	0.041**	-0.152
Strategic Acts	Strategy Assertive	557	0.722***	0.422***	0.716
Strategic Acts	Strategy Neutral	557	-0.053	-0.032**	-0.502
Persuasion Tactics	Persuasion Influential	557	0.116***	-0.000	-0.575
Persuasion Tactics	Persuasion Manipulative	557	0.048	0.000	-0.544

Notes: Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

7.4 Robustness to Annotator Effects

A potential concern when analyzing human-coded textual data is that annotator-specific coding patterns might influence the estimated treatment effects. To address this concern, we examine the impact of including annotator fixed effects in our main specifications. If annotator idiosyncrasies were confounding our results, we would expect substantial changes in coefficient estimates when accounting for annotator identity.

Table 7 presents a comparison of models with and without annotator fixed effects for our key outcome variables. The results demonstrate remarkable stability in the treatment effect estimates across specifications. For both Hard Skills and Soft Skills treatments, the coefficients remain virtually identical whether or not annotator fixed effects are included, with percentage changes consistently at or near zero. This pattern holds across all outcome dimensions: strategic

acts, persuasion tactics, language sentiment, and conflict management.

The stability of these estimates provides strong evidence that our results are not driven by annotator-specific coding patterns. This robustness is particularly noteworthy given the inherently subjective nature of textual annotation. It suggests that our annotation protocols successfully minimized annotator-specific measurement error and that the experimental randomization effectively balanced annotator assignments across treatment conditions.

Given this stability, we present the models without annotator fixed effects as our primary specifications in the main text for parsimony, while noting that our conclusions are unaffected by their inclusion. These findings strengthen confidence in the internal validity of our treatment effect estimates.

Table 7: Impact of Annotator Fixed Effects on Treatment Estimates

Outcome	Hard Skills Treatment			Soft Skills Treatment		
	Basic Model	With FE	% Change	Basic Model	With FE	% Change
Strategy Cooperative	0.031 (0.073)	0.031 (0.073)	+0.0%	0.058 (0.075)	0.058 (0.075)	-0.0%
Persuasion Manipulative	-0.051 (0.077)	-0.051 (0.077)	-0.0%	0.019 (0.078)	0.019 (0.078)	-0.0%
Language Negative	0.002 (0.078)	0.002 (0.078)	+0.0%	-0.003 (0.078)	-0.003 (0.078)	+0.0%
Conflict Neutral	0.024 (0.103)	0.024 (0.103)	-0.0%	0.045 (0.104)	0.045 (0.104)	-0.0%

Notes: Table shows coefficient estimates for treatment effects from models with and without annotator fixed effects. Standard errors in parentheses. The % Change column shows the percentage change in coefficient magnitude when adding annotator fixed effects.

8 Conclusion

This study provides causal evidence on how structured educational interventions shape negotiation behaviors and outcomes among young adults in a developing economy. By implementing a randomized controlled trial that compares hard and soft skills curricula within the SEED program, we isolate the specific components of negotiation training that drive improvements in economic outcomes.

Our findings reveal a striking asymmetry between the two training approaches. Soft skills training significantly improves the quality of negotiated agreements, with participants securing more favorable financing terms and project timelines conditional on reaching agreement. These improvements operate through enhanced behavioral flexibility rather than rigid tactical application. In contrast, hard skills training produces smaller and largely insignificant effects on negotiation outcomes, suggesting that technical business knowledge alone is insufficient for maximizing negotiation effectiveness.

A central contribution of this paper is the development of a semantic classification framework for analyzing negotiation language across three tactical dimensions: persuasion, sentiment expression, and conflict management. Using both automated zero-shot classification and professional human annotation, we identify specific behavioral mechanisms through which soft skills training affects performance. Soft skills participants demonstrate greater tactical flexibility, deploying assertive conflict management strategies while also knowing when strategic avoidance serves their objectives. This behavioral adaptability—the capacity to modulate approach based on contextual demands—represents a sophisticated negotiation capability that transcends one-dimensional tactical frameworks.

The human annotation analysis reveals patterns that complement and extend the automated classification results. Soft skills trainees show substantially stronger effects on influential persuasion tactics and, notably, increased use of negative sentiment expression. This counterintuitive finding suggests that effective negotiators learn to strategically deploy emotional expressions—including frustration or disappointment—as negotiation tools rather than simply maintaining positive affect. Both treatment groups show reduced reliance on explicit Win-Win framing, indicating a shift toward more sophisticated persuasion approaches.

Our methodological approach—combining a field experiment with dual computational and human text analysis—offers several advantages over existing methods. By systematically classifying persuasion tactics, sentiment, and conflict management approaches, we provide a more objective assessment of negotiation behavior than traditional self-report or limited observational measures. The inter-rater reliability analysis between human and automated annotations reveals substantial heterogeneity across tactical dimensions, with strong agreement on assertive strategies but weaker concordance on more nuanced categories such as influential and manipulative persuasion. This pattern underscores the practical challenges of causal inference on text-based outcomes and validates our use of annotator fixed effects and multiple robustness checks.

These results have implications for the design of business training and workforce development programs. The substantial returns to soft skills development suggest that educational programs may be underinvesting in interpersonal and communicative capabilities relative to technical knowledge. This is particularly relevant given the centrality of negotiation skills to economic outcomes in labor markets and entrepreneurial settings, where the ability to secure favorable terms directly affects human capital accumulation and wealth creation.

Future research should examine the persistence of training effects over longer time horizons and across varied negotiation contexts. The differential effects of skills training across demographic groups, particularly gender, represent another important direction given documented gender gaps in negotiation outcomes. Finally, the development of more robust automated classification systems that better align with human judgment on nuanced tactical categories would enhance the scalability of negotiation behavior research.

References

- Adair, Wendi L. and Jeanne M. Brett, “The Negotiation Dance: Time, Culture, and Behavioral Sequences in Negotiation,” *Organization Science*, February 2005, 16 (1), 33–51.
- Afantenos, Stergos, Nicholas Asher, Farah Benamara, Anais Cadilhac, Cedric Dégremont, Pascal Denis, Markus Guhe, Simon Keizer, Alex Lascarides, Oliver Lemon et al., “Modelling strategic conversation: model, annotation design and corpus,” in “Proceedings of SemDial 2012 (SeineDial): The 16th Workshop on the Semantics and Pragmatics of Dialogue” 2012, pp. 167–168.
- Ahmad, Zishan, Suman Saurabh, Vaishakh Menon, Asif Ekbali, Roshni Ramnani, and Anutosh Maitra, “INA: An Integrative Approach for Enhancing Negotiation Strategies with Reward-Based Dialogue Agent,” in “in” 01 2023, pp. 2536–2549.
- Ambrus, Atilla, Eric Chaney, and Igor Salitskiy, “Pirates of the Mediterranean: An empirical investigation of bargaining with asymmetric information,” *Quantitative Economics*, 2018, 9 (1), 217–246.
- Arnstein, Sherry R., “A Ladder Of Citizen Participation,” *Journal of the American Institute of Planners*, 1969, 35 (4), 216–224.
- Artstein, Ron and Massimo Poesio, “Inter-Coder Agreement for Computational Linguistics,” *Computational Linguistics*, December 2008, 34 (4), 555–596.
- Arulampalam, Wiji and Alison L. Booth, “Training and Labour Market Flexibility: Is There a Trade-off?,” *British Journal of Industrial Relations*, 1998, 36 (4), 521–536.
- Ashraf, Nava, Natalie Bau, Corinne Low, and Kathleen McGinn, “Negotiating a Better Future: How Interpersonal Skills Facilitate Intergenerational Investment,” *The Quarterly Journal of Economics*, 2020, 135 (2), 1095–1151.
- Backus, Matthew and Steve Tadelis, “Empirical analysis of bargaining,” *NBER Reporter*, 2020, (4), 20–23.
- , Thomas Blake, Brad Larsen, and Steven Tadelis, “Sequential Bargaining in the Field: Evidence from Millions of Online Bargaining Interactions,” *The Quarterly Journal of Economics*, 2020, 135 (3), 1319–1361.
- , –, –, and –, “Sequential Bargaining in the Field: Evidence from Millions of Online Bargaining Interactions*,” *The Quarterly Journal of Economics*, August 2020, 135 (3), 1319–1361.
- Bai, Yuntao, Andy Jones, Kamal Ndousse, Amanda Askell, Anna Chen, Nova DasSarma, Dawn Drain, Stanislav Fort, Deep Ganguli, Tom Henighan, Nicholas Joseph, Saurav Kadavath, Jackson Kernion, Tom Conerly, Sheer El-Showk, Nelson Elhage, Zac Hatfield-Dodds, Danny Hernandez, Tristan Hume, Scott Johnston, Shauna Kravec, Liane Lovitt, Neel Nanda, Catherine Olsson, Dario Amodei, Tom Brown, Jack Clark, Sam McCandlish, Chris Olah, Ben Mann, and Jared Kaplan, “Training a Helpful and Harmless Assistant with Reinforcement Learning from Human Feedback,” 2022. Version Number: 1.
- Bandelj, Nina, “Relational Work and Economic Sociology,” *Politics & Society*, 2012, 40 (2), 175–201.
- Bazerman, Max H et al., *Negotiation*, Harvard Business School Press, 2001.
- Bazerman, Max H., Jared R. Curhan, Don A. Moore, and Kathleen L. Valley, “Negotiation,” *Annual Review of Psychology*, 2000, 51 (Volume 51, 2000), 279–314.
- Binmore, Ken, Ariel Rubinstein, and Asher Wolinsky, “The Nash Bargaining Solution in Economic Modelling,” *The RAND Journal of Economics*, 1986, 17 (2), 176.
- , John McCarthy, Giovanni Ponti, Larry Samuelson, and Avner Shaked, “A Backward Induction Experiment,” *Journal of Economic Theory*, May 2002, 104 (1), 48–88.

- Boothby, Erica J., Gus Cooney, and Maurice E. Schweitzer**, “Embracing Complexity: A Review of Negotiation Research,” *Annual Review of Psychology*, January 2023, 74 (1), 299–332.
- Bottom, William P., James Holloway, Gary J. Miller, Alexandra Mislin, and Andrew Whitford**, “Building a Pathway to Cooperation: Negotiation and Social Exchange between Principal and Agent,” *Administrative Science Quarterly*, 2006, 51 (1), 29–58.
- Bowles, Hannah Riley**, “Psychological Perspectives on Gender in Negotiation,” in “The SAGE Handbook of Gender and Psychology,” 1 Oliver’s Yard, 55 City Road London EC1Y 1SP: SAGE Publications, Ltd, 2013, pp. 465–483.
- Boyle, Elizabeth A, Thomas M Connolly, and Thomas Hainey**, “The Role of Psychology in Understanding the Impact of Computer Games,” *Entertainment Computing*, 2012, 3 (2), 69–74.
- Brown, Tom B., Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, Sandhini Agarwal, Ariel Herbert-Voss, Gretchen Krueger, Tom Henighan, Rewon Child, Aditya Ramesh, Daniel M. Ziegler, Jeffrey Wu, Clemens Winter, Christopher Hesse, Mark Chen, Eric Sigler, Mateusz Litwin, Scott Gray, Benjamin Chess, Jack Clark, Christopher Berner, Sam McCandlish, Alec Radford, Ilya Sutskever, and Dario Amodei**, “Language Models are Few-Shot Learners,” 2020. Version Number: 4.
- Buechel, Sven and Udo Hahn**, “Emobank: Studying the impact of annotation perspective and representation format on dimensional emotion analysis,” *arXiv preprint arXiv:2205.01996*, 2022.
- Burt, George, George Wright, Ron Bradfield, George Cairns, and Kees Van Der Heijden**, “The Role of Scenario Planning in Exploring the Environment in View of the Limitations of PEST and its Derivatives,” *International Studies of Management & Organization*, 2006, 36 (3), 50–76.
- Caliskan, Aylin, Joanna J. Bryson, and Arvind Narayanan**, “Semantics derived automatically from language corpora contain human-like biases,” *Science*, April 2017, 356 (6334), 183–186.
- Card, David**, “Strikes and Bargaining: A Survey of the Recent Empirical Literature,” *Papers and Proceedings of the Hundred and Second Annual Meeting of the American Economic Association*, 1990, 80 (2), 410–415.
- Charnes, Gary and Uri Gneezy**, “Incentives to Exercise,” *Econometrica*, 2009, 77 (3), 909–931.
- Chernozhukov, Victor, Denis Chetverikov, Mert Demirer, Esther Duflo, Christian Hansen, Whitney Newey, and James Robins**, “Double/debiased machine learning for treatment and structural parameters,” *The Econometrics Journal*, February 2018, 21 (1), C1–C68.
- Chioda, Laura, David Contreras-Loya, Paul Gertler, and Dana Carney**, “Making Entrepreneurs: Returns to Training Youth in Hard Versus Soft Business Skills,” Technical Report w28845, National Bureau of Economic Research, Cambridge, MA May 2021.
- Coase, Ronald**, “The Federal Communications Commission,” *The Journal of Law and Economics*, 1959, (2), 1–40.
- Conneau, Alexis, Douwe Kiela, Holger Schwenk, Loic Barrault, and Antoine Bordes**, “Supervised Learning of Universal Sentence Representations from Natural Language Inference Data,” 2017. Version Number: 5.

- Core, Mark G and James Allen**, “Coding dialogs with the DAMSL annotation scheme,” in “AAAI fall symposium on communicative action in humans and machines,” Vol. 56 Boston, MA 1997, pp. 28–35.
- Cortés, Patricia, Jacob French, Jessica Pan, and Basit Zafar**, “Gender Differences in Negotiations and Labor Market Outcomes: Evidence from an Information Intervention with College Students,” February 2024.
- Crawford, Vincent P.**, “A Theory of Disagreement in Bargaining,” *Econometrica*, May 1982, 50 (3), 607.
- Cullen, Zoë B. and Bobak Pakzad-Hurson**, “Equilibrium Effects of Pay Transparency,” *Econometrica*, 2023, 91 (3), 765–802.
- Cullen, Zoë, Bobak Pakzad-Hurson, and Ricardo Perez-Truglia**, “Pushing the Envelope: The Effects of Salary Negotiations,” Technical Report w33903, National Bureau of Economic Research, Cambridge, MA June 2025.
- de Oliveira Dias, Murillo, João Lafraia, Thiago Schmitz, and Patrícia Vieira**, “Systematic Literature Review on Negotiation Conflict Management,” *European Journal of Theoretical and Applied Sciences*, 2023, 1 (3), 20–31.
- Dong, Shi, Xiaobei Niu, Rui Zhong, Zhifeng Wang, and Mingzhang Zuo**, “Leveraging Label Semantics and Meta-Label Refinement for Multi-Label Question Classification,” *arXiv preprint arXiv:2411.01841*, 2024.
- Dustmann, Christian, Bernd Fitzenberger, Uta Schönberg, and Alexandra Spitz-Oener**, “From Sick Man of Europe to Economic Superstar: Germany’s Resurgent Economy,” *Journal of Economic Perspectives*, 2014, 28 (1), 167–188.
- Edum-Fotwe, Francis T and Ronald McCaffer**, “Developing Project Management Competency: Perspectives from the Construction Industry,” in “Proceedings of the 16th Annual ARCOM Conference” Association of Researchers in Construction Management 2000, pp. 1–10.
- Endriss, Ulle, Nicolas Maudet, Fariba Sadri, and Francesca Toni**, “Negotiating Socially Optimal Allocations of Resources,” *Journal of Artificial Intelligence Research*, 03 2006, 25.
- Estevez-Abe, Margarita, Torben Iversen, and David Soskice**, “Social Protection and the Formation of Skills: A Reinterpretation of the Welfare State,” 2001.
- Farbmacher, Helmut, Martin Huber, Lukáš Laffers, Henrika Langen, and Martin Spindler**, “Causal mediation analysis with double machine learning,” *The Econometrics Journal*, May 2022, 25 (2), 277–300.
- Fehr, Ernst and Simon Gächter**, “Fairness and Retaliation: The Economics of Reciprocity,” *Journal of Economic Perspectives*, 2000, 14 (3), 159–181.
- Fisher, Joseph, James R Frederickson, and Sonja A Pfeffer**, “Budget Negotiations in Multi-Period Settings,” *Accounting, Organizations and Society*, 2006, 31 (6), 511–528.
- Fisher, Roger, William Ury, and Bruce Patton**, *Getting to Yes: Negotiating Agreement without Giving In*, Houghton Mifflin, 1991.
- Frayling, Erlend, Jake Lever, and Graham McDonald**, “Zero-shot and Few-shot Generation Strategies for Artificial Clinical Records,” 2024. Version Number: 2.
- Friedman, Raymond A and Steven C Currall**, “Conflict escalation: Dispute exacerbating elements of e-mail communication,” *Human relations*, 2003, 56 (11), 1325–1347.
- Geva, Mor, Yoav Goldberg, and Jonathan Berant**, “Are We Modeling the Task or the Annotator? An Investigation of Annotator Bias in Natural Language Understanding Datasets,” 2019. Version Number: 2.
- Gneezy, Uri, Werner Güth, and Frank Verboven**, “Presents or investments? An experimental analysis,” *Journal of Economic Psychology*, October 2000, 21 (5), 481–493.

- Greer, Lindred L., Bart A. De Jong, Maartje E. Schouten, and Jennifer E. Dannals,** “Why and when hierarchy impacts team effectiveness: A meta-analytic integration,” *Journal of Applied Psychology*, June 2018, *103* (6), 591–613.
- Grennan, Matthew,** “Price Discrimination and Bargaining: Empirical Evidence from Medical Devices,” *American Economic Review*, February 2013, *103* (1), 145–177.
- , “Bargaining Ability and Competitive Advantage: Empirical Evidence from Medical Devices,” *Management Science*, December 2014, *60* (12), 3011–3025.
- Hall, Robert E and Paul R Milgrom,** “The Limited Influence of Unemployment on the Wage Bargain,” 2008.
- He, He, Derek Chen, Anusha Balakrishnan, and Percy Liang,** “Decoupling Strategy and Generation in Negotiation Dialogues,” 2018. Version Number: 1.
- Hua, Yuncheng, Lizhen Qu, and Gholamreza Haffari,** “Assistive Large Language Model Agents for Socially-Aware Negotiation Dialogues,” 2024.
- Jindal, Pranav and Peter Newberry,** “To Bargain or Not to Bargain: The Role of Fixed Costs in Price Negotiations,” *Journal of Marketing Research*, December 2018, *55* (6), 832–851.
- Jäger, Simon, Christopher Roth, Nina Roussille, and Benjamin Schoefer,** “Worker Beliefs About Outside Options,” Technical Report w29623, National Bureau of Economic Research, Cambridge, MA December 2021.
- Kagel, John H. and Alvin E. Roth, eds,** *The Handbook of Experimental Economics*, Princeton University Press, May 2020.
- Kahn, Lawrence M.,** “Labor market policy: A comparative view on the costs and benefits of labor market flexibility,” *Journal of Policy Analysis and Management*, 2012, *31* (1), 94–110.
- Kherallah, Mylene and Johann F Kirsten,** *The New Institutional Economics: Applications for Agricultural Policy Research in Developing Countries*, International Food Policy Research Institute, 2002.
- Kiessling, Lukas, Pia Pinger, Philipp Seegers, and Jan Bergerhoff,** “Gender differences in wage expectations and negotiation,” *Labour Economics*, April 2024, *87*, 102505.
- Kim, Jay and Joseph T Mahoney,** “Property Rights Theory, Transaction Costs Theory, and Agency Theory: An Organizational Economics Approach to Strategic Management,” *Managerial and Decision Economics*, 2005, *26* (4), 223–242.
- Kojima, Takeshi, Shixiang Shane Gu, Machel Reid, Yutaka Matsuo, and Yusuke Iwasawa,** “Large Language Models are Zero-Shot Reasoners,” 2022. Version Number: 4.
- Koles, Paul, Adrienne Stolfi, Nicole Borges, Stuart Nelson, and Dean Parmelee,** “The Impact of Team-Based Learning on Medical Students’ Academic Performance,” *Academic medicine : journal of the Association of American Medical Colleges*, 09 2010, *85*, 1739–45.
- Koles, Paul G et al.,** “The Impact of Team-Based Learning on Medical Students’ Academic Performance,” *Academic Medicine*, 2010, *85* (11), 1739–1745.
- Kong, Dejun Tony, Kurt T. Dirks, and Donald L. Ferrin,** “Interpersonal Trust within Negotiations: Meta-Analytic Evidence, Critical Contingencies, and Directions for Future Research,” *Academy of Management Journal*, October 2014, *57* (5), 1235–1255.
- Kopelman, Shirli, Ashleigh Shelby Rosette, and Leigh Thompson,** “The three faces of Eve: Strategic displays of positive, negative, and neutral emotions in negotiations,” *Organizational Behavior and Human Decision Processes*, January 2006, *99* (1), 81–101.
- Krugman, Paul,** “What Should Trade Negotiators Negotiate About?,” *Journal of Economic Literature*, 1997, *35* (1), 113–120.

- Kuang, Xi and Donald V Moser**, “Wage Negotiation, Employee Effort, and Firm Profit under Output-Based versus Fixed-Wage Incentive Contracts,” *Contemporary Accounting Research*, 2011, 28 (2), 616–634.
- Kumar, Manish, Himanshu Rai, and Surya Prakash Pati**, “An Exploratory Study on Negotiating Styles: Development of a Measure,” *Vikalpa: The Journal for Decision Makers*, October 2009, 34 (4), 37–50.
- Lachowska, Marta, Alexandre Mas, Raffaele Saggio, and Stephen A. Woodbury**, “Wage Posting or Wage Bargaining? A Test Using Dual Jobholders,” *Journal of Labor Economics*, April 2022, 40 (S1), S469–S493.
- Larsen, Bradley**, “The Efficiency of Real-World Bargaining: Evidence from Wholesale Used-Auto Auctions,” Technical Report w20431, National Bureau of Economic Research, Cambridge, MA August 2014.
- **and Anthony Lee Zhang**, “A Mechanism Design Approach to Identification and Estimation,” Technical Report w24837, National Bureau of Economic Research, Cambridge, MA July 2018.
- **and –**, “Quantifying Bargaining Power Under Incomplete Information: A Supply-Side Analysis of the Used-Car Industry,” *SSRN Electronic Journal*, 2021.
- Lazear, Edward P.**, “Leadership: A personnel economics approach,” *Labour Economics*, January 2012, 19 (1), 92–101.
- Leduc, Sylvain and Zheng Liu**, “Automation, Bargaining Power, and Labor Market Fluctuations,” Working Paper Series 2019-17, Federal Reserve Bank of San Francisco May 2022.
- Lewis, Mike, Denis Yarats, Yann N. Dauphin, Devi Parikh, and Dhruv Batra**, “Deal or No Deal? End-to-End Learning for Negotiation Dialogues,” 2017. Version Number: 1.
- Li, Yuang, Yu Wu, Jinyu Li, and Shujie Liu**, “Prompting Large Language Models for Zero-Shot Domain Adaptation in Speech Recognition,” 2023. Version Number: 1.
- Mannix, Elizabeth A.**, “The influence of power, distribution norms and task meeting structure on resource allocation in small group negotiation,” *International Journal of Conflict Management*, 1993, 4 (1), 5–23.
- Mateen, Haaris, Franklin Qian, and Ye Zhang**, “The Microstructure of the U.S. Housing Market: Evidence from Millions of Bargaining Interactions,” 2020.
- Mazei, Jens, Joachim Hüffmeier, Philipp Alexander Freund, Alice F. Stuhlmacher, Lena Bilke, and Guido Hertel**, “A meta-analysis on gender differences in negotiation outcomes and their moderators.,” *Psychological Bulletin*, 2015, 141 (1), 85–104.
- McClellan, Andrew**, “Dynamic Outside Options and Optimal Negotiation Strategies,” *American Economic Review*, October 2024, 114 (10), 3284–3313.
- Mcdonald, Ian M. and Robert M. Solow**, *Wage bargaining and employment*, Dordrecht: Springer Netherlands,
- Menzner, Tim and Jochen L. Leidner**, “Experiments in News Bias Detection with Pre-trained Neural Transformers,” in Nazli Goharian, Nicola Tonellotto, Yulan He, Aldo Lipani, Graham McDonald, Craig Macdonald, and Iadh Ounis, eds., *Advances in Information Retrieval*, Vol. 14611, Cham: Springer Nature Switzerland, 2024, pp. 270–284. Series Title: Lecture Notes in Computer Science.
- Meshkin, Hamed, Joel Zirkle, Ghazal Arabidarrehdor, Anik Chaturbedi, Shilpa Chakravartula, John Mann, Bradlee Thrasher, and Zhihua Li**, “Harnessing large language models’ zero-shot and few-shot learning capabilities for regulatory research,” *Briefings in Bioinformatics*, July 2024, 25 (5), bbac354.
- Messina, Julián and Anna Sanz de Galdeano**, “Wage Rigidity and Disinflation in Emerging Countries,” *American Economic Journal: Macroeconomics*, January 2014, 6 (1), 102–33.

- Modarressi, Iman, Jann Spiess, and Amar Venugopal**, “Causal Inference on Outcomes Learned from Text,” 2025. Version Number: 1.
- Muffels, Ruud and Ton Wilthagen**, “Flexicurity: A New Paradigm for the Analysis of Labor Markets and Policies Challenging the Trade-Off Between Flexibility and Security,” *Sociology Compass*, 2013, 7 (2), 111–122.
- Muthoo, Abhinay**, *Bargaining Theory with Applications*, 1 ed., Cambridge University Press, August 1999.
- Naveed, Humza, Asad Ullah Khan, Shi Qiu, Muhammad Saqib, Saeed Anwar, Muhammad Usman, Naveed Akhtar, Nick Barnes, and Ajmal Mian**, “A Comprehensive Overview of Large Language Models,” 2023. Version Number: 10.
- Norambuena, Brian Keith, Exequiel Fuentes Lettura, and Claudio Meneses Villegas**, “Sentiment analysis and opinion mining applied to scientific paper reviews,” *Intelligent data analysis*, 2019, 23 (1), 191–214.
- Ozaki, Muneto**, “Negotiating flexibility : the role of the social partners and the state,” in “in” 1999.
- Pacella, Daniela and Davide Marocco**, “Understanding Negotiation: A Text-Mining and NLP Approach to Virtual Interactions in a Simulation Game,” *Applied Sciences*, 2022, 12 (10).
- , **Elena Dell’Aquila, Davide Marocco, and Steven Furnell**, “Toward an Automatic Classification of Negotiation Styles Using Natural Language Processing,” in Jonas Beskow, Christopher Peters, Ginevra Castellano, Carol O’Sullivan, Iolanda Leite, and Stefan Kopp, eds., *Intelligent Virtual Agents*, Vol. 10498, Cham: Springer International Publishing, 2017, pp. 339–342. Series Title: Lecture Notes in Computer Science.
- , – , – , and – , “Toward an Automatic Classification of Negotiation Styles Using Natural Language Processing,” in Jonas Beskow, Christopher Peters, Ginevra Castellano, Carol O’Sullivan, Iolanda Leite, and Stefan Kopp, eds., *Intelligent Virtual Agents*, Vol. 10498, Cham: Springer International Publishing, 2017, pp. 339–342. Series Title: Lecture Notes in Computer Science.
- Pakzad-Hurson, B.; Perez-Truglia-R. Cullen Z.;**, “Pushing the Envelope: Effects of Salary Negotiations,” *Manuscript*, 2024.
- Pang, Bo, Lillian Lee et al.**, “Opinion mining and sentiment analysis,” *Foundations and Trends® in information retrieval*, 2008, 2 (1–2), 1–135.
- Paola, Maria De, Rosetta Lombardo, Valeria Pupo, and Vincenzo Scoppa**, “Do Women Shy Away from Public Speaking? A Field Experiment,” *Labour Economics*, June 2021, 70, 102001.
- Pyatkin, Valentina, Frances Yung, Merel C. J. Scholman, Reut Tsarfaty, Ido Dagan, and Vera Demberg**, “Design Choices for Crowdsourcing Implicit Discourse Relations: Revealing the Biases Introduced by Task Design,” *Transactions of the Association for Computational Linguistics*, August 2023, 11, 1014–1032.
- Rahim, M. A.**, “A MEASURE OF STYLES OF HANDLING INTERPERSONAL CONFLICT,” *Academy of Management Journal*, June 1983, 26 (2), 368–376.
- Rahim, M Afzalur**, “Toward a theory of managing organizational conflict,” *International journal of conflict management*, 2002, 13 (3), 206–235.
- Ramlall, Sunil**, “A Review of Employee Motivation Theories and Their Implications for Employee Retention Within Organizations,” *Journal of American Academy of Business*, 2004, 5 (1/2), 52–63.
- Read, Jesse, Antti Puurula, and Albert Bifet**, “Multi-label classification with meta-labels,” in “2014 IEEE international conference on data mining” IEEE 2014, pp. 941–946.

- Recalde, María P. and Lise Vesterlund**, “Gender Differences in Negotiation: Can Interventions Reduce the Gap?,” *Annual Review of Economics*, September 2023, 15 (1), 633–657.
- Rubinstein, Ariel**, “Perfect Equilibrium in a Bargaining Model,” *Econometrica*, 1982, 50 (1), 97–109.
- Sala, Hector, José I. Silva, and Manuel Toledo**, “Flexibility at the Margin and Labor Market Volatility in OECD Countries*,” *The Scandinavian Journal of Economics*, 2012, 114 (3), 991–1017.
- Schelling, Thomas**, *The Strategy of Conflict*, Harvard University Press, 1980.
- Sclar, Melanie, Yejin Choi, Yulia Tsvetkov, and Alane Suhr**, “Quantifying Language Models’ Sensitivity to Spurious Features in Prompt Design or: How I learned to start worrying about prompt formatting,” 2023. Version Number: 2.
- Sokolova, Marina, Vivi Nastase, Mohak Shah, and Stan Szpakowicz**, “Feature selection in electronic negotiation texts,” in “in” 01 2005.
- Stiglitz, Joseph**, *Globalization and its discontents revisited: Anti-globalization in the era of Trump*, WW Norton Company, 2017.
- Suleman, Raja M., Riichiro Mizoguchi, and Mitsuru Ikeda**, “A New Perspective of Negotiation-Based Dialog to Enhance Metacognitive Skills in the Context of Open Learner Models,” *International Journal of Artificial Intelligence in Education*, December 2016, 26 (4), 1069–1115.
- Sullivan, Brandon A., Kathleen M. O’Connor, and Ethan R. Burris**, “Negotiator confidence: The impact of self-efficacy on tactics and outcomes,” *Journal of Experimental Social Psychology*, September 2006, 42 (5), 567–581.
- Thelen, Kathleen**, “Institutional Change in Advanced Political Economies,” 2009.
- Touvron, Hugo, Louis Martin, Kevin Stone, Peter Albert, Amjad Almahairi, Yasmine Babaei, Nikolay Bashlykov, Soumya Batra, Prajjwal Bhargava, Shruti Bhosale, Dan Bikel, Lukas Blecher, Cristian Canton Ferrer, Moya Chen, Guillem Cucurull, David Esiobu, Jude Fernandes, Jeremy Fu, Wenyin Fu, Brian Fuller, Cynthia Gao, Vedanuj Goswami, Naman Goyal, Anthony Hartshorn, Saghar Hosseini, Rui Hou, Hakan Inan, Marcin Kardas, Viktor Kerkez, Madian Khabsa, Isabel Kloumann, Artem Korenev, Punit Singh Koura, Marie-Anne Lachaux, Thibaut Lavril, Jenya Lee, Diana Liskovich, Yinghai Lu, Yuning Mao, Xavier Martinet, Todor Mihaylov, Pushkar Mishra, Igor Molybog, Yixin Nie, Andrew Poulton, Jeremy Reizenstein, Rashi Rungta, Kalyan Saladi, Alan Schelten, Ruan Silva, Eric Michael Smith, Ranjan Subramanian, Xiaoqing Ellen Tan, Binh Tang, Ross Taylor, Adina Williams, Jian Xiang Kuan, Puxin Xu, Zheng Yan, Iliyan Zarov, Yuchen Zhang, Angela Fan, Melanie Kambadur, Sharan Narang, Aurelien Rodriguez, Robert Stojnic, Sergey Edunov, and Thomas Scialom**, “Llama 2: Open Foundation and Fine-Tuned Chat Models,” 2023. Version Number: 2.
- Traum, David R. and Staffan Larsson**, “The Information State Approach to Dialogue Management,” in Nancy Ide, Jean Véronis, Jan Van Kuppevelt, and Ronnie W. Smith, eds., *Current and New Directions in Discourse and Dialogue*, Vol. 22, Dordrecht: Springer Netherlands, 2003, pp. 325–353. Series Title: Text, Speech and Language Technology.
- Viebrock, Elke and Jochen Clasen**, “Flexicurity and welfare reform: a review,” *Socio-Economic Review*, 02 2009, 7 (2), 305–331.
- Visser, Jelle**, *Negotiated flexibility, working time and transitions in the Netherlands* 09
- von Neumann, John and Oskar Morgenstern**, *Theory of Games and Economic Behavior*, Princeton University Press, 2007.
- Waltz, Kenneth**, *Theory of International Politics*, Addison-Wesley Publishing Company, 1979.

- Wilthagen, Ton and Frank Tros**, “The concept of ‘flexicurity’: a new approach to regulating employment and labour markets,” *Transfer: European Review of Labour and Research*, 2004, 10 (2), 166–186.
- Yang, Diyi, Jiaao Chen, Zichao Yang, Dan Jurafsky, and Eduard Hovy**, “Let’s Make Your Request More Persuasive: Modeling Persuasive Strategies via Semi-Supervised Neural Nets on Crowdfunding Platforms,” in “Proceedings of the 2019 Conference of the North Association for Computational Linguistics Minneapolis, Minnesota 2019, pp. 3620–3630.

Online Appendix

A Data Annotation Protocol

A.1 Negotiation Context and Classification Framework

The annotation protocol classified negotiation transcripts from a controlled experimental setting where participants assumed roles as buyers (Commissioners of the Ministry of Lands) or sellers (owners of Butagira Farms) negotiating land transactions. All negotiations focused on two primary dimensions: financing terms and project start dates.

Our classification framework comprised four primary categories presented in Appendix Table A.1.

Table A.1: Negotiation Styles and Tactics Classification

Panel A: Classification of Language Sentiments		
Positive sentiment. Language expressing favorable or uplifting emotions, such as enjoyment or excitement, which promote positivity and influence others constructively.	Negative sentiment. Language conveying unfavorable or distressing emotions, such as anger, contempt, or terror, often used to challenge or disrupt.	Indifferent sentiment. Language devoid of strong emotional undertones, maintaining a balanced and unbiased tone without evoking positive or negative feelings.
<i>Enjoyment:</i> Expressions of pleasure or satisfaction.	<i>Anger:</i> Expressions of anger or frustration.	<i>Indifference:</i> Neutral or flat expressions where no particular sentiment is implied, often used in factual or transactional exchanges.
<i>Excitement:</i> Expressions of enthusiasm or anticipation.	<i>Contempt:</i> Dismissive or scornful attitudes towards others.	
<i>Satisfaction:</i> Indicates a positive response, reflecting contentment or pleasure with the circumstances or outcomes.	<i>Distress:</i> Expressions of sadness or discomfort.	
<i>Confidence/Assurance:</i> Reflects a positive tone as it conveys certainty and reliability.	<i>Terror:</i> Expressions of extreme fear or anxiety.	
	<i>Humiliation:</i> Feelings of embarrassment or shame.	
	<i>Startle:</i> Reactions of surprise or shock.	
	<i>Urgency:</i> It relates more to the timing of actions putting pressure to finish the exchange.	
Panel B: Classification of Conflict Management Tactics		

<p>Collaborative. Tactics that emphasize cooperation, teamwork, and mutual benefit to resolve conflicts constructively.</p>	<p>Assertive. Tactics that prioritize individual goals or viewpoints, often through strong or competitive actions to address conflicts.</p>	<p>Avoiding. Tactics that neither engage actively in resolving nor escalating conflicts, maintaining a balanced or passive stance.</p>
<p><i>Collaborating:</i> Working together towards a common goal.</p>	<p><i>Competing:</i> Asserting one's own interests over others'.</p>	<p><i>Avoiding:</i> Avoiding escalation of conflict or confrontation.</p>
<p><i>Accommodating:</i> Yielding to others' preferences or viewpoints or giving in during the negotiation process.</p>	<p><i>Escalating:</i> Intentionally amplifies the conflict to pressurize the situation or force a resolution; it imposes stress or urgency upon the other party.</p>	
<p><i>Compromising:</i> Finding middle ground or reaching a consensus in the final offer or outcome.</p>	<p><i>Defensive:</i> Protects one's own position without overtly attacking or conceding, maintaining a balanced and somewhat passive stance without engaging in active conflict.</p>	

Panel C: Classification of Persuasion Tactics

<p>Influential. Influential tactics convince or influence others, using truthful arguments or appeals that aim to change beliefs or behaviors.</p>	<p>Manipulative. Manipulative tactics address or challenge persuasive efforts using arguments with limited credibility, by using exaggerations, false promises, or misleading claims.</p>
<p><i>Appeal to sympathy:</i> Eliciting emotions such as pity or compassion, asking the other to "put yourself in my shoes."</p>	<p><i>Embellishment:</i> Deliberately exaggerating or enhancing facts or claims to mislead or deceive, often making them appear more impressive or persuasive than they are.</p>
<p><i>Side offers:</i> Offering additional incentives or benefits separate from the main proposal.</p>	<p><i>Cheap talk:</i> Informal conversation with non-committal promises or false assurances.</p>
<p><i>Social Proof:</i> Persuading by indicating that others, especially similar people or large numbers of people, have made a choice.</p>	<p><i>Authority:</i> Using one's position of power or expertise to influence or convince others.</p>
	<p><i>Fear Appeal:</i> Tactics that attempt to persuade by evoking fear or concern about the consequences of not taking a certain action or decision.</p>

A.2 Annotation Process and Team Organization

We implemented a partial specialization workflow where annotators focused on specific category pairs to maximize consistency while minimizing cognitive burden:

- Team 1: Speech Forms and Persuasion Tactics
- Team 2: Sentiment in Language and Conflict Management

The speech form category serves as a methodological calibration benchmark, establishing ground truth classifications based on linguistically unambiguous semantic patterns in negotiation discourse. This classification of fundamental communicative acts, detailed in Appendix Table A.2, provides a validation framework against which our more nuanced tactical annotations can be assessed for reliability and accuracy.

Each team of annotators comprised both male and female annotators to ensure gender balance in interpretation. Annotators followed a five-step process:

- Reviewing annotation protocols for assigned categories
- Studying category-specific labels and meta-labels
- Reading full transcripts to establish context
- Assigning appropriate labels at the round level
- Proceeding systematically through all rounds within transcripts

Table A.2: Classification of Speech Forms

Category	Description	Examples
Greet	Expressions of salutation or welcome	‘Hello! How are you today?’
Disagree	Expressions of disagreement or opposition	‘I’m sorry, but I don’t agree with your proposal.’
Agree	Expressions of agreement or consent	‘Yes, I think that’s a great idea.’
Inform	Providing information or facts	‘According to the report, sales have increased by 10%.’
Insist	Persistently asserting or demanding something	‘I really think we should reconsider this approach.’
Inquire	Asking questions or seeking clarification	‘Could you please clarify how this process works?’
Propose	Putting forward suggestions or ideas	‘I suggest we meet tomorrow to discuss this further.’
Counter	Offering an opposing viewpoint or response	‘On the contrary, I believe we should focus on a different strategy.’
Offer	Presenting something for consideration or acceptance	‘I can provide additional resources to support the project.’
Accept	Agreeing to or approving something	‘Yes, let’s go ahead with your plan.’
Threat	Expressions of potential harm or consequence	‘If we don’t meet the deadline, there will be serious consequences.’

A.3 Computational Implementation

For zero-shot classification using LLMs, we processed transcripts with minimal pre-processing, retaining punctuation and linguistic markers. For human annotation, we developed specialized interfaces that displayed full transcript context while enabling round-level classification. Inter-annotator agreement was formally assessed using correlation coefficients, Cohen’s κ , and intraclass correlation metrics.

The Win-Win classification warranted particular attention as a complex meta-label requiring at least one primary indicator (explicit mutual benefit language, value creation attempts, interest-based problem solving, or shared goal articulation) supplemented by supporting indicators (side offers, collaborative conflict management, positive emotional tone, future relationship consideration).

B Additional Tables and Figures

B.1 Tables

Table B.1: Outcome Variables and Descriptions

Outcome Variable	Description and Reporting Units
Measures of Agreement	
Agreement on final offer	Indicator variable. Whether a final agreement was reached.
Final agreement on financing	Financing terms agreed (USD PPP)
Final agreement on start date	Project start date agreed (months)
Measures of Dynamics	
Subject's 1st counteroffer for financing	First counteroffer on financing terms (USD PPP)
Subject's 1st counteroffer for start date	First counteroffer on start date (months)
Number of rounds	Total number of negotiation rounds (percentage)
Subject's total number of words	Total words used by the subject
Split the Difference & Negotiation	
Sequential Negotiation (Financing)	Use of sequential negotiation for financing (percentage points)
Sequential Negotiation (Start Date)	Use of sequential negotiation for start date (percentage points)
Split the Difference (Financing)	Use of "split the difference" strategy for financing (percentage points)
Split the Difference (Start Date)	Use of "split the difference" strategy for start date (percentage points)
Aggregated Anderson Index	
Strategies index	Index Anderson

Table B.2: Descriptive Statistics at Baseline By Treatment Group

	Control	Treatment		P-values		
		Hard Skills	Soft Skills	Hard vs Control	Soft vs Control	Hard vs Soft
Demographics and Expectations						
Age at baseline	19.98 (1.48)	19.98 (1.47)	20.00 (1.50)	0.95	0.79	0.71
Female	0.33 (0.47)	0.36 (0.48)	0.36 (0.48)	0.12	0.15	0.90
Boarding Student, yes	0.75 (0.42)	0.73 (0.43)	0.74 (0.43)	0.22	0.53	0.51
Plans to Attend Uni.	0.72 (0.45)	0.71 (0.45)	0.72 (0.44)	0.60	0.80	0.40
Family Background						
Parental Socioeconomic Status, index	0.01 (0.52)	-0.01 (0.53)	0.00 (0.54)	0.43	0.78	0.59
Housing index (Anderson)	0.02 (0.79)	0.01 (0.84)	0.02 (0.83)	0.90	0.96	0.86
Subjective 10-year Wealth	0.01 (1.00)	0.02 (1.00)	0.01 (0.97)	0.77	0.93	0.66
Big Five (z-core)						
Extraversion	2.74 (0.95)	2.76 (0.93)	2.71 (0.92)	0.58	0.52	0.18
Openness	4.16 (0.76)	4.15 (0.74)	4.14 (0.75)	0.85	0.62	0.74
Agreeableness	3.62 (0.67)	3.61 (0.65)	3.62 (0.67)	0.75	0.93	0.80
Conscientiousness	3.89 (0.71)	3.90 (0.70)	3.88 (0.65)	0.77	0.83	0.56
Plasticity index	0.01 (1.01)	0.02 (1.00)	-0.03 (0.99)	0.76	0.43	0.23
Emotional Stability	0.00 (1.02)	0.01 (1.01)	-0.01 (0.97)	0.79	0.89	0.65
Personal Traits (z-score)						
Intelligence (Raven's Score)	0.00 (1.02)	0.04 (1.00)	-0.01 (0.98)	0.33	0.87	0.20
O-Levels Score	-0.07 (1.00)	0.01 (1.00)	-0.01 (1.00)	0.07	0.18	0.62
Math & Business Score	0.02 (0.96)	0.03 (0.99)	0.00 (1.01)	0.89	0.58	0.45
Leadership index	-0.02 (0.99)	0.02 (0.96)	0.06 (0.95)	0.32	0.07	0.35
Psychosocial Indices						
Perceived Control index	0.00 (0.98)	-0.01 (0.95)	0.02 (0.96)	0.95	0.62	0.53
Self-confidence index	0.07 (0.91)	-0.02 (1.00)	0.02 (0.96)	0.01	0.15	0.28
Prosocial Behavior index	-0.04 (0.99)	0.02 (0.99)	0.05 (0.93)	0.17	0.02	0.32
Patience index	-0.04 (1.03)	0.01 (1.00)	0.01 (0.95)	0.25	0.30	0.88
Willingness To Take Risks index	-0.01 (1.01)	0.01 (1.00)	0.02 (0.99)	0.57	0.45	0.83
Anxiety and Depression index	-0.06 (0.97)	0.00 (0.98)	0.04 (1.03)	0.12	0.02	0.37
Travel Time						
Distance to Hard Skills School	1.44 (1.12)	1.47 (1.14)	1.46 (1.14)	0.47	0.64	0.79
Distance to Soft Skills School	1.18 (1.08)	1.23 (1.10)	1.24 (1.12)	0.25	0.19	0.85
F-test of joint significance				1.26	1.18	0.44
p-value				0.17	0.24	0.99
N	966	1,387	1,348			

Notes: This following table shows the means and standard deviations of baseline characteristics in columns 1 to 3. Standard deviations are shown in parentheses. Columns 4 to 6 show the p-values of pairwise mean comparisons across the groups indicated on the header titles. The bottom row reports the F-test of joint significance and its respective p-value.

Table B.3: Hard and Soft Skills Training Effects: Negotiation Outcomes Estimated with DML

		First counteroffer		Final agreement	
		Financing (log USD PPP) (1)	Start Date (log months) (2)	Down payment (log USD PPP) (3)	Start date (log months) (4)
Hard Skills	β	0.069	0.065	0.048	0.071
	se	[0.121]	[0.107]	[0.119]	[0.103]
	p -value	0.569	0.544	0.685	0.492
Soft Skills	β	0.335***	0.294***	0.300***	0.263***
	se	[0.115]	[0.105]	[0.114]	[0.102]
	p -value	0.004	0.005	0.008	0.010
Mean Control Group		5.236	0.559	5.106	0.399
p -value Hard skills = Soft skills		0.111	0.127	0.127	0.185
Observations		3,701	3,701	3,701	3,701

Notes. The coefficients reported in this table are analogous to those reported in Table 2. The dependent variables in columns 1 through 3 are binary. The point estimates and standard errors are computed using the median across splits, following the approach of Chernozhukov et al. (2018). To address multiple hypothesis testing, we apply the Romano-Wolf step-down procedure to calculate p -values, using 1,000 bootstrap repetitions for accuracy. Standard errors are reported in parentheses. Significance levels: $p < 0.1(*)$, $p < 0.05(**)$, $p < 0.01(***)$.

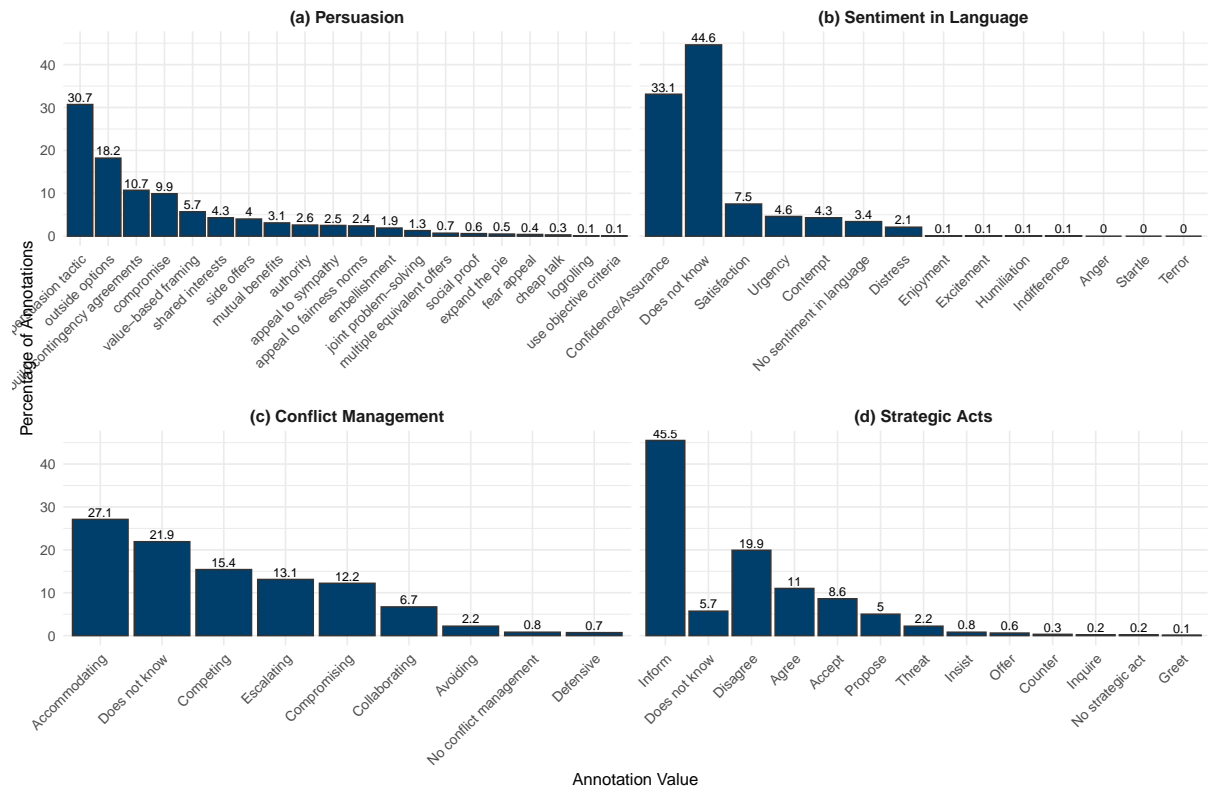
Table B.4: Hard and Soft Skills Training: Strategies Usage

		Sequential Negotiation		Split the Difference		Anderson Index (5)
		Financing (log USD PPP) (1)	Start date (log months) (2)	Financing (log USD PPP) (3)	Start date (log months) (4)	
Hard Skills	β	0.038*	0.018	-0.004	0.002	0.052
	se	[0.021]	[0.021]	[0.019]	[0.020]	[0.042]
	p -value	0.068	0.394	0.844	0.938	0.221
Soft Skills	β	0.050**	0.057***	0.007	0.015	0.117***
	se	[0.021]	[0.021]	[0.019]	[0.020]	[0.042]
	p -value	0.017	0.008	0.723	0.437	0.005
Mean Control Group		0.561	0.472	0.273	0.303	0.000
p -value Hard skills = Soft skills		0.691	0.200	0.696	0.619	0.270
Observations		3,701	3,701	3,701	3,701	3,701

Notes. The coefficients were estimated using Double Machine Learning (DML) with 5-fold cross-validation and 100 sample splits to estimate our models. The dependent variables in columns 1 through 3 are binary. The point estimates and standard errors are computed using the median across splits, following the approach of Chernozhukov et al. (2018). To address multiple hypothesis testing, we apply the Romano-Wolf step-down procedure to calculate p -values, using 1,000 bootstrap repetitions for accuracy. Standard errors are reported in parentheses. Significance levels: $p < 0.1(*)$, $p < 0.05(**)$, $p < 0.01(***)$.

B.2 Figures

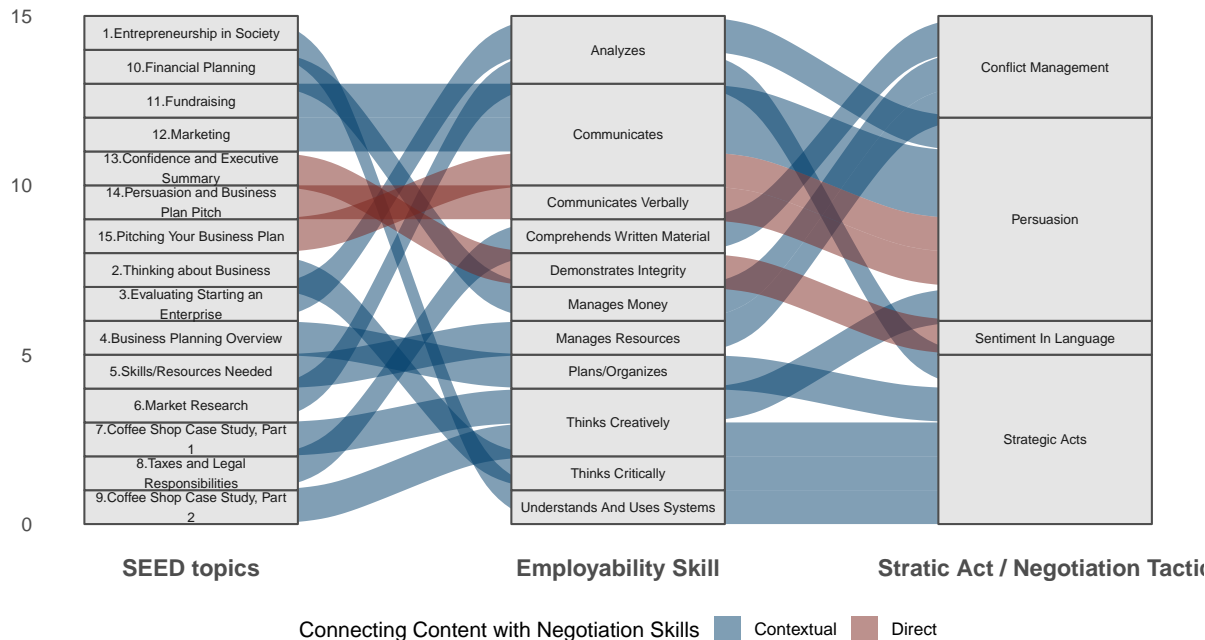
Figure B.1: Distribution of Annotation Categories Across Strategies and Tactics Categories



Notes: The graph displays the distribution of annotation categories across *strategy acts* and *tactics* that include, persuasion, sentiment in language and conflict management. The total amount of negotiation transcripts is 2,838. Percentages are calculated based on the total number of annotations within each classification.

C SEED Training Program

Figure C.1: Business Plan Curriculum — Correspondence of SEED Topics to Employability Skills and Negotiation Categories



Notes: The figure shows the mapping between topics in the business plan curriculum, the Employability Skills compiled by the Office of Career, Technical, and Adult Education (OCTAE) at the U.S. Department of Education and Negotiation Tactics (T_i). The Employability Skills taxonomy of skills is a comprehensive framework skills necessary for success in all sectors of the labor market.

Table C.1: Overview of Topics by Curriculum in SEED Program

Curriculum 1: Hard Skills	Curriculum 2: Soft Skills
<ol style="list-style-type: none"> 1. Defining Entrepreneurship 2. Self-Employment 3. Generating Business Ideas 4. Identifying Business Opportunities 5. Selecting a Suitable Market 6. Ways of Getting into Business 7. Legal Forms of Business Ownership 8. Hiring and Managing People 9. Knowing the Cost of an Enterprise 10. Money Needed to Start an Enterprise 11. Obtaining Money to Start an Enterprise 12. Managing Money 13. Investment Simulation 14. Using Financial Statements 15. Managing Sales 16. Selecting Suppliers 17. Using Technology in Small Business 	<ol style="list-style-type: none"> 1. Defining Entrepreneurship 2. Entrepreneurial Identity 3. Self-Management 4. Identifying Business Opportunities 5. Communication 6. Win-Win Judgment 7. Personal Power 8. Negotiation Simulation 9. Leadership and Team Building 10. Goal Setting 11. Decision Making Skills 12. Group Decision Making 13. Risk-Taking 14. Social Networking 15. Public Speaking 16. Formal Presentation of Business Plan 17. Using Technology in Small Business
Curriculum 3: Business Plan	
<ol style="list-style-type: none"> 1. Entrepreneurship in Society 2. Thinking about Business 3. Evaluating Starting an Enterprise 4. Business Planning Overview 5. Skills/Resources Needed 6. Market Research 7. Coffee Shop Case Study, Part 1 8. Taxes and Legal Responsibilities 9. Coffee Shop Case Study, Part 2 10. Financial Planning 11. Fundraising 12. Marketing 13. Confidence and Executive Summary 14. Persuasion and Business Plan Pitch 15. Pitching Your Business Plan 	