Annals of Operations Research
https://doi.org/10.1007/s10479-025-06711-8

ORIGINAL RESEARCH

Predicting negotiation behavior to support decision making in civil dispute resolution

Wen Zhang[1] · Jingwen Shi[2] · Xiaojun Wang[3] · Henry Wynn[4]

Received: 29 December 2022 / Accepted: 12 June 2025

Abstract
Despite the advocacy of leveraging data analytics to improve operational efficiency, there is a paucity of research on how analytical technologies afford professional service innovation and enhancement. We propose a data-driven decision support framework for civil litigation negotiation, which is a routine business activity in legal service firms. It is typically conducted in a traditional manner with the conflicting parties drawing on their past experiences and prior knowledge to guide decision-making. This model predicts human negotiation behavior based on historical records and incorporates the behavioral insights into the decision-making process. We introduce a sequential directed acyclic graph to characterize the causal relationships between offers and employ different approaches to predicting the opponent's next moves. By integrating utility analysis, each player can decide whether to accept the opponent's offer or counter back. The proposed framework is illustrated through a field experiment based on the UK MoJ Portal for handling low-cost injury claims and 88 cases with complete negotiation history. We find that better outcomes for both parties can be delivered by implementing the proposed model. The analysis result also represents convincing evidence that low-cost cases should ideally be settled out of the court via negotiation to maximize shared benefits. This paradigm could be easily generalized to other types of civil dispute resolutions negotiation to enhance both operational efficiency and service quality.

Keywords Behavior operations · Decision support systems · Negotiation · Insurance claims · Civil litigation

1 Introduction

The time and financial cost of civil litigations have been receiving growing attention in many countries. For instance, while this issue has been highlighted by the famous Woolf report (Woolf, 1995) and the more recent Jackson report (Jackson, 2010) in the United Kingdom (UK), the problem is further accentuated by the long-tail of funding cuts by the government such as the ending of legal aid for civil cases and the ongoing need for better

Extended author information available on the last page of the article

Published online: 29 July 2025

utilization and allocation of scarce legal resources at the aggregate level. In order to expedite dispute resolution processes and encourage collaborative approaches between conflicting parties to reach out-of-court settlements, several online Pre-Action Protocols have been introduced in the UK since 1998 (Justice, 2017) to provide the platform for information exchange, and the negotiation is required prior to the filing of a claim if the possibility of later cost sanctions is to be avoided.

One typical Pre-Action Protocol is the Ministry of Justice (MoJ) Road traffic accident (RTA) Portal (hereinafter referred to as Portal). Initially introduced in 2010, Portal is a "Pre-Action Protocol for Low Value (up to £25,000) Personal Injury Claims in RTA from 31 July 2013" (Justice, 2017). Portal attempts to facilitate the dispute resolution by negotiating toward attaining the ideal outcome that the defendant pays damages and costs as agreed upon by both parties before the claimant starts proceedings. Within the UK legal system, Portal probably presents the most structured environment for negotiation in resolving litigation-based disputes, with strict rules governing the timing and order of negotiation offers. The Portal process involves three stages: *Stage one*, within which the liability is investigated and evaluated; *Stage two*, where conflicting parties seek to negotiate a settlement agreement; and *Stage three*, where an oral or paper hearing will be issued if two parties cannot come to a final agreement through negotiation. A significant portion of decision-making within the Portal process occurs during *Stage two*, as highlighted with the red box in Fig. 1, and both parties need to decide whether to accept the current offer, or counter back, or leave the bargaining table in rare cases.

Negotiation conducted in Portal adopts a sequential bargaining game with both players taking turns to make their moves, and the final outcomes can be either agreements reached by the involved parties or decisions made by judges in court cases when negotiations fail. The defendant has 15 days to consider the claimant's initial offer, which is followed by 20

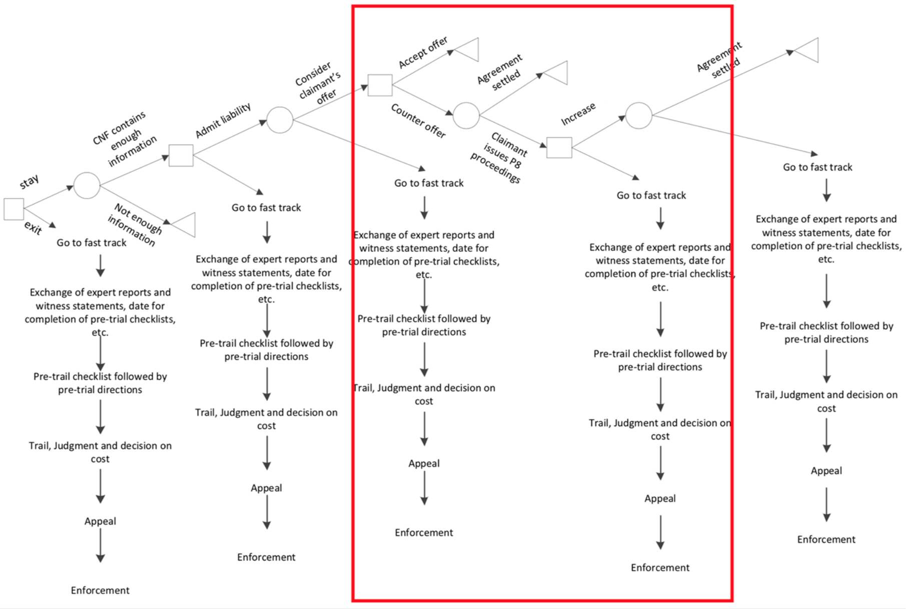


Fig. 1 MoJ RTA portal process negotiation stage decision tree

days that allow for an iterative two-way communication between the conflicting parties, yielding a rough estimate of 35 days in total. Considering the time spent evaluating current offers and deciding next moves, i.e. accepting or making a counteroffer, this time window can be interpreted as three or four rounds of negotiation, seldom exceeding six runs. In RTA cases, the scope of negotiation is usually narrowed down to two fundamental cost components: the *general cost* that is primarily associated with the claimant's injury characteristics, including type and severity, and the *special cost* that takes into account other explicit or implicit costs incurred, such as income loss, repairs cost, physiotherapy cost, etc. With the special cost largely driven by idiosyncratic factors, we focus on negotiations over the general cost and seek to exploit the predictive value of claimants' injuries to improve cost-benefit analysis and inform negotiation decision-making. Specifically, a crucial figure behind a negotiation decision is the *reserve* that indicates the resistance points where negotiators are indifferent between reaching an agreement and walking away (Walton & McKersie, 1991), in other words the minimum to accept for claimants and the maximum to pay for defendants. The negotiation is complicated by the fact that reserves are usually treated as confidential and thus both parties have to bargain under *incomplete information*. Having a good sense of opponents' reserves empowers bargainers to make more effective decisions, and one way to estimate opponents' reservation values is to learn from their previous offers.

While Portal has put a structured negotiation infrastructure in place, the negotiation itself still needs to be conducted in its traditional sense, via back-and-forth proposals. So far, lawyers still draw heavily on individual experiences and have not fully realized the benefits of the growing data availability for more efficient settlements. According to our fieldwork within a top 50 UK legal service company, lawyers are constantly questioning themselves throughout the negotiation process: "Should we accept the opponent's offer or make a counteroffer now?". Despite that Portal guides the joint efforts from both parties to avoid prolonged haggling processes (Fisher et al., 2011), the legal service community still has a long way to go in unleashing the tremendous potentials of decision science tools to inform their decision-making processes and to maximize both sides' interests, such as the utility-based perspective (Kuster, 2017).

There has been an ongoing discussion in the operation management community on how to leverage data analytics to improve the operation efficiency and service quality with the growing accessibility of big data in the recent years (McAfee, 2002; Hendricks et al., 2007; Choi et al., 2018). However, there is relatively little research about how innovative analytics approaches are changing the service industry, especially professional service (Lewis & Brown, 2012; Dobrzykowski et al., 2016), both theoretically and practically. Although alternative dispute resolution (ADR) is encouraged from the extant literature (Shavell, 1995) and our interaction with the key stakeholders in the legal service sector to avoid the costs of the issuing legal proceedings in civil disputes, there are rare applications of innovative analytics models to support legal dispute settlement. To fill this gap, this research addresses some key questions: how to unlock the data potential in civil dispute negotiation, an issue that legal service firms face on a daily basis; how to use innovative analytics models to help legal professionals make a more informed decision in a civil disputes negotiation.

To address the above questions, we propose a sequential Negotiation Decision Support Framework (Fig. 2) to enhance negotiator engagement in the Portal process or to promote utility-based decision-making by incorporating behavioral elements (Gino & Pisano, 2008; Roels & Staats, 2021). The proposed framework learns patterns by observing behavior from

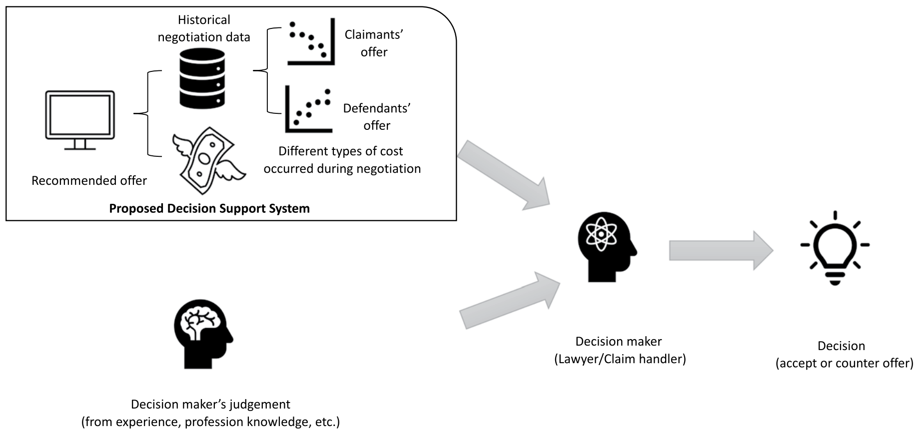


Fig. 2 Overview of the proposed decision support system in the context of legal negotiation

historical records, establishes estimates of negotiation costs, and approaches a utility-maximizing combination of choices. On the individual level, the lawyer/claim handler can then combine the system's recommendations with their own experience and expertise into final decisions for specific cases. At an organizational level, it will improve the operational efficiency as well as the service quality of legal service companies in dealing with broader civil litigation negotiation problems, especially for low-value claims which are straightforward and well suited for analytical modeling. On the societal level, the system will contribute towards meeting national objectives of reducing the amount of time and expense spent on civil litigations, including better allocation of judicial resources with smaller-value cases being settled out of courts. This study is therefore not only beneficial to the insurance or legal companies, but also to the social welfare, hence contributes to the increasing discussion of AI/data science for social good (Taddeo & Floridi, 2018; Tomašev et al., 2020).

The decision support framework consists of two parts: a Directed acyclic graph (DAG) model that characterizes the iterative exchange of proposals in historical records and a sequential decision-making process that builds on cost-utility evaluations of current situations. Overall, the paper introduces a protocol for exploiting data-driven and model-based approaches in a civil litigation context, grounding the negotiation in a behavioral model, but one within which actual decisions (offer or settle) can still be freely made. The game then amounts to Player 1 using the model to predict Player 2's future behavior, conditional on Player 1's action and vice versa. An ideal version would be for Player 1 to predict the entire future behavior, but we restrict to the prediction of the Player 2 action at the next stage only. Part of a useful protocol should be to study the transition from fixing the reserves to the first, and critical, offer and counteroffer, but this is empirically difficult to achieve in incomplete information bargaining where reserves are highly confidential. The obstacles to adopting the Bayesian estimation method in practice, the commonly adopted approach to estimating reserves (Zeng & Sycara, 1998), lie in the following constraints: lack of prior knowledge and the limited number of iterations (six to the maximum).

Therefore, this research contributes to the literature by proposing a practical data-driven sequential decision framework for negotiation under incomplete information, which takes players' behavior into account and thus overcomes the assumptions required for Bayesian-based approaches. The application of this proposed framework is demonstrated with 88 real-world portal cases with full negotiation paths collected from the partner company. We further illustrate how better negotiation outcomes could have been delivered with the system, which identifies behavioral patterns, forms reasonable predictions, and performs utility-based decision-making. Our approach facilitates more informed decision-making in litigation negotiation promoting efficient dispute resolution and effective use of legal resources, and therefore maximizing the collective benefit of the negotiation parties and reducing unnecessary and adversarial litigation at public expense.

The rest of the paper is organized as follows. Section 2 reviews the related studies, namely negotiation with incomplete information and negotiation in the legal context. Section 3 describes the formulation of the system while Sect. 4 demonstrates the practical application via a field experiment. Section 5 discusses the reserve, Bayesian learning and other related topics and Sect. 6 summarizes our main findings and potential directions for future research.

2 Literature review

As one of the three main ADR processes for settling legal disputes without litigation, negotiation (Goldberg et al., 2014) is one of the most routine activities of legal service firms. Since negotiation has been extensively studied by researchers from different areas in the past several decades (Nash, 1950; Rubinstein, 1982; Raiffa, 1982), we mainly focus on studies closely related to ours: namely negotiation with incomplete information and negotiation in the legal service context.

2.1 Negotiation with incomplete information

Most theoretical negotiation research assumes that negotiators have complete information about each other and then gives pre-computed solutions to specific problems (Rosenschein & Zlotkin, 1994). However, this perfect information assumption in many domains is not realistic, and many negotiations are conducted without complete information in practice such as the uncertainty of the opponent's reserves (Chatterjee & Samuelson, 1983). To address the issue of information unavailability, much research has been done to better understand the opponent through the negotiation history, for example to infer the opponent's utility (Nielsen & Jensen, 2004). According to Baarslag et al. (2016), there are roughly four types of methods for learning the opponent, i.e., Bayesian learning, non-linear regression, kernel density estimation, and artificial neural network. More recent work includes reinforcement learning for negotiating team formation (Bachrach et al., 2020). For comprehensive literature of negotiation with incomplete information, we refer to Baarslag et al. (2016) and Kiruthika et al. (2020).

Among the methods described above, Bayesian sequential decision is one of the most popular methods in the literature. For example, Zeng and Sycara (1998) design a sequential decision-making model capable of characterizing the opponent's reserve via Bayesian learning. Lin et al. (2008) apply the Bayes theorem to update their beliefs of the opponent's type. However, a proper prior distribution should be held to form a Bayesian learning, which is not easy in practice. What's more, in our problem, it is difficult to estimate the opponent's reserve or negotiation strategies since each party usually only has three or four opportunities to propose a new offer. Instead, the approach proposed in this study is closer to the non-linear regression approach, where the opponent's future behavior is estimated from the negotiation history, with the difference being that we predict the behavior based on the aggregate preferences drawn from similar historical records rather than the specific individual's negotiation path. The idea is in line of Cohen (2018)'s suggestions of predicting future outcomes with the great volume of available data collected by firms to inform future operational decisions. In other words, negotiation patterns derived from the study of groups will help estimate the behavioral patterns of the opponent, which is particularly suitable for the automatic processing of similar, low-valued and structured cases.

2.2 Negotiation in the legal context

Litigation can be viewed as a "bargaining under the shadow of the law", and the lawyer resolves the dispute by convincingly recommending what would happen if the court considers and decides on this issue (Mnookin & Kornhauser, 1979). The economic analysis of litigation and settlement decisions can be traced back to Landes (1971) and Gould (1973), which investigate the problem mainly from a legal perspective without explicitly modeling the bargaining process nor considering the possibility of informational asymmetry between the parties. Png (1983) and Ordover and Rubinstein (1983) thereby provide several bargaining models of settlement decisions in the presence of asymmetric information. Bebchuk (1984) argues that the strict assumption held by these models that parties are not free to choose their settlement terms presents some limitations. He therefore proposes a model in which parties are free to determine the size of their settlement offers.

Nonetheless, in Bebchuk (1984)'s model, the claimant knows the actual harm while the defendant knows only the probability distribution of possible harm, which cannot properly represent the concept of *incomplete information*. In practice, the actual harm in this type of claim is estimated from the doctor's opinion (or that of another relevant expert) which is (1) usually a range rather than an accurate number that is known exactly by either party and (2) not authoritative, in that a judge in a subsequent hearing may diverge from the estimated value. A more practical definition of *incomplete information* could be the "reserve" of each party as discussed before. Therefore, to understand and approach the opponent's reserve, it seems natural to spend time on negotiating to reveal more information. However, this assumption may not always be true due to different situations or the high cost of information discovery (Bone, 2003). For detailed economic analysis of legal procedure, see Cooter and Rubinfeld (1994) and Bone (2003). Thus, how to negotiate by efficiently utilizing available information, either from estimating the opponent's reserve or employing other proxy methods, has not been fully exploited.

Computer scientists have also shown great interest in analyzing and resolving legal disputes via negotiation, and these systems are usually categorized as Negotiation Support Systems (NSS)s. Depending on different negotiation theories, NSSs can be developed based on rules reasoning, cases reasoning and so forth (Zeleznikow, 2021). Carneiro et al. (2013) establish the UMCourt that attempts to explore the potential of the combined use of different technologies such as case-based reasoning and multi-agent system to solve legal disputes in the context of the Portuguese labor law. Zeleznikow (2021) provides an extensive state-of-the-art survey of NSSs. Nevertheless, most existing research is theoretical and few of them really "make the move from the laboratory to the world of user" (Leith, 2016). Hence, we believe it is valuable to analyze practical data and develop an applicable paradigm that satisfies needs and desires of legal practitioners.

3 Methodology

3.1 Mathematical formulation

Assuming constant reserve for the sake of simplification, we let $R^{(c)}$ denote the claimant's reserve, and x_s denote her offer at the negotiation stage *s*; similarly, the defendant's reserve and offer are given by $R^{(d)}$ and y_s, respectively. We further assume $R^{(d)} > R^{(c)}$ to ensure the existence of a zone of possible agreement (ZOPA) (Raiffa, 1982), as graphically depicted in Fig. 3. At each negotiation stage *s*, both parties establish bottom lines (i.e. reserves) that signify the worst acceptable outcomes, the minimal amount to accept for claimants and the maximum amount to pay for defendants, while attempting to benefit as much as possible from negotiations. Accordingly, the reserve figures are determined in advance of discussions based on their respective anticipation of the case's general cost using the information set available at time *t*, while the actual offers at each stage tend to be more ambitious, higher than reserves for claimants and lower for defendants. The negotiation will not proceed further when either side pushes too much at the negotiating table, such as claimants asking higher than the defendants' bottom lines and vice versa.

Since the claimant takes the first move by making claims, we naturally assume that her first offer x_1 reflects various considerations that combine her most optimistic expectation, the room for concessions, and her bottom line $R^{(c)}$. As illustrated in Fig. 4, if x_1 is not accepted, the defendant re-offers it with a counter-offer of y_2 based on his own reserve $R^{(d)}$ and his estimates $\hat{R}_1^{(c)}$ of the claimant's reserve $R^{(c)}$ based on the updated information set expanded by the extra variables x_1, signaling the negotiation stage $s = 2$. In practice, we observe substantial gaps between x_1 and y_2, which leaves a wide negotiation space except in cases where y_2 drops below the walkaway positions of claimants $R^{(c)}$. In subsequent rounds before settlement, as exemplified in stage $s = 3$ in Fig. 4, both parties make counter-offers drawing on insights from the realized negotiation path and their own reserves while

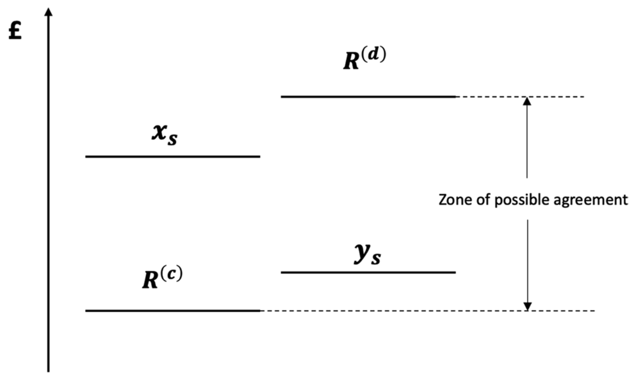


Fig. 3 Relationship among $R^{(c)}$, x_s, $R^{(d)}$ and y_s at stage *s*

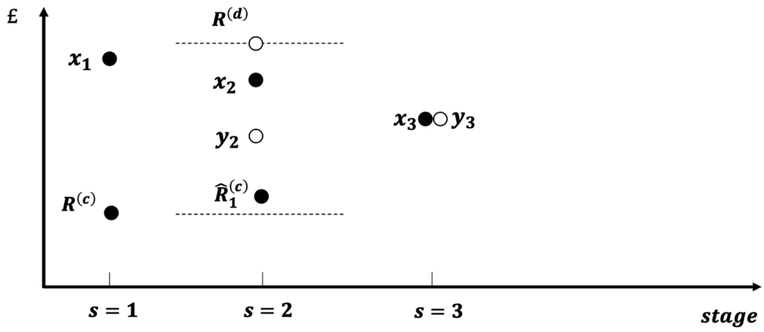
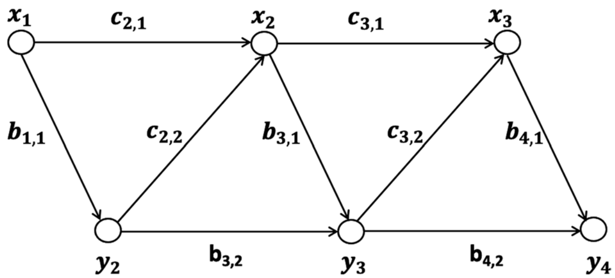


Fig. 4 Negotiation example

Fig. 5 Negotiation DAG



attempting to guess their counterpart's bottom lines to make a more "effective" offer that approaches their opponents' reserves without violating them.

3.2 Prediction

Our proposed negotiation flow involves two fundamental components: the prediction of negotiation behavior and decision-making support. Understanding and anticipating the behavioral patterns of specific opponents would be difficult in the absence of track records. However, this cognitive process can be performed at the group level rather than at the individual level. With the increasing availability of data, participants can weave together data records from multiple cases in similar negotiation situations to identify and exploit behavioral patterns. Further accounting for the stage of negotiation allows greater accuracy in behavior recognition as negotiators may respond differently across negotiation phases (Faratin et al., 1998; Cao et al., 2015). To put it into practice, both parties can integrate the well-learned knowledge to better estimate the opponent's moves and/or counteroffers based on the realized negotiation path. Figure 5 summarizes the model with a DAG and illustrates how both parties' counteroffers are linked to the negotiation path, for example, their previous offers plus their opponent's latest offer, with b and c specifying the weighting for each of the decision drivers. Further, to highlight the sequential nature of the negotiation process, the different phases can be marked by either the physical time t or the negotiation stage s, as depicted in Fig. 6.

To be more specific, the negotiation behavior consists of the accept/reject decision and the proposing of counter-offers in rejection scenarios. Negotiation participants can refer to

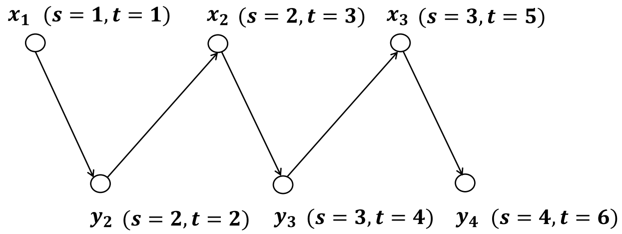


Fig. 6 Sequential DAG

historical records at the corresponding stage s to evaluate the acceptance rate P_s of the candidate counter-offer figures under consideration. Following the essence of the Markov process, we illustrate the implementation assuming that $P_{i,s}$ of a specific case i is determined by his/her counter-offer to make $p_{i,s}$, the opponent's latest offer $q_{i,s}$, and the estimated true cost z_i, which can be calculated with the logistic regression:

$$P_{i,s} = \frac{e^{\phi_0+\phi_1 p_{i,s}+\phi_2 q_{i,s}+\phi_3 z_i}}{1+e^{\phi_0+\phi_1 p_{i,s}+\phi_2 q_{i,s}+\phi_3 z_i}}, \tag{1}$$

where ϕ_0, ϕ_1, ϕ_2, ϕ_3 are regression coefficients

3.3 Utility-based decision making

Negotiation is not frictionless as costs will be incurred; players in this game are *impatient* (Fatima et al., 2014) as they have to balance incremental costs against the incremental benefits of a lengthy negotiation process. Adopting a conventional utility-based approach, both parties seek to maximize their utility, the most straightforward approximations of which are the expected compensation net of costs for claimants and the negative of total payments including case compensation and various costs incurred during the process. Despite the complexity of accurately identifying all occurrences of costs in practice, various costs can be categorized into three types: fixed costs C^f paid by defendants that are constant irrespective of the trial result (about £500 on average in this case study according to the fieldwork), time-dependent costs C_t that accumulate over time $C_t = f(t)$, and result-dependent costs C^r beared by the unsuccessful party (around £800).

To keep costs down, disputes ideally should end in settlement or compromise before being taken to court proceedings. If a quick resolution is not achieved, the court becomes involved and reaches its verdict by considering the evidence, primarily the medical report in the road accident dispute cases, and both parties' first offers, the only available offers to the court. In our general cost injury case, the defendant wins when the trial decision exceeds the defendant's first offer, the probability of which P^d can be predicted with logistic regression given that the court decision is binary in nature. In real-world cases, as shown in Fig. 14, notable discrepancies between court decisions and defendants' expectations are empirically observed, marked by low values of P^d. To account for the impact of both parties' first offers $x_{i,1}$, $y_{i,2}$ and the court decision z_i proxied by the model-implied intrinsic injury cost on the winning probability P^d, similar with $P_{i,s}$, P^d can be expressed as

$$P^d = \frac{e^{\theta_0+\theta_1 x_{i,1}+\theta_2 y_{i,2}+\theta_3 z_i}}{1+e^{\theta_0+\theta_1 x_{i,1}+\theta_2 y_{i,2}+\theta_3 z_i}}, \tag{2}$$

where θ_0, θ_1, θ_2, θ_3 are regression coefficients

Let U denote the utility function that quantifies the payoff for each party, where E(U) represents its expected value. For claimants, the utility function U^c measures the net benefit considering compensation received minus costs incurred, while for defendants, U^d represents the negative of total payments including compensation and costs. Assuming that we are dealing with *N* full rounds of negotiations that begin from the claimants' asking and end with defendants' offerings, following which the claimant will decide whether to accept the final offer or not. Adopting a utility-based analytical framework, we can evaluate their utilities at stage *s* ($s = 1 \ldots N$) and time *t* ($t = 1 \ldots 2N$) after incorporating the cost considerations and apply backward induction reasoning to guide decision-making in each iteration, as explained below. In the last round of offer proposals *N*, both parties' decisions are affected by their anticipation of the judge's perception. After the final offer from the defendant has been extended, the claimant evaluates her expected utility at stage $s = N + 1$ and time $t = 2N + 1$ to make the final "Accept or Court" decision:

$$\mathbb{E}(U^c_{N+1}) = \begin{cases} \mathbb{E}(y_N) - C_{2N} := \mathbb{E}(U^c_{N+1,1}), & \text{Accept } y_N, \\ G - C_{2N} - \mathbb{E}(C^{c,r}) := \mathbb{E}(U^c_{N+1,2}), & \text{Reject } y_N \text{ and go to court,} \end{cases} \tag{3}$$

where G represents the expected court decision and $\mathbb{E}(C^{c,r})$ denotes the cost dependent on the expected result of the claimant. While both parties can estimate the expected court decision based on medical reports and similar historical cases, their estimates may differ due to information asymmetry and different interpretations of available evidence. Therefore, if $\mathbb{E}(U^c_{N+1,1}) > \mathbb{E}(U^c_{N+1,2})$, where $\mathbb{E}(\cdot)$ denotes the expected value operator, that is, $G < y_N + \mathbb{E}(C^{c,r})$, the claimant should accept y_N.

Similarly, taking one further step backward, the expected utility function for the defendant at stage $s = N$, $t = 2N$ is given by

$$\mathbb{E}(U^d_N) = \begin{cases} -(x_N + C_{2N-1} + C^f) := \mathbb{E}(U^d_{N,1}), & \text{Accept } x_N, \\ -[P_N \cdot (y_N + C_{2N} + C^f) + (1-P_N)\cdot(G + C_{2N} + C^f + \mathbb{E}(C^{d,r}))] := \mathbb{E}(U^d_{N,2}), & \text{Counter with } y_N, \end{cases} \tag{4}$$

where P_N is the probability that the claimant will accept y_N. When $\mathbb{E}(U^d_{N,1}) > \mathbb{E}(U^d_{N,2})$, i.e. $G > \frac{x_N - m - (1-P_N)\mathbb{E}(C^{d,r}) - P_N y_N}{1-P_N}$, she should accept x_N. The defendant's decision at this step relies on the predictive tool, which uses trained regression models to estimate P_N based on historical patterns. These probability estimates help evaluate the expected utilities of two options: accepting x_N immediately or making a counter-offer y_N. Moving further backward, the utility for the claimant at $t = 2N - 1$ is

$$\mathbb{E}(U^c_N) = \begin{cases} y_{N-1} - C_{2N-1} := \mathbb{E}(U^c_{N,1}), & \text{Accept } y_{N-1}, \\ P_N \cdot (x_N - C_{2N}) + (1-P_N)\cdot \mathbb{E}(U^c_{N+1}) := \mathbb{E}(U^c_{N,2}), & \text{Counter with } x_N. \end{cases} \tag{5}$$

Similar analysis applies when $s = N - 1$ with U^d_{N-1} for the defendant

$$\mathbb{E}(U^d_{N-1}) = \begin{cases} -(x_{N-1} + C_{2N-2} + C^f) := \mathbb{E}(U^d_{N-1,1}), & \text{Accept } x_{N-1}, \\ -[P_{N-1} \cdot (y_{N-1} + C_{2N-1} + C^f) + (1 - P_{N-1}) \cdot \mathbb{E}(U^d_N)] := \mathbb{E}(U^d_{N,2}), & \text{Counter with } y_{N-1}, \end{cases} \tag{6}$$

and U^c_{N-1} for the claimant

$$\mathbb{E}(U^c_{N-1}) = \begin{cases} y_{N-2} - C_{2N-3} := \mathbb{E}(U^c_{N-1,1}), & \text{Accept } y_{N-2}, \\ P_{N-1} \cdot (x_{N-1} - C_{2N-2}) + (1 - P_{N-1}) \cdot \mathbb{E}(U^c_N) := \mathbb{E}(U^c_{N-1,2}), & \text{Counter with } x_{N-1}. \end{cases} \tag{7}$$

4 Field experiment

In this section, we seek to investigate the practical implications of our proposed prototype and explore how the real world cases, either balanced or imbalanced, can be harnessed to generate insights. Portal process is chosen due to its structured format of negotiation in litigation-based dispute resolution mechanism, which means similar results can be relatively easily replicated.

4.1 Background

Negotiation conducted in the Portal is a sequential process within which the claimant and the defendant will make an offer in turn and each party will have three or four opportunities to make an offer. There are four possible results at the end of a negotiation as shown in Fig. 7:

1. Claimant and defendant reach an agreement by the end of *Stage two*.
2. Claimant and defendant fail to reach agreements at *Stage two*, and the judge's final decision is lower than the defendant's final offer after court.
3. Claimant and defendant go to court, and the judge's final decision is between two the parties' final offer at *Stage two*.
4. The judge's final decision is higher than the claimant's final offer after trial.

From the defendant's point of view, result 1 and 2 are preferred as they will lead to lower cost compared with result 3 and 4, while which one is better requires weighing the final

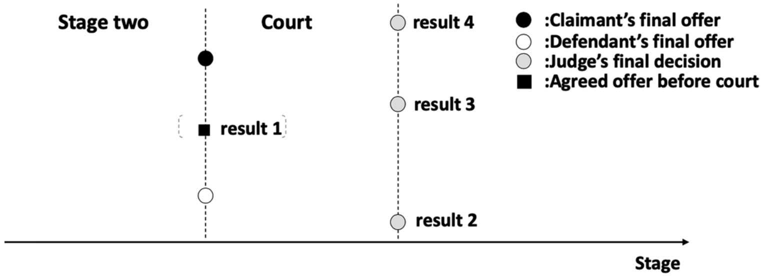


Fig. 7 Possible results of Portal negotiation process

verdict plus trial cost against the agreed offer of result 1. Result 3 is the most common result when two parties go to court hence is regarded as a neutral result to the defendant, which is worse than result 2. The outcome that appeals least to the defendant is result 4, under which situation the defendant will pay not only more compensation compared with accepting the claimant's offer during the negotiation but also issue fees and other overheads incurred along with certain penalties. In short, the defendant pays differently for different outcomes and his ultimate goal is to minimize the payment, and a similar analysis applies to the claimant.

4.2 Tests on case data

To investigate the negotiation pattern and validate the proposed negotiation support model, 88 cases with full negotiation paths and final court decisions are collected within a UK legal service firm from 2018 to 2020 (data in the legal service with highly confidential information is difficult to obtain). Figures 8 and 9 visualize the claimants' and defendants' conduct by displaying the offers they made (y-axis) at each stage (x-axis). Not surprisingly, both parties make compromises for the majority of time with claimants lowering expectations and defendants increasing counteroffers before reaching a settlement. The length of iterations, i.e. the x-axis range, varies across cases and is often influenced by the time spent on each round within the negotiation time window (35 days in this case).

Adopting the DAG negotiation model shown in Fig. 5, we assume that the defendant's first counter-off at $s = 2$ would be influenced to a certain degree by the claimant's first offer even in the absence of an immediate agreement. Both the graphical representation in Fig. 10, which displays the defendant's first offer against the claimant's first offer, and the simple linear regression in Table 1,which reveals the statistical significance of the relationship, lend empirical support to the argument (Fig. 11). Examining the Residuals versus Fits plot, as shown in Fig. 12, further detects the presence of nonlinearity. This could be attributed to the fact that only one observation is available to the claimant to base his judgment on at this stage, which might lead to claimants' first counter-offers varying significantly across cases.

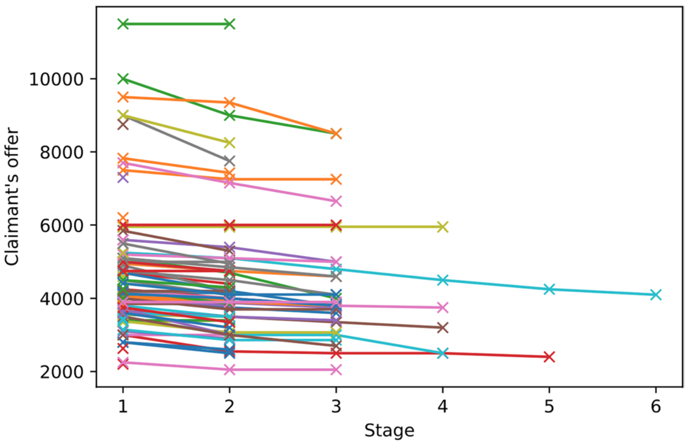


Fig. 8 Claimant's offer for general cost records

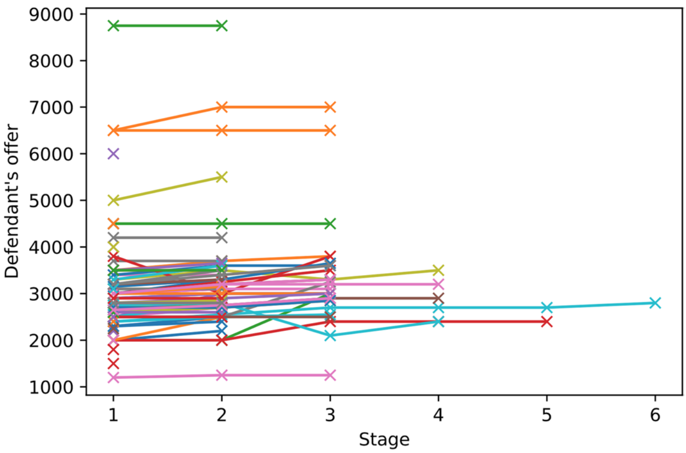


Fig. 9 Defendant's offer for general cost records

Fig. 10 Relationship between the defendant's first offer and the claimant's first offer

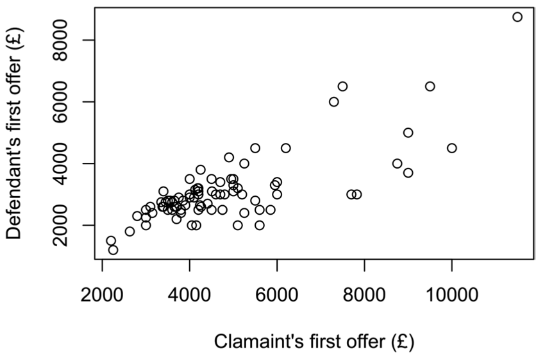


Table 1 Simple linear regression of the defendant's first offer on the claimant's first offer

Variable	Coefficient	t value	Pr(> |t|)
Intercept	817.89	3.78	0.00***
Claimant's first offer	0.48	11.09	< 2.2e−16***

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

Common non-linear models such as cubic splines including B-Splines and natural splines, as well as quadratic functions, can be employed to characterize the non-linear associations, as demonstrated in Fig. 13 that displays the fitting of different models versus the plain linear regression and Table 2 that quantifies the model performance. As implied in Fig. 13, the relationship seems to change around £6,000 and £8,000 and knots in B-splines and natural splines models are specified to reflect the locality.

As shown in Table 2, B-splines with the baseline interior knot (default to the median) and with the specified knots (£6,000 and £8,000) outperform the other models, exhibiting lower AIC (Akaike Information Criterion) (Akaike, 1974) and BIC (Bayesian Information Criterion) (Schwarz, 1978) values, which assess model performance by balancing goodness of fit with model complexity, as well as higher R^2 values, both adjusted and unadjusted. Combing

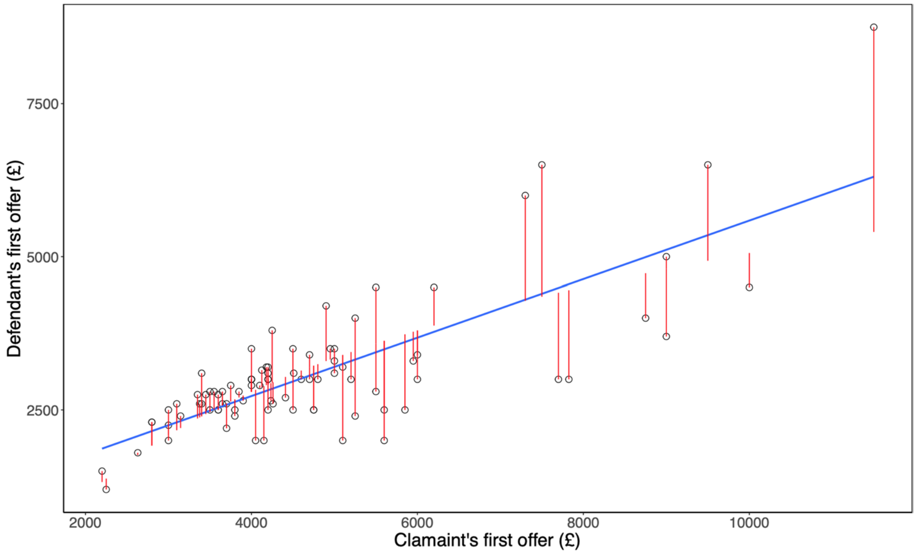


Fig. 11 Simple linear regression of the defendant's first offer on the claimant's first offer

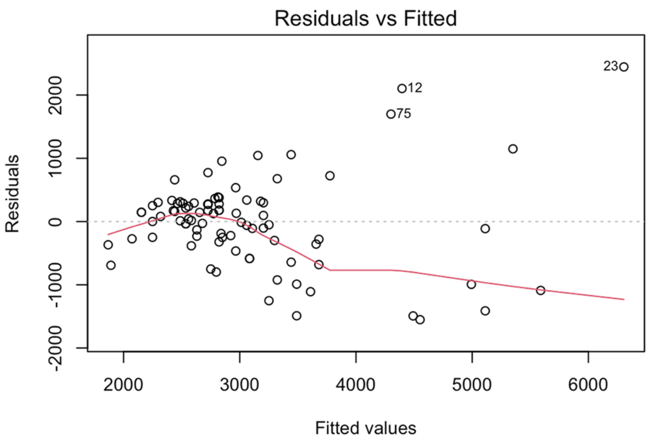


Fig. 12 Residuals versus Fits plot of defendant's first offer and the claimant's first offer

these performance evaluation metrics, we select the B-spline with specified knots on the basis of its lowest AIC and RMSE (Root Mean Squared Error) as well as highest R^2 values. In practical applications, expert knowledge can be exploited to locate these pre-specified interior knots to better account for the bargaining styles of negotiators. Accordingly, the model to predict the defendant's first offer y_2 based on the information set at stage $s = 2$ from the claimant's perspective i is

$$y_{i,s} = \sum_{k=1}^{K+d+1} \beta_k B_k^d(x_{i,s-1}), \tag{8}$$

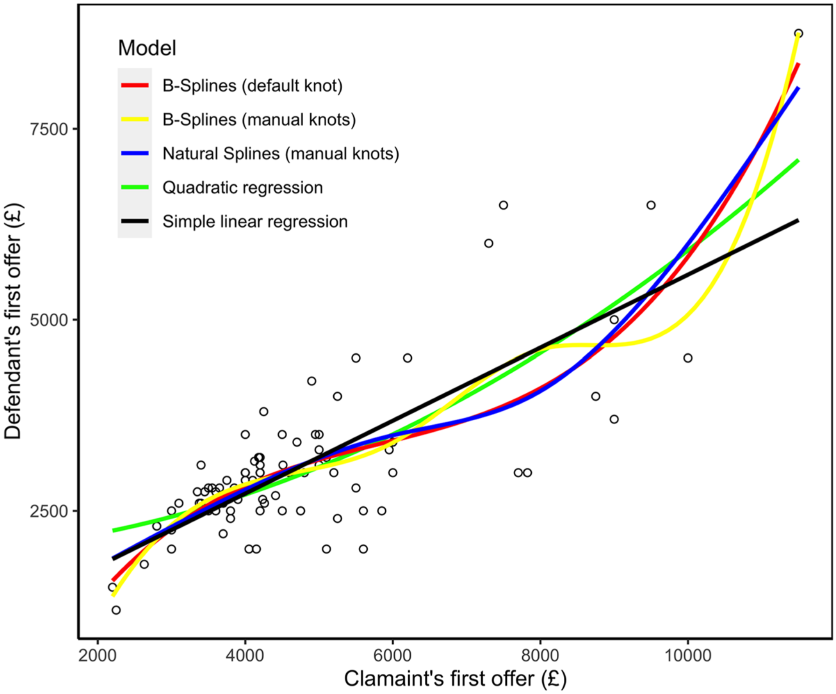


Fig. 13 Different non-linear models of the defendant's first offer and the claimant's first offer compared with linear regression

Table 2 Non-linear model performance comparison

Model	AIC	BIC	R^2	R^2 (adj.)	RMSE
B-splines (baseline)	1395.68	1408.07	0.65	0.64	635.39
B-splines (specified knots)	1393.33	1410.67	0.68	0.66	612.86
Natural splines (specified knots)	1399.82	1412.21	0.64	0.63	650.53
Quadratic function	1404.70	1414.61	0.61	0.60	676.44

Table 3 B-spline regression results for predicting defendant's first offer from claimant's first offer

Variable	Intercept	bs1	bs2	bs3	bs4	bs5
coefficient	1379.9	1965.7	1032.1	4281.4	2235.7	7380.9
t-value	3.734^{***}	2.851^{**}	2.230^{*}	4.912^{***}	2.252^{*}	10.040^{***}

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

where $B_k^d(x_{i,s-1})$ denote the B-spline basis functions of degree d ($d = 3$) based on K knots ($K = 4$ in our model) with corresponding spline coefficient β_k, with $i = 1, ..., n$ referring to each of the sample case $n = 88$ in this research. Table 3 reports the estimate model parameters $\hat{\beta}_k$, based on which we project the model-implied offer value $\hat{y}_{i,s} = \sum_{k=1}^{K+d+1} \hat{\beta}_k B_k^d(x_{i,s-1})$.

From the claimant's viewpoint, the information set expands with the arrival of the latest offer from her counter-party while her response will likely influence the decision-making of her opponent at the next stage. As indicated by Figs. 8 and 9, when countering back and forth, both parties display reluctance to deviate from their own latest expectations while making compromises towards their opponents' offers. To understand the role played by these two elements, we perform similar data visualization as in the first step and seek to characterize the relationships using multiple linear regressions. To be more specific, the defendant's offer at stage $s(s > 2)$ based on current information set in case *i* is given by

$$y_{i,s} = b_{s,0} + b_{s,1}x_{i,s-1} + b_{s,2}y_{i,s-1} + \epsilon_{i,s}, \quad i = 1, \cdots, 88. \tag{9}$$

Similarly, when the defendant's counter-off comes out, it can be fed into the regression to predict the claimant's offer at $s(s > 1)$

$$x_{i,s} = c_{s,0} + c_{s,1}x_{i,s-1} + c_{s,2}y_{i,s} + \epsilon_{i,s}, \quad i = 1, \cdots, 88. \tag{10}$$

Table 4 reports the performance of the one-step-ahead predictive regressions at different stages. According to the coefficients, offers from both parties at the second round are predominantly driven by their own latest offers, as marked by the coefficients over 90%, which reveals the stickiness of their counteroffers and reluctance to compromise much at early stages of negotiation. The reluctance fades only to a limited extent as time evolves, as indicated by the 6% (95–89%) reduction in the regression coefficients when predicting the defendant's counteroffers, which suggests the defendant's intention to settle when the negotiation period has to come to an end.

To measure the prediction performance of models described above, we calculate the predicted R^2, Mean Absolute Error (MAE) and RMSE with Leave One Out Cross Validation (LOOCV). Results in Table 5 show that prediction works reasonably well with a high predicted R^2 value except for the first model, which predicts y_2 via a B-spline model with two specified interior knots. The inferior performance stems from the difficulty of predicting y_2 solely based on x_1 in the absence of information about defendants' preferences, while the other prediction models derive insights from both claimants' and defendants' preferences.

Table 4 Summary of linear regression results for the claimant's and defendant's offers at different stages

Dependent variable	Independent variable	Coefficient	Coefficient value
Claimant's second offer	Constant	$\hat{c}_{2,0}$	−105.61
	Claimant's first offer	$\hat{c}_{2,1}$	0.90^{***}
	Defendant's first offer	$\hat{c}_{2,2}$	0.11^{***}
Defendant's second offer	Constant	$\hat{b}_{3,0}$	77.90
	Claimant's second offer	$\hat{b}_{3,1}$	0.04
	Defendant's first offer	$\hat{b}_{3,2}$	0.95^{***}
Claimant's third offer	Constant	$\hat{c}_{3,0}$	88.65
	Claimant's second offer	$\hat{c}_{3,1}$	0.89^{***}
	Defendant's second offer	$\hat{c}_{3,2}$	0.07
Defendant's third offer	Constant	$\hat{b}_{4,0}$	296.65
	Claimant's third offer	$\hat{b}_{4,1}$	0.04
	Defendant's second offer	$\hat{b}_{4,2}$	0.89^{***}

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $.p < 0.1$

Table 5 Prediction performance of different models

Model	R^2	MAE	RMSE
Defendant's first offer prediction	0.57	475.84	724.17
Claimant's second offer prediction	0.98	185.51	239.10
Defendant's second offer prediction	0.97	125.38	182.28
Claimant's third offer prediction	0.98	146.43	217.58
Defendant's third offer prediction	0.91	209.52	313.64
Claimant's third offer prediction	0.98	145.01	211.60

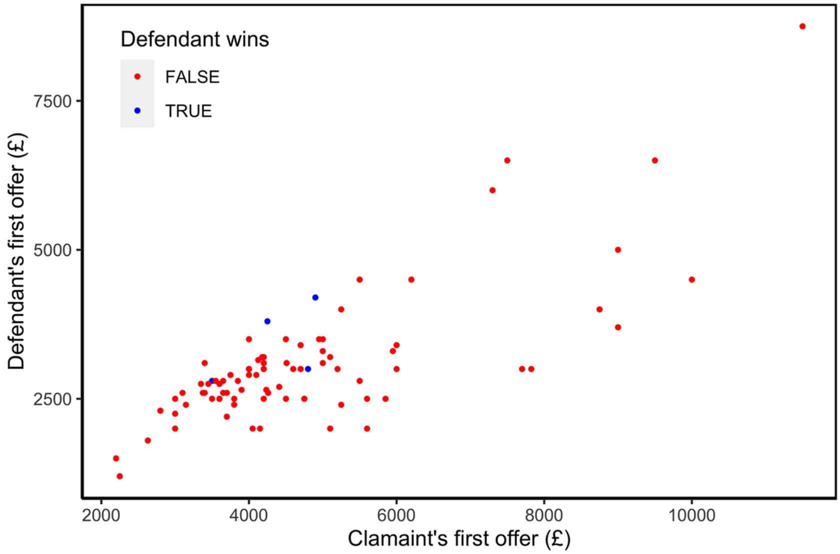


Fig. 14 Cases that the defendant wins versus the claimant wins

Should some prior information on defendants' preferences be accessible, the predictability will be further enhanced.

As neither party accepted the other's offer in all the cases, we are not able to train $P_{i,s}$ for utility analysis. Instead, we try to overcome this limitation with scenario analysis in the next section while we believe extra valuable insights will be gained when a more balanced data set is available. Next, to predict P_d, although the data set is quite imbalanced as Fig. 14 demonstrated, we tend to train the classification model without resampling to build a more balanced data set because in most situations, the judge's decision is between the claimant and the defendant offer, i.e., the defendant will pay C^r, according to lawyers' opinions. In other words, the model trained from an artificial balanced data set may be misleading by providing a fake higher P^d.

The regression result presented in Table 6 indicates that the defendant's offer is the most significant variable compared with the others. This is reasonable since it is mainly the defendant's decision rather than the claimant's that affects whether the defendant's offer is lower or higher than the judge's decision. With the probability P^d trained by historical data, $C^{d,r}$, the result-dependent cost paid by the defendant is calculated as $C^r(1 - P^d)$, i.e., the cost paid by the defendant if his offer is defeated; and $C^{c,r}$, the result-dependent cost paid by the claimant is calculated as $C^r P^d$, i.e., the cost paid by the claimant if her offer is beaten. Note

Table 6 Logistic regression for P^d

Variable	Intercept	claimant's first offer	defendant's first offer	predicted injury cost
coefficient	0.7182	-0.0099	0.0029	-0.0024
z-value	0.309	-1.324	2.541	-2.020
p-value	0.7572	0.1857	0.0110*	0.0434*

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$,. $p < 0.1$

that the result-dependent cost is affected by both parties' first offer, rather than the final offer by the end of the negotiation, which means in practice, the judge would expect that reasonable offers are proposed by both sides from the start. Unreasonable offers will increase the probability of penalties and other additional costs.

4.3 Scenario analysis

Since the data set in this field experiment is imbalanced with all cases unsettled, to illustrate how the proposed model can facilitate decision-making under a more generalized condition, we extend the analysis with 87 cases (one high-cost case with permanent injury is removed due to the incapability of predicting true cost) and artificial offers for a typical three-stage negotiation with six decision-makings in total. Specifically, we adopt the initial offer made by the claimant and predict the opponent's next offer with the regression models if one party's current offer is rejected. Due to the absence of data on accepted offers, we assume that the probability of the opponent accepting the current offer varies with time, i.e. the closer to the deadline, the higher the acceptance probability, by assuming $P_s = \gamma_s \frac{y_s}{x_s}$ where $\gamma_s = 0.3, 0.4, 0.5$ for $s = 1, 2, 3$. To simulate a more general negotiation process, inspired by the coefficients from the true negotiation records listed in Table 4 and the experts' opinions, we assume that the claimant/defendant's counter offer could be 15%, 10% or 5% higher/lower than the defendant/claimant's current offer, given the true record is not available. Finally, the negotiation cost (specifically, we assume the time-dependent cost C_t is $f(t) = 50t + 50$ in this analysis based on real cost) are included in the utility analysis.

Under the above assumptions, Table 7 demonstrates how the negotiator should counter or accept the opponent's current offer in different scenarios. For convenience, we denote defendant's decision at t under scenario S as D_t^S and claimant's as C_t^S. Especially, the claimant's decision at $t = 6$ will be either accepting the defendant's offer or rejecting it without being able to propose a new offer since this is the last decision both parties can make during the negotiation. It can be observed that as the deadline approaches, the number of cases where decision makers should accept the opponent's offer rather than countering back is increasing. This is in stark contrast to both sides' decisions during the initial negotiation rounds where parties prefer countering rather than accepting out of the belief that countering will bring higher benefits.

This scenario analysis explains why parties are reluctant to accept offers in reality, i.e. they *believe* countering will bring larger economic gains. However, what is overlooked by decision-makers in reality, at least in these 87 cases, is that accepting offers earlier during the negotiation may actually yield higher utilities. For instance, as shown in Table 8, the utility for the claimant to accept the defendant's offer earlier is always higher than later in

Table 7 Decision making at different t in different scenarios

Defendant's decision at t	Reject and counter	Accept	Claimant's Decision at t	Reject and counter	Accept
D_1^1	87	0	C_2^1	87	0
D_1^2	87	0	C_2^2	87	0
D_1^3	87	0	C_2^3	87	0
D_3^1	87	0	C_4^1	87	0
D_3^2	85	2	C_4^2	87	0
D_3^3	79	8	C_4^3	74	13
D_5^1	39	48	C_6^1	23	64
D_5^2	45	42	C_6^2	8	79
D_5^3	40	47	C_6^3	1	86

Table 8 Decision making at different t in different scenarios

Defendent(Def.)'s decision at t	Claimant(CLMT)'s utility	Def.'s utility	CLMT's decision at t	CLMT's utility	Def.'s utility
$D_1^1 = \text{Accept}$(same for all SCNs)	4545.38	−5245.38	$C_2^1 = \text{Accept}$	3798.57	−4598.57
$D_3^1 = \text{Accept}$	4340.86	−5240.86	$C_2^2 = \text{Accept}$	4030.84	−4830.84
$D_3^2 = \text{Accept}$	4398.93	−5298.93	$C_2^3 = \text{Accept}$	4263.11	−5063.11
$D_3^3 = \text{Accept}$	4433.77	−5333.77	$C_4^1 = \text{Accept}$	3787.42	−4787.42
$D_5^1 = \text{Accept}$	4165.34	−5265.35	$C_4^2 = \text{Accept}$	3972.65	−4972.65
$D_5^2 = \text{Accept}$	4261.30	−5361.29	$C_4^3 = \text{Accept}$	4174.14	−5174.14
$D_5^3 = \text{Accept}$	4323.29	−5423.29	$C_6^1 = \text{Accept}$	3751.61	−4951.61
–	–	–	$C_6^2 = \text{Accept}$	3906.52	−5106.52
–	–	–	$C_6^3 = \text{Accept}$	4084.10	−5284.10
–	–	–	$C_6 = Reject$	3384.00	−5384.00

all of the three scenarios; while it may not be the best choice for the defendant to accept the claimant's first offer immediately, he should accept the offer after one round of negotiation rather than keeping countering. Further, regardless of scenarios, settling via negotiation yields higher utilities for both parties than going to court in most cases under the same cost assumption, except for the situation that the defendant accepts an offer at $t = 5$ in scenario three. The reason for the slightly lower utility for the defendant to accept the offer at $t = 5$ in scenario three is that both sides are reluctant to concede under this scenario and benefits brought by negotiation are not significant.

In summary, the scenario analysis reveals that an early negotiated settlement is more beneficial to both parties than ongoing negotiation, and even more so than going to court. Therefore, we argue that by implementing the proposed predicting and utility analysis, the negotiation will be conducted more rationally, which may lead to an earlier settlement. In this way, the claimant's compensation will be paid in time, which is important in the legal realm since "*Justice delayed is justice denied*".

5 Discussion

5.1 Reserve and Bayesian learning

Reserves are important in the negotiation since both parties cannot offer beyond each other's reserve and either party is able to opt out of the negotiation if this rule is violated as Fig. 3 depicts. Both players therefore should provide reasonable offers if they want to continue negotiating, which can also be reflected from Eqs. (9) and (10) as each party can drag the next turn's offer arbitrarily by changing their own offer at the current stage if there is no constraint. We can form a simple linear relationship between the reserve and offers from both parties. When $s \geqslant 2$, the claimant's offer is affected by her own reserve and her estimation of the defendant's reserve

$$x_{i,s} = \alpha R_i^{(c)} + (1-\alpha)\hat{R}_{i,s}^{(d)}; \tag{11}$$

where $0 < \alpha < 1$. Similarly, when $s \geqslant 2$, the defendant's offer is affected by her own reserve and her estimation of the claimant's reserve in the previous round

$$y_{i,s} = \beta R_i^{(d)} + (1-\beta)\hat{R}_{i,s-1}^{(c)}; \tag{12}$$

where $0 < \beta < 1$. Here, α and β denote how much each party is willing to gain from this negotiation. The higher α and β are, the less willing they are to concede. Since Bayesian learning is one of the most studied learning techniques in automatic negotiation to understand the opponent's reserve, we demonstrate below how Bayesian learning can be implemented in our problem.

In line with Figs. 8 and 15 demonstrates that the claimant's final offer is usually slightly lower than her first offer, and the average rate of difference is around 7%. Without further information, it is reasonable to assume that the final offer represents the claimant's bottom line to a certain extent. We can therefore form a priori that claimants will firstly make an offer that is 7% higher than their reserve, and the defendant can update his knowledge of the claimant through Bayesian learning. Figure 16, on the other hand, displays the relationship

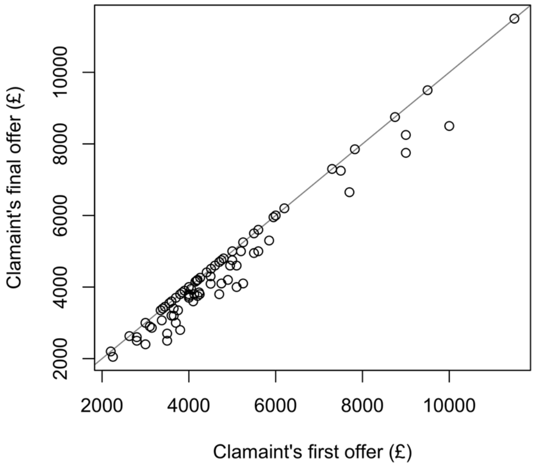


Fig. 15 Relationship between the claimant's first and final offer (with 45-degree line)

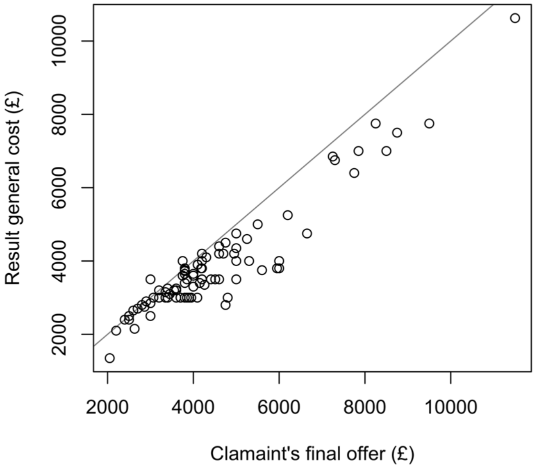


Fig. 16 Relationship between the claimant's final offer and the result general cost (with 45-degree line)

between the claimant's final offer and the result general cost after court, which shows that the claimant's final offer is about 20% higher than the result on average. Combining the views that the result after trial reveals the actual value of general cost and the claimants' final offer is the lowest value that they are willing to accept in order to reach an agreement, the prior knowledge will be "claimant's reserve is about 20% higher than the judge's decision". A similar analysis applies to the defendant as well. Equations (11) and (12) are constraint equations with new parameters α and β which are not yet harmonized with the proposed negotiation model. Each contains two elements: a known reserve and a guess or estimate of the opponent's reserve. A fully-fledged model would be a Bayesian dynamic model with α and β compatible with the time changing parameters of the dynamic model. A key point is whether we consider that, or better have evidence for whether the reserves are adjusted during negotiations. For example, are reserves of a claimant adaptable to allow the claim to be lowered as negotiations proceed, or are the reserves "set in stone" and remain constants? Should the defendant assume whether the claimant adjusts their reserve? Currently, these issues are not sufficiently settled, or too complex to venture deep into a Bayesian model.

We feel more confident with models with a fixed reserve but in which a Bayesian model is applied to guess the reserve using only the first claim x_1 and the first offer y_2. Then the change in the dynamic model parameter gives estimations for the change in the α and β in our simple empirical model. We consider this approach practical because the importance attached to reserves as part of company reserve portfolios would, over time, attributes extra meaning to α and β, in the same way that an "initial stake" may affect the bets in various games of chance.

5.2 Rule-based negotiation?

The central point of this paper is that negotiation can be cast as a predictive model-based decision process or, with the more challenging terminology, a predictive model-based sequential game. The conundrum central to such problems is that the modeling is based on passive observation, whereas the decision making (game) involves intervention. We only have to think of the tension between the massive government interventions during the pandemic, with the huge role played by epidemiological modeling. It is frequently observed that predictions are conditional on the strategy adopted.

A related question is whether the behavior is subject to rules, either well-established or discovered via the modeling. Our own view, and in fact one could immodestly call it a discovery, is that in the early stages of the negotiation it seems very much as if there are some rules, perhaps one could say “rules of thumb”. For example, as shown in Table 4, the second claim is always more than 90% of the first offer. Interviews with senior lawyers to some extent confirm this. For instance, one senior lawyer stated “Most lawyers will stick within about 90% of their initial offer in the early stages of Portal negotiation. The offers made should be pitched accurately, i.e., we will not make very low offers just to give ourselves room for maneuver later. Accurate initial offers only allow minimal room for later negotiation, but most will feel that they need to make a concession to try and bring about the settlement before the additional cost of *Stage three*.”

A question that we have pondered is whether there is some kind of “tipping point” at which the claimant and defendant, in a sense, are liberated from the early rules to become freer in negotiation. There is some evidence that this takes place around $t = 4$. Specifically, the defendant tends to negotiate with a *Boulware* strategy (Fatima et al., 2005), i.e., maintaining the initial price until the deadline is approaching. Table 4 demonstrates that the defendant sticks 95% of his previous offer on the second offer but then this ratio is lowered to 89% later, indicating his desire to reach an agreement before trial. By contrast, the claimant insists on her offer throughout the whole negotiation, confirming the anchor effect, which is extensively studied in psychology.

5.3 Sequential games based on causal model

Directed Acyclic Graphs (DAGs), on which the modeling in this paper is based, are at the foundation of modern causal modeling (Pearl, 2009). In addition, within this framework, the B-spline model and the first-order linear models of the type we fit here occupy an important place in the theory. That is to say for any node the model is represented by the edge (arrows) into that node.

There is considerable literature on sequential games under Markov assumptions, so it is worth mentioning that our model is indeed Markovian with respect to time, but *second* order Markov. Thus if the sequence is $\{x_1, y_2, x_2, y_3 \ldots\}$ with time sequence $\{1, 2, 3, 4 \ldots\}$ then in say, predicting x_3 at time 5, we use x_2 and y_3 at times 3 and 4. The two-step prediction would be to use y_2 and x_2 at time points 2 and 3 to predict x_3.

Research issues in complex DAG models are associated with the relationship between intervention allowing forward conditioning to remove feedback and how to learn from purely observational studies. Here we simply build conditional regression models based on observed offer values and make the standard assumption that, mathematically, the conditional distribution is the same whether a passive observation study or an active, purposive offer. However, there cannot be anything more purposive than playing a game, and as we have suggested above, that game “gets serious” as time goes on. This paper shows one way of combining the DAG-based model with a game, namely, using a one-step-ahead approach for the modeling, the utility structure and the decision making. A full theory will be developed in further work and will cover at least the issues mentioned above.

6 Conclusion and future work

This study presents a novel decision support framework for insurance and civil litigation negotiations by focusing on the UK Ministry of Justice's RTA Portal process. Leveraging 88 real-world cases from a legal service company, we first demonstrate that predicting the defendant's initial offer from the claimant's initial offer is particularly challenging, though B-splines provide a certain level of predictive capability. Subsequently, our findings indicate that each party's new offer is primarily influenced by its own previous offer and, to a lesser extent, by the opposing party's most recent offer. Notably, the defendant tends to make more pronounced concessions in later negotiation rounds. Integrating utility analysis into this framework enables both sides to systematically decide whether to accept the current proposal or continue negotiating.

Moreover, scenario-based analyses suggest that all cases could have been resolved through negotiation rather than incurring high legal costs by proceeding to court. This observation underscores the practical importance of rational and data-driven negotiation strategies, aligning with broader policy objectives to reduce litigation expenses and conserve judicial resources for more complex disputes. While our empirical work focuses on the Portal process, the proposed negotiation and utility analysis framework readily generalizes to other Pre-Action Protocols or small-value compensation cases. In addition, the sequential negotiation model introduced here provides a novel lens for decision-making under incomplete information, contributing to the broader negotiation literature (Baarslag et al., 2016; Kiruthika et al., 2020).

Despite its promise, this research also has certain limitations that suggest potential directions for future inquiry. First, we focus solely on the general cost in traffic accident claims. In practice, special costs—such as case-specific medical expenses or property damage—must also be negotiated. Unlike general costs, which largely depend on injury type and severity, special costs are highly case-dependent and often more challenging to predict in a structured manner. Incorporating special costs would transform the single-issue negotiation into a multi-issue negotiation, extending the applicability of our framework. Second, we treat the negotiation as a two-player process-claimant versus defendant-primarily for simplicity. However, in reality, both sides often involve solicitors. While claimants/defendants and their solicitors usually share common interests, solicitors may benefit financially from protracted negotiations or court proceedings. Analyzing these potential conflicts of interest among four parties would offer valuable insights into negotiation dynamics and outcomes. Third, our predictive models currently rely on the most recent offers, aligning with the Markov property for computational tractability and robustness given the maximum of six negotiation rounds. Still, incorporating the complete negotiation history might capture more nuanced behavioral patterns, especially in cases involving prolonged or more complex negotiations. Future research could explore the balance between increased model complexity and predictive performance when integrating full historical data, potentially leading to more refined negotiation support tools.

While this paper focuses on predictive modeling and decision analysis, future research could explore how negotiators actually learn and adapt their strategies through bargaining interactions. This includes investigating sequential learning processes during negotiations, different learning mechanisms between parties, and how historical bargaining experiences shape future negotiation behaviors. Of particular interest is understanding how negotiators adapt their strategies through active learning during the bargaining process, and how reinforcement learning approaches could leverage historical case outcomes for real-time strategy adjustments. Such learning-based perspectives could provide deeper insights into the dynamic nature of legal negotiations while maintaining practical applicability. Collectively, these directions open up new possibilities for advancing negotiation analytics and decision-making, both within the RTA Portal context and in broader legal or business negotiation environments.

Acknowledgments We dedicate this work to the memory of our colleague Professor Henry Wynn, who passed away before this research was completed. His foundational contributions to experimental design and his mentorship will be deeply missed.

Declarations

Conflict of interest The authors declare no conflict of interest related to this work.

References

Akaike, H. (1974). A new look at the statistical model identification. *IEEE Transactions on Automatic Control,196*, 716–723.

Baarslag, T., Hendrikx, M. J., Hindriks, K. V., & Jonker, C. M. (2016). Learning about the opponent in automated bilateral negotiation: A comprehensive survey of opponent modeling techniques. *Autonomous Agents and Multi-Agent Systems,305*, 849–898. https://doi.org/10.1007/s10458-015-9309-1

Bachrach, Y., Everett, R., Hughes, E., Lazaridou, A., Leibo, J. Z., Lanctot, M., & Graepel, T. (2020). Negotiating team formation using deep reinforcement learning. *Artificial Intelligence,288*, 103356.

Bebchuk, L. A. (1984). Litigation and settlement under imperfect information. *The RAND Journal of Economics,15*, 404–415.

Bone, R. G. (2003). Agreeing to fair process: The problem with contractarian theories of procedural fairness. *BUL Rev.,83*, 485.

Cao, M., Luo, X., Luo, X. R., & Dai, X. (2015). Automated negotiation for e-commerce decision making: A goal deliberated agent architecture for multi-strategy selection. *Decision Support Systems,73*, 1–14.

Carneiro, D., Novais, P., Andrade, F., Zeleznikow, J., & Neves, J. (2013). Using case-based reasoning and principled negotiation to provide decision support for dispute resolution. *Knowledge and Information Systems,363*, 789–826.

Chatterjee, K., & Samuelson, W. (1983). Bargaining under incomplete information. *Operations Research,315*, 835–851.

Choi, T.-M., Wallace, S. W., & Wang, Y. (2018). Big data analytics in operations management. *Production and Operations Management,2710*, 1868–1883.

Cohen, M. C. (2018). Big data and service operations. *Production and Operations Management,279*, 1709–1723.

Cooter, R. D., & Rubinfeld, D. L. (1994). An economic model of legal discovery. *The Journal of Legal Studies,23S1*, 435–463.

Dobrzykowski, D. D., McFadden, K. L., & Vonderembse, M. A. (2016). Examining pathways to safety and financial performance in hospitals: A study of lean in professional service operations. *Journal of Operations Management,421*, 39–51.

Faratin, P., Sierra, C., & Jennings, N. R. (1998). Negotiation decision functions for autonomous agents. *Robotics and Autonomous Systems,24*(3–4), 159–182.
Fatima, S., Kraus, S., & Wooldridge, M. (2014). *Principles of automated negotiation*. Cambridge University Press.
Fatima, S. S., Wooldridge, M., & Jennings, N. R. (2005). Bargaining with incomplete information. *Annals of Mathematics and Artificial Intelligence,443*, 207–232. https://doi.org/10.1007/s10472-005-4688-7
Fisher, R., Ury, W. L., & Patton, B. (2011). *Getting to yes: Negotiating agreement without giving in*. London: Penguin.
Gino, F., & Pisano, G. (2008). Toward a theory of behavioral operations. *Manufacturing & Service Operations Management,104*, 676–691.
Goldberg, S. B., Sander, F. E., Rogers, N. H., & Cole, S. R. (2014). *Dispute resolution: Negotiation, mediation and other processes*. Netherlands: Wolters Kluwer.
Gould, J. P. (1973). The economics of legal conflicts. *The Journal of Legal Studies,22*, 279–300.
Hendricks, K. B., Singhal, V. R., & Stratman, J. K. (2007). The impact of enterprise systems on corporate performance: A study of ERP, SCM, and CRM system implementations. *Journal of Operations Management,251*, 65–82.
Jackson, R. M. (2010). *Review of Civil Litigation Costs* (Vol. 2). London: The Stationery Office.
Justice (2017). Pre-action protocol for low value personal injury claims in road traffic accidents from 31 july 2013. https://www.justice.gov.uk/courts/procedure-rules/civil/protocol/pre-action-protocol-for-low-value-personal-injury-claims-in-road-traffic-accidents-31-july-2013. Accessed 10 Jan 2021.
Kiruthika, U., Somasundaram, T. S., & Raja, S. (2020). Lifecycle model of a negotiation agent: A survey of automated negotiation techniques. *Group Decision and Negotiation,296*, 1239–1262.
Kuster, R. (2017). Utility function and rational choice as support mechanisms to maximize mediation and legal negotiation settlement output. *Pepp. Disp. Resol. LJ,17*, 263.
Landes, W. M. (1971). An economic analysis of the courts. *The Journal of Law and Economics,141*, 61–107.
Leith, P. (2016). The rise and fall of the legal expert system. *International Review of Law, Computers & Technology,303*, 94–106.
Lewis, M. A., & Brown, A. D. (2012). How different is professional service operations management? *Journal of Operations Management,301–2*, 1–11.
Lin, R., Kraus, S., Wilkenfeld, J., & Barry, J. (2008). Negotiating with bounded rational agents in environments with incomplete information using an automated agent. *Artificial Intelligence,1727–7*, 823–851. https://doi.org/10.1016/j.artint.2007.09.007
McAfee, A. (2002). The impact of enterprise information technology adoption on operational performance: An empirical investigation. *Production and Operations Management,111*, 33–53.
Mnookin, R. H., & Kornhauser, L. (1979). Bargaining in the shadow of the law: The case of divorce. *The Yale Law Journal,885*, 950–997. https://doi.org/10.2307/795824
Nash, J. F. (1950). Equilibrium points in n-person games. *Proceedings of the National Academy of Sciences,361*, 48–49. https://doi.org/10.1073/pnas.36.1.48
Nielsen, T. D., & Jensen, F. V. (2004). Learning a decision maker's utility function from (possibly) inconsistent behavior. *Artificial Intelligence,1601–2*, 53–78.
Ordover, J. A., & Rubinstein, A. (1983). *On bargaining, settling, and litigating: A problem in multistage games with imperfect information*. CV Starr Center for Applied Economics, New York University.
Pearl, J. (2009). *Causality*. Cambridge University Press.
Png, I. P. (1983). Strategic behavior in suit, settlement, and trial. *The Bell Journal of Economics*. https://doi.org/10.2307/3003655
Raiffa, H. (1982). *The art and science of negotiation*. Harvard University Press.
Roels, G., & Staats, B. R. (2021). Om forum people-centric operations: Achievements and future research directions. *Manufacturing & Service Operations Management,234*, 745–757.
Rosenschein, J. S., & Zlotkin, G. (1994). *Rules of encounter: Designing conventions for automated negotiation among computers*. Cambridge: MIT Press.
Rubinstein, A. (1982). Perfect equilibrium in a bargaining model. *Econometrica: Journal of the Econometric Society*. https://doi.org/10.2307/1912531
Schwarz, G. (1978). Estimating the dimension of a model. *The Annals of Statistics,6*, 461–464.
Shavell, S. (1995). Alternative dispute resolution: An economic analysis. *The Journal of Legal Studies,24*(1), 1–28.
Taddeo, M., & Floridi, L. (2018). How AI can be a force for good. *Science,3616404*, 751–752.
Tomašev, N., Cornebise, J., Hutter, F., Mohamed, S., Picciariello, A., Connelly, B., Belgrave, D. C., Ezer, D., Haert, F. C., Mugisha, F., & Abila, G. (2020). AI for social good: Unlocking the opportunity for positive impact. *Nature Communications,111*, 1–6.
Walton, R. E., & McKersie, R. B. (1991). *A behavioral theory of labor negotiations: An analysis of a social interaction system*. New York: Cornell University Press.

Woolf, H. (1995). Access to justice: Interim report to the lord chancellor on the civil justice system in England and Wales (Vol. 1). Lord Chancellor's Department.

Zeleznikow, J. (2021). Using artificial intelligence to provide intelligent dispute resolution support. *Group Decision and Negotiation,30*(4), 1–24.

Zeng, D., & Sycara, K. (1998). Bayesian learning in negotiation. *International Journal of Human-Computer Studies,481*, 125–141. https://doi.org/10.1006/ijhc.1997.0164

Authors and Affiliations

Wen Zhang[1] · **Jingwen Shi**[2] · **Xiaojun Wang**[3] · **Henry Wynn**[4]

✉ Wen Zhang
wen.zhang@bristol.ac.uk

Jingwen Shi
phd15js@mail.wbs.ac.uk

Xiaojun Wang
x.wang.18@bham.ac.uk

Henry Wynn
H.Wynn@lse.ac.uk

[1] Business School, University of Bristol, Bristol, UK

[2] State Street Global Advisors, London, UK

[3] University of Birmingham, Birmingham, UK

[4] London School of Economics and Political Science, London, UK