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Abstract

When deciding about surgical treatment options, an important aspect of the decision-making process is the potential risk of complications. A risk assessment performed by a spinal surgeon is based on their knowledge of the best available evidence and on their own clinical experience. The objective of this work is to demonstrate the differences in the way spine surgeons perceive the importance of attributes used to calculate risk of post-operative and quantify the differences by building individual formal models of risk perceptions. We employ a preference-learning method - ROR-UTADIS - to build surgeon-specific additive value functions for risk of complications. Comparing these functions enables the identification and discussion of differences among personal perceptions of risk factors. Our results show there exist differences in surgeons' perceived factors including primary diagnosis, type of surgery, patient's age, body mass index, or presence of comorbidities.

Introduction

When deciding about surgical treatment, an important factor driving a surgeon's decision-making is the perceived risk for post-surgical complications. Spine surgery is no exception, especially considering that introduction of new surgical implants makes even more patients eligible for spine surgery[1]. Moreover, significant variability is observed in the use of spine surgery, among different hospitals, as well as at the level of an individual surgeon[2,3]. Because risk is inherent in any procedure, reducing the number of unnecessary, or high-risk operations is an important issue in patient safety and will improve overall patient outcomes, reduce complication rates, and reduce the need for repeated surgery.[4] Thus, the ability to correctly and consistently assess the risk of post-surgical complications plays an important role in deciding if a patient is eligible for surgery and what type of surgical procedure should be considered.

A spinal surgeon's risk assessment is based on their knowledge of the best available evidence as well as on their own clinical experience. Commonly used risk assessment tools in spinal surgery include SpineSage[5] and spinalRAT[6], and we use these as baselines in this work. These tools consider patient demographics and additional attributes such as patient condition, comorbidities, pre-surgical diagnoses, surgical and complication detail, and others. Although little is known about how surgeons weigh available evidence and clinical experience, emphasis on experience is likely increased when little scientific evidence exists, the surgeon is unaware of that evidence, or the surgeon has discounted that evidence based on its quality. For these reasons, differences exist among spinal surgeons while assessing the risk of post-surgical complications for the same patient. These differences translate into uneven application of standards of care and inconsistent selection of patients eligible for surgery. Identification and analysis of differences should help mitigate these inconsistencies and is the topic of the research described in this paper.

The objective of our work is to identify how spinal surgeons weigh the importance of the variables in risk assessment tools. Towards this end we assess the differences in the way spinal surgeons assess risk by building formal models of risk perceptions of 6 spinal surgeons working in a large academic hospital in Canada. We employ a preference-learning method - ROR-UTADIS[8]- to build preference models that capture surgeon-specific perception of risk of complications. We previously used a similar approach to capture the professional opinions of physicians when evaluating the relevance of medical evidence for decision making[9]. While other research on preference elicitation involving surgeons has focused on treatment options[10–12], our work is more concerned with identifying the differences in post-surgical risk assessment and attempts to discover the most relevant clinical factors, and how surgeons balance them when making such an assessment.

Related Work

Surgical decision-making has evolved over time. What was once an intuitive matter for surgeons has now become a complex multi-faceted decision process[13]. Risk assessment has a substantial subjective element, thus there is a need for objective tools and methods. Such approaches aid surgeon decision making but also provide realistic expectations for the patient, helping them make an informed decision.

Scoring systems that focus on postoperative outcomes are a common method for predicting risk. For example, www.riskprediction.org.uk, lists 12 risk assessment tools related to various procedures[14]. Scoring tools are generally based on prognostic factors including age, disease severity and co-morbidity and procedure specific considerations are available to surgeons. For example, the well-known POSSUM system (Physiological and Severity Score for the Enumeration of Mortality and Morbidity), and its variants, compute information on the surgical risk in terms of morbidity and mortality by combining physiological parameters (e.g. age, cardiac status, respiratory status) with operative parameters (e.g. the type of operation, the urgency of the operation and the number of procedures)[15].

Spinal surgery is a complex procedure and requires clinicians to evaluate the relative risk of several risk factors including age, gender, medical comorbidities, substance abuse, body mass index (BMI), medical comorbidity, previous spinal surgery, primary diagnosis and surgical approach. Given the large number of possible risk factors, many approaches to assessing spinal surgery risk have used statistical techniques such as regression and multivariate analysis[6,16]. Although predictions from systems such as those described by[6,16] can be individualized, they largely pertain to populations rather than an individual. SpineSage[5] is a tool that attempts to individualize the risk assessment of spine surgery by taking into consideration patient-specific risk factors, specifically a patients' comorbidity profile as well as the invasiveness of the procedure. It utilizes a multivariate log-binomial approach. Other work has employed machine learning, for example Ehlers et al.[17] have developed a Naive Bayes algorithm that uses 300 predictors to predict risk of adverse event or death within 90 days of different types of surgery including spine surgery. Karhade et al.[18], compared four machine learning algorithms for preoperative prediction of non-routine discharges for elective inpatient lumbar degenerative disc disorders and found a neural network approach to be the best performing with an AUC of 0.823.

In addition to the large number of factors to be evaluated, there are other emerging issues that cause poor consistency in risk assessment for spine surgery. These include an increasing number of available surgical interventions with collateral adverse outcomes that may be traded off against each other[19]. Furthermore, risk factors vary considerably with comorbidities[20] and different patient populations present very specific concerns. For example, surgical risk is especially challenging in elderly patients because of their levels of frailty which is not commonly considered by risk prediction systems and scoring systems or machine learning algorithms based on population level characteristics do not generalize well to all patient groups[21]. Our approach in analyzing the preferences of a number of surgeons for multiple and heterogeneous risk factors aims to shed light on what the important decision-making inconsistencies are among spinal surgeons. We believe this is first time such an analysis has been conducted in the spine surgery domain.

Methods

The ROR-UTADIS method

In our work we assume a preference model that captures perceptions of risk of complications and is represented as an additive value function. An additive function is the sum of marginal value functions associated with specific criteria characterizing alternatives. Here alternatives correspond to patients and criteria to variables characterizing patients that are listed in Table 1. The additive value function not only provides a comprehensive assessment of a patient (in terms of perceived risk) but also, through marginal value functions, gives insight into risk perceptions associated with individual variables which is crucial for achieving our research goals.

Most methods for building additive value functions establish parameters of marginal value functions from indirect preferential information provided by a decision maker for a subset of alternatives (so-called *reference alternatives*), e.g., their pairwise comparisons. Usually, there are multiple additive value functions compatible with preferential information. A simple approach involves selecting any of these functions, while an advanced one takes into account and exploits all these compatible functions for more robust results. The latter approach is known as *robust ordinal regression* (ROR) [8].

In our study we employed the ROR-UTADIS method[8] that follows the ROR principle. It aims to solve a sorting decision problem, i.e., assignment of alternatives to predefined and ordered classes (e.g., risk classes). In addition to a resulting additive value function it also establishes a set of thresholds that can be imposed on obtained quantitative assessments to translate them into class recommendations. ROR-UTADIS accepts rich and diversified preferential information, including class assignments (possibly imprecise) of references alternatives, their assignment-based pairwise comparisons, and desired class cardinalities. In our analysis we focused solely on the value function and ignored the thresholds. Moreover, we used only the first type of preferential information, i.e., assignment of reference (paper) patients to risk classes, as it was most relevant from a practical perspective and easiest to obtain from surgeons.

Below we briefly summarize the outline of the ROR-UTADIS method. In this description we use terminology specific for our clinical problem:

1. A set of value functions that are compatible with provided assignments of patient cases to risk classes (low, medium and high) is constructed by solving a linear programming model. If this model has no solution, it indicates that some of the provided class assignments are problematic and need to be revised, and the method proceeds to step 2. Otherwise, it skips to step 3.
2. Problematic class assignments are identified by solving a 0-1 linear programming model. Found class assignments are presented to a decision maker who needs to decrease their precision, e.g., an initial assignment of a specific patient to the medium risk class is changed into an assignment to medium or high classes (the obtained solution also points to whether the assignment should be expanded towards a lower or higher risk). Once all problematic assignments have been revised, ROR-UTADIS returns to step 1.
3. A set of compatible additive value functions established in step 1 is explored and a representative additive function is constructed. This step involves solving another linear programming model that is aimed at maximizing the differences in evaluations between patient cases assigned to different risk classes and then minimizing differences in evaluations between patients assigned to the same risk classes.

Study Design

Our study population consists of 6 staff surgeons (4 orthopedic and 2 neurosurgical surgeons) from the Division of Orthopedic Surgery at The Ottawa Hospital (TOH), Ottawa, Ontario, Canada. The participants are academic, fellowship-trained spinal surgeons, with training at Canadian, American, British, and Australian hospitals. All of the surgeons work closely in a combined orthopedic and neurosurgical spine program. This study population excluded residents and included all but one of the staff spine surgeons at TOH. While all 7 staff surgeons agreed to participate, one did not provide answers. Yet this study population represents almost the entirety of the TOH spine program and thus represents the group's thoughts. All the surgeons were considered to have the same experience level.

Table 1. List of features considered in the study.

Concept	**Feature name**	**Value domain**
Procedure type and approach	Proc_Approach_CdGrp	1=Anterior cervical 2=Posterior cervical 3=Posterior thoracolumbar
Diagnosis	MRDx_10_CdGrp	1=Degenerative 2=Trauma
Diabetes	ncdDiabetes	1=Yes, 0=Otherwise
Hypertension	ncdHypertension	1=Yes, 0=Otherwise
Bleeding diathesis	ncdBleeding	1=Yes, 0=Otherwise
Age	Age	18-100
BMI	ncdBMI	15-50

Study participants were provided with a set of 15 representative hypothetical patient cases described by a set of 7 features that are available at the time of first consult. First consult is typically when surgery is planned and considered when evaluating risk of post-surgical complications (see Table 1). These features include type of the surgical procedure and how it was conducted (often called "approach"), diagnosis, features associated with comorbidities such as diabetes, hypertension, and known bleeding diathesis, age, and BMI. The patient cases were developed by an independent spinal surgeon on the basis of cases recorded in The Ottawa Hospital Institutional National Surgical Quality Improvement Program (NSQIP) database for patients undergoing spinal surgery. The patient cases were developed based on EHR data and represent the patient population that is being treated in the academic center. This population covers different age groups, resulting in the age variation seen across patient cases.

As a starting point, we elicited individual risk assessments from surgeons asking them to assess the risk of post-surgical complications for each patient case on a low/medium/high risk scale. In the first stage of the analysis assessments were used to construct a common additive value function representing a perception of risk by all participating surgeons. The second stage of analysis focused on building a set of surgeon-specific additive value functions to highlight differences in individual risk assessment.

Results and Discussion

The patient cases considered in this study and the assignments to risk classes provided by the participating surgeons are given in Table 2. As summarized in the bottom portion of the table, there exists a fairly large number of disagreements among surgeons with regards to the perceived risk of post-surgical complications. Indeed, only one patient case (P6) had the same risk assessment from all spinal surgeons, while one third (5/15) of the patients had risk assessments that span the whole spectrum from low to high risk.

Table 2. Risk assessment of the 15 paper cases (P1-15 in columns) by the 6 spine surgeons (S1-6 on rows). The bottom part of the table reports frequency of risk classes for each patient when pooling all surgeon assessments together.

	Paper patient caracteristics														
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	P13	P14	P15
Proc_CdGrp	1	1	3	1	1	1	2	1	1	2	1	1	1	2	1
MRDx_10_CdGrp	1	2	1	1	1	1	1	1	2	1	2	1	1	2	1
ncdDiabetes	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0
ncdHypertension	0	0	1	1	0	0	0	1	1	1	0	1	1	0	1
ncdBleeding	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
Age	64	60	70	61	85	74	65	55	61	71	62	96	83	85	68
ncdBmi	38.0	29.9	38.2	39.9	29.9	25.4	18.6	38.1	29.9	16.5	29.9	29.9	30.1	29.9	32.0
	Surgeon assignments to risk class														
S1	L	L	M	M	M	L	M	M	L	H	M	H	M	H	L
S2	M	L	M	M	L	L	L	M	L	L	L	M	L	M	L
S3	M	M	H	M	M	L	M	M	M	L	L	M	L	L	L
S4	M	L	H	L	M	L	L	H	L	L	L	H	L	M	M
S5	M	H	H	M	M	L	M	M	M	M	H	M	M	M	M
S6	L	H	M	H	M	L	L	H	M	L	H	M	L	H	M
	Frequency of assigned risk class														
Low (L)	2	3	0	1	1	6	3	0	3	4	3	0	4	1	3
Medium (M)	4	1	3	4	5	0	3	4	3	1	1	4	2	3	3
High (H)	0	2	3	1	0	0	0	2	0	1	2	2	0	2	0

In the first stage of the analysis, we combined individual assessments to build an overall additive value function capturing common risk perception by all participating surgeons. Merging responses provided by specific surgeons resulted in imprecise risk class assignments that were provided as input to the ROR-UTADIS method. For example, patient P1 was assigned to low or medium risk classes, P2 to all risk classes, and P3 to medium and high risk classes. Figure 1a shows the marginal risk functions obtained for the combined assessments. Each marginal function describes how values of a specific feature contribute to the perception of risk with feature values being reported on the X-axis and the contribution on the Y-axis. The latter is expressed using a scale from 0 (no contribution) to 1 (maximum risk).

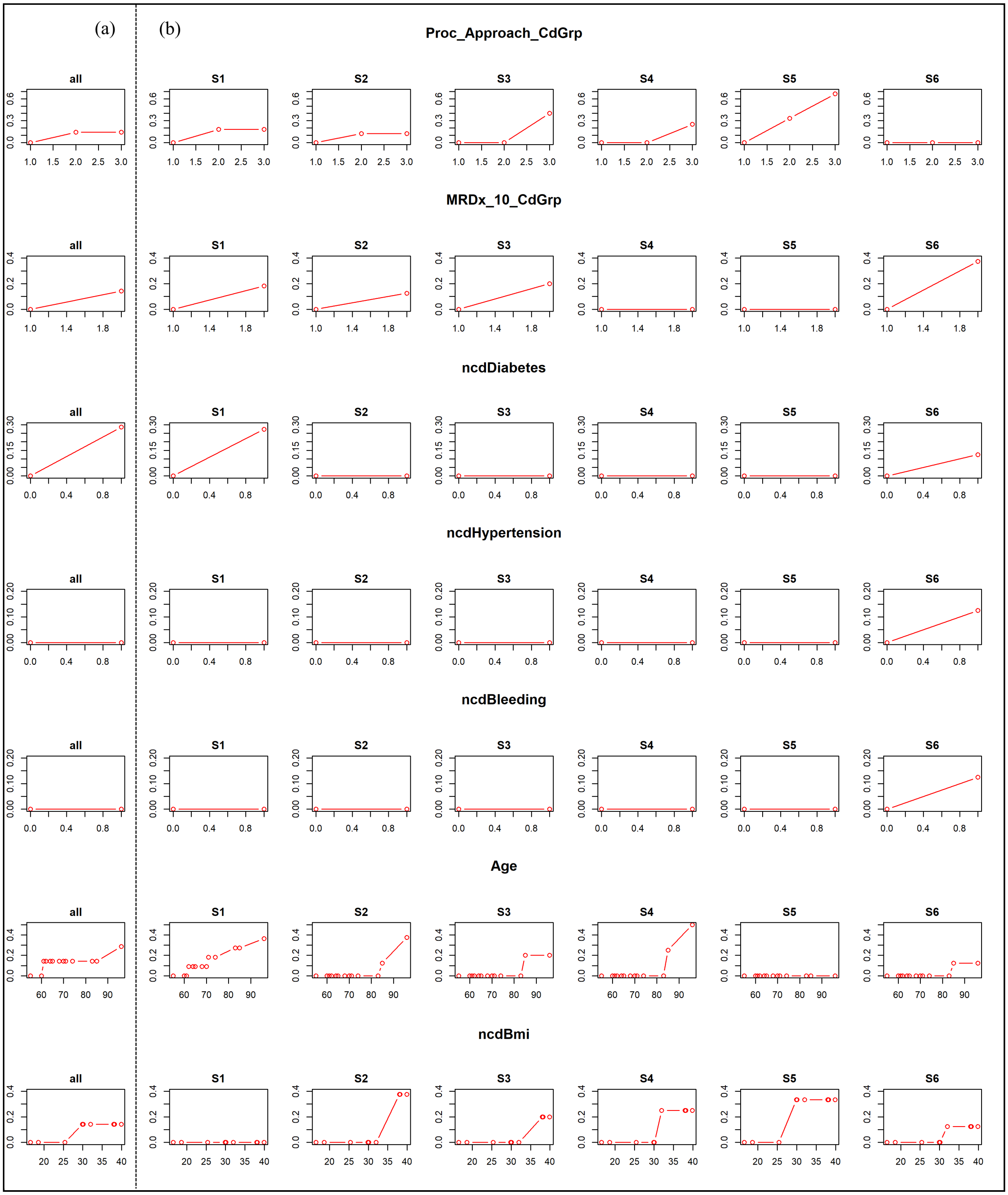

Figure 1. Marginal risk functions for combined assessments of all surgeons (a) and for individual surgeons (b). Functions on a single row refer to a specific feature, while columns represent either the group of all participating surgeons or individual surgeons (S1-S6).

Findings from this stage of our study align with common clinical practice and general guidelines for spine surgery. Procedure type/approach and diagnosis all emerged as contributing to the risk of post-surgical complications. The same can be said about diabetes. Age and BMI contributions depend on values recorded for a patient. Initially for low values these two features are not contributing to risk, this starts to change after a threshold of 60 years of age and BMI of 25 (this is aligned with what clinical guidelines state), to finally become major drivers for risk of complications for high values - age greater than 85 and BMI greater than 30. Hypertension and bleeding diathesis do not impact the perceived risk of post-surgical complications.

In the second stage of the analysis we applied ROR-UTADIS again in order to discover if individual surgeons differed in the ways they evaluate the importance of specific features and their values. The method was not initially able to construct additive value functions for S3, S4, S5 and S6 and identified problematic class assignments for some patient cases (P2, P4, P7, P8, P9, P11 and P14). These assignments had to be revised by making them less precise (e.g., the risk class assignment of P2 by S3 was changed from medium to low or medium), while the remaining precise assignments reported in Table 2 were kept unchanged.

Surgeon-specific marginal value functions are reported in Figure 1b. Interestingly, surgeon-specific models highlight how the two categorical features characterizing the type of procedure type/approach and the diagnosis have different impact on risk according to individual surgeons. S6 does not attribute any additional risk to the different procedure type/approach categories used in this study; S1 and S2 consider anterior cervical surgeries to be associated with smaller risk and attribute the same risk to the surgeries with posterior approach; finally, S3, S4 and S5 consider thoracolumbar surgeries considerably more risky than cervical ones. A somewhat similar consideration is true for the diagnosis feature where S4 and S5 consider operating on patients with degenerative and traumatic lesions as associated with the same risk, while the other surgeons attribute more risk (with different intensities) to traumatic lesions. These observations are explained by the fact that procedure type/approach and diagnosis together describe the overall complexity of a patient case. However clinical experience of each surgeon and the frequency of operating on a specific group of patients (e.g. trauma) or performing a specific type of surgery (e.g. posterior approaches, or thoracolumbar) are likely to influence the risk propensity that they ascribe to individual features.

Diabetes, hypertension, and known bleeding diathesis are all well-known risk factors but the specific weighting of each of them in the risk assessment process is subjective to the individual surgeon considering both evidence and experience. This is reflected in the fact that only a subset of surgeons attribute marginal risk when any of these features is present. For example, S2, S3, S4 and S5 do not consider operating on diabetic patients riskier, while S1 and S6 attribute an important (0.30) risk contribution to having diabetes. The observed variability of weights attributed to the same feature by different surgeons (e.g. hypertension has a non-zero weight only for S6) is also an example of subjectivity as a result of surgeons' experience and available evidence.

Features such as age and BMI are also commonly considered risk factors, but little is known as to whether the risk increases linearly, exponentially, or in a stepwise fashion at certain threshold levels. Furthermore, chronological age does not necessarily accurately reflect physiological age or general health. These considerations make the contribution to risk of factors like age and BMI very subjective in terms of cut-off points. Surgeon-specific models shown in Figure 2 reflect this variability, but still highlight the fact that age and BMI influence risk for all but one surgeon. After discussing the results with the participating surgeons, it was confirmed that for some a threshold impacting risk assessment can be set at BMI=25 while for others at BMI=30 or even more. Similarly, some surgeons will not operate on patients over 90 years old as they consider this age group to be of too high risk of post-surgical complications.

While the list of features considered in our study is small compared to existing tools such as SpineSage[5] and spinalRAT[6], we can still make several observations applicable to these tools. SpineSage uses age, surgical invasiveness score, bleeding disorder, congestive heart failure, and diagnosis of spine trauma and spine infection to predict any complication and age, surgical invasiveness score, gender, chronic pulmonary disease, hypertension, previous cardiac history, and diagnosis of spine trauma and spine infection to predict major complications[5]. spinalRAT uses age, gender, comorbidities, preop diagnosis, location of surgery, use of BMP, fusion status, and instrumentation status for predication[6]. While these features are more comprehensive than ours, we have commonalities (age, comorbidities, diagnosis) in our feature set. These common features, and proxies for others, allow us to deduce that surgeons will perceive the importance of the features in a similar manner when using SpineSage, spinalRAT, and other similar tools.

Conclusion

Spinal surgeons' decision-making process is driven by the scores reported by risk assessment tools they use to quantify post-surgical complications. However, their interpretation and weighing of the importance placed on each attribute used to calculate these scores varies. The relative contribution of each attribute is vital in making accurate predictions of complications and should be considered when using these assessment tools for surgical decision-making. As such, the relative importance of the attributes that make up each score, as determined by a surgeon, should be better explained to inform the construction of the surgical plan and to educate the patient.

In this work, starting from data collected from 6 experienced spinal surgeons, we built a formal additive model summarizing contribution of specific factors to the risk of complications for spine surgical patients. The overall model elicited for all surgeons aligns with available scientific evidence, highlighting variables that the majority of surgeons deemed important for risk assessment. However, significant differences were observed in the way individual surgeons assign importance to attributes used to evaluate risk. Our preference-learning-based method proved effective in discovering these differences and enabled in-depth discussion with the clinical experts involved. Results suggest that factors such as overall complexity of the surgery, presence of comorbidities, age, and BMI all play an important but highly subjective role in complication risk assessment for spine surgery and ultimately need to be carefully considered during spine surgery planning.

Our study includes several limitations that are mentioned below:

- The preference model represented as an additive value function assumes independence of different variables and does not consider interactions among them;
- The number of surgeons participating in the study is limited to 6 and all of them practice in the same institution;
- Evaluations were conducted on patient cases that, albeit realistic, constitute a simplified approximation of a real patient case;
- Patient cases evaluated by surgeons excluded day surgeries, which represents a relevant proportion of spine surgical interventions, but are intrinsically low risk.

Future research will address some of the limitations of our current approach. For example, considering rule-based preference models that are able to capture interactions between features, using richer description of patients and involving a larger number of participants. Collecting more preference-oriented data (e.g. including surgeons still in training, as well as across different sites) will result in creating a decision support tool that allows insight into the trade-offs between the different factors involved when evaluating risk.

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