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Predicting early versus late recovery from sport-related concussion using decision tree analysis

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OBJECTIVE Accurately predicting early (≤ 14 days) versus typical (15–27 days) or delayed (≥ 28 days) recovery from sport-related concussion (SRC) may allow for improved resource utilization and precision in planning and carrying out rehabilitation. In this study, the authors sought to develop an algorithm that enables accurate differentiation of recovery periods and duration after SRC. The authors hypothesized that data regarding initial symptom burden as quantified by a Post-Concussion Symptom Scale (PCSS) score, time to presentation, and number of prior concussions would be the most useful for analyzing predictive factors for concussion recovery duration.

METHODS A retrospective case-control study was conducted to assess the primary outcome of days to clinical recovery following SRC in pediatric patients. Data from patients 12–18 years old presenting within 28 days of injury to an SRC clinic between November 11, 2017, and October 10, 2020, were analyzed. Patients with positive evidence of injury on head imaging or incomplete records were excluded. The primary outcome was duration of clinical recovery, grouped as early (≤ 14 days), typical (15–27 days), or delayed (≥ 28 days). Recovery was defined as follows: 1) symptom resolution or return to baseline, or 2) initiation of graduated return to play. CHAID (chi-square automatic interaction detection) analysis was used to optimize a decision tree based on 16 input factors, including age, sex, initial PCSS score, time to clinic presentation, number of prior concussions, and presence of defined symptom clusters. The cohort was randomized into training (70%) and test (30%) samples for algorithm validation.

RESULTS A total of 493 patients met the inclusion criteria (mean age 15.7 ± 1.5 years, 68.2% male, 70.0% White). The median time to presentation was 5 days (IQR 2–10 days). Most patients (52.3%) recovered within 14 days of injury, 21.5% recovered within 15–27 days, and 26.2% had a recovery period of 28 days or longer. The variables most predictive of recovery were initial PCSS score (cutoffs ≤ 6, 7–28, or ≥ 29), time to presentation (≤ 7 vs > 7 days), or prior concussions (0 vs ≥ 1). The model accurately discriminated between early versus typical or delayed recovery duration groupings (area under the curve 0.80, Youden index 0.44), and correctly classified > 90% of patients who recovered early.

CONCLUSIONS This novel three-factor predictive tool enabled accurate discrimination of early versus typical or delayed SRC recovery to better allocate resources, counsel patients, and make timely referrals.

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KEYWORDS sport-related concussion; concussion recovery; pediatric concussion; traumatic brain injury; trauma; diagnostic technique

Sport-related concussions (SRCs) are a major public health concern, with significant effects on cognitive, physical, and emotional well-being in young patients.[1–4] Most pediatric patients experience resolution of symptoms within 2 weeks of injury.[5–7] However, approximately 10%–30% experience prolonged symptoms, which may interfere with scholastic, social, and athletic activities.[8–13] Understanding risk factors associated with delayed recovery may allow for improved prognostication, expanded access to focused therapies, and safer return-to-

ABBREVIATIONS ADHD = attention-deficit/hyperactivity disorder; AUC = area under the curve; CHAID = chi-square automatic interaction detection; PCSS = Post-Concussion Symptom Scale; PPCS = persistent postconcussion symptoms; ROC = receiver operating characteristic; SRC = sport-related concussion; 5P = Predicting and Preventing Postconcussive Problems in Pediatrics.

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play processes.[14] Conversely, identification of individuals likely to experience an uncomplicated recovery also impacts resource utilization and follow-up.[15]

Many factors related to concussion severity and recovery have been identified and studied. Broadly, these factors can be grouped into 1) preinjury factors, 2) injury characteristics, and 3) postinjury factors. Predisposing factors may include age, sex, genetics, or personal/family history of headaches, learning disability, mental health problems, or prior concussions.[1,3,4,13,16–22] Injury characteristics include type of sport, mechanism of injury, and on-field characteristics such as disorientation, loss of consciousness, immediate headache or dizziness, or amnesia, although these factors are thought to be somewhat less predictive of eventual time to recovery.[16,19,21,23–26] Delay in removal from play has been identified as a potential risk factor for prolonged recovery as well.[27,28] Acute symptom severity (e.g., headache, dizziness, sensitivity to noise or light, balance problems, or mood symptoms) after the injury is associated with longer recovery.[13,29–32] In addition, recent evidence has identified longer time from injury to clinic presentation as a risk factor for delayed recovery, with presentations beyond 7 days being associated with prolonged recovery.[33]

Many retrospective studies and systematic reviews have assessed the utility of these factors in predicting concussion recovery.[16,34–36] However, organizing these factors into a usable clinical tool for projecting recovery may allow for improved resource utilization, including clinic appointments and therapy sessions. The multicenter Predicting and Preventing Postconcussive Problems in Pediatrics (5P) study generated a clinical tool to predict persistent postconcussion symptoms at 28 days postinjury (area under the curve [AUC] 0.68, sensitivity 93.5%, specificity 18.1%).[37] However, this model was developed using data for patients presenting to an emergency department within 48 hours of injury and required validation in other populations. Howell et al. externally validated the 5P model in a sports concussion clinic setting, finding that high 5P score was associated with greater odds of persistent postconcussion symptoms (PPCS).[38] However, this analysis has limitations as patients presented soon after injury (< 10 days), patients were much more likely to develop PPCS relative to the SRC population as a whole, and the sensitivity (approximately 75%) and specificity (approximately 66%) suggested reduced clinical value compared to the original 5P model. Additionally, not all factors that contribute to the 5P score were associated with delayed recovery, suggesting that practical improvements could be made toward decreased complexity of scoring (or reliance on factors that are already commonly assessed). Furthermore, additional retrospective studies have focused primarily on identification of patients at risk for delayed recovery or PPCS.[13,21,30–32,36,37] It is not well established whether negative findings on the 5P scale or on other injury variables are predictive of early recovery, limiting utility for clinical decisions affecting resource utilization for these patients.

Recognizing the combined value of improved prognostication with practicality, we sought to develop a novel recovery prediction algorithm that could accurately discriminate between three broad groupings of recovery duration following SRC. We conducted a retrospective, case-control study of pediatric SRCs, with a subsequent decision tree analysis to identify which factors best predicted early (≤ 14 days) versus typical (15–27 days) versus late (≥ 28 days) recovery. Based on prior literature,[1–4,16–28,31–33] we hypothesized that symptom severity, time to presentation, and prior concussion history would be useful in discriminating between early and late recovery.

Methods

Study Design

Data analyzed were retrospectively obtained from the electronic medical records of all patients presenting to a dedicated concussion clinic in the Southeastern United States between November 1, 2017, and October 1, 2020. This study was approved by the institutional review board, and data extraction and storage were performed in accordance with the Health Insurance Portability and Accountability Act (HIPAA). Patient consent was not required as the study was considered secondary research involving only information, collection, and analysis of identifiable health information regulated under HIPAA for the purposes of health care operations or research. The data supporting the findings of this study are available on reasonable request to the corresponding author.

Study Population

Included patients were middle school and high school athletes aged 12–18 years diagnosed with and treated for an SRC. Patients with positive acute head imaging, non–sport injury mechanism, prior head injury in the study period, or who were injured in a collegiate sporting event were excluded. Of the eligible patients, those missing initial postinjury Post-Concussion Symptom Scale (PCSS) scores or outcomes data (i.e., time to clinical recovery) were excluded, as were patients who presented to the clinic > 28 days postinjury. Patients excluded for incomplete outcome data or delayed presentation were similar in demographics and injury characteristics to included patients. A flow diagram of study population inclusion and exclusion criteria is shown in Fig. 1.

Variables

Patient records were manually reviewed, and extracted data were stored securely using Research Electronic Data Capture (REDCap) databases.[39] Extracted data included each athlete's preinjury medical history, injury characteristics, and PCSS responses and scores from the initial clinic visit. Factors included as independent candidate variables in the analysis were age, sex, sport contact level, loss of consciousness (yes or no), anterograde amnesia (yes or no), initial PCSS score, time to clinic presentation (in days), number of prior concussions, personal or family history of attention-deficit/hyperactivity disorder (ADHD), migraines, or psychiatric diagnosis. Sport contact level was categorized as collision, contact, limited contact, or noncontact as described by Rice et al.[35] Additionally, Karr and Iverson's four-factor model[40] was utilized to establish cognitive-sensory, vestibular-somatic, sleep-arousal, and affective clusters based on PCSS inventory items. The se-

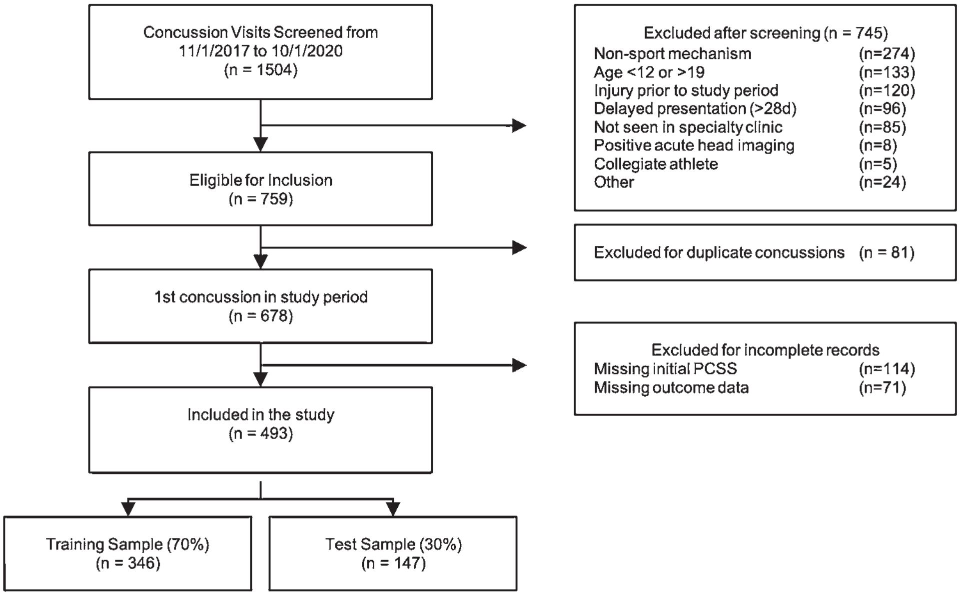

FIG. 1. Inclusion and exclusion criteria for the study population. Patients who were excluded for incomplete data were similar in demographics and injury profiles to included patients. Included patients were randomized to training and test samples for algorithm validation.

verity of each symptom cluster was included as an independent candidate variable with cutoffs determined by the decision tree algorithm.

Primary Outcome

The primary outcome was time to clinical recovery, as defined by self-reported symptom resolution or initiation of a graduated return-to-play protocol under athletic trainer oversight. The continuous primary outcome was categorized as early (≤ 14 days), typical (15–27 days), or delayed (≥ 28 days) recovery based on the typical length of recovery in this population in published literature.[41]

Statistical Analysis

Sample size was ultimately determined by number of records available, and a power analysis suggested that 220 records were necessary to achieve 80% power with 16 variables (20 degrees of freedom, 0.3 effect size). Categorical variables are presented as frequency and proportion. Continuous variables are presented as mean ± standard deviation (SD).

Chi-square analysis was used to compare categorical variables and independent-samples t-test or Mann-Whitney U-tests were used to compare continuous variables. Chi-square automatic interaction detection (CHAID) analysis was performed to develop a decision tree of exposures impacting the primary outcome. This method uses a nonparametric procedure with the goal of determining how continuous or categorical independent variables best predict the outcome of interest. Once input variables are selected, the algorithm first performs a chi-square test for each pair of categories of the predictor (independent) variables in relation to the target variable with significance (α) set at 0.05. Categories of the predictor variable are merged if $p > 0.05$, or not merged if $p \leq 0.05$, with missing data allowed to join either category of the predictor variable for this step. Bonferroni adjustment is used for merged category p values to control for type I error. After all possible merges, predictor variables are compared to select which variable best splits the starting node. Chi-square tests using adjusted p values are conducted, and the node is split on the predictor with the smallest p value if the user-defined minimum node sample size limit to prevent overfitting (n = 10) is met for all subsequent nodes. If no predictor variable splits the node with significance or if these minimum node sizes are not met, the node is terminal.

For the CHAID analysis, participant data were randomized to a training (70%) or test (30%) sample for algorithm validation. Significance level for merging and splitting nodes was set a priori at $p < 0.05$. The CHAID analysis prediction of the primary outcome for each patient was then compared to the grouped time to recovery. These comparisons were used to generate a receiver operating characteristic (ROC) curve to determine the performance of the decision tree model in predicting the primary outcome. Analysis was performed in IBM SPSS version 27 (IBM Corp.).

Results

Study Cohort Characteristics

A total of 493 patients met the inclusion criteria (mean age 15.7 ± 1.5 years, 68.2% male, 70.0% White). The most common sports being played when SRC occurred were football (41.4%), basketball (13.6%), and soccer (13.4%). The median time to clinic presentation was 5 days (IQR 2–10 days). In total, 258 (52.3%) of the patients recovered within 14 days of injury, and 106 (21.5%) patients reached symptom resolution between 15 and 27 days and

TABLE 1. Demographics and injury characteristics

Demographics	Training Sample (n = 346)	Test Sample (n = 147)
Age, yrs	15.7 ± 1.5	15.7 ± 6
Sex		
Male	239 (69.1)	97 (66.0)
Race		
White	241 (69.7)	104 (70.7)
Black	61 (17.6)	23 (15.6)
Other	6 (1.7)	6 (4.1)
Unknown	38 (11.0)	14 (9.5)
School type		
Private	81 (23.4)	29 (19.7)
Public	157 (45.4)	71 (48.3)
Unknown	108 (31.2)	47 (32.0)
Sport contact level		
Noncontact	2 (0.6)	0 (0)
Limited contact	26 (7.5)	15 (10.2)
Contact	116 (33.5)	50 (34.0)
Collision	196 (56.6)	82 (55.8)
Unknown	6 (1.7)	0 (0.0)
Initial presentation		
ED	72 (20.8)	41 (27.9)
Urgent care	20 (5.8)	6 (4.1)
Sports medicine	201 (58.1)	78 (53.1)
Neuropsychology	17 (4.9)	11 (7.5)
PCP/pediatrician	32 (9.2)	10 (6.8)
Other	4 (1.2)	1 (0.7)
Loss of consciousness	40 (11.6)	24 (16.3)
Amnesia	80 (23.1)	30 (20.4)
Time to CC presentation, days		
≤7	236 (68.2)	93 (63.3)
>7	110 (31.8)	54 (36.7)
Prior concussions		
0	244 (70.5)	105 (71.4)
1	68 (19.7)	32 (21.8)
2+	34 (9.8)	10 (6.8)
Comorbid conditions		
ADHD	46 (13.3)	20 (13.6)
Psychiatric conditions	33 (9.5)	11 (7.5)
Migraine	27 (7.8)	18 (12.2)
Family history		
Psychiatric conditions	37 (10.7)	21 (14.3)
Migraine	97 (28.0)	38 (25.9)
Initial PCSS score		
0–10	130 (37.6)	46 (31.3)
11–20	25 (7.2)	16 (10.9)
21–30	89 (25.7)	42 (28.6)
31–40	39 (11.3)	18 (12.2)
41–50	24 (6.9)	7 (4.8)
>50	39 (11.3)	18 (12.2)

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TABLE 1. Demographics and injury characteristics

CC = concussion clinic; ED = emergency department; PCP = primary care provider.
Values are presented as number (%) of patients or mean ± SD. The cohort was randomized into training (70%) and test (30%) samples for algorithm validation.

129 (26.2%) recovered after 28 days or longer. Training (n = 346) and test (n = 147) samples were similar in demographics and injury-related factors, demonstrating their random allocation. Complete demographic and injury data are reported in Table 1.

CHAID Analysis and Clinical Decision Tree

Sixteen input variables were used for the CHAID analysis. Variables and thresholds for splitting decision tree nodes were determined by the algorithm. According to the algorithm the study population was first split by initial symptom burden as quantified by the PCSS score, with cutoffs at scores of 6 or less, 7 to 28, and greater than 28. Patients with low initial symptom burden (PCSS ≤ 6) were more likely to recover early (within 14 days), while those with higher symptom scores (PCSS > 28) were more likely to have typical (15–27 days) or delayed (> 28 days) recovery.

In the next step, the CHAID algorithm split the resulting nodes by time to clinic presentation, with a cutoff at 7 or fewer days from injury. Among patients with earlier presentations (≤ 7 days), more than 90% recovered early, whereas patients presenting beyond 7 days were more likely to recover within the typical or delayed period. More than 75% of patients in the high symptom burden, delayed presentation grouping took 28 days or longer to recover.

Last, the algorithm identified one node of the training sample decision tree that could be further split by history of concussions, whereas the other nodes were terminal. Among patients with high symptom burden and early presentation, further splitting by number of prior concussions (0 vs 1 or more) resulted in a higher likelihood of early recovery if the athlete had no prior concussions. Complete training and test trees are presented in Figs. 2 and 3.

Similar proportions of early, typical, or delayed time to recovery were observed in both the training and test sample trees. In the final nodes of the validation (test) tree, only the split based on the number of prior concussions failed to reach statistical significance. Notably, this node also did not reach the a priori threshold for minimum number of patients to allow for a split but was tested to analyze the performance of the model despite the small sample size.

An ROC curve was generated to evaluate the performance of the model in predicting early versus typical or delayed recovery. Area under the ROC curve was 0.80 (95% CI 0.76–0.84) for this prediction. In the test sample, the algorithm correctly predicted the recovery of 90.3% of patients who recovered early. Prediction of typical (versus early or delayed) or delayed (versus early or typical) recovery was less accurate, with AUC of 0.69 (95% CI 0.63–0.74) and 0.76 (95% CI 0.71–0.81), respectively. Overall,

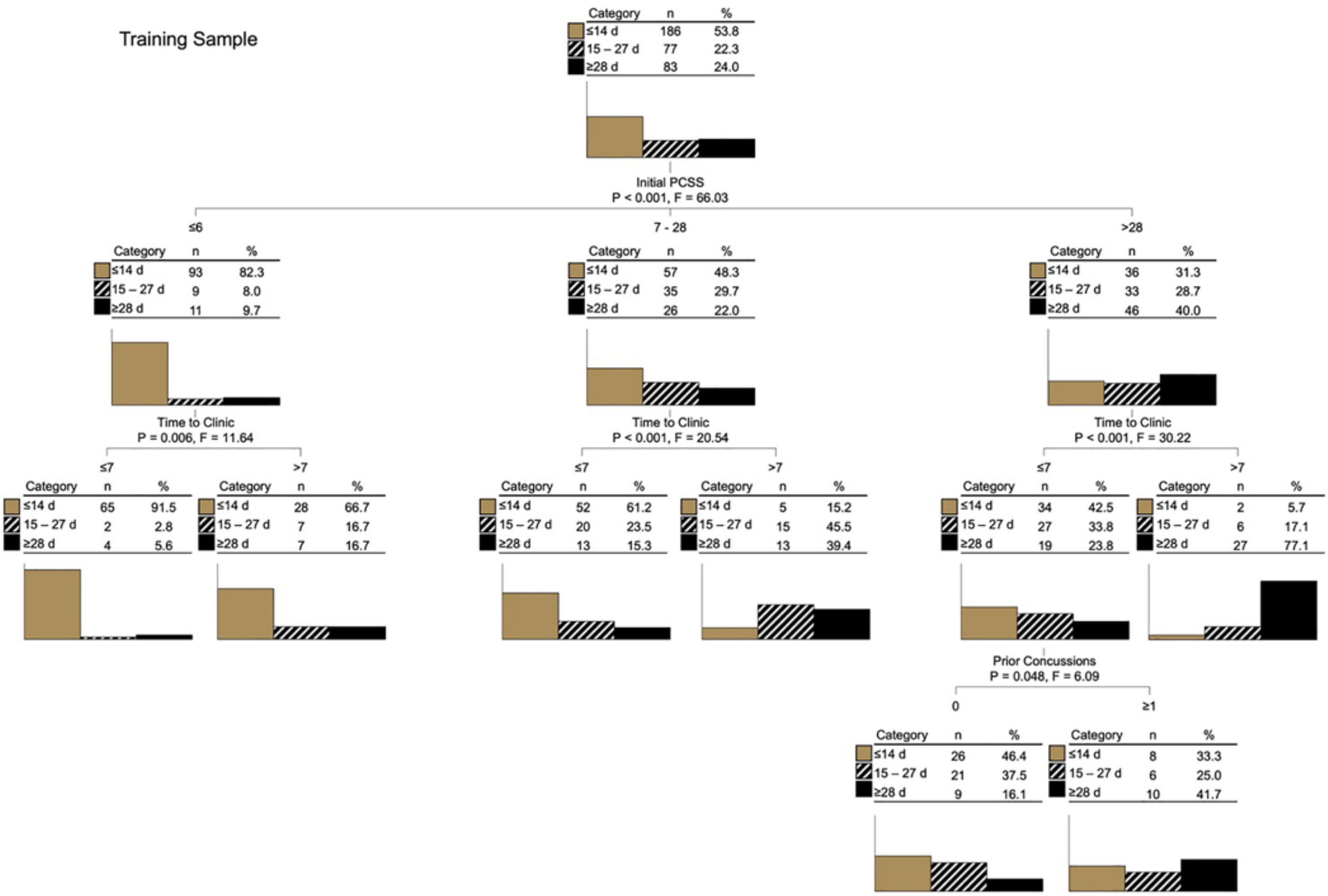

FIG. 2. Decision tree generated by use of the CHAID algorithm for prediction of time to symptom resolution utilizing the training cohort, with p values representing chi-square significance used to determine node splitting for further branches of the tree. Figure is available in color online only.

the model correctly predicted the recovery status (early, typical, or delayed) of 64.5% of the training and 60.5% of the test sample. ROC curves for the validation sample are shown in Fig. 4.

To maximize sensitivity for detection of early recovery (versus typical or delayed recovery), the cutoff for this prediction was selected at a probability of 0.29 (i.e., a prediction of early recovery if the probability predicted by the model was 0.29 or greater). At this cutoff, the model achieved a sensitivity and specificity of 96.1% and 23.4%, respectively, for the identification of patients with delayed recovery. When a cutoff is chosen for optimal sensitivity and specificity (via Youden's index), sensitivity and specificity were 78% and 67%, respectively, for the identification of early versus typical or delayed recovery. Sensitivities and specificities at all cutoff points of the model are shown in Fig. 4.

The current model therefore identifies initial symptom burden (by PCSS score), time to presentation, and prior concussion history as the most important factors in discriminating recovery duration. Figure 5 depicts these results as a clinical support tool for the assessment of pediatric SRC patients in the clinical setting, and shows tabulation of the proportion of early, typical, or delayed recovery for all nodes of the decision tree, utilizing all patients in the full study cohort.

Discussion

In the current study we investigated whether previously postulated risk factors for prolonged concussion recovery could be combined into a practical algorithm to broadly predict duration of recovery in pediatric SRC patients. While several factors have previously been suggested as typical to strong predictors of recovery,[3,4,16,37] translating these factors into a coherent prognostic tool has proved challenging. Using a decision tree analysis, we generated a clinical support tool based on three factors to translate these results more easily into a framework for clinical evaluation. From this initial prediction, clinicians may add their expertise, conduct additional assessments or testing, or simply provide clear prognostic possibilities for patients to guide shared medical decision-making. Future subgroup analyses may also allow for improved predictions. For example, recent studies have identified differential recovery timelines between races and social determinants of health such as median income and insurance status.[42] Within our cohort, assessing subgroups based on socio-

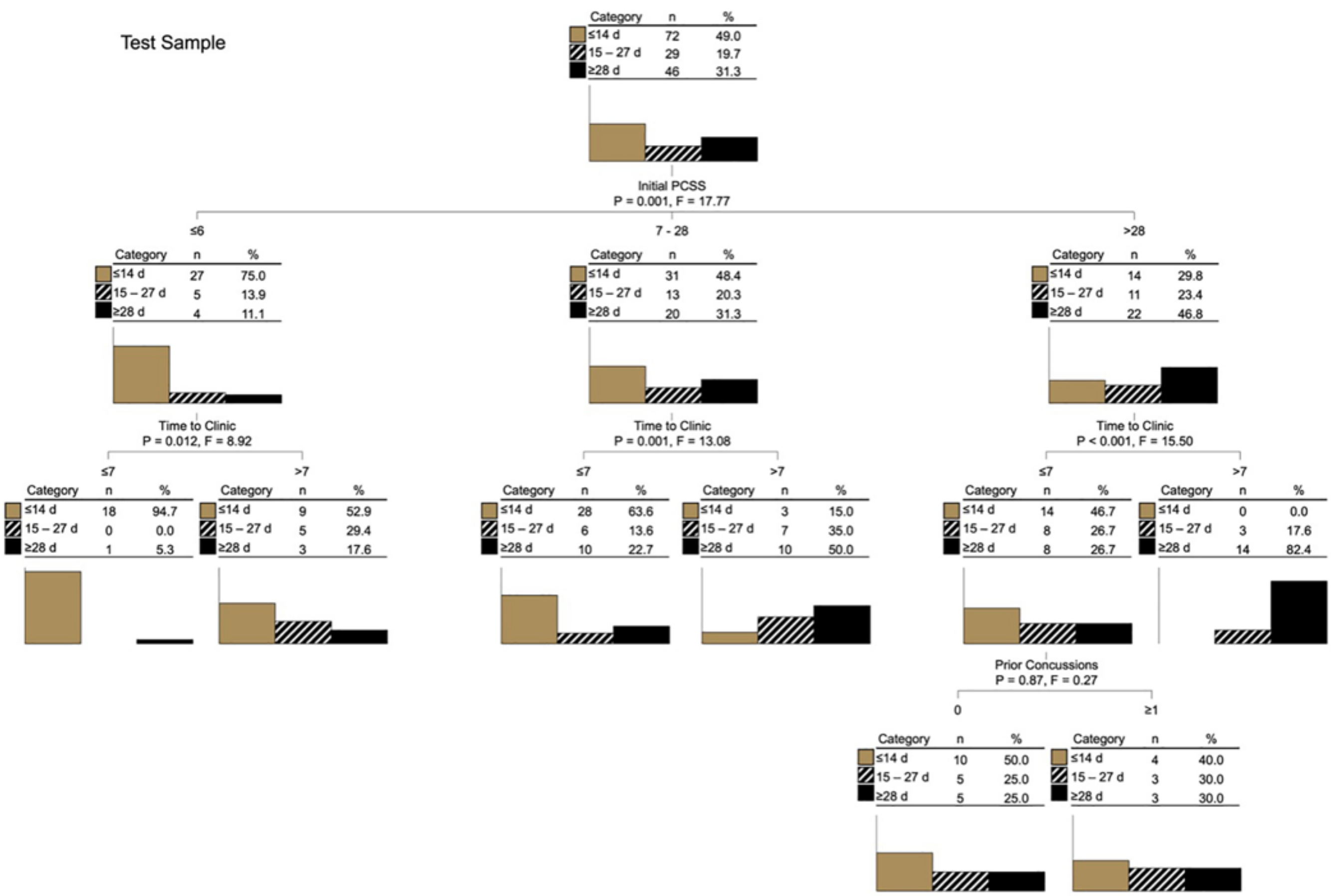

FIG. 3. Decision tree generated by application of the CHAID algorithm to a separate validation sample, with p values representing chi-square significance of differences in recovery time for nodes split by the indicated factor defined by the prediction algorithm. Figure is available in color online only.

economic status, access to an athletic trainer at school, or other social determinants may yield higher fidelity predictions for these groups. Similarly, subgroup analysis considering the levels of play in which athletes were injured (recreation, high school sports, or competitive independent leagues) may make substantial impact on their access or desire to seek additional therapies that aid in recovery.

Our results support prior analyses that identified several factors as impactful regarding time to recovery from SRC, including initial symptom severity, time to presentation, and prior concussion history. Acute symptom severity and concussion history have been shown to increase the odds of postconcussion symptoms lasting more than 28 days by more than fivefold and threefold, respectively.[21,31] Prior concussion history was associated with differences in recovery in our training sample, but the results did not achieve clinical significance in the relatively smaller test population, likely due to the small size of the node to be split in the test sample, which did not meet our a priori minimum size for a split that was applied in the training subset. Given literature supporting prior concussions as a risk factor in concussion severity and recovery,[21,31] we suspect that the size of this sample limited detection of an effect of prior concussions on recovery and suggest providers continue to consider concussion history a relevant factor in recovery, although further validation is warranted.

In support of recent reports detailing time to specialty clinic presentation as a prognostic factor, our model identified this factor to be useful in discriminating between early and late recovery, especially for patients presenting with high symptom burden.[34] Moreover, the approximate 1-week threshold identified by the algorithm recapitulates work by Eagle et al.[43] and supports the value of early specialized care after concussion. Identifying the cause of a delayed presentation to a dedicated concussion clinic may provide an avenue for intervention for improved outcomes.

Interestingly, in our analysis several factors previously shown to be associated with delayed recovery proved not as useful for decision tree development and recovery duration discrimination, including age, female sex, and personal or family history of health conditions like psychological disorders and ADHD.[21,22] One reason for these findings may be that initial segmentation of the study population by the strongest predictive factors (PCSS followed by time to presentation) led to other factors being more predictive in these subpopulations than would be expected based on prior regression models that analyze the full spectrum of patients and presentations. In the pursuit of developing a

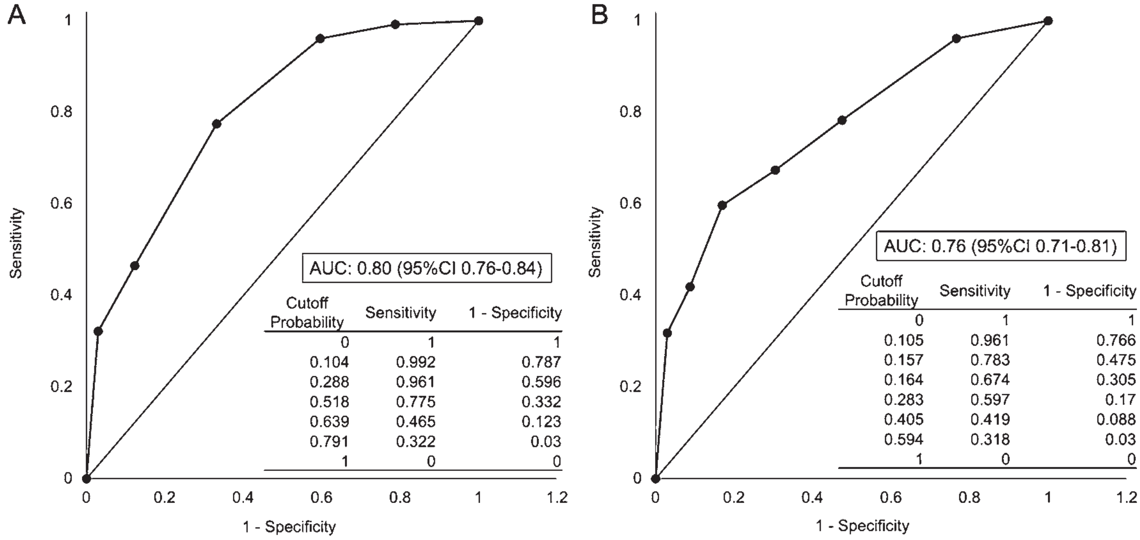

FIG. 4. ROC curve for prediction of early versus moderate or delayed recovery (**A**) and delayed versus moderate or early recovery (**B**). AUCs for the model predictions are as shown. Coordinates of the curve (i.e., probability cutoffs and sensitivity and 1 − specificity) are presented for each curve.

clinically useful, predictive tool, we prioritized this initial segmentation of the population over relatively smaller differences in recovery to which these previously described factors may contribute. Overall, the final nodes of our decision tree align with the clinical expertise of many physicians treating concussion patients as well as prior literature, and suggest that it is critical to understand patients' symptom burden, personal history, and postinjury course to formulate a recovery plan.

Organizing concussion-related variables into a clinically relevant tool is a key step for improved prognostication. For example, the 5P tool is useful for identification of potentially delayed recovery in more acute settings but has some limitations and relies on several factors that may not be routinely collected, especially by providers who are less experienced in assessing concussion patients. In contrast, the present model relies on three factors that are commonly collected or known at the time of evaluation: the initial symptom burden using PCSS, the time to presentation, and any prior concussion history. With the use of these factors alone, this model achieved high sensitivity (96.1%) and relative specificity (23.4%) for the identification of early versus typical or delayed recovery (AUC 0.80). In contrast, the original 9-factor 5P scale targeted > 90% sensitivity and achieved a sensitivity of 93.5% and specificity of 18.1%, with an AUC of 0.68.[37] Similarly, Howell et al.'s application of the 5P model in the clinical setting predicted delayed recovery, with an AUC of 0.75.[38] The current model achieved similar or improved ability to discriminate between duration of recovery, albeit with markedly reduced complexity.

Additionally, recent studies have explored the use of artificial intelligence (AI) techniques to predict concussion recovery outcomes.[44,45] While these models have advantages in parsing large amounts of data or finding unique patterns in recovery, they have so far been limited when applied to validation samples. For example, the sensitivity and specificity reported in a recent pilot study (59% and 65%, respectively) may improve substantially as these techniques are refined and may have been limited by the relatively small cohorts used to train and validate these models compared to those in the current study.[44] Comparable to the predictive ability of the model used in the study we present here, another AI-generated algorithm recently demonstrated improved predictive and discriminative abilities (AUC 0.78–0.84) compared to previous human-derived models of protracted concussion recovery in a cohort of 655 pediatric SRC patients.[45]

The use of clinical decision trees allows for better understanding of the relationships between concussion-associated factors rather than as standalone predictors. For example, our decision tree highlights patients presenting with a high symptom burden more than a week after their injury, who are highly likely to experience delayed recovery regardless of other potentially predictive factors. On the other hand, this decision tree presents a clear, logical prognosis for patients who present soon after injury with relatively low symptom burden; these athletes have a high probability of a quick, uncomplicated recovery. For the clinician assessing pediatric SRC patients in clinic, translation of the multitude of concussion-associated factors into a straightforward framework for prognostication would be an invaluable tool. Figure 5 uses the most predictive factors for recovery duration identified in the current study to build such a framework and aid in identification of these patients.

Study Limitations

As this study was retrospective, there was limited ability to control for confounding treatment decisions or medical conditions which may have had impacts on factors in the analysis or the outcome of time to symptom resolution.

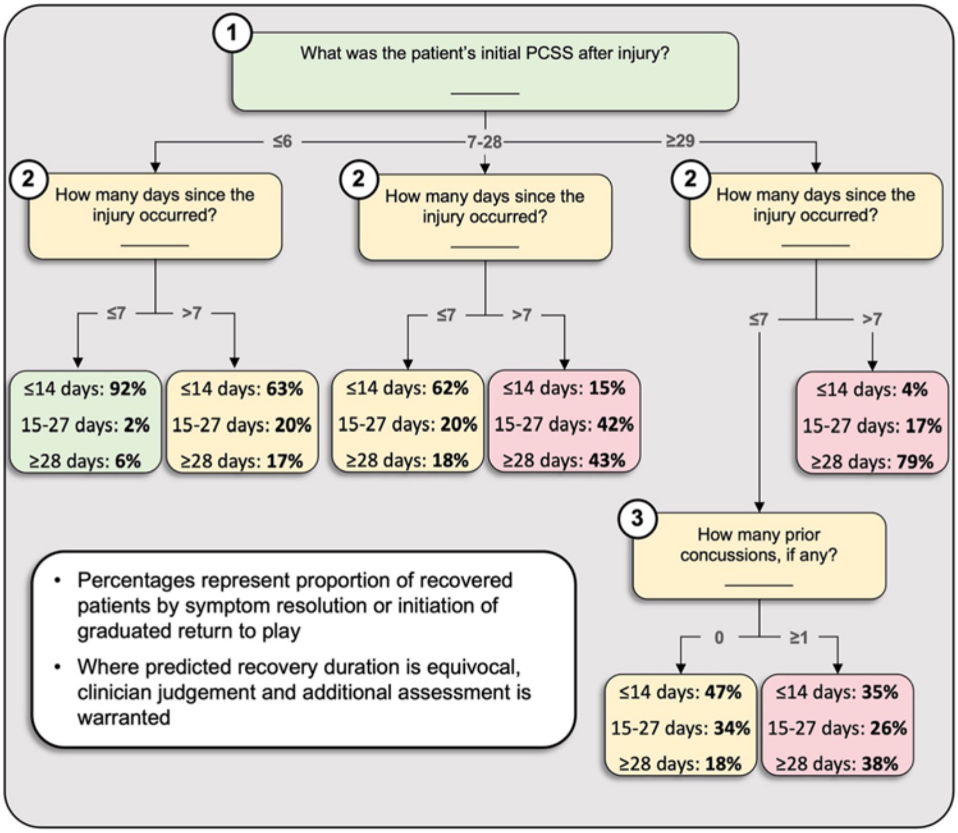

FIG. 5. Clinical support tool based on the decision tree model. Proportions of patients with early, moderate, or delayed recovery for each node are shown and represent patients from the entire (training and validation) study sample. Clinical judgement based on presenting symptoms, prior history, and access to follow-up is warranted. Figure is available in color online only.

Patients in the study received individualized assessments and care based on the judgement of treating physicians with the information available at the time, with the goal of recovery and return to activity as soon as possible. A multitude of treating physicians, clinical sites, and geographic locations are represented in the patient sample, which may serve to minimize the directionality of any bias introduced by these treatment decisions. An initial prospective study seeking to validate the findings presented here could be designed to assess athletes using the predictive algorithm. Specifically, a prospective study where athletes presenting to clinic within 7 days of injury are randomized to protocolized care based on the predictive algorithm versus typical care. A pragmatic block study design where each month clinicians treating with usual care and those following predictive algorithm cross over to account for differences among clinicians. Using this design would allow for validation of the predictive algorithm prospectively as well as analysis of resource utilization.

We also considered that access to care, social and structural determinants of health, and related factors may impact recovery probabilities and times to return to academic or athletic activities. Unfortunately, while broad geographic data are available for the study population, the patient-level socioeconomic data needed to accurately analyze these relationships were not available. There is an immediate need for further investigation into how social and structural determinants of health influence SRC recovery.

We recognize that the current model does not achieve the upper extremes of predictive power, nor does it delve deeply into the relative influence of all variables previously associated with recovery duration. However, the primary aim of the study was to understand and characterize factors most influential for early or late recovery specifically, as these patients are those in whom straightforward tools to predict broad outcomes are most impactful. We expect that the clinical judgement and expertise of treating physicians is most important in predicting and managing recovery in these patients. Furthermore, we recognize the limitations of utilizing self-reported symptom data (via repeat PCSS) at follow-up visits for the primary outcome of time to recovery. As many patients without injury may have an elevated PCSS at baseline, symptom recovery was defined as a reported PCSS score of 0 or return to the patient's preinjury baseline, if available. Additionally, this method is in keeping with clinical assessments for improvement and recovery and allows for greater tracking of outcomes in patients who may otherwise be lost to follow-up. Analysis of time to recovery may also be limited by the nature of scheduling follow-up appointments. Those patients who present earlier may be more likely to have their first follow-up within the period for early recovery. As patients may not track the exact date of their symptom resolution or have the opportunity to report any change in symptoms prior to the first follow-up, earlier follow-up evaluation may provide a greater opportunity to report symptom resolution within the early recovery period among those who initially presented early. Again, the use of self-reported symptom resolution or return to baseline has benefits in tracking patients that may outweigh potential error introduced by the necessities of scheduling.

Last, this study was conducted at a single institution serving a majority suburban population in the Southeastern United States. Demographic factors, including common sports, culture surrounding participation, and reporting of symptoms after injury may differ from those of other regions and practice settings. As this study was limited to adolescent patients (aged 12–18 years), generalizability to the overall pediatric population should be performed with caution. These results are most applicable to the study-specific population and region but should motivate further regional and national studies.

Conclusions

Through a retrospective decision tree analysis of pediatric SRC patients at a regional concussion center over 3 years, we constructed a decision support tool utilizing initial symptom burden, time to presentation, and prior concussion history that effectively predicted time to recovery for most patients. Our decision support tool provides a practical framework to predict an athlete's recovery trajectory and in doing so may lead to enhanced resource utilization by shifting clinic visits and early referrals from patients with the most expedient recoveries to those most likely to benefit.

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Disclosures

Dr. Zuckerman reported serving as an Unaffiliated Neurotrauma Consultant for the National Football League. Dr. Terry reported personal fees from HitIQ outside the submitted work. Dr. Yengo-Kahn reported personal fees from BlinkCNS as a Scientific Advisor and personal fees from Annalise.AI as a consultant outside the submitted work.

Author Contributions

Conception and design: Yengo-Kahn, Allen, Tang, Grusky, Bonfield, Zuckerman. Acquisition of data: Yengo-Kahn, Allen, Tang, Hajdu, Hou, Grusky. Analysis and interpretation of data: Yengo-Kahn, Allen, Hajdu, Grusky, Chen, Terry. Drafting the article: Allen, Bonfield, Terry. Critically revising the article: Yengo-Kahn, Allen, Tang, Hou, Grusky, Bonfield, Zuckerman, Terry. Reviewed submitted version of manuscript: Yengo-Kahn, Allen, Tang, Hajdu, Grusky, Bonfield, Zuckerman, Terry. Approved the final version of the manuscript on behalf of all authors: Yengo-Kahn. Statistical analysis: Allen, Chen. Administrative/technical/material support: Grusky, Zuckerman. Study supervision: Yengo-Kahn, Bonfield, Zuckerman, Terry.

Supplemental Information

Previous Presentations

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