# **Title Page**

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Automating the Treatment Planning Process for 3D-Conformal Pediatric Craniospinal Irradiation Therapy

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**[Abbreviations Key]**

|  |  |
| --- | --- |
| **CSI** | Craniospinal Irradiation |
| **LMICs** | Low- and middle-income countries |
| **DSC** | Dice similarity coefficient |
| **HD** | Hausdorff distance |
| **AI** | Artificial intelligence |
| **JXN** | Junction |
| **SSD** | Source to surface distance |
| **ROI** | Region of interest |

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# **Abstract**

**Purpose:** Pediatric patients with medulloblastoma in LMICs are most treated with 3D conformal photon craniospinal irradiation (CSI), a time-consuming, complex treatment to plan, especially in resource-constrained settings. Therefore, we developed and tested a 3D conformal CSI autoplanning tool for varying patient lengths.

**Methods and Materials**: Autocontours were generated with a deep learning model trained:tested (80:20 ratio) on 143 pediatric medulloblastoma CT scans (patient ages, 2-19 years, median=7 years). Using the verified autocontours, the autoplanning tool generated 2 lateral brain fields matched to a single spine field, an extended single spine field, or 2 matched spine fields. Additional spine sub-fields were added to optimize the corresponding dose distribution. Feathering was implemented (yielding 9-12 fields) to give a composite plan. Each planning approach was tested on 6 patients (ages, 3-10 years). A pediatric radiation oncologist assessed clinical acceptability of each autoplan.

**Results:** The autocontoured structures’ average Dice similarity coefficient ranged from 0.65-0.98. The average V95 for the brain/spinal canal for single, extended, and multi-field spine configurations was 99.9±0.06%/99.9±0.10%, 99.9±0.07%/99.4±0.30%, and 99.9±0.06%/99.4±0.40%, respectively. The average maximum dose across all field configurations to the brainstem, eyes (L/R), lenses (L/R) and spinal cord were 23.7±0.08 Gy, 24.1±0.28 Gy, 13.3±5.27 Gy, 25.5±0.34 Gy, respectively (prescription=23.4 Gy/13 fractions). Of the 18 plans tested, all were scored as clinically acceptable as-is or clinically acceptable with minor, time-efficient edits preferred or required. No plans were scored as clinically unacceptable.

**Conclusion:** The autoplanning tool successfully generated pediatric CSI plans for varying patient lengths in 3.50 ± 0.4 minutes on average, indicating potential for an efficient planning aid in resource-constrained settings.

**Key words:** craniospinal irradiation therapy, pediatric medulloblastoma, automated treatment planning, automated contouring, global radiation therapy access

# Introduction

Eighty percent of children with cancer live in low- and middle-income countries (LMIC), where a relatively larger pediatric population (under the age of 15 years) compared to high-income countries, prevails (37% vs. 17%, respectively, in 2015).1 The 5-year survival rate of patients in LMICs is much lower than in high-income countries (20% compared with 80%).2 Radiation therapy is a key component to a multimodality cancer treatment for more than half of pediatric patients in LMICs.3 In 2012, 4 million adult and pediatric patients in LMICs required radiation therapy, and the Collaboration for Cancer Outcomes, Research and Evaluation projects this number to increase by 78% by 2035.3 Access to high-quality radiation therapy in LMICs is variable, in part due to a lack of properly trained radiation oncologists and medical physicists to prepare and deliver the radiation treatment plans; with both professions requiring many years of technical training.4–7 Having limited personnel creates demanding workflows, with medical physicists dedicating 50% of their time to generating treatment plans and 50% to completing other necessary clinical tasks.8

To alleviate demanding workflows, artificial intelligence (AI) has been used to develop radiation therapy treatment planning tools,9 and our group has focused specifically on the clinical needs of LMICs.10 All algorithms have used AI’s powerful image segmentation and classification capabilities to automate contouring, treatment planning, and quality assurance for radiation therapy to various disease sites such as the cervix, chest wall, spine and head and neck (HN).10–15 To date, these algorithms have been trained, validated, and tested exclusively on adult patient cohorts. More widely, while AI has been introduced to pediatric healthcare, it has yet to be integrated into pediatric radiation oncology.16,17

In this study, our purpose was to expand the use of AI in pediatric radiation therapy by automating the generation of 3D conformal radiotherapy treatment plans for craniospinal irradiation therapy. We selected medulloblastoma as the testing disease site because it is the most common malignant pediatric brain tumor in both high-income countries (20-25%) and LMICs (up to 49%),18 it is a solid tumor, and it requires craniospinal irradiation therapy.19 Medulloblastoma requires a multistage treatment: surgery to remove the solid tumor, followed by radiation therapy and chemotherapy. Our work automated the first arm of radiation therapy, craniospinal irradiation (CSI), which is the standard treatment recommended for all patients with medulloblastoma older than 3 years.18

The CSI planning process is a challenging task because it requires irradiating the brain and spinal canal. To cover the large treatment volume requires multiple treatment fields around multiple isocenters that must be created and optimized. In addition to accounting for multiple fields to cover the long treatment volume, these treatment plans must also allow the fields to be shifted periodically during treatment to mitigate the possibility of inhomogeneous dose distributions in structures residing in immediately adjacent or overlapping treatment field regions (“feathering”).20

To our knowledge, this is the first work to develop autocontouring and autoplanning tools specifically for pediatric radiation oncology. While medulloblastoma was selected as the disease site for this work, the autocontouring tool and autoplanning tool developed herein are translatable to various clinical implementations (e.g., autocontouring for other pediatric disease sites requiring radiation therapy and autoplanning for other disease sites requiring CSI).

# Methods

We developed a comprehensive automated contouring and planning tool for 3D-conformal craniospinal irradiation therapy and assessed its performance on a cohort of pediatric patients with medulloblastoma. Retrospective patient data used in the testing and development of the autocontouring approach was collected following an institutional review board approved protocol at our institution.

## Autocontouring

Normal tissue contours and landmark contours were automatically generated to guide the automation of CSI treatment plans. The structures defined included the brain, brainstem, left and right (L/R) eye, L/R lens, L/R lung, L/R kidney, spinal canal, thyroid, and heart. We also elected to contour landmark structures (i.e., structures that guide field apertures, which physicians may not always contour for manual planning). The landmark structures defined included the cribriform plate, vertebral column, mandible, and shoulders.

### Adult HN Model Testing

An in-house autocontouring tool originally designed to contour 16 adult HN normal tissue volumes14 was tested on a data set of patients with medulloblastoma to generate 6 overlapping pediatric structures. The structures tested included the brain, brainstem, L/R eye, and L/R lens. The data set consisted of 143 pediatric patients with medulloblastoma CSI CT scans. Of the 143 CT scans, 1, 127, and 36 were performed on Philips, GE, and Siemens machines, respectively. The median (range) number of slices, slice thickness, and tube voltage peak was 347 (133-523), 2.5 (1.25-2.5) mm, and 120 (80-120) kVp, respectively. The patients in the data set had a median age of 7 years (range, 1.5-19 years) and a male to female ratio of 2:1. The age and sex distribution of our data set is comparable to that reported in the literature for pediatric medulloblastoma.21

### Pediatric Autocontouring using nn-UNet

The remaining normal tissue and landmark structures needed for treatment planning were the thyroid, L/R kidneys, cribriform plate, vertebral column, mandible, spinal canal, and shoulders. The landmark structures were manually contoured and added to the existing clinical structure set. The spinal canal was contoured to begin at the base of the brainstem and continue through the S2/S3 interspace, as this is where 75% of spinal canal contours end in pediatric patients.22 The cribriform plate was contoured as the thin horizontal plate of ethmoid bone between the two medial orbital walls.23 The vertebral column volume was defined to cover the lateral extent of the vertebral bodies.

To automatically generate the pediatric specific models for these structures, we divided the same data set of 143 pediatric patients into training and testing sets (3:1 ratio) for a nn-UNet model.24 This architecture was selected for the experiment because it has proven to be successful for limited and heterogeneous data sets.24 One advantage of the nn-UNet model is that it generates a data signature to optimize the training hyperparameters for the data set, making the training process less sensitive to heterogeneities in the data (e.g., patient positioning, image scanning protocols, anatomy variation with age). Using the optimized hyperparameters, a 3D full-resolution nn-UNet model was trained with 5-fold cross validation to further maximize the limited data set.

Additional post-processing algorithms were applied to improve the consistency of the autocontours and to prevent autocontouring errors from propagating through to treatment planning. For example, the spinal canal and mandible were post-processed within the treatment planning system. The spinal canal post-processing was designed to remove any slice of the contour that had an area <0.10 cm2. Additionally, the algorithm checks for a gap between the auto-contoured spinal canal and brain stem contour. If a gap is present, the algorithm extends the spinal canal superiorly to fill the gap so that the final target volume is a continuous structure. The mandible post-processing algorithm removes any mandible contour that extends below the top of the shoulders. This is to prevent the final mandible structure from containing a volume that may have been misidentified as mandible by the autocontouring algorithm (i.e., high attenuation areas like the humerus, radius, or ulna).

## Autoplanning

The autoplanning approach was designed based on recommendations from the International Society of Paediatric Oncology (SIOP) Paediatric Oncology in Developing Countries radiotherapy working group18. In summary, the recommendations provided guidance for field generation, field matching, and field feathering. Fields must treat the brain and spinal canal while emphasizing coverage of critical areas such as the cribriform plate, skull base, and thecal sac. We used a standard supine CSI beam arrangement with 2 lateral head fields and either 1 or 2 matching posterior spinal fields. A collimator rotation was applied to the lateral head fields to match the beam divergence of the spinal field. The lateral fields were designed to extend as far inferiorly as possible without reaching the shoulders. The junction of the brain and spine fields was shifted twice during treatment to ensure dose homogeneity and limit risk of over or under exposure due to setup inaccuracies during treatment. Moreover, none of these junctions should reach the shoulders.

Once the design of the planning workflow was approved by an experienced pediatric radiation oncologist, the workflow (Fig. 1) was scripted in RayStation 10B (RaySearch Laboratories, Stockholm, Sweden)25. International collaborators supplied patient data to test and refine the script design. In summary, the inputs of the planning code included a CSI CT scan, the automatically generated contours, the energy of the beams, and the dose prescription. After the input parameters are configured, the number of necessary spine fields is calculated, the isocenters are placed, the target volumes are defined, the treatment fields are created, sub-fields are added for dose optimization, and feathering is performed. Finally, a composite treatment plan is created to calculate and sum the dose of each individual plan. The output of the planning code includes 3 individual plans (1 for each junction position) and a composite plan.

### Isocenter Placement

The brain isocenter is the first to be determined (Fig. 2). To do this, the longitudinal distance between the mandible and shoulder landmark contours is calculated. If this distance is less than 2 cm, the algorithm warns the user that there is insufficient space between the shoulders and the mandible to safely (automatically) feather the junction. If the distance is greater than or equal to 2 cm, the brain isocenter is placed 2 cm superior to the shoulders. If the distance is greater than or equal to 2.5 cm, the brain isocenter is placed 2.5 cm superior to the shoulders. In all cases, the brain isocenter is placed laterally at the center of the spinal canal.

Once the brain isocenter is placed, the length of the spine field required for the patient is determined by calculating the longitudinal distance between the brain isocenter and the most inferior slice of the vertebral column contour (S2/S3 interspace). If the distance is less than or equal to 40 cm, a single spine field is used. If the distance is greater than 40 cm, the tool either uses an extended source to surface distance (SSD) to increase the effective field size or uses 2 fields with 2 spine isocenters. The spine field choice is a patient-specific parameter that is configurable.

Once the spine field configuration has been determined, the spine isocenter coordinates are set according to the field configuration generated by the treatment planning algorithm. Each field configuration is outlined in Fig. 2. In a single PA field setup, the spine isocenter is placed 20 cm inferior to the brain isocenter coordinate, and the lateral and AP/PA coordinates are kept the same as the brain isocenter. In the extended field setup, the AP/PA coordinate of the isocenter is shifted posteriorly to be placed at the upper surface of the treatment couch. In a multiple field setup, 2 spine isocenters are created. The first is placed 20 cm below the brain isocenter and the second is placed at the halfway point of the remaining length of the spine field.

### Target Definition

Target contours are generated for both the brain and spine fields to guide jaw and multi-leaf collimator placement. The brain target volume is defined as a combination of the brain, brainstem, cribriform plate, and upper spinal canal autocontours. The spine target is defined as the vertebral column autocontour.

In addition to target contours, planning volumes are defined according to the prescribed dose. The brain field prescription contour is set to the brain autocontour. The spine field prescription volume is a truncation of the spinal canal autocontour to longitudinally shift the structure away from the field borders by 3 cm superiorly and 1 cm inferiorly. In the multi-field configuration, the spinal canal is separated into two volumes, one for the upper spine field and another for the lower. The same truncation method is applied to each volume.

### Field Generation

One to two spine fields are generated depending on the required field configuration of the patient, after which two lateral opposed brain fields are generated and matched to the spine field. All fields are blocked to their respective target volumes described in the Target Definition section. All field expansions applied to the brain and spine target may be re-configured to cater to user preferences.

The superior border of the spine field is set to the longitudinal location of the brain isocenter point. The inferior border of the spine field is set to match the z-location of the most inferior slice of the vertebral column contour (S2/S3 interspace). The Y2 (superior) jaw of the spine field(s) is set to 20 cm to allow for more consistent treatment setup. The multi-leaf collimators are set to apply a 0.5-cm lateral expansion of the vertebral column autocontour and automatically conform to the curvature of the vertebral column autocontour. In the multi-field configuration, an additional spine field is generated around the lower spine isocenter to cover the remaining length of the spinal canal.

After the spine field(s) are generated, the brain fields are generated and matched to the spine field. The brain field is automatically generated to cover a default 1-cm expansion of the brain target volume. The Y1 jaw is set to 0 to create a half-beam block and avoid a couch rotation. A parallel opposed field is generated to create the second brain field.

A collimator rotation is required to match the brain field to the divergence of the spine field. Because the Y2 jaw of the most superior spine field is set to a constant 20 cm in the single and multi-field configurations, the collimator angle is kept constant to allow for simpler and more consistent patient setup. In the extended field configuration, the collimator rotation is calculated using Equation 1, where L1 is defined as the length of the spine field and S is defined as the source to isocenter distance.

) (1)

### Dose Calculation and Optimization

Once all beams are generated, matched, and blocked, the dose is prescribed. The dose prescription and fractionation scheme are defined by the user and are a configurable parameter. The default prescription is 23.4 Gy in 13 fractions with a 5,5,3 fractionation scheme for each of the feathered fields. The 95% isodose line is prescribed to cover 95% of the brain and 98% of the spine prescription volumes defined in the Target Definition section.

After the initial dose has been calculated, automatic optimization is applied to the spine field. The objective of the spine field optimization algorithm is to minimize the volume of 95% of the prescription dose that lies 5 mm or more anterior of the spinal canal autocontour. The framework for the optimization algorithm is summarized in Fig. 3. To achieve this, a planning structure is created to include the over-coverage region (volume of 95% isodose more than 5 mm anterior to the canal). A sub-field is then generated to block this over-coverage region and given an initial weight of 1% of the primary field. The algorithm re-calculates the over-coverage volume region using the new 95% isodose line. If the volume is increased from the non-optimized plan, the algorithm deletes the sub-field. If the volume is decreased, the algorithm continues to weigh the beam from 1% to 10% and iteratively recalculates the over-coverage region until the volume is no longer minimized. The final beam weighting is then used to calculate the optimal dose distribution. The sub-field weight is kept to ≤10%, as we found that larger weights could have unintended consequences, such as an excessive dose to the anterior tissue or posterior neck region.

### Feathering

The next step in the autoplanning workflow is feathering. To do this, the beams from the junction 1 (JXN1) plan are copied onto 2 new plans (JXN2 and JXN3). The borders of the inferior brain and superior spine field are shifted by 1 cm and 2 cm on JXN2 and JXN3 plans, respectively. In the multi-field configuration, both fields are feathered to optimize the dose distribution at both match lines. Once each junction plan has been created, a composite plan is generated to assess the summed dose distribution.

## Algorithm Testing

The performance of the autocontouring model was quantitatively assessed using the Dice similarity coefficient (DSC) and Hausdorff distance (HD). The performance metrics of the pediatric autocontours that were generated from the adult model were compared with those achieved on the adult data set using an unpaired *t* test for each structure (*P* < 0.05 as statistically significant). The performance of the landmark autocontouring models (shoulders and mandible) was also quantified with sensitivity.

The end-to-end CSI autoplanning tool was used to generate single, extended, and multi-field spine configuration plans on 6 patients, resulting in 18 treatment plans. The patients in the testing cohort ranged from 3 to 10 years old (median, 7).

The autoplanning tool’s ability to cover the necessary targets and limit the dose to organs at risk was quantified using dose coverage metrics and mean and maximum dose, respectively. The optimization component of the autoplanning tool was assessed by calculating the excessive depth of penetration of the prescription dose past the spinal target volume (“over-coverage region”) in the spine field before and after optimization.

The autoplanning tool’s performance was then qualitatively assessed using physician review. First, the outputs of each step of the autoplanning code were reviewed by an experienced pediatric radiation oncologist and physicist. Second, the plan quality for each patient and field configuration was assessed individually for clinical acceptability by the same experienced radiation oncologist. The pediatric radiation oncologist evaluated the total plan with individual scores allocated for the brain and spine dose distributions. The lower of the two scores was assigned as the overall plan distribution score. All scoring took the dose distributions at the junctions into account. Each plan was scored on a scale of 1-5 where 5=acceptable – use -as-is, 4=acceptable – preferred stylistic minor edits, 3=acceptable – minor clinically necessary edits, 2=Unacceptable – major edits, 1=Unacceptable – unusable. Further details of the planning score rubric can be found in Table 1 of the supplementary documentation.

# Results

## Autocontouring

The performance of the autocontouring algorithms is shown in Fig. 4. The average DSC and HD achieved on the structures translated from the adult algorithm (brain, brainstem, L/R eye, and L/R lens) ranged from 0.65 to 0.98 and 0.46 to 0.97 cm, respectively. The difference between the DSC and HD achieved on the pediatric and previously published adult data sets14 was not statistically significant for each structure tested (*P* < 0.05), suggesting that adult contouring algorithms can be used to accurately contour structures in the HN region for pediatric patients.

The mean DSC and HD of the L/R kidney, spinal canal, thyroid, cribriform plate, vertebral column, mandible, heart, L/R lung, and shoulders ranged from 0.73 to 0.95 and 0.90 to 3.10 cm, respectively. Five structures achieved a mean DSC >0.90 and a HD <1 cm. The models were able to identify the superior slice of shoulders and inferior slice of the mandible with 100% sensitivity.

## Autoplanning

The algorithm successfully generated treatment plans for all 3 spine field configurations. Fig. 5 is a dose-volume histogram showing the average dose metrics for various structures across 18 plans. Plans were evaluated for a standard prescription dose of 23.4 Gy in 13 fractions. The average V95 for the brain for single, extended, and multi-field spine configurations was 99.9 ± 0.06%, 99.9 ± 0.07%, and 99.9 ± 0.06%, respectively. The average V95 for the spinal canal for single, extended, and multi-field configurations was 99.9 ± 0.10%, 99.4 ± 0.30%, and 99.4 ± 0.40%, respectively. The average V95 for the cribriform plate was 96.8 ± 2.50% across all 3 spine field configurations. Finally, the average V20 for the kidneys was 5.54 ± 3.07% across all 3 spine field configurations.

The mean and maximum doses were quantified for selected normal tissue contours of interest. The average maximum dose across all field configurations to the brainstem, L/R eye, L/R lens, and spinal cord were 23.7 ± 0.08 Gy, 24.1 ± 0.28 Gy, 13.3 ± 5.27 Gy, and 25.5 ± 0.34 Gy, respectively. The average mean dose to the heart, lungs, and thyroid across all 3 field configurations was 11.3 ± 1.10 Gy, 2.56 ± 0.15 Gy, and 16.5 ± 2.41 Gy, respectively.

The performance of the spine optimization algorithm is summarized in Fig. 6. The algorithm was able to reduce the spine over-coverage region for all 18 plans tested. The average amount of over-coverage length reduction was 11.5 ± 7 cm, 13.5 ± 6 cm, and 9.50 ± 2.4 cm for single, extended, and multiple field configurations, respectively. The weight of the sub-field ranged from 4% to 5% for single field, 3% to 5% for extended field, and 5% to 6% for multi-field configurations. The number of monitoring units given to the sub-field ranged from 7 to 12 across all spine configurations.

An experienced pediatric radiation oncologist concluded that the algorithm correctly placed isocenters, generated fields, optimized field match lines, and feathered junctions for each of the 18 plans tested. Of the 18 plans tested, all were clinically acceptable with no or minor edits. The individual brain and spine dose distributions of the 18 plans were scored ≥3 across each spine field configuration. For the brain dose distributions across all spine field configurations, 50% were scored as clinically acceptable with minor, stylistic edits preferred (score=4) and 50% were scored as acceptable with minor, clinically necessary edits required (score=3). For single, extended and multiple spine field configuration dose distributions, all were clinically acceptable with majority scored as ‘use-as-is’. Ten, 5, and 3 plans were scored as 5, 4, and 3, respectively. For the overall dose distribution (brain and spine), 9 plans were scored as clinically acceptable with minor, stylistic edits preferred (score=4), and 9 plans were scored as acceptable after incorporating minor clinically necessary edits that are more efficient than creating a new plan (score=3). No plans required major edits or were clinically unacceptable (score <3).

# Discussion

In this work, we successfully autocontoured selected normal tissue and landmark structures to guide CSI autoplanning. Nine of the tested structures achieved a DSC score above 0.90 and an HD less than 1 cm. We used the autocontours to successfully script a comprehensive autoplanning workflow that mimicked the manual planning workflow of pediatric radiation oncologists. In summary, the autoplanning tool successfully generated, optimized, and feathered 18 treatment plans across 3 spinal field configurations to cater to spine length variability observed in pediatrics. The dose metrics of the target volumes and the selected normal tissue contours was comparable to what has been recommended by the results of clinical trials in pediatric radiation oncology.26,27 Finally, of the 18 plans tested, all were clinically acceptable and did not require major edits.

To our knowledge, this is the first work to test an adult autocontouring algorithm on pediatric patients. Our results suggest that adult contouring algorithms can be used to accurately contour structures in the HN region, including the brain, brainstem, eyes, and lenses of pediatric patient scans. The DSC and HD achieved on the pediatric autocontours were comparable to published data from adult patient cohorts.14,28 Careful review must be done before using the contours, especially for small patients.

The overall dose distributions for all the tested autoplans were scored as clinically acceptable with no or minor edits. For the brain fields, examples of minor edits included adjusting multi-leaf collimator positions to optimize cribriform plate coverage and adding optimization fields to eliminate small hotspots (107%) in the frontal lobe. Under-coverage was attributed to the autocontouring model’s inconsistently identifying the most superior slice of the cribriform plate. The results of the review emphasized that cribriform plate coverage is prioritized at the expense of increased lens dose. To this end, the autocontouring model could be improved with additional patient data. For the spine fields, examples of minor edits include adjusting the weighting of the optimization sub-fields. In patients with very small anatomy, the 107% isodose line began to approach the posterior spinal canal. The physician review suggested that the dose distribution in this scenario could be improved by adjusting the sub-field beam weighting or adding an additional sub-field.

A major benefit of our work is the potential to expedite radiation therapy workflows by decreasing the treatment planning time. Significant delays in radiation therapy have been associated with poor outcomes of pediatric brain tumor patients in resource-constrained centers.29 Recent trials from the SIOP group have emphasized a need for expediting radiation therapy planning because delaying treatment more than 7 weeks increases the risk of relapse.30,31 Our experience indicates that CSI treatment plans can take hours to generate, as they require making multiple plans that each contain multiple fields that must be properly matched to each other. The comprehensive CSI autoplanning tool proposed in this work was able to generate clinically acceptable treatment plans in an average of 20 ± 1.2 minutes for autocontouring and 3.50 ± 0.4 minutes for autoplanning, indicating potential for strong clinical impact, and we expect that further optimization could speed this up significantly. The autocontouring and autoplanning process do not require user intervention, which allows the radiation oncology team to dedicate saved planning time to other necessary clinical tasks.

As in manual planning, errors in the autoplanning design can introduce risk.32 CSI cases are difficult to plan as they require multiple, matched fields to cover the target volume. If the fields are not matched correctly, serious complications can occur.33 To this end, QA checks have been designed in our autoplanning workflow to check the jaw positions in the composite plan to make sure that the junctions’ shifts are correctly spaced. Moreover, our algorithm uses autocontours to perform additional QA checks such as evaluating and flagging the mandible dose from spine field beam divergence. The algorithm makes use of pre-determined beam geometries, which allows for a more consistent approach to patient setup. Additional QA algorithms may be integrated into the workflow to reduce risk. Examples of such algorithms include automatically identifying and flagging hotspot volumes above a certain tolerance and automatically verifying field shapes.34

Our study has some limitations. While the autocontouring tool was tested on 30 patients, final testing of the autoplanning tool was limited by the number of available CT images compatible with the planning technique. To this end, future, extensive testing will assess robustness of the planning tool on a larger dataset. The autoplanning tool described in this work is limited to a single approach to CSI planning based on recommendations from an experienced pediatric radiation oncologist and SIOP.18 However, the autoplanning tool may easily be re-configured to cater to alternative planning approaches such as different brain field shapes, different brain field gantry angles, and different field margins. Moreover, the autoplanning tool proposed in our work addresses a single radiation therapy planning technique (3D-conformal CSI), although this technique was selected because 84% of resource-constrained clinics have access to and are regularly using it to treat pediatric medulloblastoma .18

In conclusion, we quantitatively assessed the use of an adult autocontouring model in a pediatric cohort of 143 patients with medulloblastoma. We generated pediatric-specific autocontouring models for normal tissue structures and used them to guide an autoplanning tool. The end-to-end autoplanning tool successfully generated composite plans for 18 plans tested across 3 spine field configurations, indicating that the algorithm is robust in its adjustment to spine field-length variations found in pediatric CSI. Automating the contouring and planning workflow for pediatric CSI has the potential to increase the efficiency of workflows in resource-constrained cancer centers and subsequently improve access to high-quality radiation therapy.

# **Conflict of Interest Statement for All Authors**

Hester Burger is currently employed by Varian Medical Affairs, with a sessional lecturing position at the University of Cape Town.

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# Legends

**Figure 1.** **Outline of craniospinal irradiation auto-planning workflow**. Normal structures and landmark structures are automatically contoured using deep learning methods. The autocontours then guide an autoplanning algorithm scripted in the treatment planning system. Auto-contours are used to automatically set isocenters and define target and prescription volumes. Fields are automatically generated and conformed to the specified targets. The dose is prescribed, and the dose to the spine field is optimized. The original plan is feathered with 2 junction shifts. Finally, a composite plan is generated.

**Figure 2. Outline of isocenter placement.** Brain isocenter is set 2.5 cm above the most superior slice of the shoulder contour (green) and centered within the spinal canal. There are 3 possible spine field configurations designed to adjust to variations in pediatric spine length with age. The algorithm automatically calculates the required length of the spine field and assigns the proper configuration. If the distance is less than or equal to 40 cm, a single spine field is used; if the distance is greater than 40 cm but less than the maximum field size achieved by a specified extended source to surface distance (SSD), an extended spine field is used. Finally, if the spine length is greater than the maximum field size achieved using an extended SSD, multiple fields are used.

**Figure 3. Outline of spine optimization algorithm.** The spine optimization algorithm begins by quantifying how much of the 95% isodose line is greater than or equal to 5 mm anterior to the spinal canal. A sub-field is generated to block this volume. The sub-field is iteratively weighted 1% to 10% of the primary beam weight until the over-coverage region is no longer minimized or the maximum beam weighting has been reached. The resulting dose distribution after optimization is shown here. ROI, region of interest.

**Figure 4. Summary of Dice similarity coefficient (DSC) and Hausdorff distance (HD) achieved on autocontoured structures.** Boxplots demonstrating the performance of the adult autocontouring algorithms (blue) and the pediatric-specific algorithms (orange). The adult autocontouring model was tested on 143 pediatric full body CSI CT scans, and the pediatric auto-contouring model was tested on 30 patients (20% of the full data set; 80% was used for training). Among 17 structures, an average DSC above 0.80 was achieved in 14, and an HD below 1 cm was achieved in 13.

**Figure 5: Dose-volume histogram (DVH) for selected organs at risk.** The DVH summarizes the dose delivered to the targets (brain and spinal canal) and normal tissues (eyes and lenses) averaged across the 18 treatment plans tested. The solid lines represent the mean DVH values, and the shaded portions represent 1 standard deviation in values across the various spine field configurations. The dotted black line represents the prescription dose of 23.4 Gy.]

**Figure 6. Summary of spine optimization algorithm performance.** (Left) Boxplot summarizing the distribution of the over-coverage region lengths across 3 spine field configurations before (blue) and after (orange) spine field optimization. (Right) Sagittal CT showcasing the reduction in over-coverage volume before (blue) and after (orange) spine field optimization for a single-field patient.