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A multiple comparison study that test the validity of Varian's RapidPlan for prostate cancer cases based on models built from outside institution.

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12/11/2019
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Abstract

Introduction

In radiation oncology treatment planning techniques and outcomes can differ from one institution to the next. With knowledge-based planning (KBP) the experience of larger institutions could help smaller institutions who may not have the opportunity to encounter certain types of cancer cases. However, this scenario is only true if the KBP software is consistent with its algorithmic output. This study investigates the validity and consistency of RP models from two different radiation oncology institutions, and compare data to determine RP quality, and consistency in planning prostate cancer cases.

Methods

In this retrospective study researchers at a Midwest cancer treatment institution, randomly selected 50 previously treated prostate cancer cases from their database to form a Rapidplan (RP) treatment estimation model (TEM). The 50 cases were used to “train” RP knowledge-based learning software to the standards of an outside institutions model. The two TEM’s were compared for variance, and 20 more cases were inserted into the TEM and evaluated to test validity of the planning model overall.

Results

Results provided from the one-way ANOVA test supported the notion that a significant difference between the mean dose volume histograms of both RP treatment estimation models was not present. Pearson’s correlation also confirmed that positive correlations were present between outside institution data points for PTV, bladder, rectum, and penile bulb and Midwest institution datapoints for PTV, bladder, rectum, and penile bulb. Paired sample t-test, and proximity matrix displayed significant similarities, and though there were significant differences between the RP produced plans vs. physician approved plans, the proximity matrix supported a significant association between the two versions of the 20 plans used for validation.

Discussion

To determine if a single RP model algorithm is robust enough to be applied between two different institutions with similar treatment intents. We hypothesized that there must be a relationship between the models produced at two different institutions. A series of statistical test were performed to evaluate differences, similarities, correlations, and reliabilities of the data pertaining to the two RP models under evaluation. Overall our findings indicated that there weren’t many statistical differences, and there were consistently strong correlations between the two institutions within our data. Literature reviewed results also confirmed common trends between our finding and findings of past related studies.

Conclusion

Based on the finding of the results within this study we have concluded that the Varian algorithm used for constructing RP models is robust enough to safety produce compatible plan outcomes across different cancer treatment institutions. Moving forward follow-up research could be done to explain why statistical differences are detected when correlations are strong, and reliability is validated. Perhaps a deeper analysis of the nature of the algorithmic function could yield conclusions.

Introduction

Carcinoma of the prostate is the most prevalent cancer found in males. The prostate is a walnut size gland which is located between the bladder and rectum and surrounds the urethra. The prostate gland produces a substance that contributes to semen and is a functional component of the male reproductive system¹. Prostate cancer diagnosis rarely occurs in men under the age of 40. However, by age 50 it is more common for men to experience changes with the prostate². In the U.S., roughly 60% of men diagnosed with prostate cancer are 65 and older, and the average age for prostate cancer is 66². Despite the strong correlation between age and prostate cancer, there are also other risk factors associated with the development of prostate cancer as well. Other known risk factors include race, genetics, and diet. The risk for developing prostate cancer is highest for African American men than any other race. Risks are also higher than average for individuals with a family history of prostate cancer³. Symptoms of prostate cancer could vary amongst different individuals. However, difficulty urinating, hematuria (blood in urine), erectile dysfunction, and painful ejaculation are common symptoms associated with prostate cancer⁴.

Most malignant tumors of the prostate are of the cell type of adenocarcinomas¹. Understanding the cell type is important because it helps professionals determine the stage and grade of a tumor, which aids in diagnosing, determining treatment measures, and survival rates. Like for many cancers, carcinoma of the prostate is characterized by the TMN staging system; while Gleason score is used for grading of prostate tumors. TMN assess the extent of the malignancy based on tumor size, metastases, and lymph node involvement. While Gleason score is determined based on the level of cellular differentiation within the tumor¹. Before health care professionals can determine stage and grade they must first detect if the individual has prostate cancer or not. For this purpose, many detection and screening methods are used. Each year men

over the age of 50 are encouraged to have digital rectal exams (DRE), this is a diagnostic examination in which a physician inserts his or her finger (digit) in the rectum to palpate for abnormalities of the prostate. Also, there is an assessment of the prostate specific antigen (PSA) which is a specific protein in the blood that is produced by the prostate. The normal PSA value is 4ng/mL, but higher PSA values may be acceptable based on age. Nevertheless, when this PSA value is exceeded in the blood, it could indicate development or escalation of malignancy associated with the prostate. The PSA value may also have an impact on the type of treatment one may receive as well⁵. Primarily Transrectal ultrasound (TRUS) guided biopsy has been the standard for prostate cancer diagnosis. Much research has been conducted to determine whether diagnosis through transrectal ultrasound guided scans are accurate enough to result in the elimination of biopsy. To be less invasive transrectal magnetic resonance imaging is a newer technique also used for evaluation⁶. As a result of findings from these examinations and imaging studies the stage of disease is determined. Classified by the American Joint Committee on Cancer (AJCC) TNM stages 1-4 occurs under different circumstances. T1 occurs when well differentiated adenocarcinomas found via fine needle biopsy, or by high PSA values. To classify as T1 typically less than 5 % of tissue show abnormality. T2 occurs with tumors in the prostate that are palpable and encapsulated. T2 is usually detected by DRE. T3 occurs in tumors that are more locally extensive, beyond the edges of the prostate to surrounding structures such as the seminal vesicles.; Typically, with poorly differentiated cells. T4 occurs when larger tumors are fixed to the pelvic wall or invade adjacent structures such as the bladder or rectum¹. N1 occurs when there is nodal involvement, and M1 occurs when there is metastases, which varies based on location⁷. The Gleason Score is obtained when prostate cancer is found on a biopsy. The Gleason score is determined by how abnormal cells look under a microscope. During pathological

grading the primary, and secondary tumor grades are added together to get the Gleason score, which ranges from 2-10¹. Usually prostate cancers that are well-differentiated are classified with scores of 6 or lower, while moderately differentiated cells tend to have a score of 7, and 8-10 are for poorly-differentiated cells⁵.

Prostate cancer is treated based on stage and grade. T1, depending on the grade of the disease, may not require any treatment until disease becomes a clinical issue¹. Depending on the grade and extent of tumor, T2 may require prostatectomy alone. In cases with patients who have stage T3, external beam radiation therapy (EBRT), typically with hormonal therapy, is the standard of practice¹. In addition, some individuals with T3 may be eligible for Low Dose Rate (LDR) brachytherapy via prostate seed implants (PSI), which is the process of physically implanting radioactive seeds into the prostate through the perineum¹. Though rarely seen, patients may undergo concurrent in T3-T4 stages of cancer as well if there is no response to hormonal therapy, and/or if disease has rapidly spread outside the prostate¹.

Favorably, prostate cancer patients have received the most dividends over the past decade from the progression of technology, especially with the emergence of IMRT and VMAT⁸. This is primarily related to the fact that dose conformity around the prostate has drastically increased. As a result of this dose conformity, there is a reduction in toxicity of critical structures which has aided in the decrease of secondary malignancies, as well as a better prognosis⁸. According to the National Cancer Institute (2019) for prostate patients with radiation therapy as their primary treatment measure, all stages of prostate cancer combined had an overall five-year survival rate of over 98%⁴. The increase in 5-year survival rates for prostate patients has been associated with higher quality of radiation therapy treatments, which are made possible by technological advancements seen in radiation therapy over the last decade⁹.

Due to the success of radiation therapy, radiation oncology has become a more widely adopted and effective cancer treatment method⁹. Today, radiation therapy leverages advanced and complex technologies for more advantageous outcomes. As progression occurs within radiation oncology, medical dosimetrists are challenged to adhere to more robust standards. A medical dosimetrist, also known as the “treatment planner”, is a member of a radiation oncology team, responsible for planning optimal dose delivery to tumor volumes while allowing the least possible dose to healthy organs. The medical dosimetrist maintains a delicate balance between delivering the prescription the physician has written while ensuring the patient will not lose healthy organ function¹⁰.

In modern radiation therapy planning, medical dosimetrists commonly utilize intensity-modulated radiation therapy (IMRT) for prostate cancer. IMRT is a radiation therapy dose delivery technique which uses the multi-leaf collimators in the head of a linear accelerator to adjust the intensity of the radiation beam to match the precise contours of a tumor and minimize the damage to surrounding tissue¹¹. Furthermore, volumetric-modulated arc therapy (VMAT) is another treatment technique used for prostate cancer treatment. VMAT delivers radiation by rotating the radiation machine through one or more arcs while radiation is continuously delivered. VMAT allows doctors to treat complex cancers while minimizing exposure to surrounding healthy tissue. This is accomplished primarily through the variation of dose rate at every angle of the arc¹¹. With the increasing prevalence of treatment techniques such as IMRT and VMAT radiation therapy treatment, planners are better able to maximize tumor control while minimizing toxicity to normal structures¹².

In addition to the prominence of IMRT and VMAT techniques, the next innovation of knowledge-based planning (KBP) looks to advance treatment planning even further. KBP

software applies the knowledge it has learned from model plans input into the software to generate plans that can be applied to new cases. It uses an automated approach that involves the use of algorithms to predict desirable outcomes for treatment plans before they are corrected by treatment planners and physicians to become deliverable plans¹³. Though KBP software, such as Varian's RapidPlan (RP), was developed for multiple intents, one of the best characteristics of RP is that knowledge-based models can be shared between institutions. This is especially beneficial for smaller institutions who may not treat as many cases and therefore may not produce an optimal quality plan due to lack of experience. Using the KBP, these institutions would be able utilize a model from larger and more experienced institution to aid them in treatment planning.

When KBP first emerged during the early 2010s, researchers attempted to validate the feasibility of KBP systems by comparing plan quality of RP generated plans to those of physician approved plans produced by a medical dosimetrist. In a particular study, a group of researchers stated that, "On average, the new knowledge-based plan is capable of achieving very comparable planning target volume coverage as the original plan, to within 2% as evaluated"¹⁴. This statement supports the legitimacy of KBP systems, such as RP, in a clinical setting.

By 2015, the knowledge of RP and other KBP systems had grown within the field of radiation oncology. A literature review published in 2019 summarizes the approaches of 73 different articles published on RP or other KBP software between 2011-2018¹³. In this literature review, it was concluded that across the 73 studies they aimed to validate KBP software to plan different anatomical cancer sites. They found that the KBP methods were generally equivalent to expert level planners in terms of plan quality, but preliminary results indicated that they were

significantly more efficient. These results suggested that clinical application of KBP to some cancer types such as prostate was very achievable¹³.

In analyzing previous studies done on KBP systems, it was recognized that there were correlations amongst these types of studies. Some of the articles have different methods or the focus of the article may be geared toward validation of knowledge-based planning for treatment of certain organs. Nevertheless, it has been frequently concluded that in these studies the KBP software often generated optimal treatment plans regardless of which structure was being treated. Based on the conclusion of other KBP studies, the researchers of this study expect RP to be able to plan prostate cancer cases adequately. Contrary to those studies, the researchers of this study aim will be to focus on the similarities and differences of RP generated models for prostate cancer from two different institutions. The conclusion of this study will help determine the level accuracy for plan outputs when sharing RP models across different organizations.

In this retrospective study, the principle researcher compared RP models for prostate cancer between two different radiation oncology institutions. An outside institution RP prostate model was compared to the RP prostate model produced at a Midwest institution. Then, comparison was conducted amongst the two models DVH's, and treatment variables evaluating the possibility of variance. Following this, the RP prostate model that was initially created was be used to plan separate prostate cases, which were then compared to physician approved plans produced by faculty treatment planners. In this study, it is hypothesized that there will be a significant relationship of similarity between the outside institution prostate cancer model and the Midwest institution prostate cancer model, thus, affirming the feasibility of sharing RP models amongst different institutions.

Null hypothesis (H_0): There is not a significant relationship between the outside institution prostate cancer model and the Midwest institution prostate cancer model.

Alternating hypothesis (H_a): There is significant relationship between the outside institution prostate cancer model and the Midwest institution prostate cancer model.

Methods

Overview

This retrospective study used a Rapidplan (RP) prostate model produced by an outside institution as a template for constructing and validating an initial RP prostate model made at a Midwest institution. The Midwest institution RP prostate model included 50 randomly selected physician approved prostate carcinoma plans from previously treated patients within their database. After the model was trained based on the treatment planning parameters of the 50 cases, researchers at the Midwest institution compared their model to the outside institutions model to see if there were any significant differences between the two models, as well as a significant relationship between the two models. Comparison was done by assessing the PTV, and organs at risk involved in the prostate cancer plans and seeing how much the variables correlated with and deviated from each other. Following this comparison, the Midwest cancer treatment institution input another 20 physician approved plans into their trained model to compare the RP produced plans to the original plans prepared by the Midwest institutions dosimetrist.

Patient selection

This retrospective study began initially with 100 previously treated prostate cancer cases which were retrieved from a Midwest cancer treatment institution's database. All cases were physician approved based on the study criteria. These cases were selected at random focusing on

patients that were treated between 2017 and 2019. Inclusion criteria into the initial 100 were males over the age 18, who received treatment to the prostate only (not to include pelvic lymph nodes) with IMRT or VMAT planning techniques. The age of the subjects ranged from 35 to 81, with the median age range being around 63.8 years. Of these initial 100 cases the first 50 cases were selected to construct the RP Treatment Estimation Model (TEM). After the Midwest institutions model was trained and compared to the outside institutions model, 20 separate cases were retrieved from the 100 cases initially collected and used to test the validity of the RP knowledge-based planning software overall. The remaining 30 cases from the initial 100, were used to replace outlier cases that may arise as confounding variables and falsely impact the calculations of the TEM.

IRB

This retrospective study was governed by a “blanket IRB continuation research report” provided by the radiation oncology department of the Midwest cancer treatment institution. This IRB was approved on 01/18/2019 by the hospitals internal review board, and covered all research conducted within the radiation oncology department at the Midwest institution. A Data Use Agreement (DUA) was also submitted to the Midwest Institution. The DUA outlined the purpose, methods, and actions taken to protect personal health information (PHI) and comply with the Health Insurance Portability and Accountability Act of 1996 (HIPAA). After the population was selected, personal identifiers were destroyed, and data was anonymized using hospital software within the computer system. All patient information was destroyed using software that is capable of destroying and anonymizing PHI. This retrospective study presents no more than minimal risk to patient privacy. The study was also approved by the Grand Valley State University (GVSU) Institutional Review Board (IRB) under the exempt review category.

Training the Treatment Estimation Model

Training the Treatment Estimation Model (TEM) consisted of a 4-step process. First, the principal researcher created a DVH Estimation Model Container. This container was used to deploy all the cases used for training the model. Second, a sample of 50 prostate cases were inserted into the DVH Estimation Model Container. These 50 cases were retrieved from a cohort of 100 randomly selected cases initially collected at the start of the study. Third, the individual DVH's for each of the 50 cases were evaluated by the RP software. This evaluation ensured that there were no underlying outliers amongst the 50 cases within the Estimation Model Container. Outliers were identified based how much they deviated from the parameters manually inputted into the DVH model configuration chart, and were determined to be an outlier based on the number of standard deviations from the mean. Software calculations request 99.8% of the data points for all organs, and treatment volumes to be within 4 standard deviations to be considered valid as seen in figure 1. Next, optimization objectives, normal tissue objectives (NTO), and smoothing parameters were set to mirror that of the outside institution. Finally, after all data points were deemed acceptable and free of statistical outliers the principal researcher employed the "train" function of the knowledge-based learning software which allowed RP to perform its algorithmic calculations to produce an official RP model that had learned from the 50 inserted cases. The RP model was then published and open to calculate new prostate cancer cases.

Validation of Rapid Plan Model

After the RP model was completely trained based on the treatment planning parameters of the 50 approved prostate cases inserted into the training model container, the RP model was ready for validation. The first step of validation was to select a new cohort of 20 prostate cancer

cases. These identical prostate cancer cases that originated as physician approved plans were re-planned using the RP model at the Midwest institution, researchers had to compare the new plans generated from the RP model to the corresponding original physician approved plan. After comparing the differences between the RP produced plans, and the original physician approved plans, researchers then observed whether the parameters of the radiation prescription were met for the RP produced plans to determine the validity of the Midwest RP model that was set by the parameters of an outside institution.

Results

Dose Volume Histogram Outliers

For this study the principle researcher at the Midwest institution used the DVH estimation model to identify outliers and replaced them with cases that were closer to the DVH of the outside institutions model. As illustrated in Figure 2, four outliers were identified. These four PTV datapoints were removed from the DVH plot and replaced with 4 other datapoints from separate cases that better fit the model DVH. Figure 3 displays the estimation model DVH plot that contained the new PTV datapoints, and this dataset was used to train the TEM. All other datapoints were within 4 standard deviations of the parameters inputted into the software and set to mimic the outside institutions model.

Treatment Estimation Model comparison

For TEM comparison, an evaluation was done to assess how much the Midwest institution's TEM differed from the outside institution's TEM. A comparative graph was made to illustrate the difference between the two models, this was based on the mean DVH for both models as seen in figure 4. A one -way ANOVA was also conducted for this comparison. Each of the 50 datapoints had a $p < .05$, meaning that there was not a significant difference between

the outside institutions model and the Midwest institution's model for the PTV (.009), bladder (.045), rectum (.048), and penile bulb variables as seen in Table 1. In measuring the relationship between the two TEMs data points, a Pearson's correlation test was performed for each variable amongst the two groups, as displayed in Table 2. Figures 5,6,7,8 depicts the correlation of each variable between both institutions' TEMs. Lastly, a Chi-Square test was performed to test the strength of the relationship between the variables of the two models, and due to the significance being represented by all of the $p < .05$, a significant relationship between the RP model from the outside institution and the Midwest institution is implied as seen in Table 5.

Analysis of RapidPlan model validation

To examine the difference between the plans produced by the RP model, and corresponding physician approved plans, a paired t-test was performed as displayed in Table 3. Next a proximity matrix was conducted to measure similarity between the RP produced prostate cases and the predicted outcomes of the RP algorithm as seen in Table 4.

Discussions

Review of Results

Results initially revealed that when the researchers first removed outlying data points that there were four outliers within the PTV DVH that were used to train the Midwest TEM. These data points were removed because they were greater than four standard deviations from the mean; this was done based on the outside institution's model parameters. After cleaning up the raw data, the researchers conducted statistical testing that would aid in the investigation of the relationship between the outside and the Midwest institution's RP model.

To start, a comparative DVH was prepared as a visual indicator between the outside institution and Midwest institution, to identify how much these two models differed and related

to each other. Next, to determine if any variance was present between the two TEMs, a one-way ANOVA test was done on the two models. Based on the p-values of the PTV, bladder, rectum, and penile bulb all being less than .05, significance was indicated. This meant that there was no significant difference between the two models. Also, the one-way ANOVA contained an F ratio score, measuring the joint variance of all variables across each group. When these variables are closer to zero than one, it indicates that all the variables from the outside institution do not significantly differ from the variables of the Midwest institution.

To further investigate the relationship between the two models, Pearson's correlation was done using the data points of each variable from both institutions RP model DVHs. With Pearson's correlation, the closer the correlation coefficient value is to 1, the stronger the correlations between variables. In statistics, any correlation greater than 0.50 usually depicts a strong correlation. Data points from both institutions' DVH variables (e.g., PTV's, bladder, rectum, and penile bulb) were compared to the mean dataset from the outside institution's RP model. As expected, the outside institution's data points matched perfectly to the datasets from its own institution's model. And the same can almost be said about the Midwest institution. Based on the findings from the Pearson's correlation, the Midwest variables of PTV ($r = .97$), bladder ($r = .81$), rectum ($r = .74$), penile bulb ($r = .89$) all had correlation coefficients greater than .50. This further indicates that a relationship does exist between the two models from both institutions.

As the relationship between the two models continued to be investigated, Chi-Square test was conducted to assess the association between the variables of the two RP models. To perform this test, 100 cases, 50 from each institute, were compared. The data was compiled in SPSS output and represented as individual entities. These entities were used for the Chi-Square

test. As seen in Table 5, the Chi-Square sig value was .048 which is $< .05$ supporting statistical significance, and as a result further affirming that an association does exist between the Midwest and outside institution's models.

In this study, the researchers also attempted to test the validity of 20 prostate cancer plans produced by the RP algorithmic software in the RP model. A before and after comparison of the Midwest institution's physician approved plans versus the RP produced plans was done by performing a paired sample t-test. The paired t-test revealed that a significant difference was present between the RP produced plans and original corresponding physician approved plans, as indicated by the .017 p value. However, in examining Table 3, it would be noted that the correlation coefficient is deemed as .998, with .000 p value indicating a significant correlation between the original physician approved plans and the plans produce by the RP model. After review of the result with professionals at Grand Valley State University statistics department, it was concluded that the paired t-test displayed a significant difference between the two plan types because the model was built from the outside institution's model, while the original plans were created by dosimetrist to meet the standards of the physician's radiation prescription at the Midwest institution. In other words, the RP model cases were planned to the standard of the outside institution, while the original corresponding plans were planned to the standards of the treatment prescription from the Midwest institution. Two different planning parameters explained why a significant difference was detected within the paired t-test. Nevertheless, the strong correlation depicted in Table 3 also indicated that though the data points showed a significant difference, there still was a similar relationship between the outcomes of two groups as represented by the high correlation coefficient.

In addition to the paired t-test and correlation test, SPSS was used to perform another comparative measure of similarity by employing the Proximity Matrix. According to SPSS, the Proximity matrix is a tool used to test the distance between pairs of cases or pairs of variables.¹⁶ When examining the relationship between the RP produced plans and the corresponding original plans, the proximity matrix was used to get a more robust comparison and to further investigate the relationship between RP produced prostate plans, and their original physician approved counterparts. Like the Pearson's correlation the closer the value is to 1 the stronger the similarity is amongst the variables. In Table 4, the proximity matrix shows the similarity that each variable has with each other. The findings from this chart shows that outcomes of the same variables between the two institutions are identical, with a 1 representing the similarity between outcomes. Based on the finding of this data the assumptions of a relationship existing between the RP produced plans and their corresponding physician approved plans are very reasonable.

Cross-reference of results from literature reviewed studies

Within this retrospective research study, multiple statistical tests were conducted to evaluate differences, similarities, correlations, and reliabilities of the data pertaining to the two RP models under evaluation. To truly draw accurate conclusions and to test the hypothesis, these tests were examined as the foundation for further escalation of research on KBP software capabilities. The findings of this study were validated by similar findings present in other studies that evaluated the validity of KBP software capabilities. In this study, it was revealed that there was a significant difference when comparing the RP model produced plans with the original physician approved plans., meaning that the two model were recognized as not being completely the same. In a study entitled "RapidPlan knowledge-based planning: iterative learning process and model ability to steer planning strategies", the researchers came to a similar conclusions. By

assessing the linear regression of two different RP models, they concluded that there too was a significant difference between the two model especially when the algorithm of RP attempted to reduce dose for parallel and series organs. However, like the findings of this study, Fogliata et al. (2019) indicated they saw an increase in correlation between both plans. According to Fogliata et al. the different models within their study were able to yield similar plans according to each original strategy¹⁷. The similarities between the finding in this retrospective study, as well as the finding displayed by Fogliata and colleagues in 2019, shows that even though the system's planning may differ based on the intent that the software is striving to meet, it still has the capabilities to produce the desired outcomes that it is commanded to reach. It would be beneficial if more research is done to further asses why significant differences occur when strong correlations, and compatible results are yielded between different RP models.

Conclusion

Within this study, the researcher elaborated on the prominence of prostate cancer within radiation oncology and how new innovations such as RP could be beneficial in treating these types of cancers as well as more complex cases across different institutions. Within this study, the researchers at a Midwest institution used previously treated prostate cancer cases to further test the robustness of RP algorithmic capabilities. A RP model was created to mirror that of an outside institution's RP model, and treatment estimation models were legitimized and compared between both institutions. Multiple statistical test was conducted to evaluate differences, similarities, correlations, and reliabilities of the data pertaining to the two RP models under evaluation. Within the results section, the findings depicted that there was a consistent relationship between the Midwest institution's model and the outside institution's model. This was confirmed by the One-way ANOVA, Pearson's correlation, and other forms of descriptive

statistics. Ultimately, these findings have led the principle researcher at the Midwest institution to reject the null hypothesis, which states that there is not a significant relationship between the outside institution prostate cancer model and the Midwest institution prostate cancer model. By rejecting the null hypothesis, the researcher can conclude that, as predicted there is a relationship between the two models. This relationship indicates that the algorithmic capabilities of RP can be considered valid, consistent, and reliable. Therefore, the feasibility of different institutions utilizing one another's RP models to combat the lack of experience or promote standardization is acceptable and safe for patients.

Overall this study underwent different processes to determine if the RP KBP software could continue its groundbreaking trends and be viewed as a legitimate option for sharing planning experience between different institutions. Based on the statistical findings within this study, such as the presence of a strong correlation coefficient amongst all output variables and p values $< .05$ for the one way ANOVA it has been revealed that a significant relationship does occur between the Midwest Institutions RP model and the outside institutions RP model. Furthermore, the principal researcher within this study rejected the null hypothesis which states that there is not a significant relationship between the outside institution prostate cancer model and the Midwest institution prostate cancer model. It is anticipated that this study can contribute to the forum of KBP related research, spark inquisitive conversations and research that would broaden knowledge of how innovations such as RP can benefit more patients undergoing radiation therapy treatments. Moving forward follow-up research could explain why statistical differences are detected when correlations are strong, and reliability is validated when comparing variables from two or more RP models. Perhaps a deeper analysis of the nature of the algorithmic function used by Varian could yield valid conclusions.

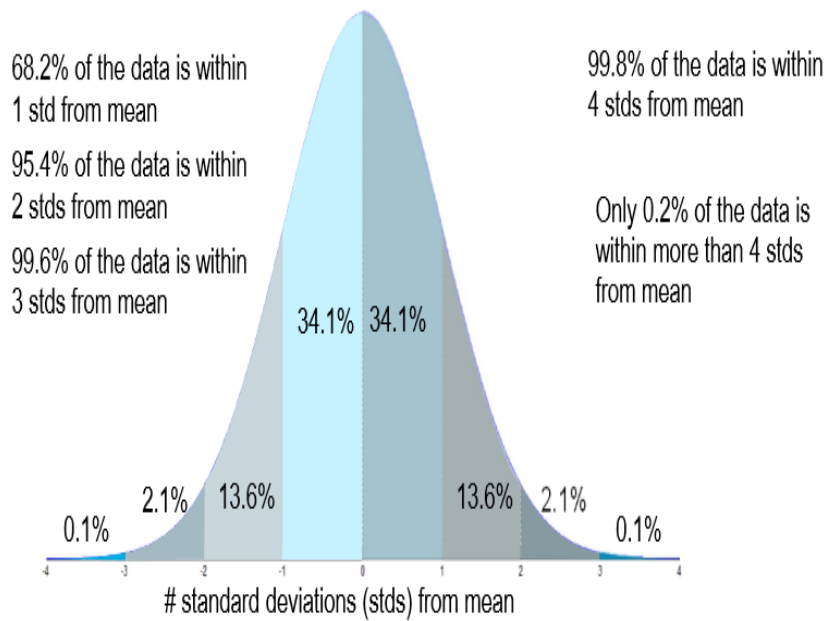
Reference

1. American Cancer Society, (2019). Risk of Prostate Cancer; Key Statistics for Prostate Cancer. Retrieved from: <https://www.cancer.org/cancer/prostate-cancer/about/key-statistics.html>
2. American Association of Medical Dosimetrist (2019) What is a Medical Dosimetrist? Retrieved from: <https://www.medicaldosimetry.org/about/medical-dosimetrist/>
3. Amin, M., Greene, F., Edge, S., Compton, C., Gershenwald, J., Brookland, R., & Winchester, D., (2017). The Eighth Edition AJCC Cancer Staging Manual: Continuing to build a bridge from a population-based to a more “personalized” approach to cancer staging. *CA: a cancer journal for clinicians*, 67(2), 93-99.
4. Brock, M., von Bodman, C., Palisaar, J., Becker, W., Martin-Seidel, P., & Noldus, J. (2015). Detecting Prostate Cancer. *Deutsches Arzteblatt international*, 112(37), 605–611. doi:10.3238/arztebl.2015.0605
5. Center for Control Disease and Prevention, (2019) Who is at risk of prostate cancer? Retrieved from: https://www.cdc.gov/cancer/prostate/basic_info/risk_factors.htm
6. Chanyavanich, V., Das, S., Lee, W., & Lo, J. (2011). Knowledge-based IMRT treatment planning for prostate cancer. *Medical physics*, 38(5), 2515-2522.
7. Dutz, A., Agolli, L., Baumann, M., Troost, E., Krause, M., Hölscher, T., & Löck, S. (2019). Early and late side effects, dosimetric parameters and quality of life after proton beam therapy and IMRT for prostate cancer: a matched-pair analysis. *Acta Oncologica*, 58(6), 916-925.

8. Fogliaa, A., Cozzi, L., Reggiori, G., Stravato, A., Lobefalo, F., Franzese, C., & Scorsetti, M. (2019). RapidPlan knowledge-based planning: iterative learning process and model ability to steer planning strategies. *Radiation Oncology*, 14(1), 187.
9. Ge, Y., & Wu, Q. J. (2019). Knowledge-based planning for intensity-modulated radiation therapy: A review of data-driven approaches. *Medical physics*. Retrieved from: <https://aapm.onlinelibrary.wiley.com/doi/full/10.1002/mp.13526>
10. IBM SPSS Statistics (2020). Overview Proximity Matrix Command, Retrieved from: http://desktop-6lp0bja:54985/help/index.jsp?topic=/com.ibm.spss.statistics.help/idh_xtab.htm
11. Khan, F., & Gerbi, B., *Treatment Planning in Radiation Oncology*, Wolters Kluwer Health, 2011. ProQuest Ebook Central, Retrieved from: <https://ebookcentral-proquest-com.ezproxy.gvsu.edu/lib/gvsu/detail.action?docID=2031860>.
12. Miller, K., Siegel, R., et, al (2016). Cancer treatment and survivorship statistics, 2016. *A Cancer Journal for Clinicians*, 66(4), 271. Retrieved from: <http://search.proquest.com.ezproxy.gvsu.edu>
13. National Cancer Institute, (2019) Cancer Stat Facts: Prostate Cancer, Surveillance, Epidemiology, and End Results Program. Retrieved from <https://seer.cancer.gov/statfacts/html/prost.html>
14. Perkins, B. B. (2017). *Cancer, Radiation Therapy, and the Market*. Routledge.
15. Podder, T., Fredman, E., & Ellis, R. (2018). Advances in Radiotherapy for Prostate Cancer Treatment. In *Molecular & Diagnostic Imaging in Prostate Cancer* (pp. 31-47). Springer, Cham.

16. Washington, C., Leaver. D., (2015) Principles and Practices of Radiation Therapy (4th edition) St. Louis, MO: Elsevier Mosby, p 754, 758, 756
17. Verburg, F., Pfister, D., Heidenreich, A., Vogg, A., Drude, N., Vöö, S., ... & Behrendt, F. (2016). Extent of disease in recurrent prostate cancer determined by [68 Ga] PSMA-HBED-CC PET/CT in relation to PSA levels, PSA doubling time and Gleason score. European journal of nuclear medicine and molecular imaging, 43(3), 397-403.

Standard Deviation: Distribution of Data Points



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Standard deviations are also commonly known as sigmas (σ)

Figure 1. Varian Rapid Plan 15.5

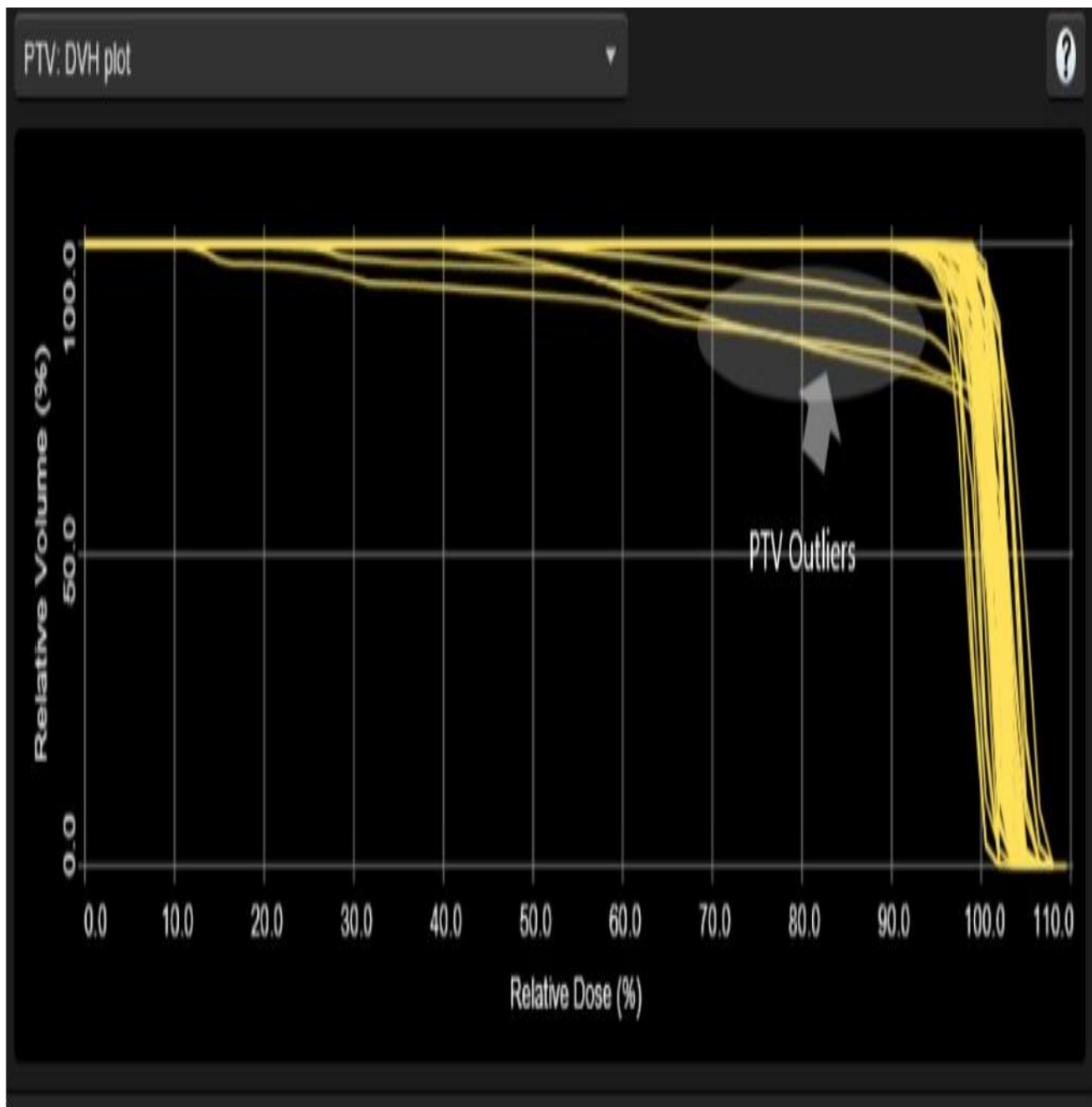


Figure 2. Midwest Institution's Initial PTV Plot

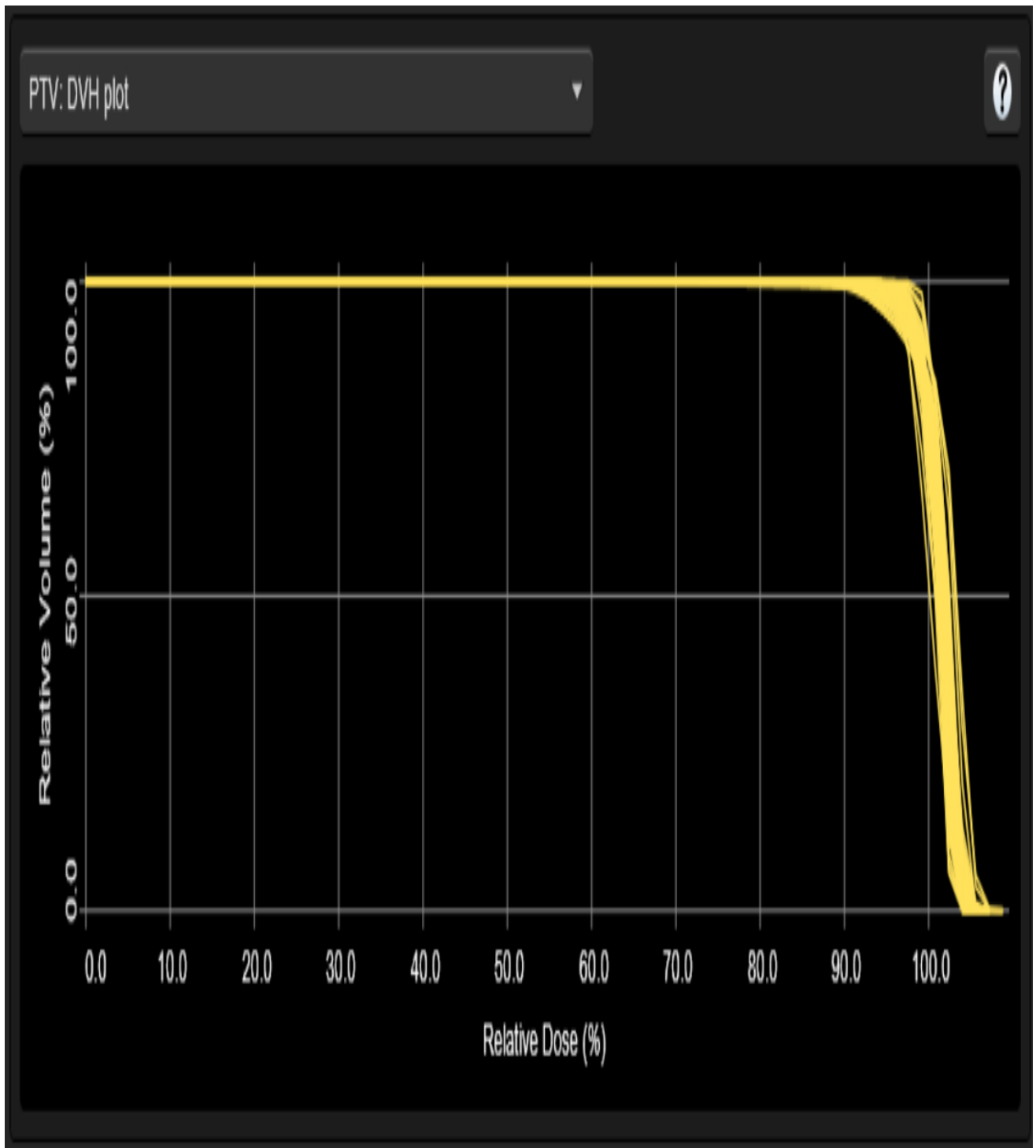
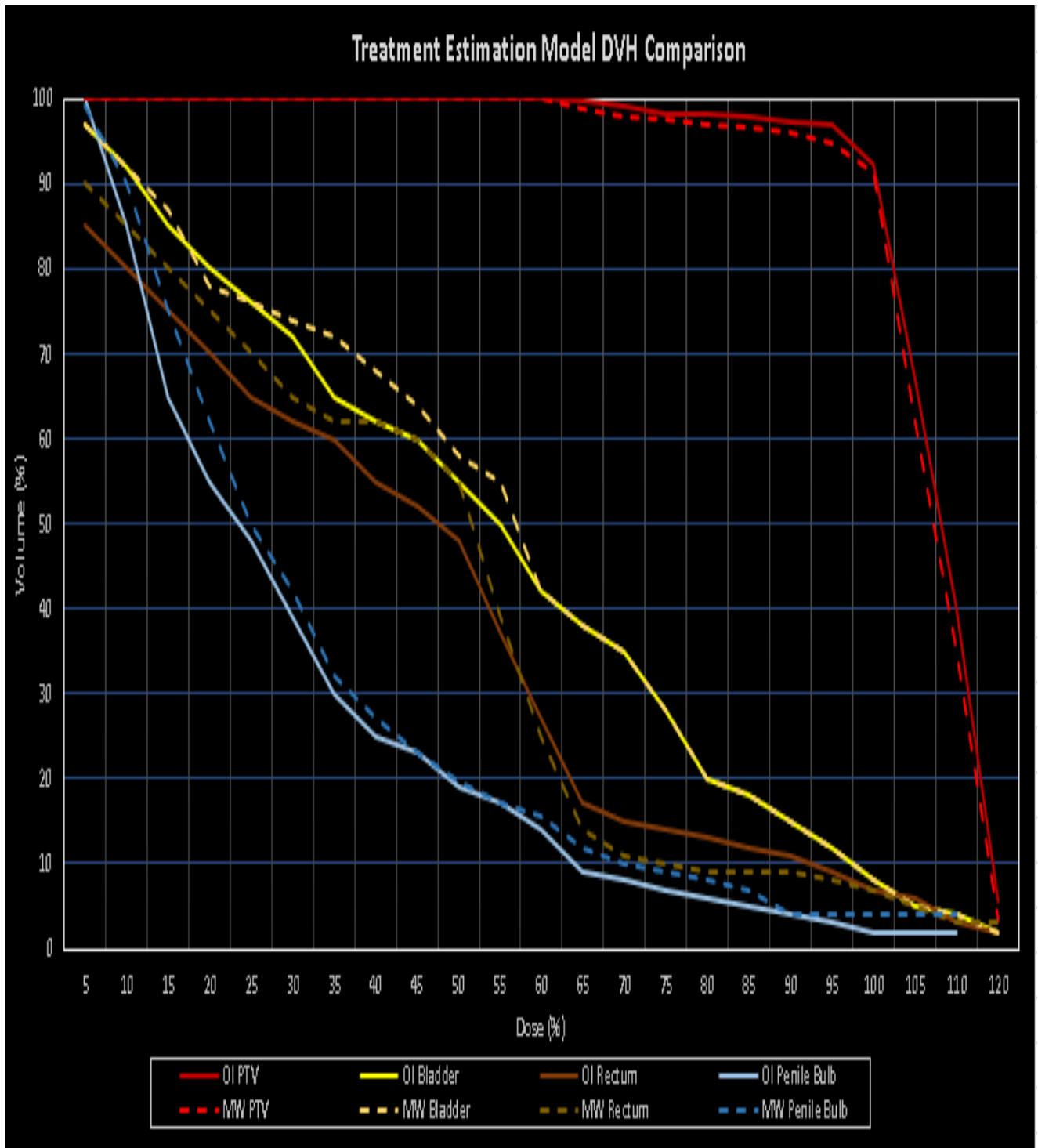


Figure 3. Midwest Institution's Corrected PTV Plot



(OI = Outside Institution, MW = Midwest Institution)

Figure 4. Comparative TEM of mean DVH's for OI and MW RP models

PTV LINEAR CORRELATION

◆ MW PTV ■ OI PTV — Linear (OI PTV)

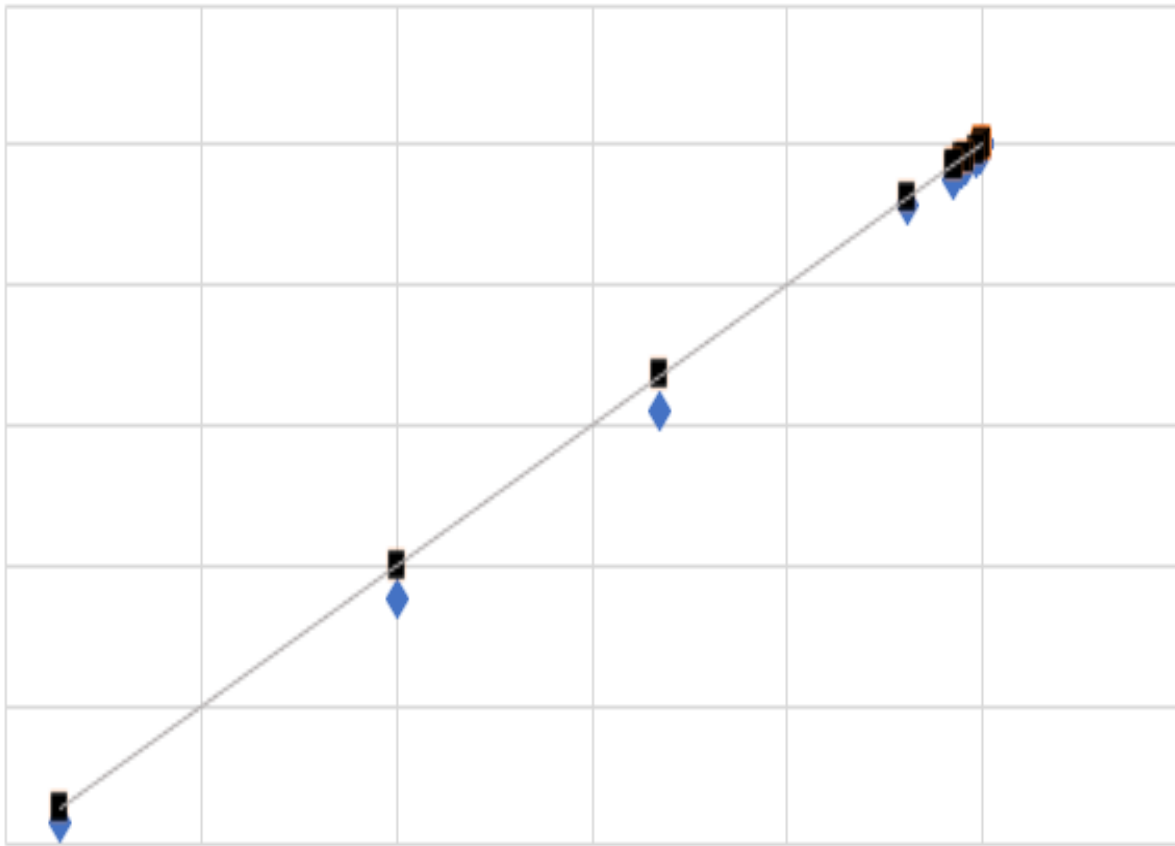
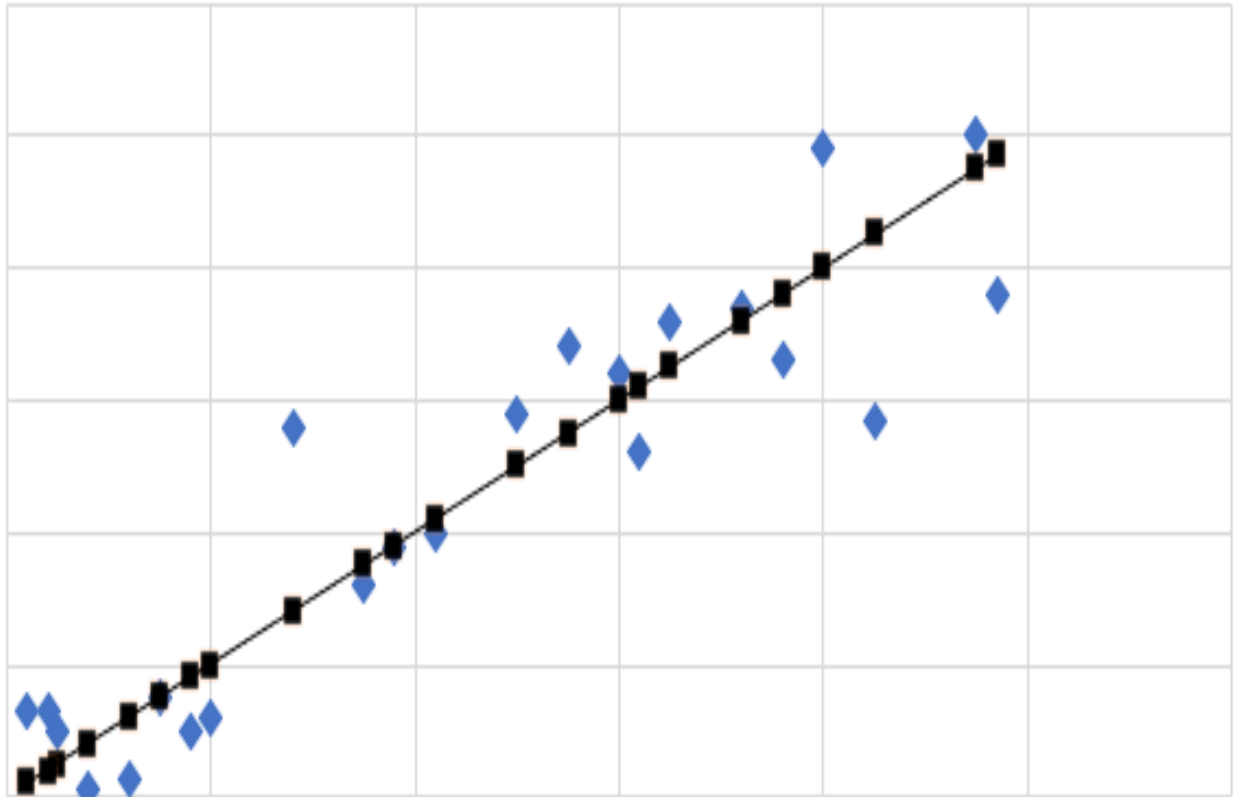


Figure 5. Pearson's Correlation (Midwest vs. Outside Institution PTV)

BLADDER LINEAR CORRELATION

◆ MW Bladder ■ OI Bladder — Linear (OI Bladder)

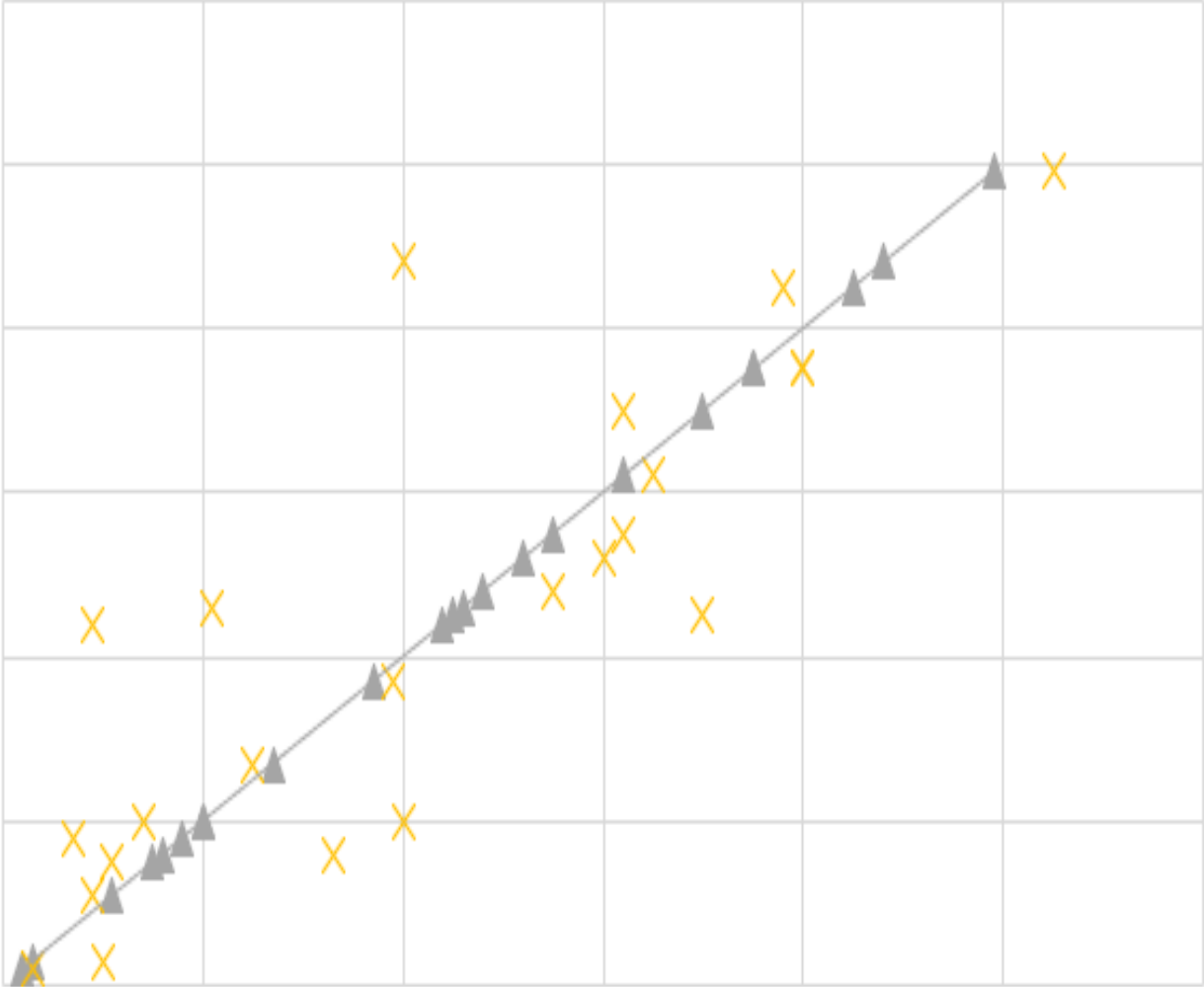


R= 0.81

Figure 6. Pearson's Correlation (Midwest vs. Outside Institution Bladder)

RECTUM LINEAR CORRELATION

▲ OI Rectum X MW Rectum — Linear (OI Rectum)



R= 0.74

Figure 7. Pearson's Correlation (Midwest vs. Outside Institution Rectum)

PENILE BULB LINEAR CORRELATION

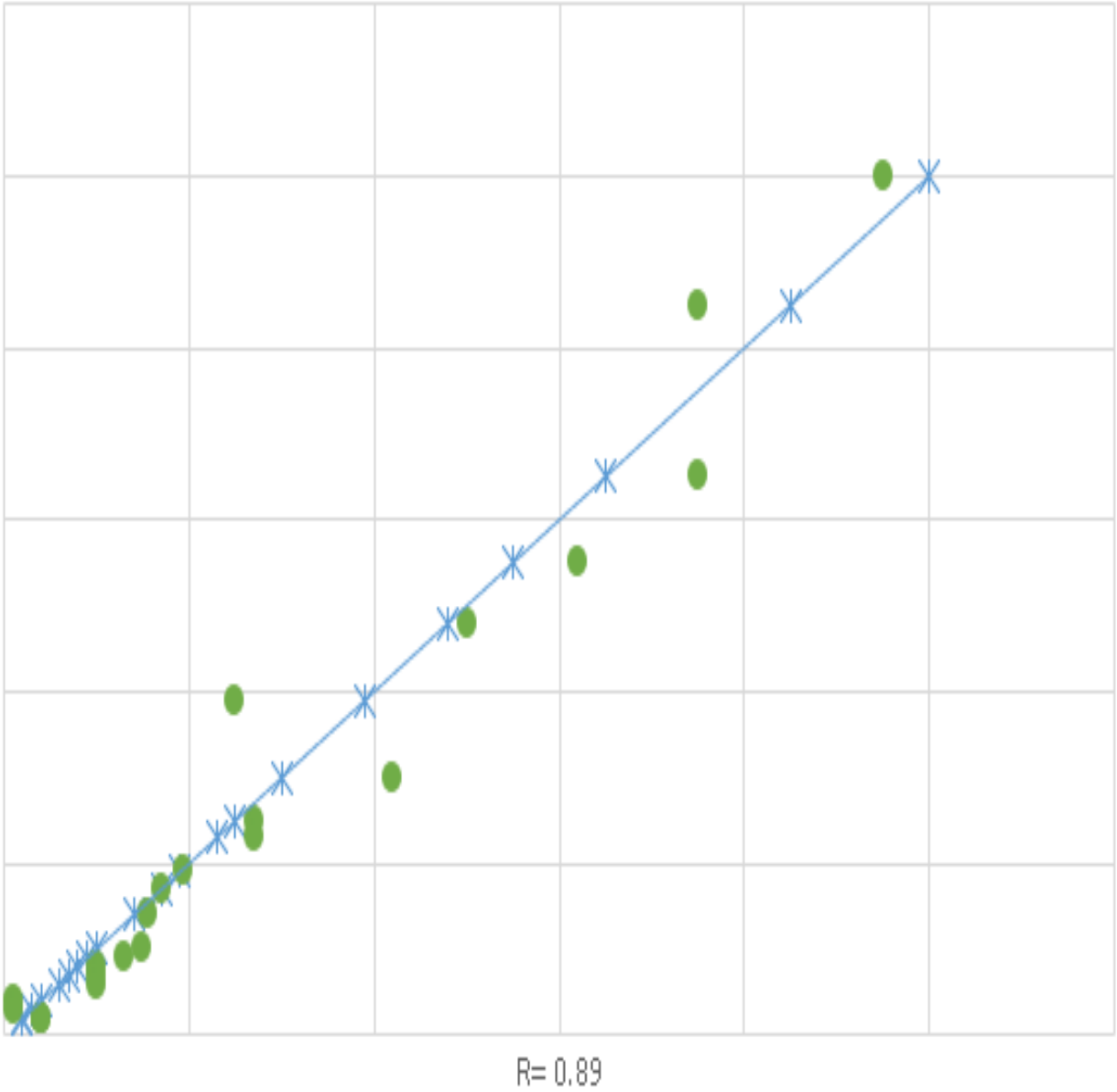


Figure 8. Pearson's Correlation (Midwest vs. Outside Institution Penile Bulb)

ANOVA

		Sum of Squares	df	Mean Square	F	Sig.
PTV	Between Groups	6.365	1	6.365	.007	.009
	Within Groups	43571.432	48	907.738		
	Total	43577.797	49			
Bladder	Between Groups	14.580	1	14.580	.014	.045
	Within Groups	48967.200	48	1020.150		
	Total	48981.780	49			
Rectum	Between Groups	10.179	1	10.179	.011	.048
	Within Groups	44614.083	48	929.460		
	Total	44624.263	49			
PenileBulb	Between Groups	37.066	1	37.066	.047	.029
	Within Groups	37673.249	48	784.859		
	Total	37710.315	49			

Table 1. One-way ANOVA (SPSS20)

Correlations

		PTV	Bladder	Rectum	PenileBulb
PTV	Pearson Correlation	.973	.689	.592	.431
	Sig. (1-tailed)		.000	.000	.001
	N	50	50	50	49
Bladder	Pearson Correlation	.689	.812	.980	.888
	Sig. (1-tailed)	.000		.000	.000
	N	50	50	50	49
Rectum	Pearson Correlation	.592	.980	.743	.905
	Sig. (1-tailed)	.000	.000		.000
	N	50	50	50	49
PenileBulb	Pearson Correlation	.431	.888	.905	.891
	Sig. (1-tailed)	.001	.000	.000	
	N	49	49	49	49

Table 2. Pearson's Correlation Test (SPSS 20)

	Mean	N	Std. Deviation	Std. Error Mean
Prostate (RapidPlan)	97.43	20	7.404	1.655
Prostate (Dr. Approved)	96.72	20	8.506	1.902

Table 3. Paired Samples & Pair t-test

	N	Correlation	Sig.
Prostate (RapidPlan) Prostate (Dr. Approved)	20	.998	.000

Table 4. Paired Samples Correlations

	Paired Differences					t	df	Sig. (2-tailed)
	Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference				
				Lower	Upper			
Prostate (RapidPlan) Prostate(Dr.Approved)	.708	1.205	.270	.143	1.272	2.625	19	.017

Tables 5. Paired Samples T-Test

Proximity Matrix

	Absolute Correlation between Vectors of Values			
	PTV	Bladder	Rectum	PenileBulb
PTV	1.000	.679	.580	.431
Bladder	.679	1.000	.979	.888
Rectum	.580	.979	1.000	.905
PenileBulb	.431	.888	.905	1.000

This is a similarity matrix

Table 6. Proximity Matrix

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	24.000 ^a	50	.048
Likelihood Ratio	33.271	50	.724
Linear-by-Linear Association	.007	1	.933
N of Valid Cases	100		

Table 7. Chi Square