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Mixture Cure Survival Model with Weibull Distribution for Brain Cancer

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Abstract

Brain cancers include primary brain tumours, and a brain tumour indicates an abnormal growth of cells in the brain that may be either benign or malignant. Benign tumours lack cancer cells, and once removed, they seldom reappear. However, benign brain tumours can lead to significant health complications and may eventually become malignant. Malignant brain tumours are cancerous, grow aggressively, invade nearby tissue, and are often life-threatening. In recent years, the treatment of many cancers, particularly brain cancer, has advanced significantly.

A mixed cure survival model is a type of survival analysis used when a portion of the individuals in a study are "immune" or "cured," meaning they will never experience the event being studied (such as death or recurrence of the disease). At the same time, the rest are exposed to that event.

Consequently, the number of patients who fail to achieve favourable outcomes, including passing, decreased. The quantitative assessment of this form of disease involves recovery models applied in place of traditional survival models. This study analysed 315 cases of brain cancer from Rzgari Hospital in Erbil city between 2020 and 2024. Among these cases, 99 patients (31.4%) were classified as cured. The data was modelled using the mixture cure approach with several statistical distributions, incorporating the cured fraction in this population and the significance of the Maller-Zhou test. Based on the research outcomes and a comparison of the Akaike Information Criterion and Bayesian Information Criterion, the cure framework employing the Weibull distribution for survival time was deemed the most suitable.

1. Introduction:

A brain tumour is characterised by irregular growth of cells found within or near the brain, which forms in brain tissue or in neighbouring areas like the nerves, pituitary gland, pineal gland, or the protective membranes that surround the brain, with those arising directly in the brain being classified as primary cancer brain. [4]

The spread of cancer from other parts of the body results in a secondary brain tumour, commonly identified as a metastatic brain tumour. Some cerebral tumours are not cancerous and are called benign brain tumours. Although they are noncancerous, they can grow over time and exert pressure

on brain tissue. On the other hand, malignant brain tumours, also called brain cancers, are cancerous and tend to grow rapidly. These cancerous cells can invade and damage healthy brain tissue.

Living with a brain tumour can be a challenging journey and greatly depends on factors such as the tumour's type, location, stage (e.g., whether it is early-stage or advanced stage 4 brain cancer) treatments, age, overall health, and available support. Some individuals may face lasting physical or cognitive challenges from the tumour or its treatment, including weakness, paralysis, difficulty speaking, memory problems, or mood and personality changes. These effects can be particularly severe in advanced cases and may require ongoing care and assistance. [10]

In the past two decades, numerous studies have been conducted on cure models, leading to significant advancements in this domain. However, these models are not widely applied across all areas, with most research focusing on diseases with a high likelihood of cure. Various statistical methods have been developed to estimate and evaluate the factors influencing mortality in such patients. Most of these methods rely on standard survival models, such as the Cox model or parametric models, which typically do not account for the high level of censoring often present in these datasets. As a result, the focus remains on the event of interest, while the high percentage of censoring is overlooked, leading to biased data analysis. [2]

cure is a primary goal for both cancer patients and their healthcare providers. Still, it is challenging to definitively confirm that a case has been completely cured of their cancer on a personal level. However, it is frequently noted that, for many cancer types, the mortality rate for those who survive after a given amount of time is equal to what would be predicted if a comparable class from the standard population were used. This is a reference to "population cure". This paper presents the mixture cure parametric models designed to estimate the cure fraction (the proportion of individuals achieving 'statistical cure') in population-based cancer studies.[6][12]

In community-based cancer research, comparable survival is commonly utilised to assess the mortality linked explicitly to the cancer being studied.

Cure models are generally classified into mixture cure models and non-mixture cure models. The mixture cure model can serve as a substitute for the Cox proportional hazard framework in cases where there is a substantial fraction of cured subjects in the cohort.

This research intended to use the mixture Weibull cure model to determine the factors influencing patients with brain cancer.

2. Mixture cure fraction model:

The mixture cure fraction model suggests the existence of two groups: individuals who have recovered from their disease and therefore exhibit a fatality ratio comparable to the broader population, and those who are ‘not cured' or deemed terminally ill from their cancer. The following equation mathematically conveys this model. (1): [4][3]

$$s(t) = \{a + (1-a)s_u(t)\} \quad (1)$$

Where a represents the cure fraction and s_u (t) is the survival function for the uncured group. On the hazard function, this can be expressed as equation (2):

$$h(t) = h^*(t) + \frac{(1-a)f_u(t)}{a + (1-a)s_u(t)} \quad (2)$$

where $f_u(t)$ represents the probability density function connected to $s_u(t)$. The mixture cure fraction model has been used extensively in population-based cancer studies, with its origins dating back to the work of De Angelis et al. examined models for the model of cure fraction, typically Considering the uncured group to have an exponential or Weibull distribution. More recently, we have advanced the method proposed, the Weibull distribution's two parameters change. This extension is crucial, as improper because inadequate modeling of the uncured group’s distribution can give inaccurate cure fraction estimates. [1]

3. Maller and Zhou test:

Cure survival models are based on the presence of a significant proportion of cured or immune individuals within the dataset. This proportion is represented by introducing an estimator for the

cured proportion when handling censored failure time data. Their approach uses one subtracted by the maximum recorded value from the Kaplan-Meier empirical distribution function. The Maller and Zhou test is a distribution-free statistical test used to evaluate whether the premises behind the cure fraction analysis are reasonable. [11]

4. Weibull distribution:

The Weibull distribution, initially introduced by Weibull in 1939 and further explored in 1951 for its significance to various malfunction scenarios, has since been widely utilised in studies of dependability and human disease mortality. [9]

Let the random variable T be the survival time that follows the Weibull distribution, and its probability density function (3) is represented by f(t),

$$f(t) = \alpha\beta(\beta t)^{\alpha-1} exp\{-(\beta t^{\alpha})\} t \geq 0 \quad (3)$$

The cumulative distribution represented by the function (4) *F* (t),

$$F(t) = 1 - exp(\beta t^{\alpha}) t \geq 0 \quad (4)$$

Then, the survival function (5) is expressed by *S* (t),

$$S\,(t) = exp\{-(\beta t^{\alpha})\} t \geq 0 \quad (5)$$

So, the hazard function represented by $h(t)$ is defined as a function (6):

$$h(t) = \alpha\beta(\beta t)^{\alpha-1} t \geq 0 \quad (6)$$

The Weibull distribution, unlike the exponential distribution, does not assume a constant hazard rate and therefore provides a broader range of applications. The exponential case arises when the shape parameter $\alpha = 1$, resulting in a continuous risk rate over time. When $\alpha < 1$, the hazard rate decreases over time, and when $\alpha > 1$, the hazard rate increases over time.

Thus, the Weibull distribution is applicable for modelling survival data of individuals with both increasing and decreasing risk, as well as constant risk. [5]

5. Akaike and Bayesian Information Criterion:

Evaluation of the model is a critical aspect of data analysis and modelling, with survival analysis being no exception. Although multiple model assessment techniques exist, many centred on error metrics, information criteria provide a robust and insightful approach to model selection.

The Akaike Information Criterion (AIC) stands as a prominent tool for evaluating and selecting models. In his work, Collett (2015) introduced the AIC specifically for survival models through the following equation. (7):

$$h(t) = \alpha\beta(\beta t)^{\alpha-1} t \geq 0 \quad (7)$$

In the case of the exponential model, the parameter k = 0, while for Weibull, log-logistic and lognormal models, k = 1, and k = 2 in the case of the generalised gamma model. Building upon this, Liang and Zou (2008) proposed the formula below (8) for the survival model:

$$AICCUR = AIC + 2(p + 2)(p + 3)\,/(n - p - 3) \quad (8)$$

This criterion quantifies the information sacrificed when we rely on a model instead of the raw data, with the model that has the smallest AIC value considered the preferred model. In model selection utilising the AIC, we identified the optimal model that yields the minimal AIC value from the set of candidate models. [6][7]

Much like AIC, the Bayesian Information Criterion (BIC) operates within the maximum likelihood framework. When a uniform prior is used across the parameter space, BIC serves as a reliable approximation of the Bayes factor. Volinsky (2000) revised BIC's penalty term, relating it to the number of uncensored events rather than the total observations. Critically, BIC and AIC differ in their approach to model complexity. AIC applies a more minor penalty for model complexity, which means AIC may favour more complex models. [8]

$$BIC = -2logLikelihood + 2 * logN * k + 3)\,/(n - p - 3) \quad (9)$$

6. Data Analysis:

This study aims to explore the survival times of patients with brain cancer treated at Rzgari Hospital. The study consists of 315 patients diagnosed with brain cancer between 2020 and 2024. Demographic factors captured a range of influential factors, including geographical origin, gender,

and age, alongside medical variables such as surgical intervention and the attending physician, which were documented as covariates in the study. The material was analysed within a survival analysis framework using R and MATLAB programs.

Table (1) :variable categorisation

Factors	Name	Categorization	Frequency	Percent %
The Age Group	Patient age at time of diagnosis	from 15 to 22 =1	22	7.0
		from 23 to 30=2	29	9.2
		from 31 to 38=3	57	18.1
		from 39 to 46=4	52	16.5
		from 47 to 54=5	73	23.2
		from 55 to 62=6	44	14.0
		from 63 to 70=7	20	6.3
		from 71 to 78=8	16	5.1
		from 79 to 86=9	2	0.6
Gender	Gender	Male =1	188	59.7
		Female =2	127	40.3
Morphology	Appearance, classification, and composition of brain cancer is Morphology.	oligoastrocytoma = 1	10	3.2
		astrocytoma anaplastic=2	8	2.5
		glioblastoma NOS=3	103	32.7
		Hemangioblastoma=4	6	1.9
		Medulloblastoma NOS=5	7	2.2
		Glioma=6	10	3.2
		astrocytoma NOS=7	49	15.6
		Astroblastoma=8	8	2.5
		pleomorphic xanthoastocytoma=9	5	1.6
		Chordoma=10	2	0.6
		Oligoastrocytoma=11	3	1.0
		Neurilemmoma=12	2	0.6
		Anaplastic astrocytoma=13	5	1.6
		Glioblastoma multiforme=14	18	5.7
		medulloblastoma nodular=15	2	0.6
		Meningioma, NOS=16	1	0.3
		Meningioma=17	10	3.2
		Astrocytoma=18	3	1.0
		Gliosarcoma=19	7	2.2
		Diffuse astrocytoma=20	6	1.9
		Transitional meningioma=21	1	0.3
		Ependymoma,NOS=22	6	1.9
		Oligodendroglioma=23	1	0.3
		Glioblastoma=24	3	1.0
		Craniopharyngioma=25	1	0.3
		Neurofbromatosis=26	1	0.3
		Medulloblastoma,NOS=27	7	2.2
		Fibrillary astrocytoma=28	1	0.3
		Oligodendroglioma anaplastic=29	1	0.3
		Gemistocytic astrocytoma=30	1	0.3
		Melanoma,NOS=31	2	0.6
		Oligodendroglioma,NOS=32	11	3.5
		Anaplastic meningioma=33	2	0.6

		Ewing's sarcoma=34	1	0.3
		Meningothelial meningioma=35	3	1.0
		Neoplasm, malignant=36	1	0.3
		Glioma, NOS=37	3	1.0
		Mixed epithelioid and spindle cell=38	3	1.0
		Hemangioendothelioma, NOS=39	1	0.3
Status	the status of patients	Alive =1	95	30.2
		Dead=2	220	69.8
Grade	grade characterizes the microscopic appearance of cancer cells as normal or abnormal	Grade I=1	21	6.7
		Grade II=2	72	22.9
		Grade III=3	46	14.6
		Grade IV=4	145	46.0
		Unknown=5	31	9.8
Occupation	Occupation	Employee	103	32.7
		Businessman	64	20.3
		Housewife	122	38.7
		Retired	21	6.7
		Student	4	1.3
		Unemployed	1	0.3
Subsite	The placement of a nod	Brain NOS=1	211	67.0
		Parietal lobe=2	25	7.9
		Temporal lobe=3	16	5.1
		Overl lesion of brain=4	16	5.1
		Cerebellum, NOS=5	8	2.5
		Frontal lobe=6	27	8.6
		Rt Frontal lobe=7	1	0.3
		Occipital lobe=8	3	1.0
		Frontal Temporal lobe=9	1	0.3
		Ventricle NOS=10	2	0.6
		Brain, NOS posterior fossa=11	1	0.3
		left Temporal=12	2	0.6
		Rt Frontal lobe=13	1	0.3
		Brain stem=14	1	0.3
Extent	Extent indicates how far a tumour spread beyond its original organs boundaries	Localized=1	155	49.2
		Regional direct extension=2	13	4.1
		Regional direct extension and lymph nodes=3	2	0.6
		Distant Metastasis=4	1	0.3
		Unknown =5	144	45.7
Behavior	Brain cancers behavior encompasses its ability to grow, infiltrate surrounding tissue regions	Insitu =1	4	1.3
		Uncertain behavior =2	2	0.6
		Malignant=3	309	98.1
Surgery	Surgical operations to remove cancerous tumours.	Yes=1	168	53.3
		No=2	147	46.7
Chemo	Chemotherapy of patient	Injected Chemotherapy=1	168	53.3
		Does not inject Chemotherapy =No	147	53.3
T	The nodes size	T1=1	13	3.5

		T2=2	13	4.1
		T3=3	4	1.3
		T4=4	10	3.2
		Tx=5	275	0.6
N	The nodes shape	N0=2	36	11.4
		NX=1	279	88.6
M	The region encompassed by the node	M0=2	41	13.0
		M1=3	3	1.0
		MX=1	271	86.0

- Table (1) displays the age of diagnosis ranged from 15 to 86 years, with the majority of patients (23.2%) falling within the 47 to 54 age group.
- 315 of the patients (59.7%) were classified as male, and 127 of the patients (40.3%) were classified as female.
- Among the 315 Brain cancer individuals, 98.1% were presented with Malignant tumours, 1.3% were diagnosed with in situ, and 0.6% exhibited unpredictable behaviour.
- Of the 315 patients, surgery was performed on only 168 of them.
- Our findings revealed that 211 individuals (67%) had brain NOS type, with 168 individuals receiving chemotherapy, and a large portion of patients are housewives (38.7%).

7. Survival Analysis:-

In traditional survival analysis methods, which do not distinguish between treated and untreated patient subgroups, the outcomes of the Kaplan-Meier model are shown in Table 2 and Figure 1. The tail's smoothing in the Kaplan-Meier plot indicates the presence of a substantial cured portion within the studied cohort.

Table (2) : Kaplan-Meier life table

Time	n.risk	n.event	lost	Survival	Std. error	Lower 95%CL	Upper95%CL
1	315	52	47	0.8216	0.0224	0.7726	0.8610
2	216	2	6	0.8139	0.0229	0.7641	0.8542
3	208	9	1	0.7786	0.0247	0.7255	0.8227
4	198	8	11	0.7462	0.0262	0.6905	0.7934
5	179	2	7	0.7377	0.0266	0.6813	0.7857
6	170	0	1	0.7377	0.0266	0.6813	0.7857
7	169	1	0	0.7334	0.0268	0.6766	0.7818
8	168	0	3	0.7334	0.0268	0.6766	0.7818
9	165	1	3	0.7289	0.0270	0.6718	0.7777
12	161	15	22	0.6560	0.0301	0.5933	0.7114
15	124	0	1	0.6560	0.0301	0.5933	0.7114
24	123	0	21	0.6560	0.0301	0.5933	0.7114
36	102	4	9	0.6291	0.0318	0.5633	0.6877
48	89	1	7	0.6217	0.0322	0.5551	0.6813
60	81	1	33	0.6121	0.0332	0.5437	0.6734
72	47	1	2	0.5988	0.0350	0.5266	0.6635
83	44	0	4	0.5988	0.0350	0.5266	0.6635
84	40	0	10	0.5988	0.0350	0.5266	0.6635
85	30	0	23	0.5988	0.0350	0.5266	0.6635
96	7	1	2	0.4990	0.0957	0.3032	0.6670
108	4	1	2	0.3327	0.1500	0.0857	0.6108
168	1	0	1	0.3327	0.1500	0.0857	0.6108

As demonstrated Kaplan-Meier plots and the table, the initial survival probability in the early days, there is a notable decline, primarily attributed to the presence of emergency patients. For more than a month, the probability of survival is $S(1) = P(T > 1) = 0.8216$. As time progresses, the amount of patients in more stable conditions will increase. We can see this being demonstrated towards the bottom of the table that the probability of survival beyond 168 months is $S(168) = P(T > 168) = 0.3327$. In Figure (1), we can see the Kaplan-Meier plot this can be interpreted as smoothing on the

right tail of the plot. This, in essence, strengthens the foundation for the concept of cure survival analysis in this study.

The survival plot comparing female and male patients as shown in Figure (1), reveals that in the first months, men had a higher probability of survival. However, this trend shifts around the 400th day mark. In other words, women have subsequently showed improved survival conditions, after stabilization. While these differences are visually apparent, this distinction is not substantial ($P > 0.05$).

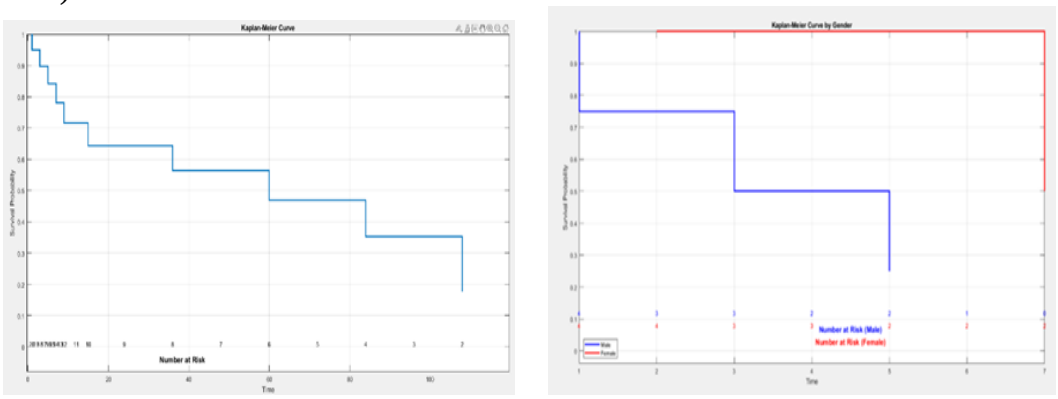

Figure (1) :Kaplan-Meier plot

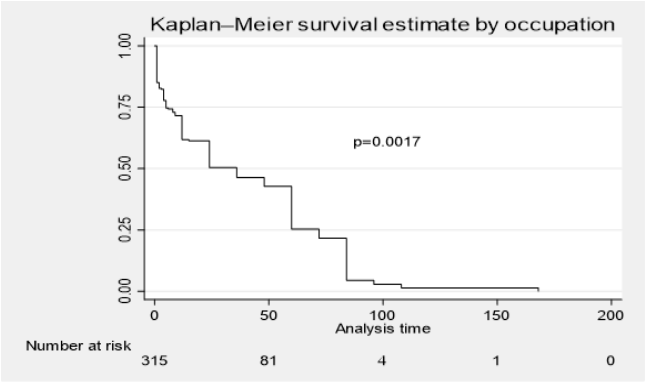

Figure (2) : Kaplan-Meier by occupation plot

In Figure (2) patients who were employees were more likely to survive, but patients who were homemakers were less likely to survive. These variations are significant ($P < 0.001$)

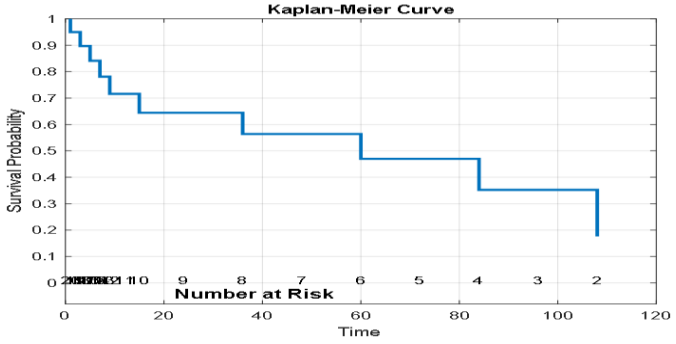

Figure (3) : Kaplan-Meier by surgery plot

Surgical intervention demonstrates a remarkable impact on brain cancer patient survival. As illustrated in figure (3), all patients who underwent surgery had significantly increased survival probability ($P < 0.001$).

8. Mixture Cure Survival Analysis:

The Maller and Zhou test offers a sophisticated approach to investigating potential cure fractions within survival datasets. It is used to test whether a survival dataset contains evidence of a cure fraction. This analysis examines the proposition that specific individuals in the population may remain permanently exempt from the specified event. The hypotheses are structured as follows:

H_0: $There is no cure fraction in the population$
H_1: $There exists a cure fraction in the population$

Table (3): Maller-Zhou test

Statistic	N	P – value
88	315	0.000123

Results in Table (3) show that (p = 0.00123 <0.01), the null hypothesis is not accepted, which means a cure fraction existed (P < 0.01). Therefore, utilising a cure model can be beneficial for this scenario.

Table (4) AIC, BIC and Log-Likelihood of the Cure Regression Models with Some Survival Time Distribution

	Weibull	Exponential	Gompertz	Lognormal
ALC	876.2929	883.7226	880.3063	903.0791
BIC	9.6907e+03	9.7992e+03	9.7369e+03	9.9989e+03
Log-Likelihood	-421.14645	-425.86137	-423.15315	-434.53953

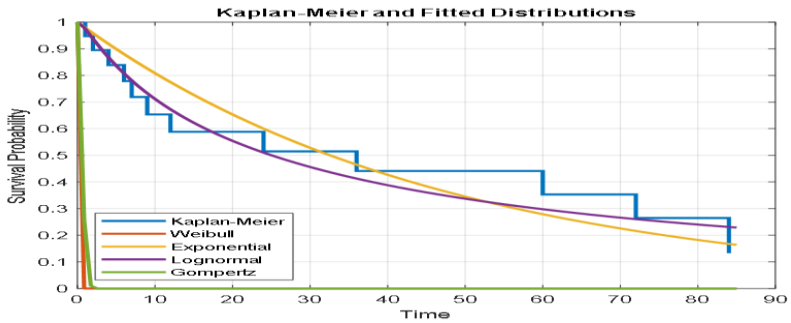

Figure (4) : Fitting Some Distributions on the Kaplan-Meier Survival Plot

To determine the most appropriate model for the dataset, a cure regression model was constructed with covariate variables, contrasting the Akaike and Bayesian information criteria (AIC and BIC). As illustrated in Table 3 and Figure 4, the Weibull distribution-based mixture cure model demonstrated optimal performance for survival time analysis. In this evaluation, AIC, BIC, and Log Likelihood criteria produced consistent outcomes. Consequently, the mixture cure Weibull model emerges as the most effective approach for examining Brain cancer patients' survival data. The detailed model outcomes are documented in Table 4. Overall, these findings suggest that implementing a mixture cure Weibull model can provide valuable insights into survival analysis for brain cancer patients' data.

Table (5): Cure Survival Regression Model Estimation Coefficient of Weibull Distribution

Covariates	Cure probability model	Failure time distribution model
Intercept	-2.9172	4.4315
Class age	0.3420	0.8915
gander	-1.2337	-0.3480
weight	-2.8988	-0.4089
occupation	-1.3274	-0.3488
morphology	- 0.8987	1.9213
subsite	0.3032	-0.3076
behavior	-2.3022	-2.0322
surgery	-0.9899	1.9332
chemo	-2.6116	-0.4495
T	-2.4795	-1.4193
N	-1.0232	-1.0230
M	-1.4454	-0.3348
Log(shape)		-0.7689

Table 5 provides a comprehensive breakdown of a survival regression model's coefficients and takes into account both the failure time (survival time) distribution and cure probability. The Cure Probability Model's coefficients reveal how each covariate relates to the chance of becoming cured. A positive coefficient suggests that the likelihood of cure increases as the covariate increases, whereas

a negative coefficient indicates that the probability of cure decreases. Failure Time Distribution Model: The coefficients in this model explore how each covariate (such as time to death, relapse, etc.) relates to the failure time. When the covariate's value is positive, it indicates longer failure times; conversely, negative values suggest shortened failure times (greater hazard rates) are linked to the covariate. From the table, the Cure Probability Model Equation (10)

$$\begin{aligned} logit(Pc) = & -2.9172 + 0.3420\ Class\ age - 1.2337\ Gender - 2.8988\ Weight \\ & - 1.3274\ Occupation - 0.8987\ Morphology + 0.3032\ Subsit \\ & - 2.3022\ Behavior - 0.9899\ Surgery - \ 2.6116\ Chemo - 2.4795\ T \\ & - \ 1.0232\ N - \ 1.4454\ M \end{aligned} \quad (10)$$

Failure Time Distribution Model Equation for the Weibull distribution, the log hazard model (11) is:

$$\begin{aligned} \log(T) = & \ 4.4315 + 0.8915\ Class\ age - 0.3480\ Gender - 0.4089\ Weight \\ & - 0.3488\ Occupation + 1.9213 Morphology - 0.3076\ Subsit \\ & - 2.0322\ Behavior + 1.9332\ Surgery - 0.4495\ Chemo - 1.4193\ T \\ & - 1.0230\ N - 0.3348 M - 0.7689 \log(shape) \end{aligned} \quad (11)$$

Where the negative coefficients for covariates mean the covariate reduces survival time or higher hazard, and the positive coefficients indicate longer survival times or reduced hazard.

9. Conclusions:

An examination of brain cancer patients' data from 315 individuals seeking treatment at a hospital in Erbil, located in the Iraqi Kurdistan region, revealed the following findings:

- A notable cure fraction was observed among patients, a result confirmed through the Maller and Zhou nonparametric test. To comprehensively examine survival-associated variables, several mixture cure regression models featuring alternative survival probability distributions were constructed and applied to the data.
- Through comprehensive assessments of model selection criteria, including AIC, BIC, and log of the likelihood function, the Weibull distribution was identified as the most appropriate distribution for our analysis.
- At the time Estimation of Coefficient in Cure Survival Regression Model, we demonstrate that the covariates (class age and subsite) are positive variables, which indicates the likelihood of cure increases as the covariate increases, whereas a negative coefficient indicates that the probability of cure decreases
- In the Failure Time Distribution Model, the variables (class age, morphology and surgery) have longer failure time because they have positive values, and the other variables, which have negative values, indicate shorter failure time.

10. Supplementary material

(None).

11. Author's Contributions

Awaz Shahab Mohamad: Designed the research. Kurdistan Ibrahim Mawlood.: Writing and editing. Nejmaddin A. Sulaiman: translation.

12. Funding

(None).

13. Data availability statement

I collected my dataset from the Ministry of Health at Rizgary Hospital Centre for Cancer Diseases, based on daily records of cancer patients.

14. Acknowledgements

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12. Conflict of interest

The authors declare no conflict of interest.

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نموذج بقاء العلاج المختلط مع توزيع ويبل لسرطان الدماغ

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المستخلص

تشمل سرطانات المخ أورام المخ الأولية، ويشير ورم المخ إلى نمو غير طبيعي للخلايا في المخ يمكن أن يكون حميدًا أو خبيثًا. تفتقر الأورام الحميدة إلى الخلايا السرطانية، وبمجرد إزالتها، نادرًا ما تظهر مرة أخرى. ومع ذلك، يمكن أن تؤدي أورام المخ الحميدة إلى مضاعفات صحية كبيرة وقد تصبح خبيثة في النهاية. أورام المخ الخبيثة سرطانية، وتنمو بقوة، وتغزو الأنسجة المجاورة، وغالبًا ما تكون مهددة للحياة. في السنوات الأخيرة، تقدم علاج العديد من أنواع السرطان، وخاصة سرطان المخ، بشكل كبير. وبالتالي، انخفض عدد المرضى الذين يفشلون في تحقيق نتائج إيجابية، بما في ذلك الوفاة. في التقييم الإحصائي لهذا النوع من المرض، يتم تطبيق نماذج التعافي بدلاً من نماذج البقاء التقليدية. حللت هذه الدراسة 215 حالة من سرطان المخ من مستشفى رزكاري في مدينة أربيل خلال الفترة من 2020 إلى 2024. ومن بين هذه الحالات، تم تصنيف 99 مريضًا (31.4٪) على أنهم شُفيوا. تم تصميم البيانات باستخدام نهج المعالجة المختلطة مع العديد من التوزيعات الإحصائية، مع دمج نسبة المعالجة في هذا السكان وأهمية اختبار مالر-زو. بناءً على نتائج البحث ومقارنة معيار معلومات أكايكي ومعيار المعلومات البايزي، تم اعتبار أنموذج المعالجة الذي يستخدم توزيع ويبول لوقت البقاء هو الأكثر ملاءمة.

معلومات البحث

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الكلمات المفتاحية:
بقاء العلاج المختلط، سرطان الدماغ، توزيع ويبل، اختبار مالر-زو ومعيار المعلومات أكايكي

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