Evaluate why survival analysis is not being applied in psychology as it is in other social sciences. Explain precisely the benefits to psychology if survival analysis were to be widely used. Show the value of this kind of analysis by reanalyzing real data and showing how survival analysis may lead to different conclusions than traditional analyses. (The committee suggests the possibility of obtaining data from Baumeister, though this is not a requirement.)

Survival analysis has been used in myriad ways due to its massive versatility. It spans both "hard" and "soft" sciences alike, provided a hypothesis contains both a time element and a measurement as to whether an event occurs. This has allowed fields such as biostatistics, political science, engineering, sociology, and to a lesser extent, psychology to paint a clearer picture of how, why, and importantly when, phenomena occur.

Stemming from a need to develop a statistical method that took into account non-standard variations over time, survival analysis began in the actuarial sciences as life tables (Kaplan & Meier, 1958; Miller, 1981). Financial firms through the early 20^{th} required a method of determining which investments, and at what times, would become potential losses. In response to this need, these institutions adapted life tables to establish the probability of when their investments would likely fail.

These tables posed a problem to researches who were interested in determining survival in their respective fields as these actuarial methods collected data at regularly set time intervals. At each interval, data were collected on failures and probabilities were calculated. Kaplan and Meier (1958), finding these methods valuable but insufficient, required a method of estimating probabilities for the survival of patients. As a result, they developed the product-limit estimator in an effort to allow for 1) randomized trials between patients 2) the natural, non-normal distribution of failure in biomedical trials and 3) censored cases. Having at the time of this writing over 40,000 citations, Kaplan & Meier's work has proved seminal in that continues to be used for time-dependent research. With advancements such as Cox's (1972) development of a regression-like approach to life tables, survival analysis is now being utilized in cancer research (Miller, 1981), ecological studies (Pollock, Winterstein, & Conroy, 1989), analyses of political trends (Olzak, 1989), and sociology of adolescent behaviors such as sexual activity (Zimmer-Gembeck & Helfand, 2006) and alcohol abuse (Mignone, Klostermann, & Chen, 2009).

Despite survival analysis' widespread acceptance and use in other fields of science, psychology has been slow to adopt it. Interestingly, there appears to be little explanation of psychology's resistance to this statistical method. The question of why survival analysis has not apparently been utilized in psychology is a much trickier one than why other fields have. Some evidence is provided by the manner in which this analysis is presented in psychology-focused research handbooks. Singer, Willett, and Graham (2013) briefly discuss the evolution of survival analysis as a statistical tool in psychology. In this passage, and in a paper by Singer and Willett (1991) over twenty years earlier, the authors assert that while biostatisticians have been using these techniques for decades, advancements in statistical packages have only recently caught up to the demand of psychological researchers. This suggestion appears to imply that while other fields employed researchers that were capable and knowledgeable enough; psychology fell behind due to lack of computer savvy. How accurate an assertion that might be is not for me to answer. However, Blossfied, Hamerle, & Mayer (1989: 25) appeared to have a similar opinion that scientists tend to avoid this type of statistical technique due to its complexity.

Unfortunately, this sentiment is supported by Van Zant's (2002) introduction to survival analysis use in cognitive science. Van Zant (2002) noted that 12 of the 15 studies appearing the February 2000 issue of *Journal of Experimental Psychology: Human Perception and Performance* used mean reaction time as the test statistic. This is particularly troubling as reaction time data typically demonstrate a skewed distribution. Comparing between subjects with test statistics computed by group means often violates the normality assumption, which as of 2000, was still acceptable practice. The most typically used survival analysis techniques, and as such, will be the ones discussed below, are non-parametric in that they make no assumptions regarding the shape of a distribution.

Another issue with the use of survival analysis in the psychology, to which I can only anecdotally validate, is that there appears to be little awareness of the analysis. Many psychologists I have spoken with have never been exposed or were never confronted with the sorts of research questions which would require it. Only with modest speculation can I propose that with the growth of psychology as field, departments have grown larger and more self-sustaining. They have begun providing statistics sequences that largely entail the most common statistical techniques used for the purpose of answering questions the field asks itself. Also, aside from perhaps a statistics department in which to take advanced classes, it is unlikely psychology students are regularly exposed to research methodology in fields that make use of survival analysis, such as ecology, biomedicine, and engineering.

The remainder of this paper will explore survival analysis' basic operations in order to familiarize the reader to the analysis in hopes of making a case for adoption of this technique for psychological use. Next, a brief demonstration of the added information available with survival analysis will consist of three analyses pitting it against more typical methods. Finally, I will conclude that survival analysis is indeed a useful statistical tool for researchers in the behavioral science to implement.

Basis components of Survival Analysis

Unlike methods typically used in psychological research in which dependent measures typically take the form of event counts or scores in experimental methodology, the measure of interest when conducting survival analysis is the time until an event occurs (Miller, 1981; Mills, 2011). As such, the components through which survival analysis is conducted differ slightly from typical statistical techniques often used in experimental psychology. This section will outline basic concepts needed to understand survival analysis.

Censoring

Longitudinal research, by definition, is designed to investigate changes over time related to a particular observational unit (Field, 2013; Laird, 1988; Laird & Ware, 1982). As it is necessary for an investigator to collect data at multiple time points, it is possible to lose access to one or more unit in order to collect data at a given time point. Thus, missing data must necessarily be addressed by longitudinal researchers that operate outside of a restrictive laboratory environment.

Many techniques have been developed to address missing data (for in-depth reviews of missing data treatments, see Gibbons, Hedeker, & DuToit, 2010, and Peng, Harwell, Liou & Ehman, 2007). "Completer" methods (retaining only cases which complete the study are included) and "last observation carried forward" (entering the last available measurement at each interval through the end of a study) are flawed in that these methods make inappropriate assumptions regarding the nature of the unobserved cases. Censoring, however, accounts for incomplete observations. Figure 1 demonstrates the potential detriment of discarding censored observations. Note the drastic mean differences for just the chemotherapy maintenance group between the censored (*M* = 23.287, *StdErr* = 2.827) and completer (*M* = 12.111, *StdErr* = 2.282) methods.

Right-censoring occurs when an event of interest is either not recorded or never occurred for a particular observation. In clinical studies, a patient might withdraw from a study as a result of her condition improving. Another patient may move away and is subsequently lost to follow up. It is possible to experience the event but from an unrelated cause (called competing risks). This might occur if a patient were killed in a car wreck while participating in a pace maker mortality study. It is also possible that a patient may simply fail to experience the event before the end of the study.

Type I and Type II censorings refer to precisely when observations will be considered incomplete and therefore censored. Type I censoring refers to observations that fail to experience an event by the end of a pre-specified time period. In medical and engineering research, a particular condition might historically show that by reaching a particular time point (t), it is unlikely any more observations will fail within an impactful span of time. Type II censoring refers to observations that outlast a pre-specified proportion of failures to total observations. Take, for instance, a doorknob manufacturing company looking to stem growing expenses in their research division. In attempting to determine whether alloy "A" or alloy "B" produces a stronger lock over time, the company may determine any differences between "A" and "B" will be uncovered by the time each condition has reached a 75% failure rate and decide to discontinue trials.

Both Type I and Type II censoring are largely practical matters determined by time and money. Academic researchers often have publishing or IRB deadlines to meet. Epidemiologists may be on the cusp of reporting a new, effective treatment which would immediately benefit many people. They might be conducting very expensive studies with limited funds with which to operate. Regardless of the area of research in which survival analysis could be conducted, it is necessary to consider very carefully the limitations censoring decisions will have on the validity of the results reported.

Data Structure

The data structures inherent to survival analysis are unique to that of typical statistical techniques. Therefore this approach requires special consideration at the outset of planning a successful and interpretable study. While only lifetime and failure need be measured in order to conduct a survival analysis, additional variables may be added depending on the particular research question of interest.

Lifetime/Duration: Denoted T, lifetime is the measurement of time until an observation either experiences the event in question or is otherwise censored. T is necessarily random as well as non-negative in that it begins at zero and moves forward with time. A specific time point t is always within the distribution T.

Event/Failure: The indication of whether an observation experiences the event in question is measured as either "1", indicating failure, or "0", indicating censorship.

Covariates: Covariates in survival analysis can take the form of either categorical or continuous variables. Categorical covariates may take the form of different treatment groups in a clinical study or experimental conditions in psychological research. Using categorical indicators will yield unique statistical functions and curves for each group identified, allowing for the evaluation of group differences. Continuous variables can also be evaluated as to the amount of unique variance they may account for. Oftentimes continuous variables are considered in an effort to control for confounding variables potentially associated with the event of interest.

Statistical Functions

Survival analysis differs from most statistical analyses in that its main interest is time. This leads to unique parameter estimates with regard to *T*, or the non-negative random variable that represents survival times. The following are necessary functions for conducting and interpreting any time-to-event analysis.

Survival Function

The survival function (denoted $\hat{S}(t)$) represents the probability that any observation has not yet experienced an event by a specified time *(t)*. Hypothetically, when assessing for when an observation is likely to experience event, it begins at $t = 0$, $\hat{S}(t) = 1$. This is to say that the probability of an observation having survived at the very onset of the study is 100%. The survival function will remain 1 until the first observation experiences a failure. As observation failures increase over time, the likelihood of any observation having not yet experienced the event decreases at a rate determined by the hazard function. The average survival time can be computed by computing the arithmetic mean of all cases which experienced a failure. Table 1 displays the average survival function for each of a chemotherapy maintenance group and a control group. The average survival function is not particularly useful as a result of failing to take into account censored cases. Also, it provides no indication as to the rate observations failed; only that they did.

Hazard Function

The hazard function *h(t)* represents the instantaneous potential of failure at a given *t*, providing an observation has not yet experienced failure. Whereas the survival function decreases over time as failures occur, the hazard function increases over time as observations fail. Unlike the survival function, however, the hazard function is inherently a rate as opposed to a probability. The hazard function's nature as a rate proves valuable in computing hazard ratios, or the chance of an event occurring in one condition divided by the chance of an event occurring in another condition. Importantly, a hazard ratio can be computed from any two hazard rates to obtain a relative risk at any point of interest. This can be computed within or across groups at any point of interest. Take for instance an investigator that is interested in the relative risk of a first sexual encounter between males and females. From these data, an estimate can be calculate to represent the relative risk at each age of interest (t = 14, 15, 16,…, n).

An average hazard rate can be computed by dividing the number of failures by the sum of survival times (including censored times, see Table 1). From these averages a hazard ratio can be computed which determines the relative risk of belonging to one group over another.

Density Function

The proportional density function (pdf) *f(t)* represents the unconditional instantaneous probability that an observation experiences an event at time *t*. The cumulative density function (cdf) *F(t)* is the probability an observation has failed by some point *t*. This function provides a running estimate of failure likelihood negatively proportionate to the survival function in that $F(t) = 1- \hat{S}(t)$.

Survival Probabilities and Visual Representation for Discrete Covariates

Kaplan-Meier (KM) Product-Limit Estimator and Curves

Kaplan and Meier (1958) devised a method to determine the likelihood of a case experiencing a failure at any given time point (t) taking into account censored observations. This function estimates the survival function $\hat{S}(t)$ at t_j for cases that have survived up until the previous failure time (t_{j-1}). The KM estimate is calculated by dividing the number of survivors at any given *t* by the total number of cases. This estimator is effective for discrete covariates, such as group affiliation, in that cases need only be separated by group before calculating $\hat{S}(t)$.

As demonstrated in Table 2, as *T* increases, the number of survivors (n_j) decreases. As observations fail over time, the likelihood that any particular observation has not yet failed $\hat{S}(t)$ decreases $\hat{S}(t)$ while the likelihood of failing next *h(t)* increases.

The calculation of KM estimates allows an investigator to produce a step-down curve representing $\hat{S}(t)$ over time. Each step down indicates one or more cases not surviving up until that particular time point. Note that a case need not fail in order to step down as censored cases are included as well.

Figure 2 presents a single curve for each level of the discrete covariate. In this case, there is one curve for each of the chemotherapy maintenance and control groups. As demonstrated here, the control group – the group that received no chemotherapy – immediately begins relapsing at a much faster rate than the treatment group and continues to do so while the treatment group appears to only approach 50% relapse by the time the remaining cases censor out. This is a clear indication that patients that do not receive treatment relapse at a much quicker rate than those treated with chemotherapy.

Cox Proportional Hazard Modeling

While the KM estimator is an effective method of computing survival curves for discreet covariates, it fails to accommodate for continuous variables such as age, income, or Likert measurements. For this reason, Cox (1972) developed a method to calculate the influence such continuous variables have on survival rates. This method (Cox proportional-hazards modeling) effectively uses a regression-like technique in order to determine the extent to any variance being accounted for by a covariate. In addition to determining the impact a particular continuous variable might have on competing survival curves, proportional-hazards modeling allows for the possibility of controlling for this particular variable in simultaneous or hierarchical models. This method provides the same survival, hazard, and density functions as KM while controlling for continuous variables. This characteristic allows for the generation of the same KM plots at with the added influence of any covariates.

Model Evaluation

In addition to visually evaluating survival curves for differences, it is also beneficial to say with some certainty that two or more groups differ statistically. By testing two groups, judgments can be made as to the likelihood group differ more than by chance. Though, depending on a priori expectations of when over the course of a study cases are likely to fail there a number of test with which KM curves can be tested statistically (see Hosmer, Lameshow, &May 2008; Klienbaum &Klein, 2005 for a review), the predominant method of analysis is the Mantel-Haenszel log-rank test (1959). This is particularly because the Mantel-Haenszel test places more weight on failures towards the end of the curve whereas other tests, such as the Tarone-Ware or Wilcoxon, place more weight on early failures (Mills, 2011).

The Mantel-Haenszel log-rank test is a chi-square test that compares the survival function log-rank estimates for each group. As this is a test of cell counts, like other categorical tests, it falls within the chi-square distribution. Each available test (eg. log-rank, Wilcoxon, Tarone-Ware) is a variation of this chi-square test.

This is useful in determining whether one treatment might be implemented over another as the former has outperformed the latter. It is important to consider, however, a critical level for making this determination based on the certainty necessary to avoid loss. For instance, a medical procedure testing a new pacemaker would require a higher alpha than a manufacturer testing door knobs as it can likely be justified loss of a life is more detrimental than door knobs.

Analysis

Data for conducting survival analysis requires no less than two main components. As mentioned above, the first necessary component is a measurement of time for each observational unit. Time may be recorded in any form so long as it is consistent (or transformable) and must be positive. The second necessary component is a measurement of failure for each observational unit. Additionally, analyses allow for the addition of categorical variables in order to test differences between groups.

For this demonstration, data have been acquired from a data collected (Lillard and Panis, 2000) regarding marriage longevity. The question of interest generated here is whether race plays a factor in marriage dissolution. The data set includes 3371 couples with records of the man's race, whether the couple are mixed race, whether they got divorced, and marriage length. In order to simplify the question at hand, only the matter of mixed race vs. same race couples will be addressed. These data will be analyzed three different ways. The first will be a basic between-groups T-test evaluating marriage length between the two groups. The next will be a Mann-Whitney test in order to determine differences without violating assumptions of normality. The third will be a survival analysis utilizing both the KM estimator and the Mantel-Haenszel log rank test.

T-test

In independent samples T-test was conducted to investigate differences in marriage dissolution between homogenous and heterogeneous raced couples. A sample of 1032 couples (797 same, 235 mixed) were followed and the length of their marriage was recorded. On average, there was no difference in marriage length between same race (M = 10.76, SD = 8.409) and mixed raced couples (M = 10.74, SD = 8.255, t(1032)= .028, p = .978, 95%CI = (-1.202, 1.237)). See Figure 2.

There are a few issues with this T-test to address. The first issue relates to the sample size. The total number of couples observed for this study amounts to 3371, however, this T-test only reports using a sample of 1032 couples. The reason for this is that nearly 70% of cases were either censored as dropping out of the study or remaining married through the end of data collection. Additionally, the cell sizes are massively discordant. Also, both groups failed the Shapiro-Wilk test for normality (*ps*<.001). As the T-test is not particularly robust to violations of normality, a non-parametric Mann-Whitney test will be conducted.

Mann-Whitney test

A Mann-Whitney test was conducted to investigate differences in marriage dissolution between homogenous and heterogeneous raced couples. A sample of 1032 couples (797 same, 235 mixed) were followed and the length of their marriage was recorded. Marriages in heterogeneous couples (*Mdn* = 8) did not differ from heterogeneous couples (*Mdn* = 9, *U* = 93520, *p* = .975).

The Mann-Whitney test is a rank order test that is used to determine differences between groups when violations of normality have occurred. In the case of these data, there have been sever violations which have been partially addressed by the use of this non-parametric test. However, the issue of the censored cases remains. Next, a survival analysis will be conducted to demonstrate its ability to extract useful information where these other tests could not.

Survival Analysis

In order to investigate the trend differences of marriage dissolution between heterogeneous and homogenous couples, 3371 couples were tracked (2730 same sex, 641 mixed) for the length of their marriages. Of the 3371 couples, 1032 divorced during the course of our study (797 same sex, 235 mixed) and 28 marriages (26 same sex, 2 mixed) remained intact through data collection (*T*=60). A Kaplan-Meier curve chart was constructed in order to visualize the rates at which Heterogeneous and Homogeneous couples' marriages were dissolving (see Figure 4). It can be seen that heterogeneous marriages both fail at a faster rate and suffer dissolution proportionately more than to homogenous couples. A Mantel-Haenszel log-rank test showed heterogeneous marriages suffered a faster survival rate drop homogenous couples $\chi^2(1) = 11.421$, $p = .001$. To investigate the survival curves, Table 3 provides a visualization of the rates at which couples fail by marriage type. Survival rates appear nearly steady until ~t = 10 ($\Delta\hat{S}(t)$=.3). From t=10, the survival functions diverge indefinitely at a greater rate until the study completes.

Conclusion

There are many benefits to using survival analysis over typical NHST techniques. For instance, when a researcher computes the mean of a group in order to compare it to another, that researcher is making inferences about those means that may not accurately represent the individuals in that group; known as the ecological fallacy. Survival analysis allows for the investigation of groups at the individual level. However, Kaplan and Meier (1958) warn that the instant that one observation is removed through censoring, the researcher is no longer explicitly describing the trend of a group, as now there is at least some amount of inference involved.

Additionally, techniques in survival analysis are steadily growing. There are methods to analyze time-varying covariates, such as education level and income. Issues like patient readmission can be accounted for through repeated occurrence methods. In the event that there are two potential outcomes, competing risks analysis can be used. It ultimately is a very useful tool if one is properly trained. Survival analysis is in no way bound for changing the face of psychological research, but as long as psychological researchers are aware of what it is capable of, it may very well open vistas to new research questions rarely before considered.

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Figure 1

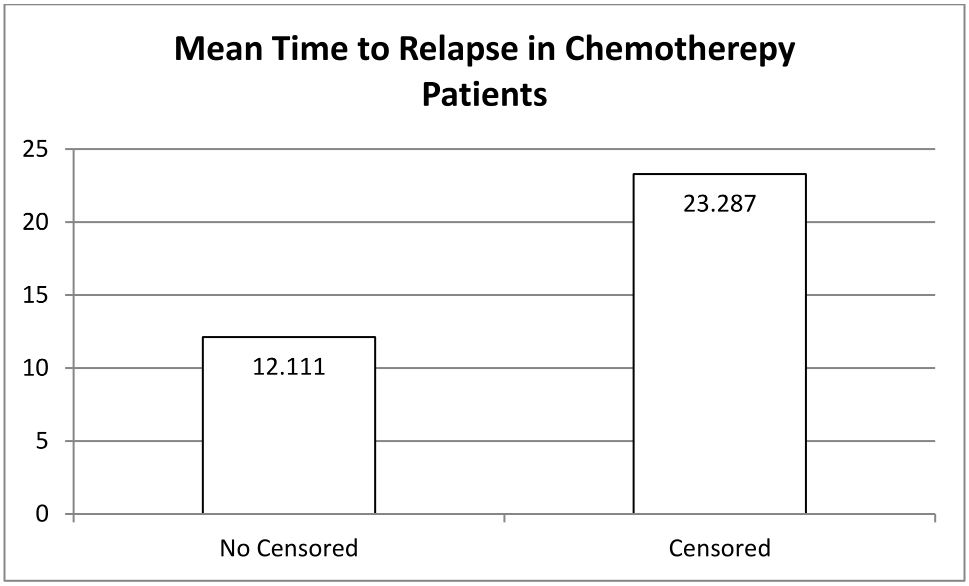
Mean Time to Relapse in Chemotherepy Patients
25
20
15
10
5
0
12.111
23.287
No Censored
Censored

Figure 2

Relapse in Weeks

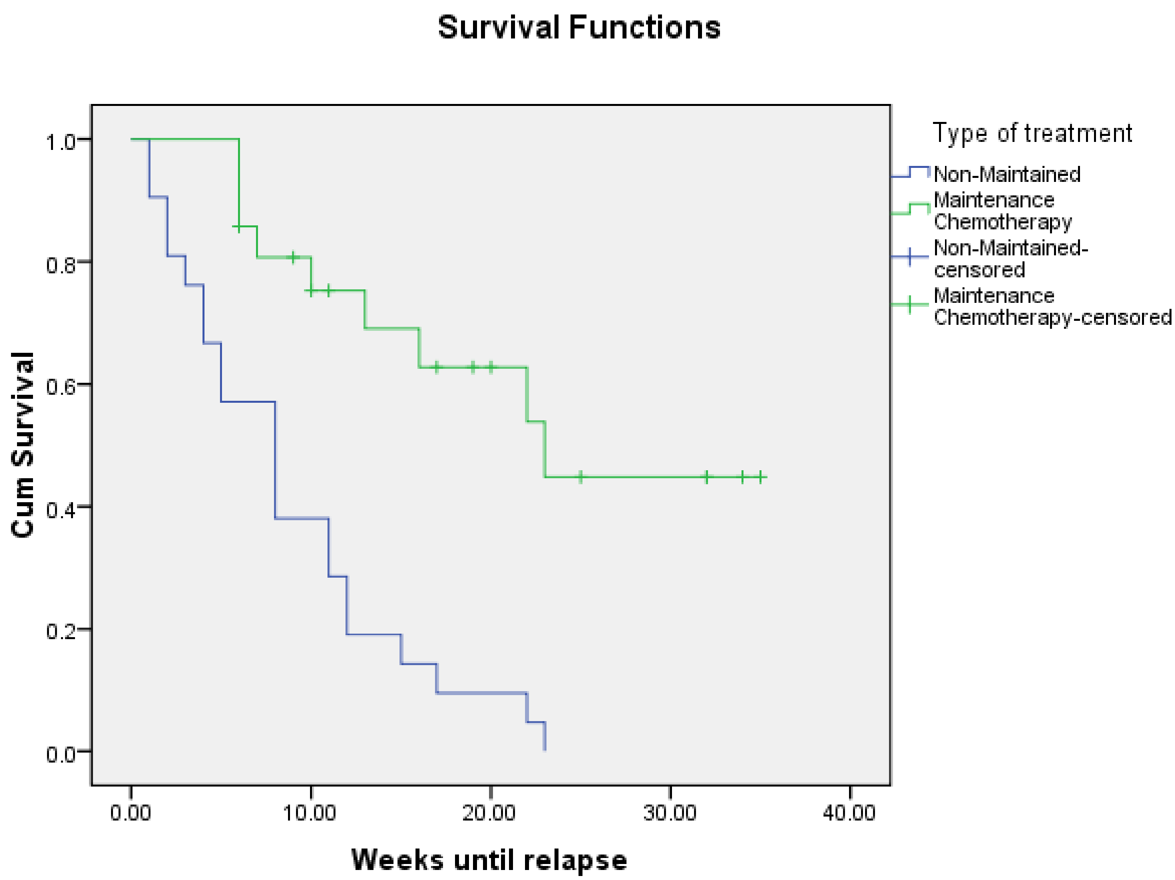

Figure 3

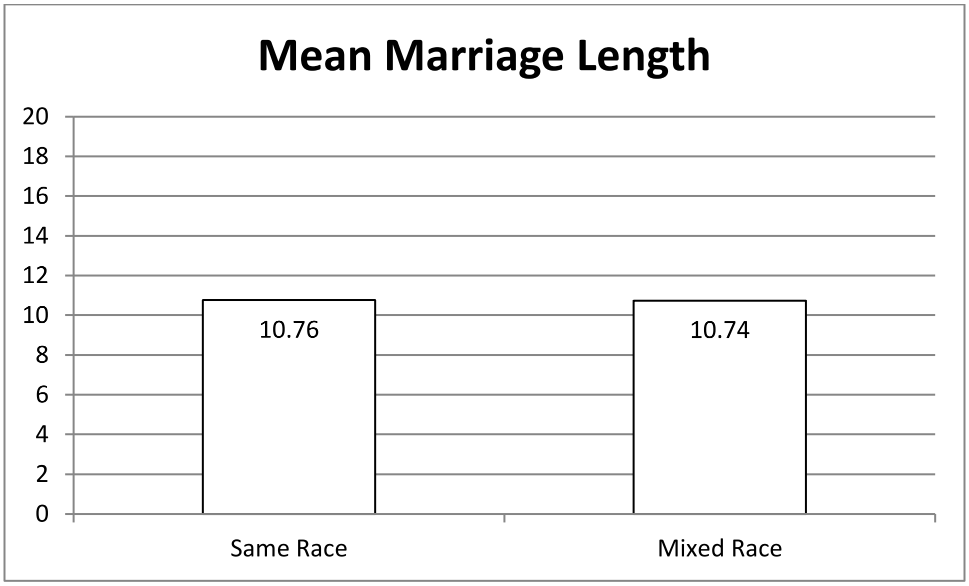
Mean Marriage Length
20
18
16
14
12
10
8
6
4
2
0
10.76
10.74
Same Race
Mixed Race

Figure 4

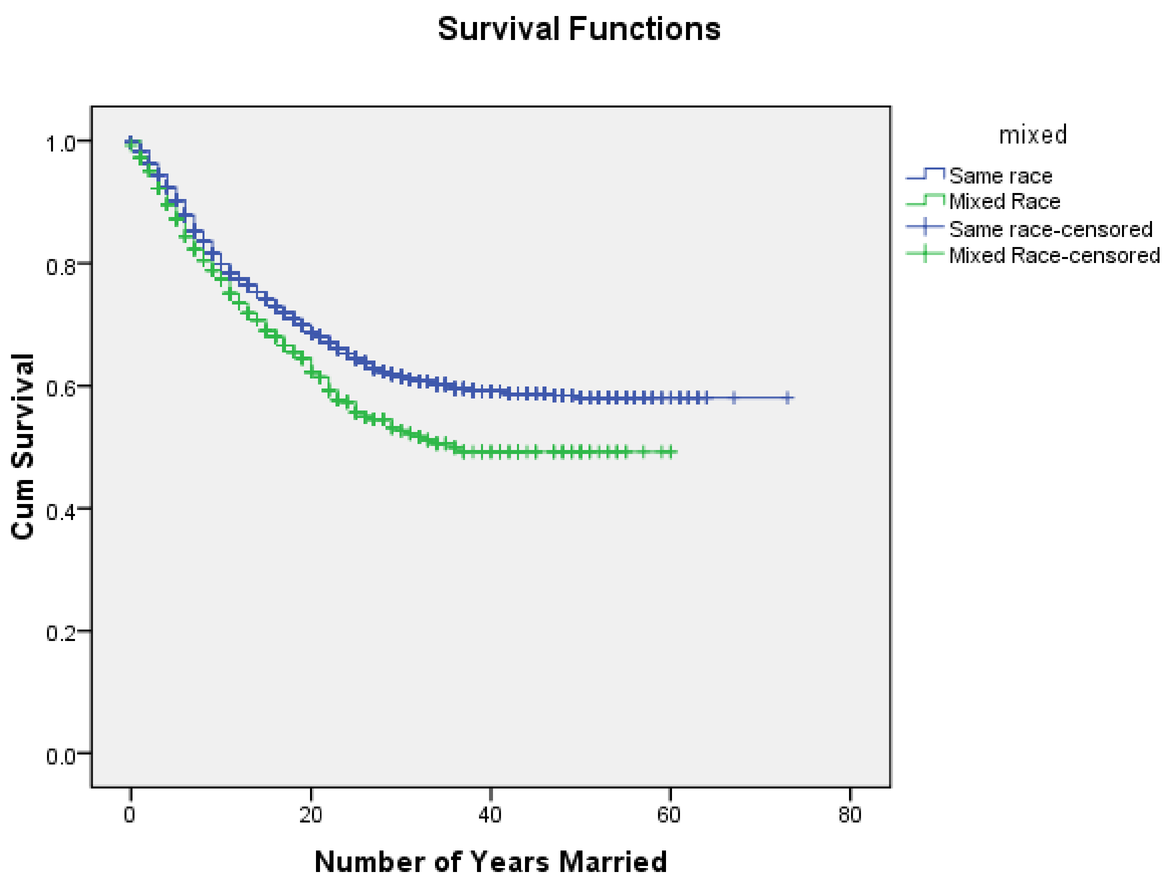
Survival Functions
mixed
Same race
Mixed Race
Same race-censored
Mixed Race-censored
Cum Survival
1.0
0.8
0.6
0.4
0.2
0.0
0
20
40
60
80
Number of Years Married

Table 1

Remission time (in weeks) for two groups of leukemia patients			
Group 1 (placebo) n=21		Group 2 (chemotherapy) n=21	
1, 1, 2, 2, 3, 4, 4, 5, 5, 8, 8, 8, 8, 11, 11, 12, 12, 15, 17, 22, 23		6, 6, 6, 7, 10, 13, 16, 22, 23, 6+, 9+, 10+, 11+, 17+, 19+, 20+, 25+, 32+, 32+, 34+, 35+	
Ave. Survival =	8.6	Ave. Survival =	17.1
Ave. Hazard =	= 21/182 = .115	Ave. Hazard =	= 9/359 =.025

Example chemotherapy data. "+" indicates censored case

Table 2

	Maintained				Non-Maintained		
	Censored included				Censored included		
Life (weeks)	S(t)	H(t)	nj	Life (weeks)	S(t)	H(t)	nj
6	0.6667	0.4055	20	1	0.90476	0.1001	20
6	0.6667	0.4055	19	1	0.90476	0.1001	19
6	0.6667	0.4055	18	2	0.80952	0.2113	18
6 +	.	.	17	2	0.80952	0.2113	17
7	0.5556	0.5878	16	3	0.7619	0.2719	16
9 +	.	.	15	4	0.66667	0.4055	15
10	0.4444	0.8109	14	4	0.66667	0.4055	14
10 +	.	.	13	5	0.57143	0.5596	13
11 +	.	.	12	5	0.57143	0.5596	12
13	0.3333	1.0986	11	8	0.38095	0.9651	11
16	0.2222	1.5041	10	8	0.38095	0.9651	10
17 +	.	.	9	8	0.38095	0.9651	9
19 +	.	.	8	8	0.38095	0.9651	8
20 +	.	.	7	11	0.28571	1.2528	7
22	0.11111	2.19722	6	11	0.28571	1.2528	6
23	0.0000	.	5	12	0.19048	1.6582	5
25 +	.	.	4	12	0.19048	1.6582	4
32 +	.	.	3	15	0.14286	1.9459	3
32 +	.	.	2	17	0.09524	2.3514	2
34 +	.	.	1	22	0.04762	3.0445	1
35 +	.	.	0	23	0.0000		

	Maintained		Non-Maintained
Mean	Std. Err	Mean	Std. Err
23.287	2.827	8.6670	1.411
Median	Std. Err	Median	Std. Err
23	5.255	8	1.669

Table 3

Life Tables by Marriage Type

Same Race						Mixed Race					
Life (years)	Cases entered	Censored	Failed	Survival ($\hat{S}(t)$)	Hazard (h(t))	Life (years)	Cases entered	Censored	Failed	Survival ($\hat{S}(t)$)	Hazard (h(t))
0	2730	14	7	1.00	0.0026	0	641	1	5	.99	0.0078
1	2709	68	38	.98	0.0143	1	635	10	13	.97	0.0209
2	2603	59	54	.96	0.0212	2	612	9	13	.95	0.0216
3	2490	64	48	.94	0.0197	3	590	15	18	.92	0.0314
4	2378	57	51	.92	0.0219	4	557	16	16	.89	0.0296
5	2270	49	54	.90	0.0243	5	525	9	14	.87	0.0273
…						…					
10	1726	49	36	.80	0.0214	10	427	19	8	.77	0.0193
...						...					
15	1366	54	22	.74	0.0166	15	319	10	8	.69	0.0258
...						...					
20	1041	35	20	.68	0.0197	20	232	12	8	.62	0.0360
...						...					
25	787	50	9	.64	0.0119	25	164	10	5	.55	0.0319
...						...					
30	605	21	4	.61	0.0068	30	112	3	1	.52	0.0091
...						...					
40	353	14	0	.59	0.0000	40	59	3	0	.49	0.0000
...						...					
50	147	24	1	.57	0.0074	50	21	6	0	.49	0.0000
...						...					
60	26	26	0	.57	0.0000	60	2	2	0	.49	0.0000