Editorial

Lost but Not Forgotten: How to Manage Follow-Up Loss in Clinical Research

Abstract: The interconnectedness of the modern world should make following patients and accessing their records much easier than in the past. For those of us old enough to remember, this once involved boxes full of papers, charts, microfiche records, images printed on radiographic films, and connecting with our patients via mailed letters. With modern electronic medical records and numerous means of electronic communication, this should be much easier. However, the demands on our patients' time are higher than ever before, mitigating some of these technological benefits. While all studies would benefit from 100% follow-up, real-world concerns lead to the inevitable loss of patients in research studies. Researchers should strive to lower and mitigate these losses and, when possible, explore potential bias introduced with attrition. Losses to follow-up risk lowering the validity of the research via the introduction of selection and attrition bias. Proper accounting for and reporting of patients throughout the inclusion, exclusion, and analysis of a study allows the reader to assess the amount of risk introduced by patient loss and its potential effect on the study outcomes and conclusion. Finally, when loss to follow-up occurs, it should be explicitly reported, accounted for by using appropriate statistical analyses (such as Kaplan-Meier), and its impact discussed in the interpretation of the results.

A 2018 *Arthroscopy* editorial, "Research Pearls: The Significance of Statistics and Perils of Pooling," acknowledged its topic to be as exciting as watching paint dry.[1] An editorial on loss to follow-up rates is also at risk of being uninteresting. However, the readers of prior research pearls likely discovered that the editorial authors were able to make those articles informative, useful, and interesting.[2-4] We hope not to "lose" readers due to a lack of excitement and intend to show the relevance, value, and nuance of accurate follow-up reporting. The conclusions, as derived from statistical analyses, hinge on accurate reporting of patient follow-up. The overall objective is to help authors design and report future studies, increase the likelihood of acceptance in *Arthroscopy*, and improve the overall quality of scientific content available to the orthopaedic community.

Importance of Follow-Up Rates

When considering the design and impact of any clinical study or outcomes-based research, the follow-up rate is of paramount importance. Many of us will recall our first epidemiology or biostatistics class, whether in college or medical school, and likely also recall the gold standard of an 80% follow-up rate in clinical studies. This remains an important benchmark, and the levels of evidence criteria used by the *Arthroscopy* family of journals continue to use this as a criterion to differentiate high-quality randomized controlled trials (RCTs) and prospective prognostic studies (Level I evidence) from lower-quality Level II studies. Now, further along in our clinical, research, reviewer, and editorial careers, we recognize greater nuance to that 80% standard. For example, a recent RCT with a 2-year follow-up comparing early active motion versus sling immobilization for arthroscopic cuff repair in *Arthroscopy*[5] shows excellence by meeting and exceeding the gold standard. Yet, there are also examples of valuable studies with a less than 80% follow-up. A 2022 study[6] with a minimum 10-year clinical and radiographic follow-up on arthroscopic rotator cuff repairs treated with platelet-rich plasma added to our collective understanding of the long-term effects of platelet-rich plasma despite a follow-up rate of 73%, which is an impressive rate for long-term; while a 10-year follow-up is always challenging for a variety of factors, a median patient age of 71 years adds additional challenges due to expected mortality beyond that of patients relocating, changing their contact information, or being unwilling to continue participating. The follow-up rate is incredibly important, and while the 80% gold standard still appropriately exists, studies with lower rates of follow-up can add to our collective understanding of longer-term outcomes.

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While there is no universally accepted minimum mandatory percentage follow-up based on short-, mid-, or long-term follow-up, studies reporting a longer time for outcome analysis tend to have a higher loss of patients. As evidenced in the 2 rotator cuff studies in the preceding paragraph,[5,6] longer follow-up times can lose patients for a multitude of reasons, and regardless of the reason, achieving 100% follow-up becomes difficult or impossible. Time itself is a continuous variable, but we often discuss it in a categorical variable fashion. Specifically, we often classify follow-up times as short-, mid-, and long-term. Determining the cutoff times for these various lengths of follow-up may be somewhat arbitrary, but having a general standard or consensus definition facilitates comparisons across studies. At *Arthroscopy*, we consider a MINIMUM follow-up of 2 years to be short-term, 5 years to be mid-term, and 10 years to be long-term. It is important to note that time data are reported as a minimum follow-up time and not the median or mean time, both of which, by definition, must exceed the minimum thresholds noted above. Although the 80% follow-up rule would ideally be achieved in all studies, it's most commonly considered the gold standard with respect to studies with short-term (2-year minimum) follow-up. Compared with short-term follow-up studies, an 80% follow-up rate is increasingly difficult to achieve in mid-term and especially in long-term follow-up studies. Regardless of the length of follow-up, an additional overlooked nuance is that of the appropriate determination of the follow-up rate.

Determination of Follow-Up Rates

We can stipulate that the follow-up rate of any study is likely inversely correlated with its follow-up length, but the determination of the follow-up rate itself is often more complex than it seems. Many factors go into the determination of the follow-up rate, and the following nonclinical example may decrease the chance that this point gets lost in the weeds. As arthroscopists and sports medicine specialists, many of us and many of our patients are or were athletes, so an example of the completion rate of a marathon may be a fitting metaphor for follow-up rates. If 800 runners complete a marathon, what is the completion rate? To answer this question, there is a surprising amount of nuance to determine the denominator for the rate calculation. If 1,000 runners crossed the starting line, our first calculation is that the completion rate is clearly 80%. However, what if 1,200 runners registered for the race, 100 dropped out before the race day, and another 100 failed to show up on race day? Is the completion rate now 800/1,200 (67%), 800/1,100 (73%), or still 800/1,000 (80%)? In another example, what if we only consider runners who crossed the finish line? That would give us a completion rate of 100%. While that calculation may seem odd, its parallel is commonly observed in research studies whose inclusion criteria include a minimum 1- or 2-year follow-up. In this marathon example, our once simple 80% completion rate can technically be reported as anywhere from 67% to 100%.

To appreciate the extent and potential impact of losses to follow-up, the primary outcome and scope of research need to be considered. If the interest is marathon running times, then runners who registered and then withdrew as well as those who didn't show up (albeit an interesting group in their own right) did not participate and therefore are outside the target population of this analysis. Reporting the total number of runners regardless of participation may provide meaningful information in terms of how often registered runners compete, but they did not start the race and therefore don't contribute to an estimate of running time and are not considered losses. Conversely, if 600 of the 800 runners who completed the marathon provided their running time for the analysis, the remaining 200 would be considered "losses." These losses could be inadvertent (didn't receive a request to provide running time) or deliberate (do not want it recorded for whatever reason) and can introduce selection bias, thereby impacting the validity of the analysis of running time. For example, the fastest runners may want access to their completion times limited for strategic reasons and therefore do not make their times available. In this case, the analysis of running time would produce a biased estimate on account of the losses of the fastest runners.

Figure 1A summarizes the flow of runners from registration to inclusion in the analysis. The study was conducted on registered runners for the fictional 2025 *Arthroscopy* marathon. Of the 1,200 registered, 1,000 competed, with 200 having either withdrawn prior to race day (n = 100) or did not show up (n = 100). Of the 1,000 who competed, 800 crossed the finish line, with 200 dropping out at some point after the start of the race. These runners need to be excluded because they didn't generate a completion time. They may introduce bias because those who competed may differ in variables of interest from those who finished the race (attrition bias). They shouldn't be considered losses to follow-up as they did not generate a completion; however, they are part of the target population (i.e., runners who participate in marathons). It's important that these participants' data are reported and differences between completers and noncompleters are explored. This exclusion leaves 800 who completed the race, of whom 600 have a running time available. The remaining 200 are lost to follow-up since they have a running time that is not available for analysis. Importantly, each step of the enrollment and analysis phases of the study is documented, allowing the reader to

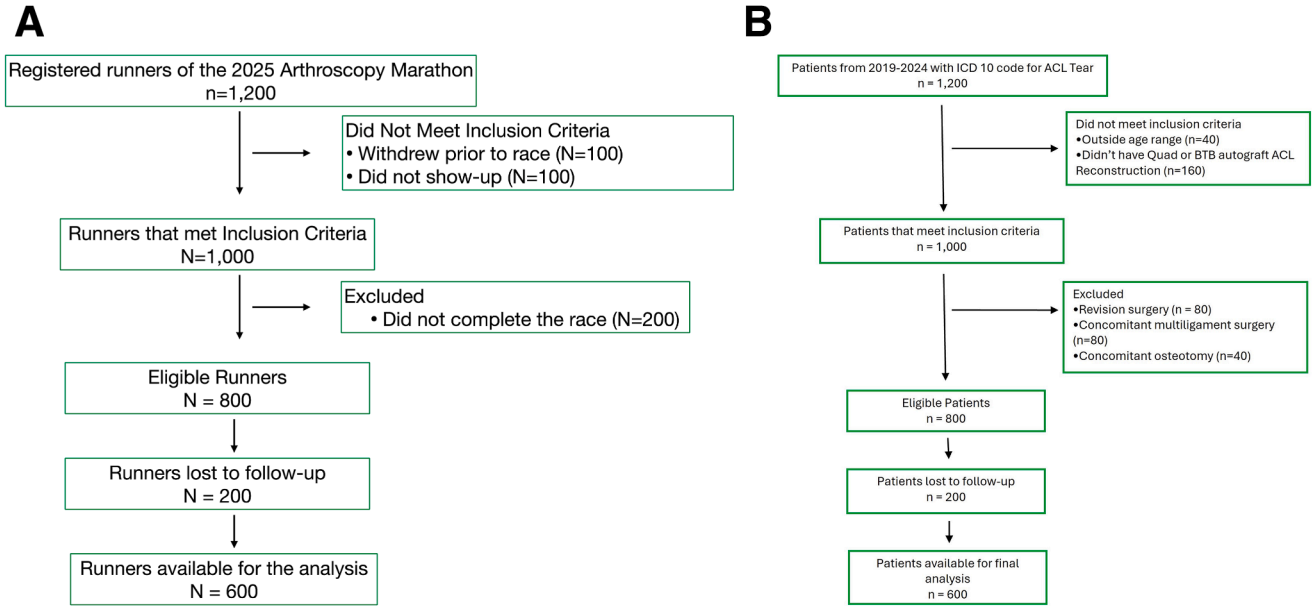

Fig 1. (A) Runner inclusion flowchart for the 2025 *Arthroscopy* marathon. (B) Optimal patient inclusion flowchart for a retrospective case series.

appreciate what different biases and threats to validity may be present and whether the authors took appropriate steps to mitigate their potential effects.

In this marathon example, the determination of the follow-up rate is dependent on the question being asked. The original wording of the question references the completion rate of the marathon. The completion rate of a marathon is the number of runners who cross the finish line divided by the number of runners who cross the starting line:

$$Completion\ rate = \frac{\#\ of\ runners\ crossing\ finish\ line}{\#\ of\ runners\ crossing\ starting\ line} \times 100\%$$

In this example, the completion rate of the marathon is 80%.

However, in our 2025 *Arthroscopy* marathon study example analyzing the finish times of runners, we are interested in the number of runners who provided their finish times relative to the total number of finishers. For this study, the follow-up rate uses different numerators and denominators:

$$Follow-up\ rate = \frac{\#\ of\ runners\ providing\ finish\ time}{\#\ of\ runners\ crossing\ finish\ line} \times 100\%$$

In this example, our follow-up rate is 75%.

So how does this 2025 *Arthroscopy* marathon metaphor relate to a clinical study? The follow-up rate of the marathon represents the true follow-up rate in a clinical study. The number of runners who dropped out before race day (inclusion criteria) and didn't complete the race (exclusion criteria) represents the entire potential pool of patients. Appropriate accounting and reporting of patients in a study would include both the total number of potentially included patients and the number of excluded patients. The percentage of patients with completed follow-up relative to the overall potential pool of patients and the number of excluded patients is not typically reported as a percentage. However, the potential pool of patients and the number of patients excluded should be reported as they can affect the validity of a study. Once the reporting is complete, the appropriate equation to determine the follow-up rate of a study is:

$$Follow-up\ rate = \frac{\#\ of\ patients\ with\ complete\ follow-up}{\#\ of\ patients\ meeting\ inclusion\ and\ exclusion\ criteria} \times 100\%$$

This simple equation can be used to determine the follow-up rate of any type of clinical study, including RCTs, prospective and retrospective cohort studies, and case-control studies. Returning for a minute, no pun intended, to our marathon example, it is worth noting that the denominator of the completion rate is determined with respect to the number of runners who crossed the finish line. If we compare this with the follow-up rate equation above, the denominator is the number of included patients. Because of the importance of having a high follow-up rate, it is tempting to artificially deflate the number of included patients in a study—the denominator—in order to artificially increase the follow-up rate. In a research study, this can be "accomplished" by requiring follow-up of a certain length to be included or not excluded from the study. However, failing to include those patients in the

denominator of a clinical study is equivalent, in our marathon example, to determining a completion rate of a marathon by not including or excluding those who started but didn't finish the race. That deflation would artificially raise the completion rate of every marathon to 100%, the absurdity of which would be clear to a reader. Requiring a certain minimum follow-up threshold time in a clinical study as an inclusion/exclusion criterion is a more subtle but equally flawed method of determining and/or manipulating the follow-up rate. With appropriate inclusion and exclusion criteria to appropriately account and report all patients, the determination of the follow-up rate becomes less nuanced and fairly straightforward, as shown in the simple follow-up rate equation above.

Bias and Study Limitations Related to Lost Patients

Having reviewed the importance of the follow-up rate and the "formula" for determining it, it is worth exploring what happens in the nearly inevitable scenario in which the follow-up rate isn't 100%. A reader or reviewer of a study with a 66.7% follow-up rate would justifiably have more concerns about the validity of that study than one with a 100% follow-up for numerous reasons that deserve further exploration. In epidemiologic terms, these reasons are explained by the potential for bias that they can introduce. Loss of patients to follow-up and low follow-up rates can introduce selection bias, as well as the more particular attrition or transfer bias.

Selection Bias

Selection bias is a broad grouping of biases in research studies that result in systematic bias in one of two different ways. One specific type of selection bias occurs when the population being studied differs from the general or intended population to be studied. This "sampling bias" occurs when the inclusion and exclusion criteria produce a sample that differs from the proposed target population. An example of this would be a study evaluating the results of the nonoperative management of Achilles ruptures in a rural community with an older population; in this case, the mean age of patients may be higher in this lower-demand aged group than the typical more demanding and younger patients with Achilles ruptures. The more typical and broad type of selection bias occurs when the groups being studied differ from each other in a nonrandom fashion: the type of bias that can be present in studies with differing rates of follow-up. An example of this second type of bias, not related to follow-up, is self-explanatory in a well-titled Editorial Commentary, "Outcomes of Shoulder Biceps Tenotomy Versus Tenodesis Are Difficult to Determine From Nonrandomized Studies Due to Selection Bias: Tenodesis Is More Commonly Performed on Younger Males."[7] This title exemplifies selection bias that is unrelated to follow-up. The effect bias has on the results of any study without 100% follow-up rates is largely the same. Patients lost to follow-up can create a similar nonrandom asymmetry between groups, which can impact the results, such as outcome measures or rates of failure that are biased on account of missing patients.

Attrition (or Transfer) Bias

Attrition bias is a subtype of selection bias that occurs when patients are not included in the final data analysis for any reason, including incomplete records, withdrawals, or patient mortality, resulting in systematic differences between the study groups.[8] An example of this would be a nonrandomized retrospective cohort study assessing anterior cruciate ligament (ACL) retear rates between bone–patellar tendon–bone (BPTB) autografts and quadriceps autografts. While the groups may appear to have equivalent demographics in terms age, sex, and concomitant procedures, the BPTB group may include a higher percentage of collegiate athletes who relocate and therefore have a higher loss to follow-up. If some of this subset of BPTB autograft patients who are lost are more likely to return to a high level of sports and retear, this may underestimate the retear rate of the BPTB autograft patients relative to the quad autograft patients.

Other Limitations and Considerations

Aside from bias, an additional point of consideration when interpreting the findings of a study is that loss to follow-up can be an important problem even when it doesn't surpass the 20% threshold. For example, consider an RCT of a new versus control rotator cuff implant with 100 patients in each group. If the study loses 20 of their 200 patients, it has 90% follow-up rate, which could be deemed acceptable. However, if all of the patients who were lost to follow-up were in the new implant group, rather than the control group (i.e., they were dissatisfied with the outcome of surgery due to a high rate of failure with the new implant), then clearly this can threaten the internal validity of the trial. Considering a worst-case scenario can help to understand whether loss to follow-up is acceptable. Only when the worst-case scenario is unlikely to change the study's findings is loss to follow-up acceptable and less likely to introduce bias.

Mitigating Bias

Mitigating Bias—Study Design

All studies will have some form of bias and limitations, and the best practice is to mitigate these with prospective planning and prevention. The ideal method of mitigating bias due to the loss of patients in a study is

Table 1. Pearls and Pitfalls in Mitigating and Managing Bias With Respect to Follow-Up

Pearls	Pitfalls
Minimizing the burden on patients through careful study design	Unnecessary, overly complicated, or too frequent demands on patient time
Frequent communication from surgeon and/or research team	Failure to continuously engage patients throughout the study period
Consistent research staff	High rates of research staff turnover
Ensuring participants feel valued and are contributing to a greater good	Failure to ensure patients feel valued and their time respected
Use of statistical tools to determine whether patient loss is more likely due to chance or systematic bias	

to make every effort to retain patients in every phase of the study (Table 1). When designing a prospective study, researchers can attempt to select patients who are likely to remain in the study. For both prospective and retrospective studies, the design of the study should minimize the burden on patients and consider incentives for follow-up. During the study, frequent communication can help patients remain engaged in the study. This can be directly from the surgeon or indirectly from clinical or research staff during clinic or research visits, phone calls, or e-mails. Effective use of communication to ensure the participant feels valued, their time feels respected, and they understand their participation will aid in the clinical care of others can be invaluable in prompting continued participation. From a structure or institutional perspective, having a "face" of the research study can be helpful in maintaining patient engagement via the above methods. While the patients' surgeon may be the ideal person to fill that role, it may not always be possible or feasible based on the study design. In that case, having a consistent research coordinator, as opposed to multiple and changing coordinators and students, can be helpful in maintaining patient relationships and follow-up.

Mitigating Bias—Appropriate Follow-Up Reporting

Although researchers can strive for 100% follow-up using the methods above, the accurate reporting of lost patients, as our marathon completion rate example revealed, is nuanced. While the Consolidated Standards of Reporting Trials statement aids in the appropriate methods and reporting for randomized controlled trials, and the Preferred Reporting Items for Systematic Reviews and Meta-Analyses guidelines aid similarly for systematic reviews and meta-analyses, many studies in orthopaedics fall outside of those categories. Our goal here is to provide guidance on the appropriate reporting of patient follow-up.

The common phrase "Sunshine is the Best Disinfectant" is often a political statement that implies transparency can help decrease corruption. In the research setting, transparency allows readers and reviewers to make their own informed opinions and judgments about a study. Therefore, with respect to follow-up reporting, more information is better. One litmus test that can be applied to a study is whether there is a patient inclusion flowchart that allows the reader a clear accounting and understanding of every patient who was assessed and considered for inclusion, those excluded, those lost, those not analyzed, and the reasons why. Many studies don't include patient inclusion flowcharts, and many that include them do not offer the level of detail needed to assess a study.

To construct a clear patient inclusion flowchart, the methods of a study should have well-defined inclusion and exclusion criteria. Specifically, the reader should be able to determine exactly which patients are included, which patients have been excluded or lost, and the reasons for each (Table 2). Inclusion and exclusion criteria should be based on patient and procedure demographics and characteristics. Minimum patient follow-up or lack of incomplete records should not be considered appropriate inclusion or exclusion criteria. If all patients who don't take part in follow-up or have incomplete records are either excluded or not

Table 2. Pearls and Pitfalls in Constructing a Patient Inclusion Flowchart

Pearls	Pitfalls
Report the total number of potential patients	Making a minimum follow-up length and inclusion criteria
Report the number of patients who were screened but did not meet inclusion criteria	Overlapping inclusion and exclusion criteria
Report the number of patients excluded and for what reason(s)	Reporting inclusion and exclusion criteria together
Report the number of patients excluded from analysis (for incomplete records, etc.)	Not reporting the reason(s) patients are excluded (and how many)
Report the number of patients lost to follow-up	Not reporting why patients are excluded (and how many)
	Not reporting the number of patients lost to follow-up

included, all research studies would have 100% follow-up rates, and readers would lose the ability to determine for themselves whether the loss of patients introduces bias and potentially affects the study validity. Further, the exclusion criteria do not need to exclude patients who are not included; for example, if the study is evaluating patients who have undergone medial portal femoral ACL tunnel drilling, patients who underwent outside-in femoral tunnel drilling do not explicitly need to be excluded since they are not eligible anyway. Including them can overly complicate the study flow diagram and obfuscate loss to follow-up. Remember that clear reporting of loss to follow-up is an essential component of managing this issue. Once the inclusion and exclusion criteria have been clearly defined and applied, the loss of patients over the time from the inclusion or initiation of the study should be clearly and separately reported.

Once the specific selection criteria are defined, the optimal flowchart for a retrospective case series (Fig 1B) can be constructed. This example is created for a study on the outcomes of ACL reconstruction with numbers that mimic the marathon completion example previously considered. In this example, the inclusion criteria are patients aged 16 to 65 years within a single institution who had an International Classification of Diseases, 10th Revision code for an ACL tear between 2019 and 2024 and underwent an ACL reconstruction with a BPTB or quadriceps autograft. In Figure 1, the number of potential patients drops from 1,200 to 1,000 by 200 patients not meeting the inclusion criteria, which in our marathon example represents the athletes who withdrew prior to the race start. After the exclusion criteria are applied, we lose another 200 patients, who, in continuing our metaphor, represent the runners who did not complete the race. The flowchart clearly represents the patients who are lost to follow-up and those included in the final analysis, representing the runners who started but dropped out of the race and those who finished the marathon. With clear delineation and reporting, the numerator and denominator here become clear as 600 and 800 for a 75% follow-up rate, using the formula presented earlier.

Clear and accurate reporting as defined above can minimize bias, but some common pitfalls can lead to inaccurate reporting that increases the risk of bias. Many studies with poor patient reporting lack a patient inclusion flowchart. Many others share some of the pitfalls described in Table 2. Because these reporting issues can be complex, it is helpful to review some of the commonly seen pitfalls in more detail:

- Using minimum follow-up as an inclusion or exclusion criterion
- Overlapping inclusion and exclusion criteria
- Failure to report the number of patients with "incomplete records" and/or those "lost to follow-up"
- Mixing the reporting of the number of patients with "incomplete records" and/or those "lost to follow-up" with the number of patients not included or excluded for other reasons

Although the pitfalls listed above may seem hard to avoid, following the pearls and the methods above should make patient reporting straightforward. In fact, many of the pitfalls and the increased complexity that comes along with them are likely not accidental; they're likely an attempt by well-meaning authors to make a report seem better by improving the follow-up rate. Unfortunately, this attempt backfires by introducing confusion in the study methods and results while providing an artificially high follow-up rate. A study with simple and clear reporting and accounting of patients is better than one without, regardless of the difference in follow-up rates.

Mitigating Bias—Statistical Methods

A good study would have both clear reporting and accounting of patients and a good follow-up rate. However, real-world implications mean that not all studies will have 100% follow-up, and in these scenarios, statistical tests can be used to assess for and possibly minimize the bias introduced when patients are lost to follow-up. Many retrospective and nonrandomized prospective trials use *t* tests to assess whether differences between the groups being studied are not due to chance. This assesses whether nonrandom between-group differences are present at the outset of a study. When there is a large or differential loss to follow-up between groups, these tests can be repeated in the conclusion of the study with the patients included in the final analysis. This can assess whether any new between-group differences have arisen that are likely due to nonrandom causes. In the case of RCTs, there is no need for a *t* test for between-group differences at the initiation of the study to determine whether between-group differences, if any, are due to chance as the randomization of patients is the reason for between-group differences. However, if the groups have a high loss of patients or differential losses of patients, those lost may not be due to chance alone, which can introduce multiple sources of bias. This is a scenario where the use of a *t* test may be appropriate in an RCT to assess whether any between-group differences are expected due to chance alone or whether there is statistical evidence to support that the loss to follow-up differs on substantive baseline variables. Like any comparison, the clinical relevance of the differences in terms of the potential impact they may have on the validity of the trial needs to be considered in conjunction with the results of the *t* test.

In addition to the *t* test, another appropriate statistical method that can help express the follow-up rate and allow the reader to assess its potential for biasing study results is the Kaplan-Meier method. The Kaplan-Meier method is a popular statistical approach used to estimate the probability of survivorship over time (e.g., survivorship of rotator cuff repair defined by being intact [Sugaya types I-III] on postoperative magnetic resonance imaging), especially when dealing with differing durations of follow-up and loss to follow-up.

The Kaplan-Meier method accounts for loss to follow-up by allowing patients to contribute to the analysis up to the point of censoring. Censoring in this context means that, for a particular individual, the event of interest (e.g., failure of cuff repair) did not occur during the study period or was not recorded. This occurs when patients are lost to follow-up, withdraw from a study, die during the study period, or have not experienced the event of interest at the end date of the study. For example, if a patient is lost to follow-up, their data are still included in the survival calculation up until the time they were last evaluated. The method then adjusts the survival probability at each time point based on the individuals still at risk and those who experienced the event of interest or were censored.

The Kaplan-Meier method assumes that loss to follow-up is random and not related to the outcome of interest (e.g., failure of repair). On this basis, it is assumed that patients lost to follow-up have the same survivorship probability (in this example, the same probability of an intact rotator cuff) as those who remain in the study. Therefore, it is important to try to determine the reasons for loss to follow-up (although this is not always feasible, strategies include collecting patient responses for failure to follow-up, as well as evaluations for common factors among those lost to follow up, e.g., treatment group, treatment outcome, socioeconomic status) to determine whether it's reasonable to assume this assumption holds. In our previous example, the loss to follow-up mostly of patients with failures would not lend itself to the use of Kaplan-Meier analyses, nor would patients lost to follow-up who had an excellent result and wished to be discharged. Simply put, loss to follow-up could bias the results of Kaplan-Meier analysis if those lost are not representative of the overall study population. If this occurs, alternative statistical methods may be needed such as likelihood-based approaches or recurrent event models.

To mitigate bias, researchers should consider methods to handle missing data, such as using competing risks models. A competing risk is one that prevents the occurrence of the primary event of interest (e.g., loss to follow-up prior to magnetic resonance imaging at a minimum 2 years postoperatively). If this occurs, then techniques such as competing risks regression can be used.

Finally, appropriate statistical methods are also important to compare Kaplan-Meier curves. The log-rank test and Cox proportional hazards model are both frequently used. The latter has the advantage of allowing adjustment for other factors that could influence survivorship (e.g., rotator cuff healing index, tear size, smoking status).

In summary, loss to follow-up remains a persistent challenge for authors, but adopting strategies to minimize it, explicitly reporting it when it occurs, and using appropriate statistical analyses can help to mitigate the risk of bias.

In this Editorial, we have attempted to explain the nuances of follow-up rates and reporting in a clear and interesting fashion. Once the appropriate follow-up reporting flowchart is created using the pearls and pitfalls above, the equation for the follow-up rate is simple and easily reproducible. If the flowchart or the equation for the follow-up rate seems too complex, it probably is. We authors find interest and see the beauty in this simplicity and trust most readers will as well. While reading this entire Editorial might still seem like watching paint dry to a select few, hopefully, even those few will acknowledge that this dried paint makes beautiful and important art.

Conclusions

Researchers should do their best to minimize patient loss by lowering the burden on patient communication and relationships with consistent research staff, ensuring that patients feel valued, and statistically assessing the risk of bias. Despite these efforts, the loss of patients in a research study is a common occurrence that can introduce selection and attrition bias. However, even if the follow-up rate doesn't meet the ideal 80% threshold, it doesn't mean the study is or should be considered invalid. A study should strive for clear accounting and reporting of inclusion criteria, exclusion criteria, missing data, and loss to follow-up. This accurate reporting will allow the reader to assess the study's validity for themselves with a clear and fair understanding of the potential for bias.

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References

1. Dhawan A, Brand JC, Provencher MT, Rossi MJ, Lubowitz JH. Research pearls: The significance of statistics and perils of pooling. *Arthroscopy* 2017;33:1099-1101.
2. Harris JD, Brand JC, Cote MP, Faucett SC, Dhawan A. Research pearls: The significance of statistics and perils of pooling. Part 1: Clinical versus statistical significance. *Arthroscopy* 2017;33:1102-1112.
3. Hohmann E, Wetzler MJ, D'Agostino RB Jr. Research pearls: The significance of statistics and perils of pooling. Part 2: Predictive modeling. *Arthroscopy* 2017;33:1423-1432.
4. Harris JD, Brand JC, Cote MP, Dhawan A. Research pearls: The significance of statistics and perils of pooling. Part 3: Pearls and pitfalls of meta-analyses and systematic reviews. *Arthroscopy* 2017;33:1594-1602.
5. Sheps DM, Silveira A, Beaupre L, et al. Early active motion versus sling immobilization after arthroscopic rotator cuff repair: A randomized controlled trial. *Arthroscopy* 2019;35:749-760.e2.
6. Randelli PS, Stoppani CA, Santarsiero G, Nocerino E, Menon A. Platelet-rich plasma in arthroscopic rotator cuff repair: Clinical and radiological results of a prospective randomized controlled trial study at 10-year follow-up. *Arthroscopy* 2022;38:51-61.
7. Ahmed AF. Editorial commentary: Outcomes of shoulder biceps tenotomy versus tenodesis are difficult to determine from nonrandomized studies due to selection bias: Tenodesis is more commonly performed on younger males. *Arthroscopy* 2025;41:2211-2213.
8. Nunan D, Aronson J, Bankhead C. Catalogue of bias: Attrition bias. *BMJ Evid Based Med* 2018;23:21-22.