Impact of Medical Academic Genealogy on Publication Patterns: An Analysis of the Literature for Surgical Resection in Brain Tumor Patients

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"Academic genealogy" refers to the linking of scientists and scholars based on their dissertation supervisors. We propose that this concept can be applied to medical training and that this "medical academic genealogy" may influence the landscape of the peer-reviewed literature. We performed a comprehensive PubMed search to identify US authors who have contributed peer-reviewed articles on a neurosurgery topic that remains controversial: the value of maximal resection for high-grade gliomas (HGGs). Training information for each key author (defined as the first or last author of an article) was collected (eg, author's medical school, residency, and fellowship training). Authors were recursively linked to faculty mentors to form genealogies. Correlations between genealogy and publication result were examined. Our search identified 108 articles with 160 unique key authors. Authors who were members of 2 genealogies (14% of key authors) contributed to 38% of all articles. If an article contained an authorship contribution from the first genealogy, its results were more likely to support maximal resection (log odds ratio = 2.74, $p < 0.028$) relative to articles without such contribution. In contrast, if an article contained an authorship contribution from the second genealogy, it was less likely to support maximal resection (log odds ratio = −1.74, $p < 0.026$). We conclude that the literature on surgical resection for HGGs is influenced by medical academic genealogies, and that articles contributed by authors of select genealogies share common results. These findings have important implications for the interpretation of scientific literature, design of medical training, and health care policy.

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A central tenet of science is that investigators should strive to be objective—to be free from the undue influence of past experience, social context, and the opinions of peers and mentors. Basic intuition, however, suggests that perceptions and conclusions are likely affected by the beliefs of those around us, particularly our mentors. This intuition is supported by a well-established literature in both the social sciences[1–9] and the physical sciences.[8–13] In particular, an emerging interdisciplinary literature suggests that mentors and mentoring environments have a strong influence on researcher attitudes, methods of investigation, and career development.[14–17]

To date, studies investigating social factors that influence scientific investigations tend to use qualitative methodologies. The notion of "academic genealogy," in which scientists are linked based on their dissertation supervisors, is a technique designed to qualitatively characterize the influence of mentors.[18–21] Genealogies have also been constructed to analyze other creative fields such as philosophy,[22] music,[23] and art[24,25] to follow the influences of teachers on their students. The emergence of dynamic network models[26,27] and

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social network analysis[28–30] now allow rigorous quantitation of genealogical influences. Here, we apply the concept of academic genealogy to medical training and use network analysis to quantitatively assess the impact of "medical academic genealogy" on medical investigations.

To this end, we study the medical academic genealogy of authors who contributed peer-reviewed articles on a subject in neurosurgery, the utility of maximal surgical resection in patients afflicted with high-grade gliomas (HGGs).[31–39] The infiltrative nature of HGGs, the most common forms of adult brain cancer, renders complete surgical resection impossible. The unresolved issue, however, is whether maximal resection leads to increased survival. Supporters of maximal resection believe that reducing the tumor burden enhances the efficacy of subsequent chemoradiation.[34] Opponents argue that maximal surgical resection is of no benefit given the inherent resistance of HGGs to chemotherapy and radiation.[37,38] Although the number of retrospective studies exploring this issue has greatly increased in recent years,[35,36] the issue has not been resolved through a well-designed randomized clinical trial.

The goal of this study is not to resolve this question. Instead, our study aims to examine whether medical training influences publication patterns. Utilizing quantitative network analysis, we find statistical associations between membership in a genealogy and results published in this field.

Materials and Methods

Identification of Key Articles

A comprehensive PubMed search was performed in December of 2014 using broad medical subject heading (MeSH) terms relating to surgical resection of HGGs. We required that all articles have a MeSH term related to HGGs ("high-grade glioma"; "astrocytoma"; "anaplastic astrocytoma"; "oligodendroglioma"; "oligoastrocytoma"; "glioblastoma*"; or "intracerebral tumor") and a MeSH term related to tumor resection ("extent of resection"; "surgical resection"; "gross total resection"; "tumor resection"; "partial resection"; or the words "resection and/or "extent" in the title or abstract). This process identified 4,047 articles for review. Articles were selected for this study if they (1) were written in English, (2) were published before December 2014, (3) presented original research results on human patients, (4) focused on adult intracranial HGGs, (5) discussed maximal resection, (6) were written as a clinical study and not a case report, (7) used mortality as an outcome, (8) performed a univariate or multivariate statistical analysis, (9) considered maximal resection as a separate comparison group in their statistical analysis, and (10) listed a primary address at an American institution for either the first or last author. The last criterion was necessary because it was often not possible to ascertain and verify the training history of authors trained at foreign institutions. This process produced 108 articles for analysis.

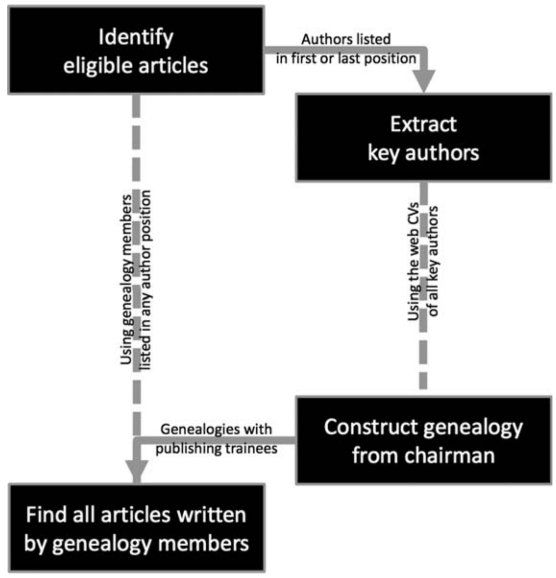

FIGURE 1: Genealogy generation. Genealogies were created by linking key authors (first and last authors) of the identified literature based on who trained whom. Once genealogies were identified, all articles written by genealogy members were compiled and analyzed. CV = curriculum vitae.

Article Classification

We classified the identified articles into 2 groups based on "publication result." Those that found a statistically significant correlation ($p < 0.05$) between maximal resection and survival as a primary or secondary result were labeled "supportive." Those that reported no statistical association between maximal surgical resection and overall survival were labeled "not supportive." This determination was performed by 2 independent readers (B.R.H. and J.A.T), and discrepant articles were discussed with senior readership (C.C.C).

Author Classification

We defined the first and last author of each article as "key authors," with the rationale that these authors play key roles in shaping the conclusion of the article.[40] To avoid oversampling from the small number of articles with joint first or last authorship (n = 9 and n = 2, respectively), we selected only the first and the last of the coauthors for our study. There were 160 unique key authors of our 108 articles, because many investigators were key authors of >1 article. Internet searches were performed to determine their medical subspecialty (if any) as well as the timing and location of their medical school, residency, and fellowship training. All information was compiled (by B.R.H. and J.A.T.) using publicly available academic or institutional résumés and verified against publicly accessible documents such as academic directory listings, alumni pages, and press briefings. Each training history was verified using at least 2 independent sources by both reviewers.

Construction of Medical Academic Genealogies

We adopted a top-down approach to identifying medical academic genealogies (Fig 1). We first identified potential "founders" of genealogies in the following manner. We identified the 21 authors who served as department chairmen, because these individuals oversee the training of multiple trainees. Next, we linked these potential founders to their trainees, trainees of trainees, and so on in a recursive manner to create what social network analysis calls the "ego network" of the chairmen.[26,28,29] Links were drawn between authors if one was a faculty member at an institution while another was a trainee (medical student, resident, or fellow) in the same discipline. To be connected, mentor and trainee had to be located at the same institution during the same calendar year. Finally, we excluded networks that did not span at least 2 generations. This process produced 11 medical academic genealogies for analysis.

Association of Genealogy and Articles

Many of the key authors were also middle authors of articles for which they did not serve as first or last author. To capture the influence of these authorships, we associated an article with a genealogy if the article had an author who was a member of that genealogy, including middle authors. In analyzing the articles produced by a genealogy, we only counted an article once no matter how many authors were members of that genealogy. If an article included authors from multiple independent genealogies, the article was assigned to each genealogy during analysis. In this way, a single article could be associated with multiple genealogies. We applied the same criteria in classifying articles by medical subspecialty. For example, we considered an article to be written by a member of a specialty if it had one of our key authors from that specialty on the article, even if he or she was a middle author.

Statistical Analysis

We considered the possibility that each article may not represent an independent investigative unit. For instance, articles contributed by the same first author may harbor similar results. We further considered the possibility that articles originating from the same data set (eg, the Surveillance, Epidemiology, and End Results database) or academic institution may share comparable results. We therefore tested the association between genealogy and publication result using a mixed logistic regression model. Publication result was treated as the dependent variable, genealogy membership was treated as a fixed effect, and the first author of the article and the data set of the article were treated as random effects. False discovery rate correction was performed for multiple comparisons.[41]

Because others have suggested that the sample size of the study, the time of publication, and the medical specialty of the author potentially influence whether a study supports maximal resection, we examined these variables using the same univariate mixed logistic model.[35,36,39,42] As article sample sizes reported in our identified literature ranged from 19 to 40,137 patients, with a skew toward the larger numbers, we performed a logarithmic conversion to meaningfully account for this distribution. Additionally, as approximately half of our articles were published prior to 2010, we used this date as our division point. Lastly, we examined whether the specialties of the first or the last author (neurosurgeons, medical oncologists, radiation oncologists, or other) or whether the presence of at least 1 neurosurgeon key author were associated with publication result.

Variables that were significantly associated with publication result in the univariate analyses were then incorporated in to a multivariate mixed logistic regression model. Specifically, the final mixed logistic regression model treated publication result as the dependent variable. Genealogy (A or B), time of publication, and the sample size of the study were treated as fixed effects. The first author and the data set of the article were treated as random effects. To take into consideration the potential effect of the senior authorship, additional models were performed incorporating the senior author of the article as random effects.

All statistical analyses were performed using R version 3.1.2 (R Foundation for Statistical Computing) and p or q values < 0.05 were considered significant. Mixed models were performed using the lme4 package version 1.1-9 and BOBYQA optimizer. Visual representation of genealogies was created using *ORA version 3.0.9 (CASOS Center, Carnegie Mellon University, Pittsburgh, PA).

Results

Univariate Association between Genealogy and Publication Result

Our search identified 108 original articles, 160 key authors, and 11 genealogies (Table 1). A majority of the articles reported results in support of maximal HGG resection (70%). Mixed model logistic regressions were performed to determine whether articles published by genealogy members were more likely to support HGG resection as compared to articles published by authors not belonging to that genealogy (first column, Table 2) using first author and data set as random effects. As there were 11 genealogies, 11 comparisons were performed. After false discovery rate correction for 11 pairwise comparisons, we identified 2 genealogies where members were more likely to publish an article in support (or not in support) of surgical resection (Fig 2). The presence of an author from Genealogy A, a genealogy of 14 neurosurgeons, increased the log odds ratio (LOR) that an article would support maximal resection by 3.50 ($q = 0.043$). The presence of an author from Genealogy B, a genealogy of 8 radiation oncologists, decreased the log odds of support for maximal resection by -2.08 ($q = 0.043$). The presence of an author from the remaining 9 genealogies did not have a statistically significant association with article results.

Notably, there was no overlap between the authors or articles that comprised the 2 genealogies (Table 3). No author was a member of both genealogies, and no articles contained authors from both genealogies. Furthermore, the 22 members of Genealogies A and B contributed to 38% of all articles studied (25% Genealogy A, 13% Genealogy B; see Table 3) while accounting for 14% of all key authors (9% Genealogy A, 5% Genealogy B).

TABLE 1. Descriptive Features of Articles Analyzed

Articles, 105 Total	Results Supportive of Maximal Resection		Results Not Supportive of Maximal Resection		All Articles	
	No. (% row)	Mean [SD]	No. (% row)	Mean [SD]	No. (% all)	Mean [SD]
Total number of articles	76 (70%)		32 (30%)		108 (100%)	
Article sample size, range = 19–40,137						
Number of patients studied	76 (70%)	1,875 [6,279]	32 (30%)	121 [80]		1,356 [5,317]
Base 10 log, number of patients	76 (70%)	2.39 [0.71]	32 (30%)	1.98 [0.32]		2.27 [0.65]
Year of publication, range = 1983–2014						
Year of publication	76 (70%)	2008 [6.9]	32 (30%)	1998 [8.5]	108 (100%)	2005 [8.5]
Published before 2010	36 (58%)	2002 [6.4]	26 (42%)	1995 [6.6]	62 (57%)	1999 [7.2]
Published during or after 2010	40 (87%)	2013 [1.3]	6 (13%)	2011 [0.8]	46 (43%)	2012 [1.4]
Medical specialty of first author						
Medical oncologist	16 (21%)		6 (19%)		22 (20%)	
Neurosurgeon	33 (43%)		8 (25%)		41 (38%)	
Radiation oncologist	16 (21%)		14 (44%)		40 (28%)	
Other	11 (15%)		4 (12%)		15 (14%)	
Medical specialty of last author						
Medical oncologist	16 (73%)		6 (27%)		22 (20%)	
Neurosurgeon	37 (76%)		12 (24%)		49 (46%)	
Radiation oncologist	14 (61%)		9 (39%)		23 (21%)	
Other	9 (64%)		5 (36%)		14 (13%)	
Medical specialty of either author						
One or more neurosurgeons	52 (74%)		18 (26%)		70 (65%)	
No neurosurgeons	24 (63%)		14 (37%)		38 (35%)	
Coauthors per article who are key authors						
Mean number of authors per article	76 (70%)	3.23 [1.39]	32 (30%)	3.63 [1.91]	108 (100%)	3.35 [1.57]
Joint first or last authorship						
Articles with joint first authorship	8 (89%)		1 (11%)		9 (8%)	
Joint first or last authorship						
Articles with joint first authorship	8 (89%)		1 (11%)		9 (8%)	
Articles with joint last authorship	2 (100%)		0 (0%)		2 (2%)	

SD = standard deviation.

TABLE 2. Analysis of Article Results by Medical Academic Genealogy

Parameter	Univariate Parameters LOR[a]	Mixed Logistic Regression Model[a]+		Mixed Logistic Regression Model[b]+	
		Genealogy A Authorship LOR	Genealogy B Authorship LOR	Genealogy A Authorship LOR	Genealogy B Authorship LOR
Medical academic genealogy					
Genealogy A, 14 neurosurgeons	3.50[c]	2.74[d]	—	2.24[d]	—
Genealogy B, 8 radiation oncologists	−2.08[c]	—	−1.74[d]	—	−1.53[d]
Nine other genealogies	NS	—	—	—	—
Known literature covariates					
Article's sample size, log transformed	1.60[e]	1.33[e]	1.49[d]	1.23[d]	1.41[d]
Published during/after 2010	1.49[e]	NS	1.10[d]	NS	1.10[d]
Author specialty					
First author[f]	NS	—	—	—	—
Last author[f]	NS	—	—	—	—
Presence of ≥ 1 neurosurgeon key author[g]	NS	—	—	—	—

[a]Accounting for data set and first author using random effects.
[b]Accounting for last author using random effects.
[c]$q < 0.05$ after Benjamini–Hochberg false discovery rate correction for 11 comparisons.
[d]$p < 0.05$.
[e]$p < 0.05$.
[f]Grouped into medical oncologists (reference group), neurosurgeons, radiation oncologists, or other.
[g]Versus absence of neurosurgery key author.
LOR = log odds ratio; NS = not significant.

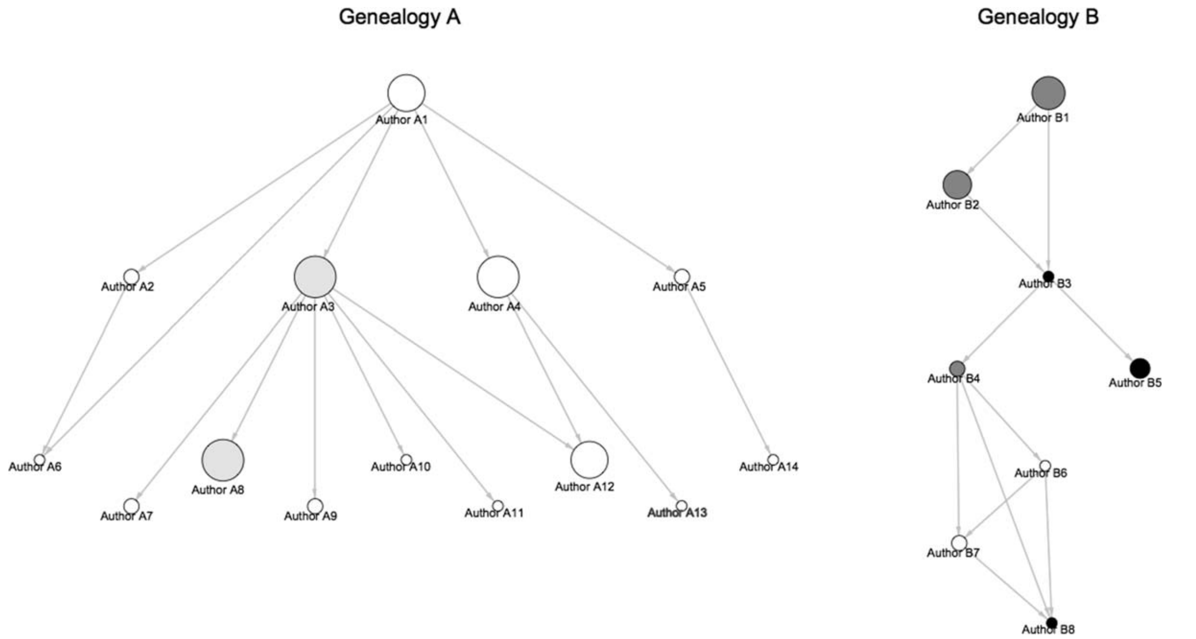

FIGURE 2: Authors from Genealogy A (left) and Genealogy B (right). Authors are colored white if all articles by that author support maximal resection, light gray if over half support maximal resection, dark gray if less than or equal to half support maximal resection, and black if none supports maximal resection. Node size is proportional to the number of articles written.

Analysis of Relation of Sample Size, Time of Publication, and Author Specialty with Result

Previous investigators have proposed that study results depend in part on the sample size of the study (with larger studies more likely to support resection due to greater statistical power[35,36] and the time of publication (with the more recent articles more likely to support resection[35,36]. We wished to determine the validity of these proposed associations in our data set. Univariate analysis showed that studies with larger cohorts (LOR = 1.60, $p < 0.01$; see first column, Table 2) and those published after 2010 (LOR = 1.49, $p < 0.01$) were more likely to support surgical resection.

Previous investigators have also proposed that author specialty may be associated with publication result, with neurosurgeons more likely to support maximal resection than non-neurosurgeons.[38,39] However, our analysis indicated that medical specialties of either the first author (all $p > 0.05$; see first column, Table 2) or the last author (all $p > 0.05$) were not associated with publication result when examined individually. We also did not find evidence of an association between publications written by at least 1 neurosurgeon key author as compared to articles without a neurosurgeon key author ($p > 0.05$).

TABLE 3. Impact of Key Medical Academic Genealogies on Publication Result

Identified Medical Academic Genealogies[a]	Number of Authors (% of data set)	Number of Unique Articles (% of data set)	Number of Articles Supporting Maximal Resection	Number of Articles Not Supporting Maximal Resection
Genealogy A, neurosurgery	14 (9%)	27 (25%)	26	1
Genealogy B, radiation oncology	8 (5%)	14 (13%)	5	9
Both genealogies combined	22 (14%)	41 (38%)		

[a]See Figure 2 for genealogy membership.

Multivariate Association between Genealogy and Publication Result

To determine whether the association of Genealogies A and B with publication result remain robust after controlling for all potential confounding variables, we analyzed our results using a multivariate mixed model logistic regression model that incorporated time of publication, sample size, and medical academic genealogy as fixed effects. Data set and first author were treated as random effects. We found that articles authored by members of Genealogy A were more likely to support maximal resection than articles without contribution from members of Genealogy A ($\mathrm{LOR} = 2.74$, $p < 0.028$; see Table 2). Conversely, articles authored by members of Genealogy B were less likely to support maximal resection than those without contribution from members of Genealogy B ($\mathrm{LOR} = -1.74$, $p < 0.026$). Similar results were observed when the mixed model logistic regression was repeated using last author as a random effect variable. The association between genealogy and publication result remained significant in a mixed model logistic regression for Genealogy A ($\mathrm{LOR} = 2.24$, $p < 0.047$) and in a mixed model logistic regression for Genealogy B ($\mathrm{LOR} = -1.53$, $p < 0.024$).

Discussion

In this article, we introduce the concept of "medical academic genealogy," which links authors by common medical mentors. Using a quantitative method developed in social network analysis, we demonstrate that articles published by authors in a medical academic genealogy are more likely to share similar conclusions in the HGG literature. Although our study examines a specific neurosurgical question, we propose that the issues raised are pertinent to critical evaluation of other medical literature. Based on this finding, we suggest that medical academic genealogy plays a previously unrecognized role in shaping medical literature. Recognition and reconciliation of these effects should improve our ability to evaluate medical literature.

Our findings have particular significance in the era of health reform. Increasingly, the effectiveness of medical practice will be evaluated by central panels which review the published literature. Care should be taken in the evaluation of medical literature disproportionately shaped by members of medical academic genealogies. Furthermore, the potential influence of medical academic genealogy on publication result challenges a fundamental premise of meta-analyses, because each individual article may not represent an independent investigative unit.[43] If so, the development of statistical tools that adjust for the influence of genealogy will be needed for future quantitative reviews.

Our results also highlight an inherent tension in medical mentorship. Whereas in clinical care it often necessary to have hierarchical interactions, in research we should strive to foster independence. The challenge of medical training lies in fostering appropriate mentor–trainee relationships while minimizing the unconscious adaptation of mentor biases. It is therefore necessary to consciously structure the educational experience to reflect these goals. In this context, an integrated educational approach involving thoughtful curriculum design, mentor self-awareness, and training individualized to the tendencies of the trainee will be necessary to minimize genealogical bias.

There are several limitations inherent in our study design. As in all retrospective studies, our conclusions were based on correlative associations, with causation inferred. We further recognize that dividing complex variables into discrete groups may have potential impact on statistical analysis. Additionally, the genealogies we created are distillations of the complex medical communities and training environments in academic medical centers, and the exclusion of non-US authors potentially limits the generalizability of our conclusion. In addition, although our analysis weights all education links equally, the literature suggests that mentor influence varies during training. Finally, the interpretation of our results is limited by publication bias, as we do not know what was not published.[43–45] Future work will be necessary to determine whether certain genealogies disproportionately pursued and/or abandoned select hypotheses. Despite this, we believe that our data compellingly demonstrate the effects of medical academic genealogy on published literature.

Conclusion

Analysis of the literature on the utility of surgical resection for HGG reveals that members of medical academic genealogies make significant contributions to the peer-reviewed literature. Articles written by authors belonging to select genealogies are more likely to support (or not support) surgical resection relative to articles written by nonmembers.

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Author Contributions

B.R.H. and C.C.C. were responsible for study conception and design. K.M.C. was responsible for the design and supervision of the network analysis. Acquisition of data was performed by B.R.H., J.A.T., and C.C.C. Statistical analysis and data analysis were performed by B.R.H., L.A.J., J.A.P., B.S.C., L.M., and K.M.C. The manuscript and figures were drafted by B.R.H. and C.C.C. The manuscript was critically reviewed by all authors.

Potential Conflicts of Interest

Nothing to report.

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