This article has been accepted for publication in IEEE Transactions on Big Data. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/TBDATA.2024.3423726

TBD-2023-02-0052

AGE: Age-Gender Effect on Faculty Career Progression in American Universities

H. Rahmani, *Member, IEEE*, A. J. Olejniczak, and G. R. Weckman

***Abstract*—This study was undertaken to examine the impact of age and gender on faculty career progression in academia and to identify key performance indicators leading to attaining promotion. To explore any evidence of age-gender effect on faculty career progression, gender compositions, promotion rates, and appointment lengths at the assistant and associate professor levels are investigated. Furthermore, the underlying factors influencing faculty performance evaluation decisions are analyzed using the commercial data provided by Academic Analytics, LLC, which comprises the scholarly records of 336,793 faculty members from 472 Ph.D.-granting universities in the United States during 2011-2020. Various machine learning techniques, including ensemble learning and association rule mining, are performed to determine the important features that provide the most significant insights into academic career growth. Our results indicate strong evidence of age-gender effect on faculty career advancement and underscore the significance of journal article and citation counts for career progression in higher education.**

***Index Terms*—Academic career, age bias, age-gender bias, association rule mining, classification, clustering, ensemble learning, extreme gradient boosting, gender bias, machine learning, random forest**

I. INTRODUCTION

INNATE by nature, aging is inevitable. Aging is often portrayed as synonymous with declines in physical and cognitive functions in our collective consciousness, which may manifest itself in implicit or explicit biases towards older adults [1]. Long-held false notions of eldership do not consider the delicate distinction between healthy aging and pathological conditions. Indeed, the detrimental effects of aging on human health are well-established in clinical research [2], [3]. However, as debunked by gerontologists who study the process of change in human capacities as a result of natural senescence, normal aging is no longer a myth revolving around misconceptions [4]. Boundaries once perceived fixed are now extended by designing age-friendly work environments. The establishment of such systems accounting for individual differences and dispositions ensures that employees can operate successfully within the constraints of their body, mind, and emotion.

Owing to gains in life expectancy, the year 2050 is expected to bear witness to a tectonic shift in population such that older adults will make up a larger proportion of people globally; older adults will comprise 16% of the population compared to 9.3% in 2020 [5]. In addition, it is projected that one out of every four Americans will be categorized as an older individual by the year 2060 [6]. These trends highlight the importance of enhancing the participation of this rapidly growing population in the workforce. Addressing gender-based barriers and biases in the workplace is equally important. Such prejudices can permeate all levels of academic structures, potentially affecting faculty career advancement. As vision takes root in academy, it is worth cultivating a diverse workplace culture at its core. Perspectives on age-gender disparities in institutions of higher education have ignited intense debates among scholars. Researchers are divided over the existence and extent of the age-gender effect (hereafter, AGE) on faculty career progression in academia; their viewpoints are discussed in the following sections.

A. AGE, Scholarly Productivity, and Visibility

Notwithstanding its inherent flaws, faculty research output as an indicator of scholarly excellence has long been of interest for a variety of reasons, among them the necessity to provide a basis for institutional practices, including annual reviews and merit raise decisions [7]. Stark gender differences in terms of research productivity and visibility have been well documented in the literature [8], [9]. Several studies exploring the link between gender and publication rate suggest that men disseminate more research papers than their female counterparts [10], [11]. Prior research also demonstrates that scientific works written by men tend to attract more recognition and citations compared to those of female scholars [12], [13]. Some researchers speculate that female academics face a myriad of professional challenges due to their work-family role conflicts, such as caregiving for children or older adults, that can hinder their scientific productivity [14], [15]. Acknowledging the disproportionate household responsibilities shouldered by female faculty, some scholars argue that systematic barriers, including unfair workload allocation, peer review, and editorial decisions are

This study was sponsored by the Ohio University Student Enhancement Awards program (awarded to H. Rahmani and G. R. Weckman). H. Rahmani conducted this research while serving as a Research Analyst Intern at Academic Analytics, LLC, http://www.academicanalytics.com. H. Rahmani and A. J. Olejniczak received data and computing resources from Academic Analytics. The funders had no role in study design, data collection and analysis, decision to publish, or preparation of the manuscript.

H. Rahmani is with the Department of Industrial and Systems Engineering, Ohio University, Athens, OH 45701. E-mail: hr367517@ohio.edu.

A. J. Olejniczak is with Academic Analytics Research Center (AARC), Columbus, OH 43220. E-mail: aolejniczak@aarcresearch.com.

G. R. Weckman is with the Department of Industrial and Systems Engineering, Ohio University, Athens, OH 45701. E-mail: weckmang@ohio.edu

This article has been accepted for publication in IEEE Transactions on Big Data. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/TBDATA.2024.3423726

determinants of the scholarly productivity gender gap [16]. In contrast, a recent study highlights the gender invariant nature of research output and impact in science, technology, engineering, and mathematics (STEM) disciplines, claiming that the difference in the career length of professors is a chief reason for the skewed distribution of gendered outcomes [17]. Notably, empirical evidence shows that faculty tend to publish increasing numbers of books and fewer journal articles as age advances; this indicates a change in the preferred mode of knowledge dissemination rather than reduced productivity among older academics [18].

Great strides have been made in the quantitative assessment of scientific literature (commonly referred to as scientometrics) with the aid of machine learning (ML) techniques [19]-[21]. Brizan et al. [22] apply several ML models, such as adaptive boosting (AdaBoost), random forest (RF), and support vector machines (SVM), to predict citation patterns and possible future impact of scholarly work. It is clear that the exclusive reliance on publication counts and citation frequencies does not provide an equitable and robust basis for evaluating research quality. Drawing on critical reviews of metrics used for analyzing scholarly work, some scholars posit that solely using quantitative metrics to evaluate research impact can undervalue other aspects of faculty's contributions that demonstrates a benefit to the community served [23]. Instead, Alperin et al. [24] urge us to integrate service, public outreach, and engagement into an institutional reward system. To this end, the use of open science and non-traditional work products, such as WikiProjects, TEDx talks, science comics, video abstract, and expression through dance and play should be equally incentivized [25], [26].

B. AGE, Promotion, and Tenure

A plethora of studies have aimed to shine light on disparities in the promotion and tenure (P&T) process through the lens of AGE [27], [28]. Recent qualitative research on 52 women between the age of 34 to 82 in academic medicine examines how gender discrimination favoring men arises in the path of women on their career progression [29]. In the 2010-2011 Higher Education Research Institute Faculty Survey, 65.3% of women (N = 13,010) regarded the P&T process as a main source of job-related stress [30]. The findings of a study conducted in research-intensive universities in the United Kingdom monitoring 12,000 reference letters written for 3,700 applicants, echo the opinions and sentiments of referees on female candidates. By applying ML techniques, such as natural language processing, it appears that women are less likely to be ascribed with terms reflecting their academic abilities and research skills when compared to men [31]. Bronstein [32] states subtle forms of ageism that older female academics encounter, such as promotion denial due to having family-related career interruptions and employment gaps in their résumés. Similarly, Acker and Armenti [33] comment that some older females may experience a drastic change in P&T criteria over time that might not have been aligned with the guidelines that were enacted when they started their profession. Consequently, those women may not be able to build a body of evidence required to advance through the academic pipeline.

While the stark gap in P&T caused by gender stereotyping reflects the dominant discourse in most studies, other possible root causes of differential gendered outcomes should not be overlooked [34]. For instance, Ceci and Williams [35] assert that one of the underlying reasons for gendered underrepresentation in science-intensive fields could be due to women's personal and professional preferences when considering tenure-track roles, regardless of whether these preferences are formed autonomously or influenced by societal factors. Further, Gino et al. [36] claim that women may envision their life goals differently than men, with career progression as an attainable goal is assigned a lower priority by female scholars. In another study, Williams and Ceci [37] designed several cognitive experiments wherein hypothetical applicants with identical scholarly backgrounds were presented to 873 tenure-track faculty at 371 U.S. universities to recommend them for assistant professorship with the intent to verify gender bias in hiring. The remarkable observation found by their experiments is that women were twice as likely to be rated as competent and hirable as men by both female and male evaluators [37]. A more recent study examining data related to academic psychologists in Germany shows that women are not only institutionally disenfranchised, but their intellectual contributions are also more highly valued toward career advancement [38]. Although some of the above findings may not hold true for the United States, demonstrated success stories of leveling the playing field for women may help alleviate the existing global gender gap.

Recent scholarship regards the lack of clarity and transparency in P&T criteria and processes as roadblocks to faculty career growth [39]. In addition, it may take significantly longer for women to achieve promotion than men [40]. An empirical examination of time in rank is essential for several reasons. This factor can shape the faculty's experience of promotion clarity and employment precarity. The body of scholarly work examining promotion and retention in higher education elucidates that remaining at the rank of associate professor for an extended period can adversely influence faculty members' perception of the P&T process's transparency and their overall job satisfaction [41]. Moreover, prolonged appointment duration serving as an associate professor without advancement to the status of full professor may potentially restrict faculty members from participating in specific administrative roles [42]. With the absence of national data on the time frame for promotion, research is taking place at local and isolated levels, such as one or a few disciplines, colleges, or universities with small sample sizes. Based on data from 401 respondents of the Associate Professor Survey, the time to promotion from associate to full professor for women and men are 8.2 and 6.6 years on average, respectively [43]. On the contrary, another report finds that on average

This article has been accepted for publication in IEEE Transactions on Big Data. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/TBDATA.2024.3423726

women spent six years at the associate professor rank while men spent seven years before they attained a promotion to full professor [44]. The aforementioned studies illustrate the complexity of identifying the underlying mechanisms that drive AGE in academia.

Research analyzing the representation of female/aging female faculty in higher education is sparse. Most intellectual work in literature is limited in scope, which compromises the generalizability and transferability of the results. The research presented in our study takes advantage of big data provided by Academic Analytics, encompassing the scholarly records of 336,793 faculty from 472 Ph.D.-granting universities in the United States during 2011-2020. The main focus of this study is to identify whether there is measurable evidence of AGE that influences faculty career progression in academia by employing statistical and ML techniques. Specifically, the following research questions are explored in this study:

1) What is the gender composition of faculty across academic ranks by discipline?
2) Do female/aging female faculty advance to the associate and full professor ranks at the same rate as their male peers?
3) What is the average number of years that female faculty spend in appointments as an assistant/associate professor before earning a promotion to the rank of associate/full professor, respectively?
4) Which key performance indicators (KPIs) can predict faculty career progression in each field?

The contributions of this paper are fourfold. To the best of our knowledge, this research is the first comprehensive longitudinal investigation of the link between AGE and faculty career growth in academia. Second, we are among the first to employ state-of-the-art ML techniques in the domain of higher education to predict the most significant criteria leading to promotions. Third, we believe this is the largest study so far documenting the average appointment time in years that faculty spend at the ranks of assistant and associate professor. Finally, the dataset that forms the foundation of our study is publicly accessible on IEEE DataPort [45]. This initiative underscores our commitment to advancing open science practices within the big data community. We trust that this contribution will support replication studies and inspire future research endeavors.

The remainder of this paper is organized as follows. Section II presents our research methodology in sequential steps. The results of our study are discussed in Section III. Section IV concludes this study by articulating the limitations of our research and suggesting areas for future investigation.

II. MATERIALS AND METHODS

Data were derived from the Academic Analytics commercial database to compare 135,714 female and 201,079 male faculty members associated with 472 American universities in terms of gender compositions, rates of promotion, and the years spent in the assistant and associate ranks by field. Furthermore, KPIs were defined by analyzing the interplay between different variables in the data. The data include information about each faculty member's gender, terminal degree year, academic rank, journal article publications, conference proceeding publications, professional honors and awards, federal research grants, book publications, book chapters, citations, and patents from the years 2011 to 2020. These features were considered as independent variables in the model. The key dependent variable of interest was "promotion," which was measured by observing a change in academic rank for a faculty member over the course of the 2011-2020 study period. As summarized in Table S1, the records of faculty associated with 171 Ph.D. programs were grouped into 11 broad fields following Academic Analytics' taxonomy of academic programs, which itself follows the National Center for Education Statistics Classification of Instructional Programs code classifications [46]. This study used a two-tier method, applying both descriptive statistics and ML techniques. Descriptive statistics were deployed to address our first three research questions regarding gender compositions, rates of promotion, and time in rank. ML methodology was employed to examine KPIs, our last research question. Data analysis was performed in Python 3.10 using the Pandas (1.4.3), NumPy (1.23.1), Sklearn (0.0), Mlxtend (0.20.0), XGBoost (1.6.1), Matplotlib (3.5.2), Plotapi [47], and JoyPy (0.2.6) libraries. Fig. 1 is a schematic representation of the methodology used in this research, which we briefly describe here.

A. Data Preprocessing

Data preprocessing is a vital stage of rigorous data analysis that ensures precision and accuracy of outcomes. As we are interested in examining the promotion patterns of academics over time, and full professorship is the highest rank that faculty can achieve, the records of people who were already full professors in the year 2011 were omitted from the dataset. Records with no assigned gender binary or terminal degree year were also excluded. Furthermore, several output variables were defined to address the present study's research questions. First, a promotion was described as a change in the academic rank status of a faculty member from a lower to a higher rank. In the present study, the term "promotion" is used in its broadest sense to refer to both tenure and promotion appointments. Also, faculty appointments were assembled into three ranks, in which Ranks 1, 2, and 3 refer to full, associate, and assistant professorship, respectively. It is worth noting that the proportion of missing values across rank variables during 2011-2020 in the dataset is approximately 40%. In this experiment, missing values were initially imputed by using the K-nearest neighbors (KNN) method, where K equals five, assuming that the variables are missing at random. However, the data with missingness were eventually analyzed, since the root mean square error of KNN as a widely used imputation

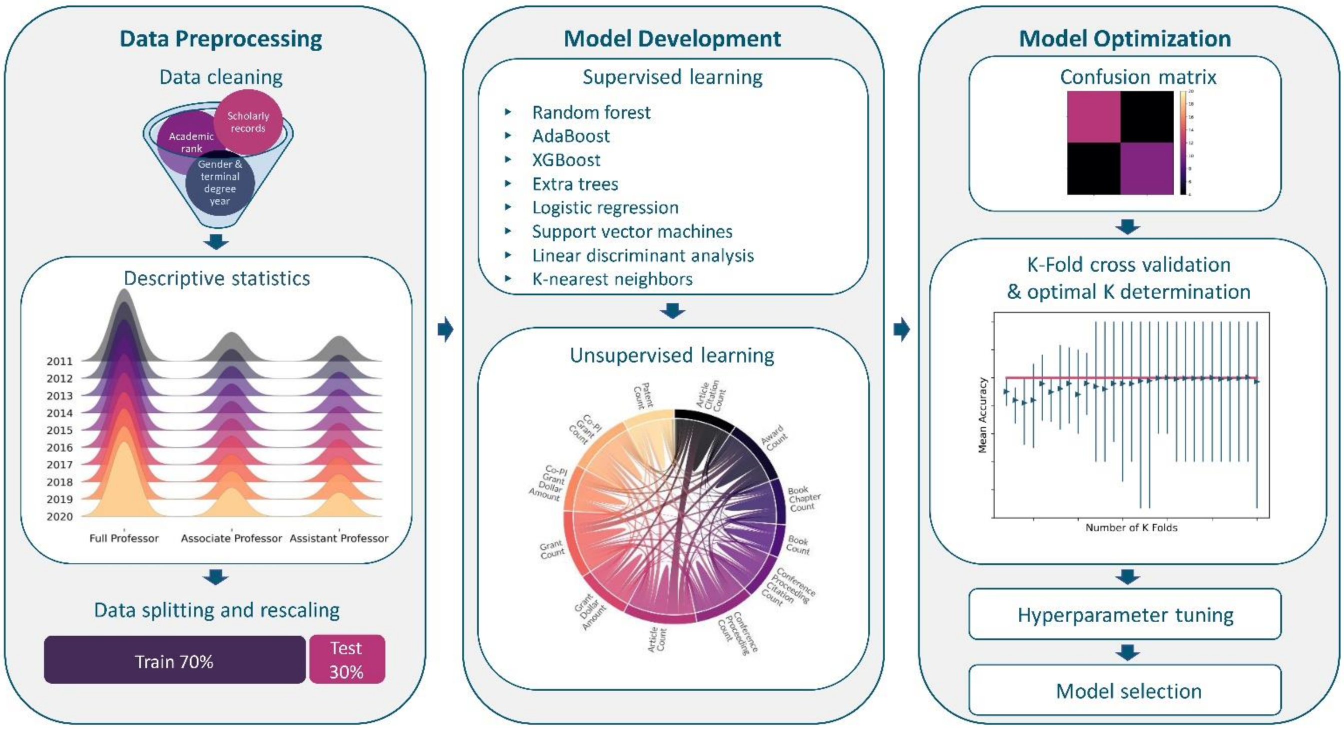

Fig. 1. Graphical illustration of methodology.

technique was above 0.5, indicating the low efficacy of the approach. Second, the length of time spent in each rank was measured from the first year that a faculty member's information initially appeared in the Academic Analytics database until the year that a change in rank was recorded. Finally, the formula for estimating the age of each faculty member in a given year was constructed by incorporating the median age at doctorate parameter of the 2020 NSF Survey of Earned Doctorates into the formula, as shown in (1) [48]. In (1), Age_i denotes the chronological age of faculty in year i. i represents the calendar year. The *MAD* (median age at doctorate) parameter indicates the median age of doctoral recipients in the relevant broad field of study in years. Also, the *TDY* (terminal degree year) parameter is included in the Academic Analytics database (see Table S1).

$$Age_i = (i - TDY) + MAD \qquad i = 2011, \ldots, 2020. \qquad (1)$$

There is no consensus on the ideal age to define "older adults" [49]. In this study, records were categorized into three age groups: those between 45 to 54 years, 55 to 64 years, and 65 years of age and above, based on age as of the year 2020. There are three reasons for adopting these age groups. First, the Age Discrimination in Employment Act of 1967 prohibits age-based discrimination in hiring and promotion against employees 40 years of age or older [50]. Second, the extracted dataset entails 10 years of collected data on scholarly records of faculty members. Therefore, creating age groups within the range of ten is desirable. Third, these age classes allow us to discern differences between early-career, mid-career, and senior faculty members in terms of attaining promotions. The next step in data preprocessing was to perform descriptive statistics to record measures of frequency, central tendency, and dispersion for different attributes present in the dataset. Then, the data were prepared for usage in ML models, including both supervised and unsupervised learning algorithms. To estimate the performance of the supervised learning models, the dataset was split into two subsets: training and testing. The former was used to build ML models, and the latter served to evaluate the performance of the algorithms. More precisely, the testing set can gauge the accuracy of the predictions on unseen and future observations by comparing predicted values with actual values of the records included in the testing set. Hence, data points were randomly divided into training and testing sets using a 70:30 ratio. Finally, data were normalized by rescaling values to the range between zero and one.

B. Model Development

Without being directly programmed, ML algorithms are potent data mining tools that solve sophisticated problems by learning from example. ML models are generally classified into two subgroups: supervised and unsupervised learning algorithms. Supervised learning models refer to algorithms in which the data labels of records included in the training set are known to the mathematical model. For example, in this study, the promotion status of each faculty was defined as a dichotomous variable having a value of one or zero, which represents the "promoted" or "not promoted" categories, respectively. Thus, the task to be carried out by supervised learning algorithms was to foresee whether a record is in the "promoted" class while also detecting the set of features that most influence the prediction. Conversely, unsupervised learning algorithms discover hidden patterns within an unlabeled dataset. In the current study, nine prominent ML algorithms were generated for classification and clustering purposes. As such, eight supervised learning models were created to predict variables influencing promotion, including RF, AdaBoost, extreme gradient boosting (XGBoost), extremely randomized trees (Extra trees), logistic regression (LR), linear discriminant analysis (LDA), SVM, and KNN. Additionally, association rule mining (ARM) as an unsupervised learning algorithm was constructed to articulate meaningful correlations and interactions between diverse features in the data. Among these models, LR and LDA can only support linear solutions, whereas other models can deal with non-linear problems. Here, each model is defined briefly, since delineating all algorithms' logical specifications is beyond the scope of this paper.

RF, AdaBoost, XGBoost, and Extra trees are ensemble-based learning models that combine several decision trees through an iterative process to make more warranted predictions. In a divide and conquer approach, decision trees as members of the ensemble infer decision rules by recursively splitting nodes into subnodes for predicting an event. The main advantage of ensemble-based learning algorithms is their robustness against outliers and missing values [51], [52]. The fundamental difference between these models lies in their data sampling methods. RF uses the bagging technique in a greedy approach, which involves random sampling of input data with replacement to create a decision tree at each iteration. At the end, the votes from all trees are considered in the final prediction, in a process called majority voting that benefits from the wisdom of the crowd. The overarching aim of bagging is to reduce variance within a learning model. In contrast, AdaBoost and XGBoost use the boosting sampling technique, which entails drawing data points that are incorrectly predicted by decision trees constructed in preceding steps. As knowledge about training data accumulates, these models can improve their estimates by assigning more weights to any misclassified observations in previous iterations to decrease bias [53]. Inversely, Extra trees are another ensemble learning model that exhaustively searches the entire dataset to create decision trees at each iteration.

Despite their differences in assumptions about underlying data, such as normality and linearity, LR and LDA share many theoretical properties. They both determine the group membership of data points in linear classification problems. SVM as a knowledge extraction technique sets non-linear decision boundaries in high dimensional data using hyperplanes that maximize the margins between classes. The KNN algorithm assigns a new observation to a category by capturing the degree to which a similarity is present in close proximity [54]. Ultimately, ARM as a clustering technique finds which attributes go together in a large set of data items by deriving rules that describe their probabilistic relationships. ARM examines the dataset to detect frequent item sets that satisfy minimum support and confidence thresholds. Support simply measures how frequently a set of items co-occur in the data. In the same vein, confidence can be expressed as the fraction of records containing both variables A and B to the total number of records that entails A. The association rule is shown as $A \rightarrow B$ wherein A is called the antecedent and B is the consequent [55]. In the current research, a deep ARM was exploited to discover the sets of frequent features, feature pairs, and feature N-tuplets that function cooperatively in predicting KPIs.

C. Model Optimization

Once ML models are developed, it is imperative to evaluate the performance of the algorithms. The accuracy of prediction as a form of classification task can be measured by using a confusion matrix. The confusion matrix can visualize when a classifier is confused and perplexed about the class membership of a data point. It categorizes the predictions into four distinct outcomes: true positives, true negatives, false positives, and false negatives. From these outcomes, metrics such as accuracy, precision, recall, and F1-score are derived, providing insight into the model's diagnostic capabilities [56]. Another approach to assess how well the predictions match the observed data is to implement K-fold cross-validation. K-fold cross-validation is a resampling strategy that partitions the dataset into K equally sized, non-overlapping subsets. Within this framework, the model undergoes training on K-1 of these subsets, while the remaining subset is used for validation purposes. This procedure is repeated K times, with the mean of the performance metrics from these iterations providing an estimate of the model's predictive accuracy. The number of folds, K, can vary from two to n-1, where n signifies the total number of data points and n-1 corresponds to the leave-one-out cross-validation (LOOCV) technique. In LOOCV, the model is trained on all data points except one, which is reserved for validation. Nevertheless, determining the optimal number of folds poses a challenge, as higher K values may lead to increased computational complexity. Establishing a robust testing condition is critical for benchmarking the performance of the model and to identify the optimal number of K. LOOCV offers a solution to this problem, serving as a gold standard for model evaluation. A sensitivity analysis was therefore executed over a spectrum of K values, ranging from two to 30, employing an RF classifier. Subsequently, the mean accuracy of model predictions for varying K values was compared against the performance derived from LOOCV. The sensitivity analysis concluded that a configuration of 17 folds in K-fold cross-validation yields the highest mean accuracy, aligning closest with the LOOCV benchmark [57].

In a meta learning sphere, hyperparameters of ML algorithms govern the learning process. Since model performance depends extensively on hyperparameters, it is of paramount importance to explore the parameter space to arrive at local optimal solutions. For hyperparameter optimization, a set of discrete model parameters, such as learning rate and number of decision trees in the forest, are defined. In the present study, the hyperparameters were tuned using the randomized grid search technique. This method uses cross-validation to select a different combination of features at each iteration in order to identify the best candidates for improved predictive accuracy. As previously stated, the K-fold cross-validation technique with K equals to 17 was configured for the experiment. The performance metrics obtained from executing the classifiers are outlined in Table 1. Once all improvement opportunities surfaced, it became evident that RF and XGBoost were the top two algorithms, outperforming the other models across all performance metrics, as shown in Table 1.

TABLE 1
MODELS PERFORMANCE METRICS

Model	Accuracy	Precision	Recall	F1-Score
RF	97%	97%	93%	95%
AdaBoost	90%	83%	86%	85%
XGBoost	98%	98%	96%	97%
Extra Tree	96%	97%	92%	95%
LR	81%	76%	61%	68%
LDA	68%	69%	6%	12%
SVM	67%	0%	0%	0%
KNN	72%	61%	42%	50%

It is worthwhile to mention that not all variables influence the prediction results of a model. There are some features that play a leading role in a model's performance and enhance the interpretability of the algorithms. Both RF and XGBoost support feature selection. They find the strongest attributes in data and assign a score to the magnitude of their relative importance to the predictive model. For this study, the types of importance scores were configured on Gini Index for RF and Information Gain for XGBoost. Gini Index captures the relevance of a feature to the learning process by measuring the probability of misclassification when that feature is selected randomly. Similarly, Information Gain is a function that quantifies how much information is required to identify the label of a data point [58]. Bringing these threads together, the results shown in Table 1 suggest that RF and XGBoost models should be selected to predict the attributes most contributing to promotion.

III. RESULTS

Our first three research questions aim to detect evidence of AGE influencing faculty career progression in higher education by identifying the gender compositions, rates of promotion, and time in rank of female and male professors. Our last research question investigates the KPIs forecasting promotion in each broad field of study.

A. Gender Composition

To advance our understanding of possible gender disparities, the total number of female professors were compared with the total number of male professors in each broad field by academic rank. Fig. 2 provides the findings of our first research question summarized as percentage distribution and demographic profile of faculty by gender and academic rank. It is apparent from Fig. 2 that engineering, physical and mathematical sciences, natural resources and conservation, agricultural sciences, biological and biomedical sciences, and business exhibited a markedly higher percentage (above 70%) of full professorship positions occupied by male faculty. Closer inspection of Fig. 2 reveals that except for business, the other fields with the higher proportion of male full professors are generally considered STEM-designated degree programs [59]. Relatedly, the percentage of male associate professors were significantly higher (70% and higher) than females in engineering and in physical and mathematical sciences. Education and health profession sciences were distinctive among all groups for having the highest representation of female faculty; above 45% at the rank of full professor and above 50% for associate and assistant appointments. Additionally, in family, consumer, and human sciences, humanities, and in social and behavioral sciences, men surpassed women in being appointed to positions at a full and associate professor level with a percent distribution of over 60% and 50%, respectively.

B. Rate of Promotion

To explore our second research question, rates of promotion from assistant to associate and from associate to full professor were determined through a longitudinal analysis of how faculty navigated the career ladder during the 2010s. The promotion rate refers to the total number of promotions received by faculty over ten years in each defined age-gender category, which includes women/men between 45 to 54 years, 55 to 64 years, and finally 65 years of age and older. This measure of frequency puts the prevalence of promotion in the perspective of the population size in each category. In fact, the rate of promotion makes it easier to see the percentage of the population size in each category that is promoted. Consequently, comparisons between genders, ages, and academic ranks are possible. Table 2 displays the total number and promotion rates of faculty in each different age-gender category, as well as their corresponding population size by broad field.

This article has been accepted for publication in IEEE Transactions on Big Data. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/TBDATA.2024.3423726

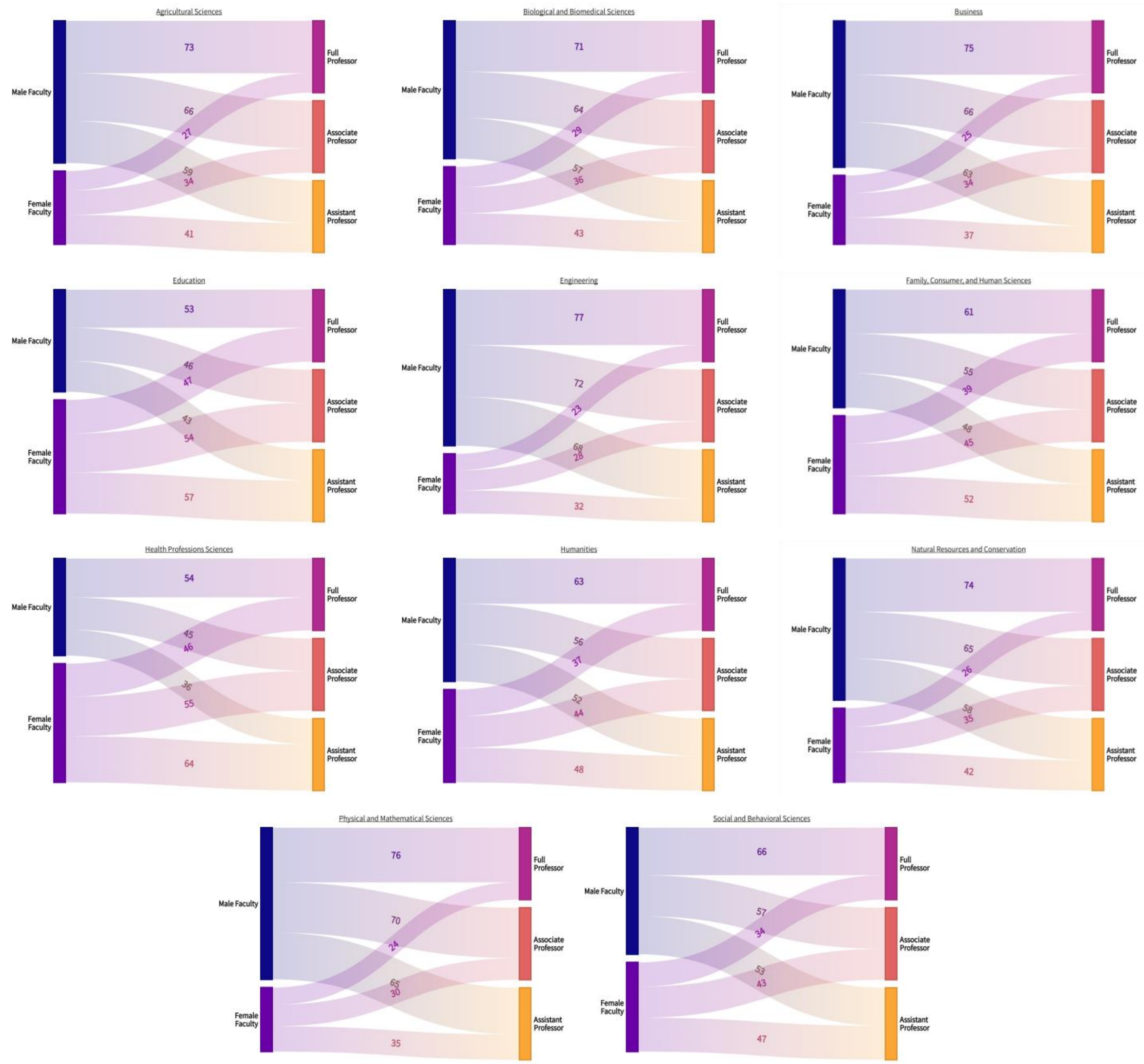

Fig. 2. Sankey diagrams of gender compositions of faculty across three academic ranks (full professor, associate professor, and assistant professor) for 11 board fields of study, including agricultural sciences, biological and biomedical sciences, business, education, engineering, family, consumer, and human sciences, health professions sciences, humanities, natural resources and conservation, physical and mathematical sciences, as well as social and behavioral sciences. The numbers displayed on the links of each diagram indicate the percentage of faculty in each rank, with their width being proportionate to the percent distribution.

This article has been accepted for publication in IEEE Transactions on Big Data. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/TBDATA.2024.3423726

TABLE 2
RATE OF PROMOTION BY AGE-GENDER CATEGORY AND BROAD FIELD OF STUDY

Broad Discipline / Age-gender Category	Agricultural Sciences	Biological & Biomedical Sciences	Business	Education	Engineering	Family, Consumer & Human Sciences	Health Professions Sciences	Humanities	Natural Resources & Conservation	Physical & Mathematical Sciences	Social & Behavioral Sciences
N	8,498	53,001	18,529	16,659	38,249	24,476	24,199	52,731	7,177	47,009	46,265
#*Female faculty	2,993	19,920	6,392	8,973	11,125	11,536	13,996	23,290	2,530	14,922	20,037
#Male faculty	5,505	33,081	12,137	7,686	27,124	12,940	10,203	29,441	4,647	32,087	26,228
#Faculty (45-54)	2,760	18,336	6,126	6,327	11,751	8,692	7,562	19,141	2,440	14,964	15,650
#Faculty (55-64)	1,460	10,843	3,406	4,655	5,745	5,084	4,120	12,219	1,298	7,236	7,743
#Faculty (> 65)	1,103	8,205	2,917	3,441	4,065	3,977	2,876	8,806	953	5,398	6,013
#Women (45-54)	1,000	7,124	2,268	3,556	3,518	4,278	4,334	8,675	894	4,854	7,035
#Women (55-64)	447	3,931	1,162	2,604	1,527	2,311	2,236	5,369	385	2,120	3,176
#Women (> 65)	222	2,034	619	1,483	649	1,315	1,050	3,053	185	968	1,686
#Men (45-54)	1,760	11,212	3,858	2,771	8,233	4,414	3,228	10,466	1,546	10,110	8,615
#Men (55-64)	1,013	6,912	2,244	2,051	4,218	2,773	1,884	6,850	913	5,116	4,567
#Men (> 65)	881	6,171	2,298	1,958	3,416	2,662	1,826	5,753	768	4,430	4,327
#Promoted women	991	6,068	1,887	2,815	3,646	3,462	3,241	8,220	775	4,868	6,774
#Promoted men	1,793	10,289	3,517	2,317	9,051	3,804	2,558	10,429	1,441	10,866	8,862
%*Promoted women	33.11%	30.46%	29.52%	31.37%	32.77%	30.01%	23.16%	35.29%	30.63%	32.62%	33.81%
%Promoted men	32.57%	31.10%	28.98%	30.15%	33.37%	29.40%	25.07%	35.42%	31.01%	33.86%	33.79%
#Promoted women to assoc.	651	3,884	1,254	1,833	2,362	2,285	2,159	5,076	510	3,150	4,411
#Promoted men to assoc.	1,053	5,846	2,187	1,442	5,224	2,322	1,541	6,025	827	6,244	5,242
#Promoted women to full	465	2,868	795	1,259	1,741	1,446	1,372	3,768	356	2,309	3,041
#Promoted men to full	948	5,631	1,710	1,099	5,031	1,813	1,279	5,329	813	6,055	4,596
%Promoted women to assoc.	21.75%	19.50%	19.62%	20.43%	21.23%	19.81%	15.43%	21.79%	20.16%	21.11%	22.01%
%Promoted men to assoc.	19.13%	17.61%	18.20%	18.76%	19.26%	17.94%	15.10%	20.46%	17.80%	19.46%	19.99%
%Promoted women to full	15.54%	14.40%	12.44%	14.03%	15.65%	12.53%	9.80%	16.18%	14.07%	15.47%	15.18%
%Promoted men to full	17.22%	17.02%	14.09%	14.30%	18.55%	14.01%	12.54%	18.10%	17.50%	18.87%	17.52%
#Promoted women to assoc. (45-54)	326	2,181	778	1,378	879	1,428	901	3,311	255	1,227	2,230
#Promoted women to assoc. (55-64)	28	358	63	350	79	181	111	462	20	119	165
#Promoted women to assoc. (> 65)	4	61	8	48	9	41	22	87	7	21	26
#Promoted men to assoc. (45-54)	490	3,380	1,338	1,100	1,894	1,468	760	3,887	416	2,537	2,620
#Promoted men to assoc. (55-64)	47	469	97	254	148	219	82	554	33	185	196
#Promoted men to assoc. (> 65)	4	93	23	49	44	49	18	126	4	61	51
%Promoted women to assoc. (45-54)	32.60%	30.61%	34.30%	38.75%	24.99%	33.38%	20.79%	38.17%	28.52%	25.28%	31.70%
%Promoted women to assoc. (55-64)	6.26%	9.11%	5.42%	13.44%	5.17%	7.83%	4.96%	8.60%	5.19%	5.61%	5.20%
%Promoted women to assoc. (> 65)	1.80%	3.00%	1.29%	3.24%	1.39%	3.12%	2.10%	2.85%	3.78%	2.17%	1.54%
%Promoted men to assoc. (45-54)	27.84%	30.15%	34.68%	39.70%	23.00%	33.26%	23.54%	37.14%	26.91%	25.09%	30.41%
%Promoted men to assoc. (55-64)	4.64%	6.79%	4.32%	12.38%	3.51%	7.90%	4.35%	8.09%	3.61%	3.62%	4.29%
%Promoted men to assoc. (> 65)	0.45%	1.51%	1.00%	2.50%	1.29%	1.84%	0.99%	2.19%	0.52%	1.38%	1.18%
#Promoted women to full (45-54)	271	1,451	412	330	1,087	654	767	1,393	211	1,472	1,809
#Promoted women to full (55-64)	145	1,019	304	723	373	602	411	1,774	98	497	882
#Promoted women to full (> 65)	21	289	71	206	80	163	69	570	29	117	221
#Promoted men to full (45-54)	558	2,868	906	275	2,998	819	709	2,155	486	3,667	2,641
#Promoted men to full (55-64)	284	1,895	615	610	1,056	709	376	2,266	231	1,363	1,298
#Promoted men to full (> 65)	55	664	161	213	364	266	109	855	51	448	449
%Promoted women to full (45-54)	27.10%	20.37%	18.17%	9.28%	30.90%	15.29%	17.70%	16.06%	23.60%	30.33%	25.71%
%Promoted women to full (55-64)	32.44%	25.92%	26.16%	27.76%	24.43%	26.05%	18.38%	33.04%	25.45%	23.44%	27.77%
%Promoted women to full (> 65)	9.46%	14.21%	11.47%	13.89%	12.33%	12.40%	6.57%	18.67%	15.68%	12.09%	13.11%
%Promoted men to full (45-54)	31.70%	25.58%	23.48%	9.92%	36.41%	18.55%	21.96%	20.59%	31.44%	36.27%	30.66%
%Promoted men to full (55-64)	28.04%	27.42%	27.41%	29.74%	25.04%	25.57%	19.96%	33.08%	25.30%	26.64%	28.42%
%Promoted men to full (> 65)	6.24%	10.76%	7.00%	10.88%	10.66%	9.99%	5.97%	14.86%	6.64%	10.11%	10.38%

Note. *The # and % symbols denote the total number and rate of promotion of faculty in each row of the table, respectively.

This article has been accepted for publication in IEEE Transactions on Big Data. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/TBDATA.2024.3423726

As depicted in Table 2, overall rates of promotion for women (%Promoted women) in five out of 11 disciplines, including agricultural sciences, business, education, family, consumer and human sciences as well as social and behavioral sciences were slightly higher than those of men. However, the disaggregated promotion rates by age-gender subgroups necessitate a more nuanced interpretation. For example, the overall rates of promotion from assistant to associate professor for women (%Promoted women to assoc.) were higher than men in all broad fields. Nonetheless, it is starkly clear from Table 2 that the rates of promotion from associate to full professor (%Promoted men to full) for males were higher than for females across all disciplines. Also, the population breakdown by age group shows that the rate of promotion from associate to full professor for women who are between 45-54 years of age (%Promoted women to full (45-54)), were lower than their male counterparts. Moreover, in the 55-64 years age group, female faculty promotion rates to full professorship (%Promoted women to full (55-64)), were lower than for male faculty in all fields with the exceptions of agricultural sciences and family, consumer, and human sciences, as well as natural resources and conservation. On the contrary, the rate of promotion to full professorship for women above the age of 65 (%Promoted women to full (> 65)), was higher than older male faculty's rates in all broad fields.

C. Time in Rank

Turning to our third research question, time in rank denotes the number of years that faculty spend in an academic rank before earning a promotion to the next higher rank. Table 3 presents the average number of years spent at the rank of assistant and associate professor by gender and discipline and conveys information regarding the variation present in the data.

In Table 3, the first column shows the broad field, and the second column displays the number of faculty who were promoted to associate and full ranks from either an assistant or associate professor level, respectively. In addition, the number of years spent in each appointment, along with its corresponding values of mean and standard deviation, are shown for women and men in the subsequent columns. Finally, the last two columns display the results of two-tailed t-tests conducted to determine whether there is a significant difference in mean values between females and males at an alpha level equal to 0.05. The signature finding derived from Table 3 is that time in rank was longer for female faculty than male faculty in either assistant or associate positions across all disciplines apart from education. In addition, it took even longer for women to be promoted to full professorship compared to men. The average number of years at the assistant professor rank for female faculty was 4.02, while it was 3.91 years for male faculty across all fields. Likewise, on average women spent 5.33 years in associate professorship, while the average time frame for men to exit from the rank of associate professor was 5.13 years across all taxonomies. The largest and smallest differences between the average number of years serving at the rank of associate professor between men and women were present in agricultural sciences and education, respectively.

D. Key Performance Indicators

Let us now consider our last research question. In our study, we sought to identify variables that explain the promotion criteria in terms of scholarly activities, KPIs, using feature selection techniques. Fig. 3 and Fig. 4 illustrate the important features extracted by RF and XGBoost, respectively. In addition, data were transformed into binary values for ARM, with minimal support set at 0.2 and minimal confidence at 0.7. Only records with the "promoted" status were input into the ARM algorithm to find common attributes, and their intertwined relationships that best describe the characteristics of faculty who earned promotions in each field, as illustrated in Table 4.

As reflected in Fig. 3, article count and article citation count are the top two features consistent across all broad fields, apart from humanities. Following article count and article citation count, the third and fourth important features include: book chapter count and grant dollar amount in agricultural sciences, heath profession sciences, and natural resources and conservation; grant dollar amount and book count in biological and biomedical sciences; book chapter count and book count in business and education, as well as in family, consumer, and human sciences; conference proceeding count and book chapter count in engineering; grant dollar amount and book chapter count in physical and mathematical sciences; and book count and book chapter count in social and behavioral sciences, respectively. In humanities, article count, book count, article citation count, and book chapter count constitute the first four KPIs. Fig. 4 presents slightly different KPIs derived from deploying the XGBoost feature selection technique. For example, Co-PI grant dollar amount is among the top four most important features in agricultural sciences, as well as biological and biomedical sciences. Also, important feature sets along with their corresponding association rules derived from executing a deep ARM can be identified in Table 4. It appears, for example, that conference proceeding count is an important factor affecting promotions in engineering. Furthermore, in physical and mathematical sciences, the number of article citations and grants received in the past can influence the monetary amount of future grants for faculty members. In education, the number of previously published articles, book chapters, and books can affect the number of citations to articles that a person receives.

This article has been accepted for publication in IEEE Transactions on Big Data. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/TBDATA.2024.3423726

TABLE 3
TIME IN RANK BY GENDER AND BROAD FIELD OF STUDY

Taxonomy	n	Women											Men											t(inf.)	p-value
		Appointment duration in years									μ^*	σ^*	Appointment duration in years									μ	σ		
		1	2	3	4	5	6	7	8	9			1	2	3	4	5	6	7	8	9				
Agricultural Sciences	# to assoc. from asst.	94	102	84	102	94	128	45	15	6	4.01	2.02	149	182	134	151	147	212	67	25	7	3.96	2.02	0.43	0.667
	# to full from assoc.	65	63	57	65	85	67	56	156	10	5.09	2.45	161	145	136	152	131	108	97	330	21	4.75	2.56	2.81	0.005*
Biological & Biomedical Sciences	# to assoc. from asst.	674	621	524	553	548	618	358	137	52	3.97	2.15	1,033	908	873	877	819	903	443	179	75	3.88	2.10	2.13	0.033*
	# to full from assoc.	493	390	396	455	431	350	301	1,141	87	5.08	2.57	1,070	875	819	904	740	637	483	2,275	137	4.94	2.62	2.79	0.005*
Business	# to assoc. from asst.	160	191	189	204	190	190	98	56	27	4.13	2.10	315	363	301	355	315	349	176	85	37	4.04	2.10	1.25	0.212
	# to full from assoc.	93	107	90	135	118	122	86	445	39	5.63	2.47	268	240	264	293	236	192	153	955	48	5.36	2.58	3.17	0.002*
Education	# to assoc. from asst.	285	292	277	283	258	322	135	46	18	3.93	2.04	230	222	187	225	223	267	100	28	15	3.95	2.03	-0.27	0.787
	# to full from assoc.	172	154	176	174	216	223	128	567	46	5.37	2.47	158	155	194	152	150	136	116	571	40	5.36	2.57	0.11	0.912
Engineering	# to assoc. from asst.	384	359	335	317	356	394	200	73	20	3.97	2.09	786	780	797	755	767	979	385	106	44	3.96	2.02	0.14	0.889
	# to full from assoc.	250	228	257	263	286	204	180	683	45	5.14	2.51	840	733	809	800	727	608	385	2,044	105	4.99	2.56	2.43	0.015*
Family, Consumer & Human Sciences	# to assoc. from asst.	304	322	332	362	309	451	204	61	24	4.13	2.04	328	356	372	330	331	437	176	47	18	3.98	2.00	2.56	0.011*
	# to full from assoc.	200	185	186	224	229	208	151	810	63	5.55	2.51	290	261	288	285	249	250	147	1,066	64	5.41	2.59	1.94	0.053
Health Professions Sciences	# to assoc. from asst.	327	327	336	342	352	354	168	69	27	4.00	2.05	260	246	250	248	235	263	98	31	10	3.82	1.98	2.78	0.006*
	# to full from assoc.	192	187	224	226	207	193	144	533	52	5.15	2.50	223	200	184	218	172	158	98	539	36	5.02	2.59	1.51	0.131
Humanities	# to assoc. from asst.	763	778	715	804	722	912	377	137	55	3.99	2.05	895	947	897	972	868	1,077	393	124	46	3.91	1.99	2.03	0.043*
	# to full from assoc.	539	499	498	527	487	532	409	2,538	199	5.74	2.55	828	740	756	830	699	700	480	3,221	212	5.51	2.59	5.34	0.000*
Natural Resources & Conservation	# to assoc. from asst.	73	69	74	75	75	90	44	20	6	4.13	2.09	156	128	141	116	107	137	48	13	7	3.70	2.01	3.69	0.000*
	# to full from assoc.	55	45	35	54	61	51	33	145	9	5.22	2.52	147	102	116	121	120	107	74	277	21	4.93	2.56	2.13	0.033*
Physical & Mathematical Sciences	# to assoc. from asst.	467	490	440	476	501	525	256	101	32	4.02	2.06	1,014	958	885	955	916	1,123	426	131	45	3.90	2.02	2.74	0.006*
	# to full from assoc.	307	280	317	352	383	318	228	937	77	5.26	2.48	1,036	888	968	969	870	689	464	2,466	155	4.99	2.58	5.21	0.000*
Social & Behavioral Sciences	# to assoc. from asst.	639	707	589	659	651	766	383	141	55	4.05	2.08	788	807	778	751	817	935	379	115	49	3.96	2.02	2.34	0.019*
	# to full from assoc.	393	362	444	487	455	418	348	1,488	129	5.46	2.49	691	718	703	710	674	561	404	2,121	133	5.18	2.57	5.61	0.000*

Note. *The difference in mean values of time in rank for males and females is significant at $p < 0.05$. μ and σ denote mean and standard deviation, respectively. The # symbol represents the total number of faculty in each row of the table.

This article has been accepted for publication in IEEE Transactions on Big Data. This is the author's version which has not been fully edited and
content may change prior to final publication. Citation information: DOI 10.1109/TBDATA.2024.3423726

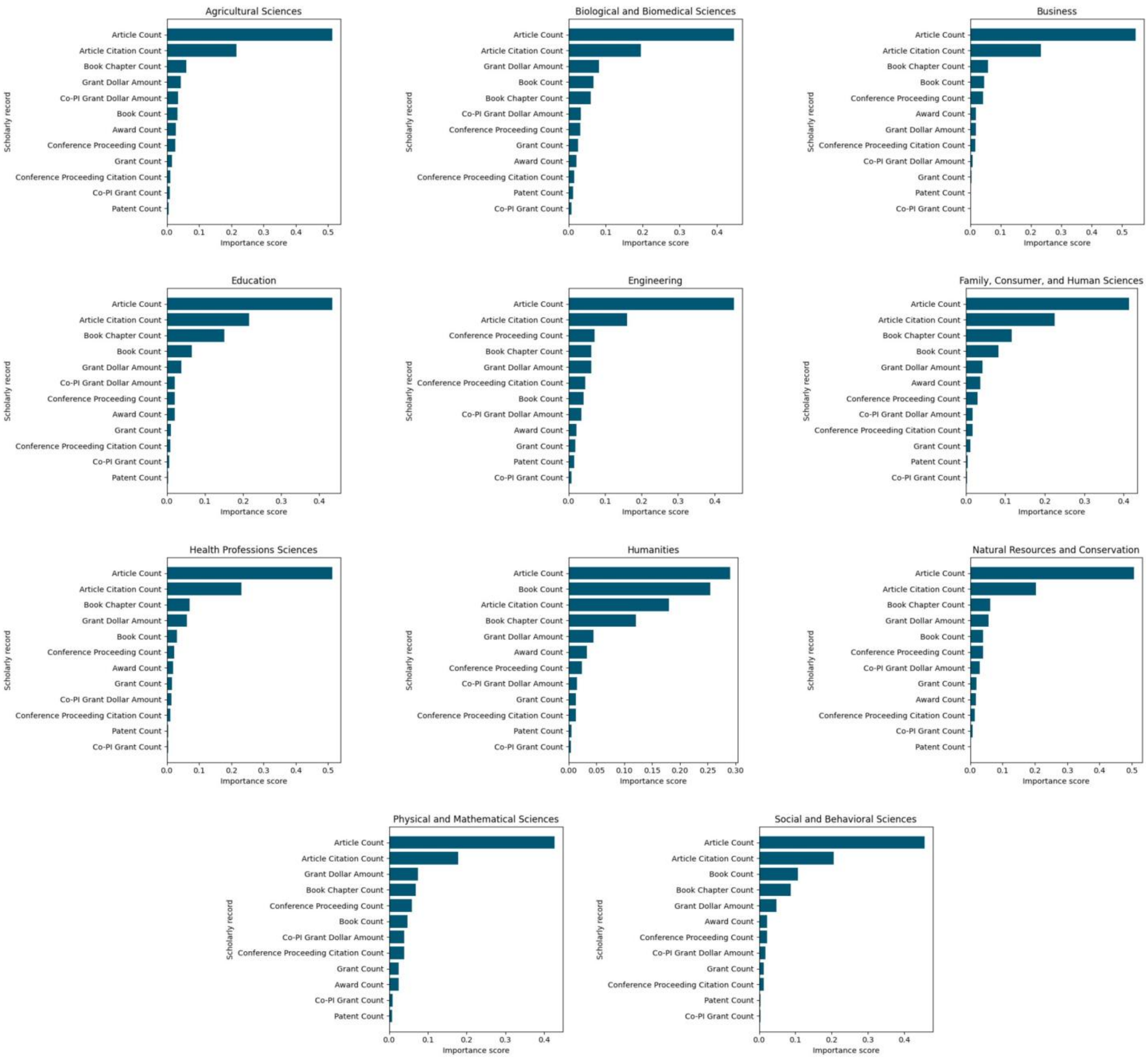

Fig. 3. Feature importance scores for various scholarly records of faculty generated by RF using Gini Index. The importance scores range from zero to one, wherein higher values indicate a greater effect of a metric on the RF model for predicting promotion. It is of note that in each diagram, the total sum of the scores of all features add up to one as they are normalized by the RF algorithm.

This article has been accepted for publication in IEEE Transactions on Big Data. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/TBDATA.2024.3423726

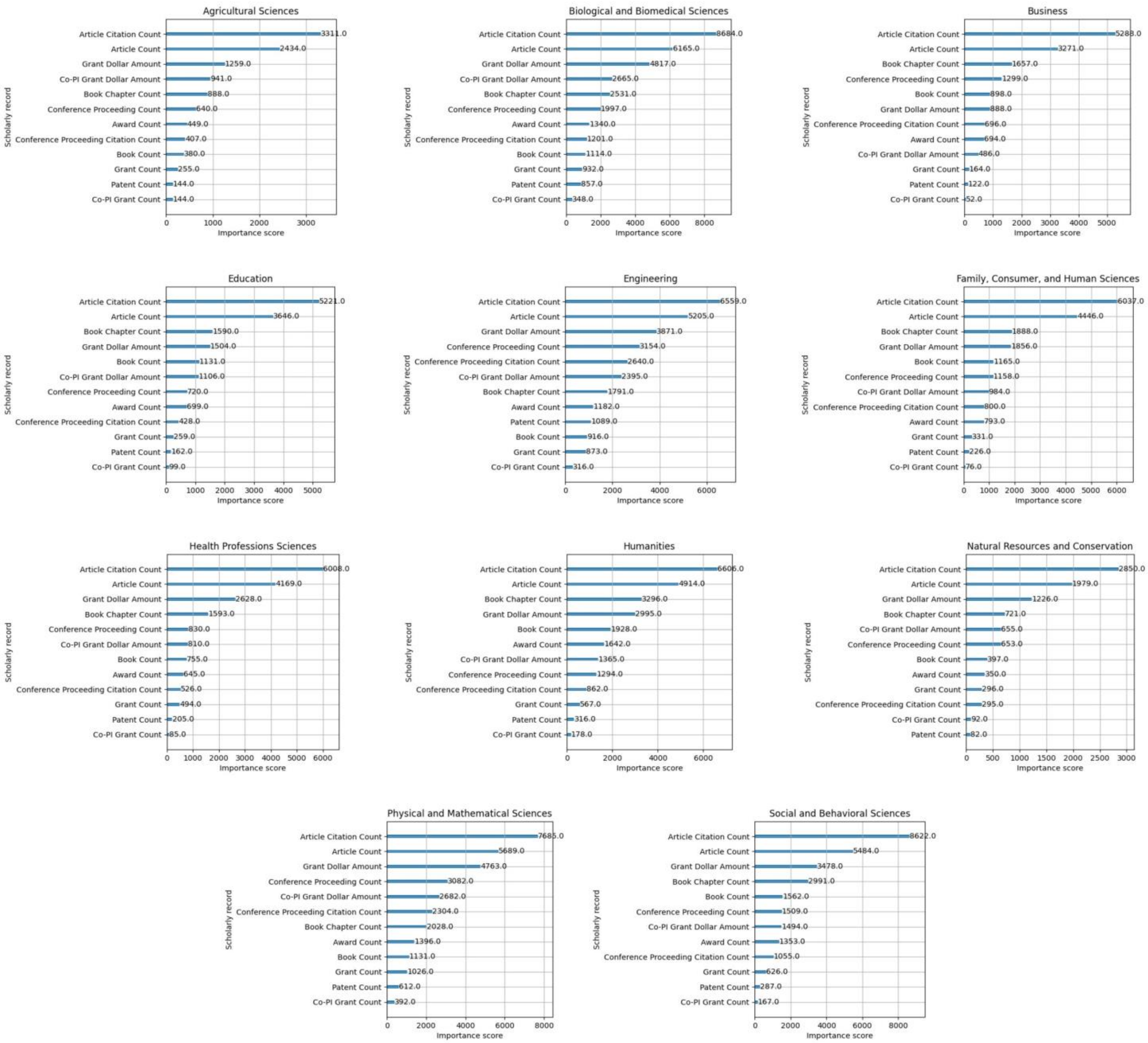

Fig. 4. Feature importance scores for different scholarly records of faculty extracted by XGBoost using Information Gain. Higher importance scores signify greater impact of a feature on the prediction task.

This article has been accepted for publication in IEEE Transactions on Big Data. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/TBDATA.2024.3423726

TABLE 4
FREQUENT ITEM SETS AND ASSOCIATION RULES

Taxonomy	Possible results	Frequent item sets (≥ support)	Association rules (≥ confidence)
Agricultural Sciences	1	support =0.95 {Article count, Article citation count}	confidence = 1 {Article citation count → Article count}
	2	support =0.48 {Article count, Book chapter count}	confidence = 0.99 {Book chapter count → Article count}
	3	support =0.47 {Article count, Article citation count, Book chapter count}	confidence = 1 {Article citation count, Book chapter count → Article count}
	4	support =0.42 {Article count, Article citation count, Grant count, Grant dollar amount}	confidence = 1 {Article citation count, Article count, Grant count → Grant dollar amount}
Biological & Biomedical Sciences	1	support =0.94 {Article count, Article citation count}	confidence = 1 {Article citation count → Article count}
	2	support =0.59 {Article citation count, Grant dollar amount}	confidence = 0.99 { Grant dollar amount → Article citation count}
	3	support =0.59 {Article count, Grant count, Grant dollar amount}	confidence = 1 {Article count, Grant count → Grant dollar amount}
	4	support =0.59 {Article count, Article citation count, Grant count, Grant dollar amount}	confidence = 1 {Article citation count, Article count, Grant count → Grant dollar amount}
Business	1	support =0.93 {Article count, Article citation count}	confidence = 1 {Article citation count → Article count}
	2	support =0.46 {Article count, Book chapter count}	confidence = 0.98 { Book chapter count → Article count}
	3	support =0.44 {Article count, Article citation count, Book chapter count}	confidence = 1 {Article citation count, Book chapter count → Article count}
	4	support =0.21 {Article count, Article citation count, Book chapter count, Conference proceeding count}	confidence = 1 {Article citation count, Book chapter count, Conference proceeding count → Article count}
Education	1	support =0.87 {Article count, Article citation count}	confidence = 1 {Article citation count → Article count}
	2	support =0.63 {Article count, Book chapter count}	confidence = 0.97 { Book chapter count → Article count}
	3	support =0.59 {Article count, Article citation count, Book chapter count}	confidence = 1 {Article citation count, Book chapter count → Article count}
	4	support =0.28 {Article count, Article citation count, Book chapter count, Book count}	confidence = 0.92 {Article count, Book chapter count, Book count → Article citation count}
Engineering	1	support =0.94 {Article count, Article citation count}	confidence = 1 {Article citation count → Article count}
	2	support =0.60 {Article count, Conference proceeding count}	confidence = 0.99 { Conference proceeding count → Article count}
	3	support =0.60 {Article count, Article citation count, Conference proceeding count}	confidence = 1 {Article count, Conference proceeding count → Article citation count}
	4	support =0.60 {Article count, Article citation count, Grant count, Grant dollar amount}	confidence = 1 {Article citation count, Book chapter count, Conference proceeding count → Article count}
Family, Consumer & Human Sciences	1	support =0.83 {Article count, Article citation count}	confidence = 1 {Article citation count → Article count}
	2	support =0.53 {Article count, Book chapter count}	confidence = 0.96 { Book chapter count → Article count}
	3	support =0.49 {Article count, Article citation count, Book chapter count}	confidence = 1 {Article citation count, Book chapter count → Article count}
	4	support =0.25 {Article count, Article citation count, Grant count, Grant dollar amount}	confidence = 1 {Article citation count, Article count, Grant dollar amount → Grant count}

This article has been accepted for publication in IEEE Transactions on Big Data. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/TBDATA.2024.3423726

TABLE 4 (continued)

Taxonomy	Possible results	Frequent item sets (≥ support)	Association rules (≥ confidence)
Health Professions Sciences	1	support =0.94 {Article count, Article citation count}	confidence = 1 {Article citation count → Article count}
	2	support =0.49 {Article count, Book chapter count}	confidence = 0.99 { Book chapter count → Article count}
	3	support =0.48 {Article count, Article citation count, Book chapter count}	confidence = 1 {Article citation count, Book chapter count → Article count}
	4	support =0.41 {Article count, Article citation count, Grant count, Grant dollar amount}	confidence = 1 {Article citation count, Grant count, Grant dollar amount → Article count}
Humanities	1	support =0.61 {Article count, Article citation count}	confidence = 1 {Article citation count → Article count}
	2	support =0.56 {Article count, Book chapter count}	confidence = 0.92 { Book chapter count → Article count}
	3	support =0.43 {Article count, Article citation count, Book chapter count}	confidence = 1 {Article citation count, Book chapter count → Article count}
	4	support =0.29 {Article count, Article citation count, Book chapter count, Book count}	confidence = 1 {Article citation count, Book chapter count, Book count → Article count}
Natural Resources & Conservation	1	support =0.94 {Article count, Article citation count}	confidence = 1 {Article citation count → Article count}
	2	support =0.59 {Article count, Grant dollar amount}	confidence = 1 { Grant dollar amount → Article count}
	3	support =0.59 {Grant count, Article citation count, Grant dollar amount}	confidence = 1 {Article citation count, Grant count → Grant dollar amount}
	4	support =0.59 {Article count, Article citation count, Grant count, Grant dollar amount}	confidence = 1 {Article citation count, Grant count, Grant dollar amount → Article count}
Physical & Mathematical Sciences	1	support =0.93 {Article count, Article citation count}	confidence = 1 {Article citation count → Article count}
	2	support =0.64 {Article count, Book chapter count}	confidence = 1 {Book chapter count → Article count}
	3	support =0.59 {Grant count, Article citation count, Grant dollar amount}	confidence = 1 {Article citation count, Grant count → Grant dollar amount}
	4	support =0.59 {Article count, Article citation count, Grant count, Grant dollar amount}	confidence = 1 {Article citation count, Grant count, Grant dollar amount → Article count}
Social & Behavioral Sciences	1	support =0.93 {Article count, Article citation count}	confidence = 1 {Article citation count → Article count}
	2	support =0.64 {Article count, Book chapter count}	confidence = 0.98 {Book chapter count → Article count}
	3	support =0.61 {Article count, Article citation count, Book chapter count}	confidence = 1 {Article citation count, Book chapter count → Article count}
	4	support =0.34 {Article count, Article citation count, Grant count, Grant dollar amount}	confidence = 1 {Article citation count, Grant count, Grant dollar amount → Article count}

IV. CONCLUSION

This quantitative study was conducted using the commercial data provided by Academic Analytics, to examine the effects of age and gender on faculty career progression in academia and to investigate KPIs that contribute to promotion. The data encompasses the scholarly records of 336,793 faculty members from 472 Ph.D.-granting universities in the United States between 2011 and 2020. The results of our initial research question are strong evidence of AGE on faculty career advancement, as women are generally underrepresented in upper academic ranks, especially at the full professor rank.

Another major finding emerging from our second research question is that the rate of promotion from associate to full professor is lower for female faculty between the ages of 45-64 as compared to their male peers. In particular, the rates of promotion of women between the ages of 45-54 are lower than those of who are between the ages of 55-64, and promotion rates of women who are between the ages of 55-64 are lower than those of females who are above the age of 65. This is an unanticipated finding, since it indicates that female faculty who are between the ages of 45-64 are subject to age prejudice, as their rates of promotion are lower than those of men and women who are above the age of 65. What is surprising is that achieving promotion becomes more attainable for women with age, which further supports that AGE influences faculty career progression. Consistent with previous studies, the average number of years that women spend at the ranks of assistant and associate professorships is greater than that of men, confirming their longer journey to sitting atop of the academic hierarchy and the existence of AGE on faculty career advancement. This finding is in accord with the results of our second research question, that it takes longer for women to earn promotion to full professorship. Finally, our last research question's results reveal that the number of journal articles and citations are the top two leading KPIs for attaining promotion. This may also indicate evidence of AGE on faculty career progression and explain the gender imbalance in P&T since the gender gap in scientific productivity and visibility [60] has consequential downstream effects on P&T decisions.

The generalizability of our results is subject to certain limitations. This research is by no means prescriptive since it falls short of embracing the indispensable roles of teaching and service indicators in the P&T process. Moreover, it is unfortunate that this work only considered records with gender binary status and did not include gender-nonconforming individuals. Furthermore, the present study did not account for epistemic exclusion of female faculty of color since the work climate may be harsher for individuals with intersectional identities [61]. Another source of weakness in this study which may have affected the measurements of age was a lack of data on the biological age of faculty. Additionally, the scope of this research is bounded by the presence of missing values of academic ranks, which could have impacted our results regarding the rate of promotion and time in rank. Thus, we leave it to future studies to explore alternative imputation techniques to address missing values that allow for more conclusive statements. To develop a full picture of underlying reasons that could explain AGE on faculty career progression, our analysis also calls for further scrutiny of turnover as the polar opposite of promotion. Additionally, future research might employ temporal analysis to observe any potential trends arising from the data while being mindful of the constraints of discrete-time approaches to data analysis. The findings of this study can be used by institutions of higher education to benchmark against our data for refining their P&T criteria and strike the best balance between the expected and actual scholarly characteristics of faculty. Also, the insights gained from this research may inform higher education stakeholders generally, by providing a snapshot of the national landscape of career progression among female/aging female faculty.

There is, therefore, a definite need to redefine the P&T process to be more inclusive, especially in the post pandemic workplace [62]. In essence, establishing effective communication strategies, as well as facilitating a smooth cadence and flow of information, could substantially enhance the clarity of P&T processes. It is of particular importance that the performance metrics for P&T, the criteria for evaluation, and the details of the P&T process be disseminated with meticulous exactitude. Moreover, fostering a workforce that is diverse with respect to age and gender is crucial, as it has been demonstrated to promote productivity and diminish rates of absenteeism [63]. Indeed, the diversity of faculty in an institution should reflect the diversity of the student body therein to help future generations of scholars unlearn implicit biases that perpetuate age and gender stereotyping. Promoting an intergenerational dialogue in the workplace will not allow the ageless tact of faculty to go unnoticed. An environment that celebrates inclusivity can allow younger and older employees to complement each other, as in Saadi's words: "And should they remove from its site the stronghold/ The youth with the sword and with wisdom the old" [64, p. 330].

Acknowledgment

For the guidance on writing about promotion and tenure, we would like to thank Dr. Bahman Shahri from Texas A&M University. In addition, we would like to recognize Dr. Diana Schwerha from Liberty University for her scholarly comments on aging and ergonomics. We would also like to acknowledge Brad Weckman for reviewing our manuscript and his insightful comments. Additionally, we would like to offer our special thanks to our audience at the 2022 IISE Annual Conference & Expo (held 21-24 May 2022, Seattle, WA, USA) for their suggestions that allowed us to improve the quality of our research. Finally, we would like to thank the editor-in-chief and anonymous reviewers for their insightful suggestions and careful reading of the manuscript.

References

[1] A. R. Donizzetti, "Ageism in an aging society: The role of knowledge, anxiety about aging, and stereotypes in young people and adults," *Int. J. Environ. Res. Public Health*, vol. 16, no. 8, Apr. 2019, doi: 10.3390/ijerph16081329.

[2] B. K. Kennedy et al., "Geroscience: Linking aging to chronic disease," *Cell*, vol. 159, no. 4, pp. 709–713, Nov. 2014, doi: 10.1016/j.cell.2014.10.039.

[3] D. L. Murman, "The impact of age on cognition," *Seminars in Hearing*, vol. 36, no. 3, pp. 111–121, Aug. 2015, doi: 10.1055/s-0035-1555115.

[4] I. Stuart-Hamilton, *An Introduction to Gerontology*. 1st ed., Cambridge, U.K.: Cambridge Univ. Press, 2011.

[5] United Nations Department of Economics and Social Affairs, Population Division, "World population ageing 2020 highlights: Living arrangements of older persons," United Nations, New York City, NY, USA, Rep. no. ST/ESA/SER.A/451, 2020. [Online]. Available: https://www.un.org/development/desa/pd/sites/www.un.org.development.desa.pd/files/undesa_pd-2020_world_population_ageing_highlights.pdf

[6] J. Vespa, L. Medina, and D. M. Armstrong, "Demographic turning points for the United States: Population projections for 2020 to 2060," United States Census Bureau, Rep. no. P25-1144, 2020. [Online]. Available: https://www.census.gov/library/publications/2020/demo/p25-1144.html

[7] I. M. Verma, "Impact, not impact factor," *Proc. Nat. Acad. Sci.*, vol. 112, no. 26, pp. 7875–7876, Jun. 2015, doi: 10.1073/pnas.1509912112.

[8] X. Wang et al., "Gendered citation practices in the field of communication," *Ann. Int. Commun. Assoc.*, vol. 45, no. 2, pp. 134–153, Jul. 2021, doi: 10.1080/23808985.2021.1960180.

[9] C. Wu, "The gender citation gap: Approaches, explanations, and implications," *Sociology Compass.*, vol 18, no. 2, Feb. 2024, Art. no. e13189, doi: 10.1111/soc4.13189.

[10] J. Gruber et al., "The future of women in psychological science," *Perspectives on Psychol. Sci.*, vol. 16, no. 3, pp. 483–516, May. 2021, doi: 10.1177/1745691620952789.

[11] G. Viglione, "Are women publishing less during the pandemic? Here's what the data say," *Nature*, vol. 581, pp. 365–366, May 2020, doi: 10.1038/d41586-020-01294-9.

[12] P. Chatterjee and R. M. Werner, "Gender disparity in citations in high-impact journal articles," *JAMA Netw. Open*, vol. 4, no. 7, Jul. 2021, Art. no. e2114509, doi: 10.1001/jamanetworkopen.2021.14509.

[13] Z. Budrikis, "Growing citation gender gap," *Nature Rev. Phys.*, vol. 2, no. 346, Jul. 2020, doi: 10.1038/s42254-020-0207-3.

[14] M. Bonawitz and N. Andel, "The glass ceiling is made of concrete: The barriers to promotion and tenure of women in American academia," *Forum on Public Policy Online*, vol. 2009, no. 2, 2009. [Online]. Available: https://eric.ed.gov/?id=EJ870462

[15] S. Stack, "Gender, children and research productivity," *Res. in Higher Educ.*, vol. 45, no. 8, pp. 891–920, Dec. 2004, doi: 10.1007/s11162-004-5953-z.

[16] S. J. Aiston and J. Jung, "Women academics and research productivity: An international comparison," *Gender and Educ.*, vol. 27, no. 3, pp. 205-220, Apr. 2015, doi: 10.1080/09540253.2015.1024617.

[17] J. Huang, A. J. Gates, R. Sinatra, and A. L. Barabási, "Historical comparison of gender inequality in scientific careers across countries and disciplines," *Proc. Nat. Acad. Sci.*, vol. 117, no. 9, pp. 4609–4616, Mar. 2020, doi: 10.1073/pnas.1914221117.

[18] W. E. Savage and A. J. Olejniczak, "Do senior faculty members produce fewer research publications than their younger colleagues? Evidence from Ph.D. granting institutions in the United States," *Scientometrics*, vol. 126, pp. 4659–4686, Apr. 2021, doi: 10.1007/s11192-021-03957-4.

[19] Y. C. Goh, X. Q. Cai, W. Theseira, G. Ko, and K. A. Khor, "Evaluating human versus machine learning performance in classifying research abstracts," *Scientometrics*, vol. 125, no. 2, pp. 1197–1212, Jul. 2020, doi: 10.1007/s11192-020-03614-2.

[20] O. Bin-Obaidellah and A. E. Al-Fagih, "Scientometric indicators and machine learning-based models for predicting rising stars in academia," in *2019 7th Int. Conf. on Smart Comput. & Commun. (ICSCC)*, Sarawak, Malaysia, Jun. 28-30, 2019, pp. 1-7, doi: 10.1109/ICSCC.2019.8843686.

[21] O. Vásárhelyi, I. Zakhlebin, S. Milojević, and E. Á. Horvát, "Gender inequities in the online dissemination of scholars' work," *Proc. Nat. Acad. Sci.*, vol. 118, no. 39, Jul. 2021, Art. no. e2102945118, doi: 10.1073/pnas.2102945118.

[22] D. G. Brizan, K. Gallagher, A. Jahangir, and T. Brown, "Predicting citation patterns: Defining and determining influence," *Scientometrics*, vol. 108, pp. 183–200, May 2016, doi: 10.1007/s11192-016-1950-1.

[23] R. G. Carter et al, "Innovation, entrepreneurship, promotion, and tenure," *Science*, vol. 373, no. 6561, pp. 1312–1314, Sep. 2021, doi: 10.1126/science.abj2098.

[24] J. P. Alperin, C. M. Nieves, L. A. Schimanski, G. E. Fischman, M. T. Niles, and E. C. McKiernan, "Meta-Research: How significant are the public dimensions of faculty work in review, promotion and tenure documents?," *eLife*, vol. 8, Feb. 2019, Art. no. e42254, doi: 10.7554/elife.42254.

[25] A. M. Kilpatrick et al., "Characterizing domain-specific open educational resources by linking ISCB communities of special interest to Wikipedia," *Bioinformatics*, vol. 38, no. Supplement_1, pp. i19-i27, Jul. 2022, doi: 10.1093/bioinformatics/btac236.

[26] T. Ross-Hellauer et al., "Ten simple rules for innovative dissemination of research," *PLoS Comput. Biol.*, vol. 16, no. 4, Apr. 2020, Art. no. e1007704, doi: 10.1371/journal.pcbi.1007704.

[27] D. K. Ginther and S. Kahn, "Women in academic economics: Have we made progress?," *AEA Papers and Proc.*, vol. 111, pp. 138-142, May 2021, doi: 10.1257/pandp.20211027.

[28] R. Durodoye Jr., M. Gumpertz, A. Wilson, E. Griffith and S. Ahmad, "Tenure and promotion outcomes at four large land grant universities: Examining the role of gender, race, and academic discipline," *Res. in Higher Educ.*, vol. 61, no. 5, pp. 628-651, Aug. 2020, doi: 10.1007/s11162-019-09573-9.

[29] M. Murphy, J. K. Callander, D. Dohan, and J. R. Grandis, "Women's experiences of promotion and tenure in academic medicine and potential implications for gender disparities in career advancement: A qualitative analysis," *JAMA Netw. Open*, vol. 4, no. 9, Sep. 2021, Art. no. e2125843, doi: 10.1001/jamanetworkopen.2021.25843.

[30] S. Hurtado, K. Eagan, J. H. Pryor, H. Whang, and S. Tran, *Undergraduate teaching faculty: The 2010-2011 HERI Faculty Survey*, Los Angeles, CA, USA: Higher Education Research Institute, UCLA, 2012. [Online]. Available: https://www.heri.ucla.edu/monographs/HERI-FAC2011-Monograph.pdf

[31] M. Eberhardt, G. Facchini, and V. Rueda, "Gender differences in reference letters: Evidence from the economics job market," *Econ. J.*, vol. 133, no. 655, pp. 2676-2708, Oct. 2023, doi: 10.1093/ej/uead045.

[32] P. Bronstein, "Older women in academia: Contemporary history and issues," *J. Women's Hist.*, vol. 12, no. 4, pp. 184–201, 2001, doi: 10.1353/jowh.2001.0004.

[33] S. Acker and C. Armenti, "Sleepless in academia," *Gender and Educ.*, vol. 16, no. 1, pp. 3–24, Jan. 2007, doi: 10.1080/0954025032000170309.

[34] S. J. Ceci, S. Kahn, and W. M. Williams, "Exploring gender bias in six key domains of academic science: An adversarial collaboration," *Psychological Sci. in the Public Interest*, vol. 24, no. 1, pp. 15-73, Apr. 2023, doi: 10.1177/15291006231163179.

[35] S. J. Ceci and W. M. Williams, "Understanding current causes of women's underrepresentation in science," *Proc. Nat. Acad. Sci.*, vol. 108, no. 8, pp. 3157–3162, Feb. 2011, doi: 10.1073/pnas.1014871108.

[36] F. Gino, C. A. Wilmuth, and A. W. Brooks, "Compared to men, women view professional advancement as equally attainable, but less desirable," *Proc. Nat. Acad. Sci.*, vol. 112, no. 40, pp. 12354–12359, Oct. 2015, doi: 10.1073/pnas.1502567112.

[37] W. M. Williams and S. J. Ceci, "National hiring experiments reveal 2:1 faculty preference for women on STEM tenure track," *Proc. Nat. Acad. Sci.*, vol. 112, no. 17, pp. 5360–5365, Apr. 2015, doi: 10.1073/pnas.1418878112.

[38] M. Lutter, I. M. Habicht, and M. Schröder, "Gender differences in the determinants of becoming a professor in Germany. An event history analysis of academic psychologists from 1980 to 2019," *Res. Policy*, vol. 51, no. 6, Jul. 2022, Art. no. 104506, doi: 10.1016/j.respol.2022.104506.

[39] A. M. Kulp, L. E. Wolf-Wendel, and D. G. Smith, "The possibility of promotion: How race and gender predict promotion clarity for associate professors," *Teachers College Rec.*, vol. 121, May 2019, Art. no. 050307, doi: 10.1177/016146811912100507.

[40] J. Misra, J. Lundquist, E. D. Holmes, and S. Agiomavritis, "Associate professors and gendered barriers to advancement," 2009. [Online]. Available: https://bpb-us-e2.wpmucdn.com/websites.umass.edu/dist/c/1972/files/2023/08/Associate-Professors-and-Gendered-Barriers-to-Advancement-Full-Report.pdf

[41] K. Mathews, "Perspectives on midcareer faculty and advice for supporting them," The Collaborative on Academic Career in Higher Education, Cambridge, MA, USA, 2014. [Online]. Available: https://coache.gse.harvard.edu/files/gse-coache/files/coache-perspectives-on.pdf?m=1447625224

[42] S. Freeman, T. Douglas, and T. Goodenough, "Toward best practices for promotion to full professor guidelines at research universities," *eJournal of Educ. Policy*, vol. 21, no. 2, 2020, doi: 10.37803/ejepF2004.

[43] S. S. Poor et al., "Standing still: The associate professor survey: MLA committee on the status of women in the profession," *Profession*, 2009, pp. 313-350. [Online]. Available: https://www.jstor.org/stable/25595935

[44] Penn State Office of Planning and Institutional Assessment, "Associate professors: Time in rank," University Park, PA, USA, 2007. [Online]. Available: http://vpfa.psu.edu/files/2016/09/assoc_prof_time_in_rank_07-1691tc7.pdf

[45] A. Olejniczak and H. Rahmani, February 8, 2023, "Age-gender Effect on Career Progression in American Universities," distributed by IEEE DataPort, doi: 10.21227/0d95-6y38.

[46] National Center for Education Statistics, "Introduction to the classification of instructional programs: 2010 Edition (CIP 2010)," Washington, D.C., USA, 2010. [Online]. Available: https://nces.ed.gov/ipeds/cipcode/files/introduction_cip2010.pdf

[47] S. Rostami. *PlotAPI*. (2020). [Online]. Available: https://plotapi.com/

[48] National Science Foundation, Nov. 2021, "Survey of Earned Doctorates: Doctorate Recipients from U.S. Universities. 2020," National Center for Science and Engineering Statistics (NCSES), Directorate for Social, Behavioral and Economic Sciences, National Science Foundation. [Online]. Available: https://ncses.nsf.gov/pubs/nsf22300

[49] M. Moon, J. Guo, and V. E. McSorley, "Issue Brief: Is 65 the best cutoff for defining "Older Americans?"," Center on Aging, American Institutes for Research, Washington, D.C., USA, Jan. 2015.

[50] 29 U.S.C. §§ 621-634 (1967, Dec. 15). *The Age Discrimination in Employment Act of 1967*. [Online]. Available: https://www.eeoc.gov/statutes/age-discrimination-employment-act-1967

[51] J. Tang et al., "A new ensemble machine-learning framework for searching sweet spots in shale reservoirs," *SPE J.*, vol. 26, no. 01, pp. 482–497, Feb. 2021, Art. no. SPE-204224-PA, doi: 10.2118/204224-PA.

[52] B. Wujek, P. Hall, and F. Güneş, "Best practices for machine learning applications," SAS Inst. Inc., Cary, NC, USA, Rep. no. SAS2360-2016,

2016. [Online]. Available: https://www.lexjansen.com/wuss/2016/154_Final_Paper_PDF.pdf
[53] R. Polikar, "Ensemble Learning," in *Ensemble Machine Learning*, C. Zhang and Y. Ma, Eds., New York, NY, USA: Springer, 2012, ch. 1, pp. 1-34.
[54] S. Ray, "A quick review of machine learning algorithms," in *2019 Int. Conf. on Mach. Learning, Big Data, Cloud and Parallel Comput. (COMITCon)*, Faridabad, India, Feb. 2019, pp. 35–39, doi: 10.1109/COMITCon.2019.8862451.
[55] D. T. Larose and C. D. Larose, *Discovering Knowledge in Data: An Introduction to Data Mining,* 2nd ed. Hoboken, NJ, USA: (John) Wiley (& Sons, Inc.), 2014.
[56] O. Caelen, "A Bayesian interpretation of the confusion matrix," *Ann. of Math. and Artif. Intell.*, vol. 81, pp. 429–450, Sep. 2017, doi: 10.1007/s10472-017-9564-8.
[57] J. Brownlee, "How to Configure k-Fold Cross-Validation." Machine Learning Mastery. Accessed: Feb. 20, 2024. [Online]. Available: https://machinelearningmastery.com/how-to-configure-k-fold-cross-validation/
[58] L. E. Raileanu and K. Stoffel, "Theoretical comparison between the Gini Index and Information Gain criteria," *Ann. of Math. and Artif. Intell.*, vol. 41, pp. 77-93, May 2004, doi: 10.1023/B:AMAI.0000018580.96245.c6.
[59] U.S. Immigration and Customs Enforcement, "DHS STEM designated degree program list," 2023. [Online]. Available: https://www.ice.gov/doclib/sevis/pdf/stemList2022.pdf
[60] M. B. Ross, B. M. Glennon, R. Murciano-Goroff, E. G. Berkes, B. A. Weinberg and J. I. Lane, "Women are credited less in science than men," *Nature*, vol. 608, pp. 135-145, Aug. 2022, doi: 10.1038/s41586-022-04966-w.
[61] I. H. Settles, M. K. Jones, N. T. Buchanan, and K. Dotson, "Epistemic exclusion: Scholar(ly) devaluation that marginalizes faculty of color," *J. of Diversity in Higher Educ.*, vol. 14, no. 4, pp. 493–507, Dec. 2021, doi: 10.1037/dhe0000174.
[62] National Academies of Sciences, Engineering, and Medicine, *Promotion, Tenure, and Advancement through the Lens of 2020: Proceedings of a Workshop–in Brief*, Washington, D.C., USA: National Academies Press, 2022, doi: 10.17226/26405.
[63] L. Fritzsche, J. Wegge, M. Schmauder, M. Kliegel, and K. H. Schmidt, "Good ergonomics and team diversity reduce absenteeism and errors in car manufacturing," *Ergonom.*, vol. 57, no. 2, pp. 148–161, Jan. 2014, doi: 10.1080/00140139.2013.875597.
[64] N. H. Dole and B. M. Walker, Eds., *The Persian Poets*, New York, NY, USA: Thomas Y. Crowell & Co., 1901.

Hoda Rahmani is a doctoral candidate in industrial and systems engineering at Ohio University. Her interdisciplinary research interests focus on machine learning, reinforcement learning, multidisciplinary design optimization, and human-robot interaction, which resulted in projects with funding from National Institute for Occupational Safety and Health (NIOSH). She is a member of the IEEE Women in Engineering.

Anthony J. Olejniczak received a bachelor's degree in anthropology from the University of Wisconsin - Madison (2000) and Master's (2004) and Ph.D. (2006) in anthropological sciences from Stony Brook University. He was a postdoctoral researcher at the Max Planck Institute for Evolutionary Anthropology (Leipzig, DE), and a Juan de la Cierva fellow at CENIEH (Burgos, ES). He is currently Director of the Academic Analytics Research Center (AARC) and has (co-)authored more than 40 peer-reviewed articles, chapters, and opinions on topics ranging from medical imaging of fossils pertinent to human evolution to scientometrics and the state of the scholarly research enterprise.

Gary R. Weckman, Professor Emeritus in the Department of Industrial and Systems Engineering at Ohio University, holds degrees in industrial engineering from the University of Louisville (B.S. 1979, M.E. 1980) and the University of Cincinnati (Ph.D. 1996). Prior to returning to university for an academic career, he had 13 years of industrial engineering experience at such firms as the Trane Company (1980-1981), Kenner Products (1981-1984), and General Electric Aircraft Engines (1984-1993). He started his academic career at Texas A&M University-Kingsville (1996-2002) in the Mechanical & Industrial Engineering Department and at Ohio University (2002 – 2021) in the Industrial & Systems Engineering Department. With over 100 peer-reviewed publications, his research focuses on data analysis and nonlinear modeling. Dr. Weckman is internationally renowned for his work in neural network modeling of complex information systems. His current research explores multidisciplinary applications using artificial neural networks (ANN) to extract user-friendly rules and enhance understanding of complex systems through machine learning. He obtained his Texas Professional Engineers License (1999 - retired) and received the University of Louisville's Professional Award in Industrial Engineering (2007) and an IARIA Fellow status (2010) for his scientific contributions.