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Predicting residency match outcomes for fourth-year medical students.

Jacob Shreffler
University of Louisville

PREDICTING RESIDENCY MATCH OUTCOMES FOR FOURTH-YEAR MEDICAL STUDENTS

By

Jacob Shreffler
B.S., Illinois College, 2012
M.S., University of Louisville, 2016

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A Dissertation Approved on

June 28, 2019

by the following Dissertation Committee

Jacob P. Gross, Ph.D.
Committee Chair

Martin Huecker, M.D.

M. Ann Shaw, M.D.

M. Brad Shuck, Ph.D.

Jeffrey C. Sun, Ph.D.

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ABSTRACT

PREDICTING RESIDENCY MATCH OUTCOMES FOR FOURTH-YEAR MEDICAL STUDENTS

Jacob Shreffler

June 28, 2019

An important goal for undergraduate medical education program leaders is to prepare their medical students to successfully match during the National Residency Match Program (Gauer & Jackson, 2017). Due to the recent increase in applications submitted during the residency process, it is critical for medical education programs to better understand the factors and attributes of those medical students who are successfully matching (Liang, Curtin, Signer, & Sawoia, 2017). As there is a larger number of medical students now enrolled than positions available for residency, the number of unmatched seniors is expected to rise (Bumsted, Schenider, & Deiorio, 2017). Additionally, the nation is facing physician shortage areas and an insufficient quantity of primary care physicians, so it is vital to understand which variables associated with medical students can predict matching into certain specialties and/or geographic regions.

Previously, researchers have used statistical methods to predict matching outcomes, but that research has only focused on a small portion of the voluminous factors. There is limited research evidence to determine which of the numerous factors taken during the admissions process and throughout the undergraduate medical education experience are the best indicators of predicting match outcomes.

The purpose of this study was to better understand which variables best predict whether or not fourth year medical students a) successfully matched, b) matched into a competitive specialty, c) matched into an in-state residency, d) matched into primary care, and e) matched into primary care in the state of Kentucky. Results are outlined below.

- The variables included in the logistic regression model for predicting matching successfully were scores on MCAT, the Family Medicine Shelf Examination scores, the Step 2 Clinical Knowledge (CK) Examination scores, and the Step 2 Clinical Skills (CS) Examination scores.
- The variables included in the logistic regression model for predicting matching into a competitive specialty were Gold Humanism membership, BCPM GPA, Surgery Shelf Examination, Step 1 Examination, and Step 2 CK Examination.
- The variables included in the logistic regression model for predicting matching into the state of Kentucky were: Kentucky resident, Gold Humanism membership, Pediatrics Shelf Examination, Step 1 Examination.
- The variables included in the logistic regression model for predicting matching into primary care were: parental status, AO GPA, and Step 1 Examination.
- The variables included in the logistic regression model for predicting matching into primary care in the state of Kentucky were: Kentucky resident, Alpha Omega Alpha membership, AO GPA, Pediatrics Shelf Examination, and Step 1 Examination.

Results indicate there were specific variables that can be used in combination to predict the matching outcomes outlined above. By having a better understanding of which variables predict these outcomes, medical education students as well as medical education institutions and stakeholders can have a better idea of what drives matching outcomes.

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CHAPTER I

INTRODUCTION

Medical Education is a substantial investment. According to the latest Graduation Questionnaire (GQ), administered by the Association of American Medical Colleges (AAMC), the median educational debt for an undergraduate medical education student is $200,000 (Graduation Questionnaire, 2018). This number is even higher for undergraduate medical education programs with limited funds for scholarships and/or those in private universities. Among the graduates of medical education programs in 2011, medical students had an average educational debt of $161,290, which was the highest it has ever been (Youngclaus, Koehler, Kotlikoff, & Weicha, 2013). One essential step to achieving the degree for this investment is the National Residency Matching Process (NRMP). This process matches fourth-year medical education students, also known as seniors of undergraduate medical education, with graduate medical education or residency positions across the nation. Many factors, which will be outlined in this study, play a role in the NRMP. This process affects the students, the undergraduate medical education institutions in which they attend, and the residency locations and directors who are hoping to obtain the most qualified applicants to ensure a successful graduate medical education program.

Undergraduate medical education is very unique compared to other higher education programs as it involves clinical teaching, a variety of structural course deliveries, high levels of student autonomy, and blocks of schedules (Kogan & Shea, 2007). One very distinctive experience is the fourth year of undergraduate medical education; during this time, students are interviewing across the nation and working on a variety of away rotations. These students are interviewing for residency positions and completing a variety of away rotations while meeting required curricular experiences at their home institution. The month of the fourth year that is most important is March. Each March the NRMP or the Match® occurs to determine residency outcomes. Each student learns where her or his training is going to continue on a preferred specialty. What is intriguing however, is while this process is vital to many stakeholders included those aforementioned, there is limited research that shows which of the many academic (e.g., grade point average, national examination scores) and nonacademic (e.g., state of undergraduate degree, gender) variables predict Match® outcomes. This chapter will provide a background to this problem, outline the research questions, describe this study's significance and the limitations. Additionally, definitions of key terms used in this study will be provided.

Background to the Problem

An important goal for undergraduate medical education program leaders is to prepare their medical students to successfully match during the National Residency Match Program (Gauer & Jackson, 2017). Due to the recent increase in applications submitted during the residency process, it is critical for medical education programs to better understand the factors and attributes of those medical students who are successfully matching (Liang, Curtin, Signer, & Sawoia, 2017). As there is a larger number of medical students now enrolled than positions available for residency, the number of unmatched seniors is expected to rise (Bumsted, Schenider, & Deiorio, 2017). Previous researchers have used statistical methods to predict match outcomes, but that research has only focused on a small portion of the voluminous factors (e.g., Medical College Admissions Test score and grade point average). There is limited research evidence to determine which of the abundant factors taken during the admissions process and throughout the undergraduate medical education experience are the preeminent indicators of predicting match outcomes. With several factors that are associated with applicants for undergraduate medical education programs, should medical schools focus more on GPA at admission or whether or not the student is from in-state if they want them to complete a residency program and practice medicine in the same state? This is one area of interest that will be examined throughout this study. To better understand what the matching process entails, the history of the NRMP is provided next.

NRMP

The National Residency Match Program (NRMP) was established in 1952 to address the highly competitive residency process amongst hospitals, while also protecting medical student interests (Ray, Bishop, & Dow, 2018; Ross & Moore, 2013). Previously, applicants and residency programs were accepting offers early in the process without allowing sufficient time to better understand what the best fit would be; therefore, the Match® was established.

Since its creation in the 1950s, the Match® has experienced an increase in the number of applicants. The 2019 Match® was the largest in the NRMP history in which 44,603 applicants submitted program choices (Match Results, 2019). The Match®, which occurs during the medical students' fourth year of undergraduate medical education, is a four-phase process (see Figure 1).

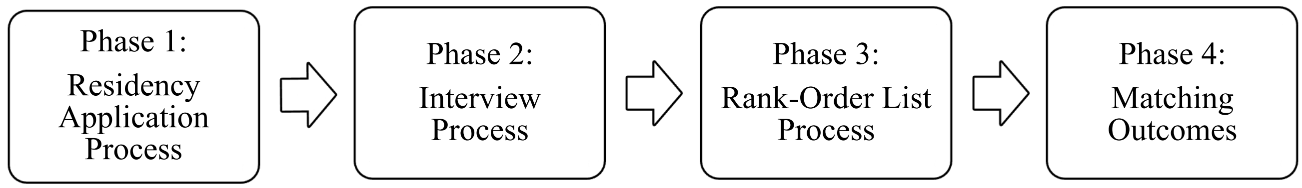

Figure 1. Match Process Simplified.

The first phase of the process occurs when medical students apply to desired residencies in the Electronic Residency Application (ERA) Platform. This phase transpires at the beginning of the fourth academic year. The second phase occurs when residency program directors invite selected students for interviews. This phase occurs after the residency directors have had the opportunity to screen the applicants that they deem are not suitable for residency and invite the ones that they believe to be the best fit. The interviews typically occur in the fall and winter.

The third phase of the matching process is the compilation of the rank-order lists (Gruppuso & Adash, 2017). For the rank-order list (ROL), each medical student and graduate medical education program creates a list that reflects the most desirable to least desirable residency outcomes. For the ROL, the students focus on residency locations and the graduate programs and directors focus on the future residents (Baker, 2013; Peranson & Radlett, 1995). The ROL plays a prominent role in the Match® process; however, available evidence on how to best optimize it is lacking (Ross & Moore, 2013). A study published in 2017 indicated that ranking strategies were different for matched compared to unmatched students; unmatched students ranked programs based on perceived chance of success, however, were less likely to rank all programs in which they were willing to attend (Liang et al., 2017). Other key findings from the study included a) matched students were more likely to rank a mix of both competitive and less competitive residencies and b) matched students were more likely to rank at least one or more specialty in preferred specialty as a safety net (Liang, et al., 2017). This research is some insight into strategies to be used by students and medical education stakeholders during the third phase of the matching process to optimize odds of success, but more work needs to be done in this area for all involved in medical education to better understand the process. Regardless of insight on best practices and the strategy implemented, the final ROLs are completed in late February before Match® results are announced in late March (Katsufrakis, Uhler, & Jones, 2016).

Finally, the fourth phase of the matching process is the final outcome. The NRMP matching algorithm yields tentative offers from the program to the applicant. Any applicant with residency offers is then matched to the program ranked as most preferred on the applicants list and the match is completed. The residency locations that are lower on the medical students preferred list are then rejected. Because of this method, it is very important that the medical students list their true preference on where they want to match on the ROL as opposed to where they believe they have the best chance (Peranson & Randlett, 1995).

The basis of the Match® is built on a concept known as the stable marriage problem (SMP). The SMP pairs each member of one group with a member from a separate group, in which any variety of unification would be acceptable. This is the case for reaching pairing, even if it was not the medical students or residency program's perfect matching outcome (Ray et al., 2018). This SMP simplified is outlined in Figure 2 below.

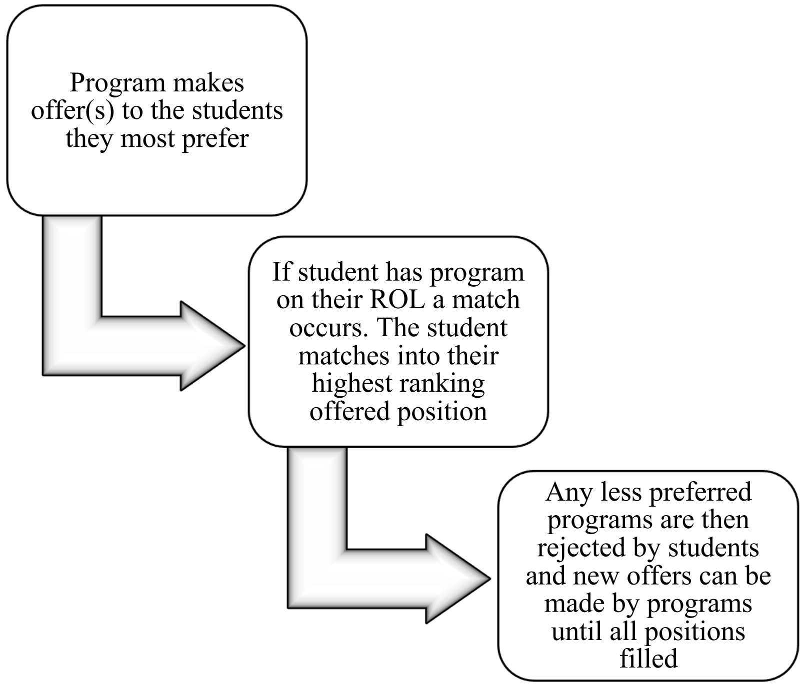

Figure 2. Matching Algorithm Simplified. This is based on narrative information from Peranson & Randlett, 1995.

The ideal outcome of the Match® process would be to place each qualified individual in a residency that is well-suited to his or her needs in order to effectively graduate qualified physicians (Katsufrakis et al., 2016). While progress has occurred in technology, which includes social media platforms, opportunities for webinars, email and other communication tools, to allow for the applicants and residency programs to better evaluate one another, the time permitted to make a systematically-sound and true evaluation in a short time span during the fourth year is insufficient. This time span does not allow for all knowledge to be shared between residency programs and medical students to depict a true picture of one another, which may diminish the quality of the matching process (Ray et al., 2018). Pairing this viewpoint with the finding that students are ranking on average about 12.91 programs, it may be difficult for students to distinguish differences in each of these many programs that students are applying to during on a short time frame (Impact of ROL, 2019).

Another problem of the current Match®, distinguished in literature, is the issue of subjective ratings. If there are only two raters assessing the residency applicants, there may be a measurement issue (Ross & Moore, 2013). Fundamentally, residency selection is based on a subjective process and the personnel interviewing students within each residency location can establish their own criteria for determining which applicants are suitable enough to interview as well as sufficiently prepared to enter their residency program (Andriole, Yan, & Jeffe, 2008).

Ultimately, it is up to the residency programs to establish their own criteria for accepting medical students. Differences in criteria are logical for specific programs, as some institutions may focus more on certain aspects of healthcare and/or weigh attributes of respective individuals differently. For example, it may be in the mission of one institution to graduate primary care physicians locally in shortage areas. Because of this, it may be of interest for these programs to outline specific criterion that would identify these individuals interested in entering primary care in the same geographic location within rating systems during the screening or application process. This is an area that will be examined in this study. While the majority of residency programs and students do find match success during the initial NRMP process, there are other options for students who do not successfully match.

One option for students who do not match is to participate in the Supplemental Offer and Acceptance Program (SOAP). This process makes an attempt to match unmatched students with unmatched positions. This program was first launched in 2012 and continues currently (Match® Results, 2019). Similar to the Match® process, applicants go into ERAs and apply to unfilled positions and offers are then extended by residency programs, including those in which a student may have previously rejected during the Match® process (Match® Results, 2019).

The SOAP process is intense as students are rapidly applying for these unfilled positions in a short timeframe (i.e., within a week), which can result in a great deal of apprehension for the students. In the 2019 Match® SOAP cycle, 1,652 out of 1,758 unfilled positions were offered to those that did not match (Match Results, 2019). The SOAP and the Match® process both can cause stress for undergraduate medical education students as there are many uncertainties that they face when applying for residency positions (Green et al., 2009). Not only is it important to better understand what drives matching success, it is important for medical education stakeholders to better understand matching outcomes as it relates to employing primary care physicians and physicians entering certain shortage geographic areas.

Physician Shortage

To further elaborate on why understanding matching outcomes is a key issue, there is a growing physician shortage in the United States due to people living longer and the population increasing, while the number of students getting medical degrees has remained relatively unchanged (O'Connell, Ham, Hart, Curlin, & Yoon, 2018). Some medical programs, across the nation, are interested in knowing how to direct students to certain locations and specialties due to a specific physician workforce need (Gauer & Jackson, 2017). Because of this, medical schools will recruit students more likely to work in careers such as primary care or those interested in being employed in underserved areas (O'Connell et al., 2018). The American Medical Association (AMA) has estimated that there are about 35 million people living in underserved areas and there will be a shortage of 91,500 physicians by 2020, ultimately affecting the underserved populations (Boscardin, Grbic, Grumbach, & O'Sullivan, 2014). Likewise, there are about 64 million Americans living in health professional shortage areas or those in high demand for primary care physicians (O'Connell et al., 2018). This number is substantial and the problem of poor distribution of physicians is especially relevant in the state of Kentucky in which 68% of the 120 counties are in these health professional shortage areas (Crump, Fricker, Ziegler, Wiegman, & Rowland, 2013).

Due to these shortage area concerns, certain institutions may be interested in knowing if they are educating future physicians who will practice medicine in their state or in underserved areas. To respond to these findings from the AMA's, medical schools have increased enrollments by 23% since 2006 and this number is expected to continue to rise significantly (Grover, Orlowski, & Erikson, 2016). While these outcomes (understanding primary care and geographic locations), may not be directly related to matching success, it is a valuable area of interest for medical education decision-makers. Undergraduate medical education programs, as well as graduate medical education programs and residency directors, may be interested in knowing how to fill these shortage areas and recruit medical students more likely to acquire positions in these underserved areas in order to alleviate health professional shortage areas in response to findings outlined by the AMA.

Purpose of this Study

It is undeniable that preparation for the Match is important. Additionally, it is imperative for medical education stakeholders to better understand what drives matching outcomes. For these reasons, the purpose of this study was to outline which variables best predict whether or not fourth year medical students a) successfully matched, b) matched into a competitive specialty, c) matched into an in-state residency, d) matched into primary care, and e) matched into primary care in the state of Kentucky. Answers to the following research questions will help guide medical students and institutions during the Match® process and also provide information for decision-making as it relates to specialty choice and region.

Research Questions

RQ_1: Which variables taken at admissions (e.g., MCAT, GPA) and during the undergraduate medical education program (e.g., Step 1 score, AOA membership) predict whether or not a student will match successfully?

RQ_2: Which variables taken at admissions and during the undergraduate medical education program predict whether or not a student will match into a competitive specialty?

RQ_3: Which variables taken at admissions and during the undergraduate medical education program predict whether or not a student will match into the state of Kentucky?

RQ_4: Which variables taken at admissions and during the undergraduate medical education program predict whether or not a student will match into primary care?

RQ_5: Which variables taken at admissions and during the undergraduate medical education program predict whether or not a student will match into primary care in the state of Kentucky?

Limitations

The limitations of this study include that the data were only drawn from one medical school. While there may be similar aspects or data patterns noted by other medical schools, the findings from this study may not be generalizable to other medical education programs. Another limitation is there are many ways to define competitive specialty. The author of this work will provide justification in determining the definition of competitive specialty for this study in Chapter III; others may view competitive specialty differently. Finally, that there are many reasons why a student may choose a certain specialty that has nothing to do with if they were a competitive applicant for a competitive position. For example, a specialty that is less competitive, pathology, may obtain students with the highest Step 1 score and best GPA because that is what they are interested in this field. These limitations will be further discussed in this study throughout the chapters.

Significance of this Study

The Match® will continue to drive the way medical education will be guiding medical students from undergraduate to graduate medical education. Because of this, it is important to understand which academic and nonacademic factors are associated with matching outcomes. There are many reasons why a student may not be successful in the Match®, including but not limited to: an increase in the number of applicants due to competitiveness, varying academic problems, and poor fit between applicants and preferred specialties (Bumsted et al., 2017). Due to the increase in the number of applications and little consensus in the literature about which selection strategies are best in selecting future doctors (Kenny et al., 2013), this study aims to better understand which factors associated with undergraduate medical graduates can predict whether students a) successfully matched, b) matched into competitive specialties, c) matched into in-state residencies d) matching into primary care, and e) matched into primary care in-state.

This research will help medical education leaders be able to guide students throughout their undergraduate medical education program to successfully match by providing more statistically-sound measures to determine whether or not their scores on exams, or grades in clerkships, or other specific variables weigh more heavily on the Match® process. Additionally, not only is this work beneficial for students and programs to better understand preparation for the Match® process, it is also an opportunity for admissions committees and medical education leaders to better understand which attributes are associated with matching outcomes to possibly determine offers based on internal strategic initiatives. For example, if a program has one slot left for two students with similar qualifications they are considering, and the committee want the student to go into primary care, there may be a certain factor that is associated with one of the students having better odds to enter primary care. Having an understanding of which factors predict this outcome could be used for guiding decision-making related to who to grant an offer of enrollment.

A 2017 study detailed that having an understanding the factors of the Match® process can be of great advantage for medical education stakeholders and these authors noted that they were the first study to statistically explore differences in Step 1 and 2 scores by Match outcomes (Gauer & Jackson, 2017). The authors of this work used multivariate analysis of variance (MANOVA) to examine matching outcomes. Using MANOVA allows researchers to see differences in groups by these variables; however, it is limited because there are more assumptions to be met and restrictions on the types and quantity of variables. Logistic regression is much more flexible compared to MANOVA as it allows for an assortment of dichotomous and continuous variables and there are less assumptions to be met. Further limitations with other methodological choices will be discussed in Chapter III. By using logistic regression to predict Match® outcomes, medical education leaders can determine which of the many factors are more critical to the success of the matching process and can ultimately be used for decision-making and advising. Next, the definitions of key terms that are used within this study are provided.

Definitions of Key Terms

The following are terms that will be used in this study.

1. Matching Outcomes – These are the outcomes that occur during the National Matching Residency Process (NRMP). This information includes the success of matching or not matching, the discipline or specialty that the applicant matches into, whether or not the student matches into the state of Kentucky, if the student matches into primary care, and if the student matches into primary care in the state of Kentucky.
2. Matching Successfully –This means that the student has obtained a residency position during the Match® process. It should be noted there are other ways to obtain a residency position outside of the NRMP.
3. U.S. Seniors – These are fourth year medical students in undergraduate medical education that are in the final year and participate in the Match® process in March.
4. MCAT – The Medical College Admission Test (MCAT) which is taken by students prior to obtaining entrance to medical school; this is often used as a screening tool by admissions committees.
5. BCPM GPA at Admission – BCPM GPA is the portion of the grade point average for a student based on the biology, chemistry, physical science and mathematics classes; this is used a screening tool by admissions committees.
6. AO GPA at Admission - AO GPA is the portion of the grade point average for a student that excludes biology, chemistry, physical science and mathematics classes; this is used a screening tool by admissions committees.

7. BCPM Hours – The number of credit hours earned based on the biology, chemistry, physical science and mathematics; this is used a screening tool by admissions committees.
8. AO Hours – The number of credit hours earned excluding biology, chemistry, physical science and mathematics; this is used a screening tool by admissions committees.
9. USMLE Examinations - United States Medical Licensing Examinations (USMLE) include a three-step testing process for licensure for medical doctors which was developed and created by content experts composed of medical educators and clinicians (USMLE Bulletin, 2018). These include Step 1 scores, which are taken by medical education students at the end of the second year and the Step 2 scores, which are taken by medical education students at the end of the third year.
10. Shelf Examinations – The National Board of Medical Examiners (NBME) Clinical Subject ("shelf") Examinations are content specific. These are taken at the end of the seven required clerkships within the University of Louisville School of Medicine.
11. Clerkships – These are the required clinical experiences that students partake in during the third year of undergraduate medical education. These include the following required clinical rotations: Family Medicine, Internal Medicine, Neurology, OB-GYN, Pediatrics, Psychiatry and Surgery.
12. Alpha Omega Alpha (AOA) – An honor society in each approximately one-sixth of each class is designated.

13. Gold Humanism – An honor society in which students are nominated into; it is separate from AOA.

CHAPTER II

REVIEW OF LITERATURE

National Residency Matching Program Data

The National Residency Matching Program (NRMP) publishes annual reports and data pieces that are critical to better understand the latest trends in each aspect of the Match® process. These reports should be used by medical education stakeholders involved in either the recruitment of residents or in assisting students obtain a position during the Match®. The following documents are included on the NRMP website and were critical in usage for this research: Results and Data: Main Residency Match®, Results of the 2018 NRMP Program Director Survey, Charting Outcomes in the Match: U.S. Allopathic Seniors, Impact of Length of Rank Order List on Match Results: 2002-2019 Main Residency Match, 2019 Match Results by State, Specialty, and Applicant Type, and Results of the 2017 NRMP Applicant Survey. These data reports are often used to identify the many key facets of the Match® process and better understand the physician workforce in general (Jolly, 2012). These NRMP documents are further discussed below.

Main Match Results

The *Main Match Results and Data 2019* is a report that covers many aspects of the Match® process. This includes the total numbers of applicants, position fill rates, and recent trends. Recent trends include the top five specialties that U.S. medical seniors matched into which were:

1. Internal Medicine – 3,366

2. Pediatrics – 1,715
3. Emergency Medicine – 1,617
4. Family Medicine – 1,601
5. Medicine – Preliminary – 1,356

Additional trends provided in this report include the ratio of positions per applicant. These data show that the ratio for positions per U.S. student was 1.7. Additionally, in 2019, a total of 6,682 U.S. seniors matched into Family Medicine, Internal Medicine, and Pediatrics which is 1,297 more than in 2009; these three specialty fields are known as primary care areas which was an area of focus for research questions 4 and 5 of this study. Another area outlined in this report that is of interest for this study is fill rates. Fill rates show the specialties that were most successful in filling their residency positions. 2019 specialties with at least 10 positions in the Match® and had perfect fill rates (100%) included:

1. Medicine-Emergency Medicine
2. Medicine-Psychiatry
3. Interventional Radiology
4. Otolaryngology
5. Peds/Psych/Child Psych
6. Physical Medicine & Rehabilitation
7. Plastic Surgery
8. Psychiatry-Family Medicine
9. Surgery

10. Thoracic Surgery

Fill rates are one way to determine competitiveness which will be discussed in chapter III of this study. Another notable finding in this report showed that the 2019 Match® was the second lowest on record for U.S. seniors matching into their first-choice program at only 47.1%. This finding is noteworthy as it shows that the majority of U.S. seniors do not obtain residency positions, they desire the most. Additionally, 31.9% of independent applicants did not match, which was the lowest on record. These findings show how the competitiveness of the Match® has increased (Match Results, 2019). The next report that will be outlined with key findings is the *Charting Outcomes in the Match: U.S. Allopathic Seniors* report.

Charting Outcomes

Another publication that is accessible to medical education stakeholders, published by the NRMP, is the *Charting Outcomes in the Match: U.S. Allopathic Seniors* report. This report provides additional detailed characteristics and qualities of applications that were associated with students successfully matching to their preferred specialties. Notable trends from this report include that applicants more likely to match to their preferred specialty are likely to rank more programs on their Rank-Order-List (ROL) than those that do not successfully match. Additionally, this report shows that successful applicants typically had higher United States Medical Licensure Examination (USMLE) Step 1 and 2 scores. Moreover, successful applicants were more likely to be members of the medical education honor society, Alpha Omega Alpha (AOA). These characteristics will further be discussed in this chapter.

Prominently, this report notes that "although measures seem to be related to matching success for some specialties, the relationships were not consistent enough to draw broad conclusions across specialties" (p. iii, Charting Outcomes, 2018). This shows more work needs to be done by the medical education community to better understand matching outcomes. Finally, this report provides insight that while there were relationships between Step scores and Match® success, the scores were distributed across applicants in relation to success; this indicates that just because a student has a high or low score on these national exams, it does not seal his or her fate in the residency matching process (Charting Outcomes, 2018). As will be discussed further in this chapter the national exams are of high pressure. The next report that will be outlined with key findings is the *Results of the 2018 NRMP Program Director Survey*.

Residency Director Survey

The NRMP publishes the *Results of the 2018 NRMP Program Director Survey* every other year. This report contains results from a survey administered to residency directors that attempts to better understand the importance of the factors directors use to screen applicants during the interview process phase as well as rank applicants after interviews to extend offers for residency. These survey data show trends for all programs as well as specialty specific trends. Trends from the latest survey show that the top five factors when selecting students to interview were:

1) USMLE Step 1 score
2) letters of recommendation
3) Medical Student Performance Evaluation (MSPE)
4) USMLE Step 2 score

5) personal statement

These data show five areas for students to focus on when applying for residency positions. When ranking applicants after the interview process the top five factors noted by program directors were: interactions with faculty during interview and visit, interpersonal skills, interactions with house staff during interview and visit, feedback from current residents, and the Step 1 score. The Step 1 score was weighted highly for both the offer of interviews as well as offer of positions, thus this report shows the importance of the Step 1 examination.

Another prominent finding from the report shows that 88% of program directors would either “never” or “seldom” consider an applicant who failed Step 1 on the first attempt and that percentage increases to 92% stating the same if an applicant failed Step 2; however, it should be noted that only 60% of programs require the Step 2 score whereas 98% of programs require the Step 1 score based on these data results. This further triangulates findings that Step 1 is vital.

Finally, data from this report show that the top five factors affecting residency success were:

1) clinical competency
2) professionalism
3) quality of patient care
4) ethics
5) communication skills

According to the survey results, of all of the competencies asked to program directors, the lowest score (or valued attribute as determined by respondents) was research and publications; this indicates that it may be less important for students to focus on research and publications if they are concerned with successfully matching (NRMP 2018 Director Survey). The next report that will be outlined with key findings is the *Results of the 2017 Applicant Survey Report.*

Applicant Survey Report

The NRMP conducts a survey to applicants participating in the Match® every other year. The purpose of this survey is to better understand applicants' reasoning for applying to programs as well as to ranking programs on their ROLs. The results of this survey are presented broadly for all programs, as well as by applicant type and specialties. Results show that when applicants apply to programs they were concerned with the location of the program, the perceived goodness of fit, and the reputation of the program.

When considering their ROL, applicants weigh those same factors highly and also include the experience during the interview. Another finding from this report shows that matched U.S. seniors ultimately ranked more programs and attended more interviews than those who did not match even though they applied to less programs; the median *N* of programs applied to for matched students was 35 compared to 54 for unmatched students (2017 Applicant Survey Report). The next report that will be outlined with key findings is the *Impact of Length of Rank Order List on Match Results: 2002-2019 Main Residency Match.*

Impact of Length of Ratio

The Impact of Length of Rank Order List on Match Results: 2002-2019 Main Residency Match report shows trends in differences in areas related to this study such as number of applications by type of student, number of programs filled, and the length of rank order lists. Figure 3 below was created by the author based on data from this report. Note that the number of U.S matched applicants has steadily increased over the last seventeen years. Additionally, it should be stated that while there is has been an increase in applicants, there has also been a higher number of programs on each applicant's ROL. In 2002, students ranked an average of 7.96 programs; in 2019, students ranked an average of 12.91. These numbers indicate that this process is becoming more competitive and ultimately shows that more time and money (for applicants, traveling for interviews, etc.) is being spent on this process (Impact of ROL, 2019).

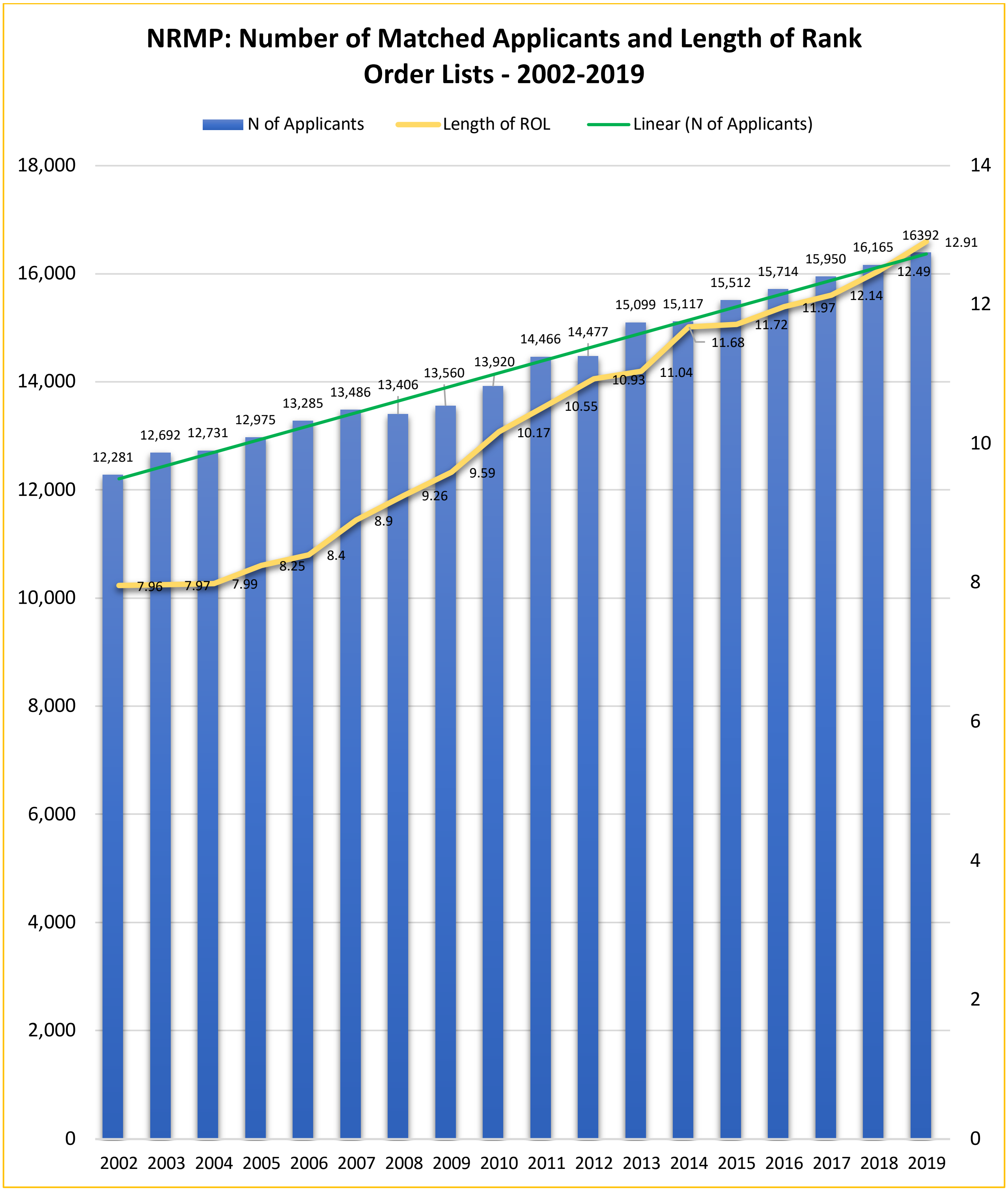

Figure 3. NRMP Trends of Applications and Rank Order Lists Created by Author of Study. Data was used from *The Impact of Length of Rank Order List on Match Results: 2002-2019 Main Residency Match* report.

Match Results by Specialty and State

The final report that will be outlined with key findings is the 2019 NRMP Main Residency Match®: Match Rates by Specialty and State report. This report provides details on the number of positions available and positions filled by program type within each state. In the state of Kentucky, the top five highest number of positions filled for 2019 were:

1) Internal Medicine (78)
2) Family Medicine (44)
3) Pediatrics (33)
4) Anesthesiology (23)
5) Emergency Medicine (23)

These numbers are comparable to the top specialties nationwide; however, for Kentucky, anesthesiology is in the top 5 replacing medicine preliminary at the national level (Match 2019 Results, Main Match by State by Specialty, 2019).

The data reports discussed above show how trends can analyzed and used to better understand residency matching outcomes. The NRMP process has several aspects leading up to these outcomes and there are distinctive stakeholder perspectives associated with the Match®. The three different perspectives that will be covered in this chapter are from the residency director, the medical education student and the medical education program.

National Residency Matching Process Stakeholder Perspectives

The residency director.

For the medical residency director, a major concern during the Match® process is to ensure they do not permit entrance to a resident that may exhibit problematic characteristics (e.g., poor communication skills, lacking professionalism, lacking necessary medical knowledge, etc.). If they do permit a resident that lacks the essential characteristics needed for success it could ultimately demand significant time, costs, and other supervision during the residency training which could affect not only that resident but the entire program (Brenner, Mathal, Jain, & Mohl, 2010). Finding these problem residents may be easier said than done as reviewing a large number of applicants with limited resources to determine best fit can be difficult (Katsufrakis et al., 2016). Due to ensuring they are obtaining the candidates that have the best chance to do well in graduate medical education, residency directors want to predict which medical students will be successful while being cost-effective and resourceful throughout the screening and interview process (Andolsek, 2016).

It is apparent based on the literature that there are many different variables of interest when considering the right applicants to interview for residency directors. According to the most recently published NRMP Residency Director Survey, the top five factors for screening applicants were: United States Medical Licensing Examination (USMLE) Step 1 and Step 2 scores, grades, the Medical Student Performance Evaluation (MSPE), and letters of recommendation (NRMP Director's Survey, 2016). The next sub-sections will further discuss these top five factors in depth.

USMLE Step 1 and Step 2.

National Licensing Examinations (NLEs) are often used as a top screening tool to better understand students' ability to perform on examinations of knowledge and skills.

These examinations are applied in medical education to ensure doctors have the capacity to demonstrate a minimum level of competence to secure effective and safe treatment for all patients (Swanson & Roberts, 2016). Essentially, these exams form the basis of affirmations on whether a person can become a doctor or not, as well as safeguarding the quality of the entire health care system (Schauber, Hecht, & Nouns, 2017). There is research suggesting national examinations have positive relationships with outcomes for patients (Norcini, Boulet, Opalek, & Dauphinee, 2014). Because of this, residency directors may use these results to determine how the applicant will do on competencies related to patient care in graduate medical education/residency. Similarly, residency program directors are interested in observing national tests scores in order to detect "early warning" problems that may occur related to poor performance on examinations for future residents (Dong et al., 2014). One set of national licensing examinations often used in residency screening and offers are the United States Medical Licensing Examinations (USMLE).

The USMLE is a three-step process for licensure for medical doctors which was developed and created by content experts composed of medical educators and clinicians (USMLE Bulletin, 2018). The three-step process consists of four separate examinations designed to assess content knowledge and clinical skills essential for providing effective care for all patients (Dong et al., 2014). The passing of all three exams is required for licensure (Zahn et al., 2012). The first phase, Step 1, of the USMLE is typically taken at the end of a medical student's second year and is often used for residency decisions (Gauer & Jackson, 2017). This exam includes approximately 350 items over an eight-hour time span which covers basic sciences (Morrison et al., 2010). The Step 1 exam is designed to measure the mastery of foundational sciences and the required principles to be successful in this career (Prober, Kolars, First, & Melnick, 2016). Researchers have identified that the Step 1 score is the only standardized objective quantitative results provided to all program directors (Liang, Curtin, Signer, & Savoia, 2017). Along with it being the only standardized quantitative measure, another reason that it is often used is there is an abundance of research that shows there are statistically significant positive relationships between Step 1 scores and later performance on residency in-training exam performance (Prober et al., 2016; Katsufrakis et al., 2016; Kay, Jackson, & Frank, 2015; Sutton et al., 2014; Tadisinia et al., 2016). However, not all medical education stakeholders are in favor of handling of Step 1 examination scores as part of the residency process.

Some medical education stakeholders have argued that Step 1 should not be used in the residency decision process because the examination was not designed for that intent (McGaghie, Cohen, & Wayne, 2011). Moreover, others have been critical of usage of Step 1 for residency decision-making due to the idea that the scores can be interpreted by program directors to varying degrees (Andriole, Yan, & Jeffe, 2008). Furthermore, there is research that shows that using the Step 1 examination scores may have undesirable effects due to standardized test scores having variability across different racial and ethnic groups (Katsufrakis et al., 2016).

Despite its intended use, many program residency directors have and will continue to use the Step 1 score as a filter to screen out applicants, with the more competitive specialties having filters requiring higher scores (Prober et al., 2016). This is evident in recent research, as a nationwide study conducted by representatives from the

NRMP revealed that the mean Step 1 score for matched U.S. seniors was 233.6 compared to U.S. seniors that did not match with a mean of 225.2 (Liang et al., 2017). While its score is not intended to be used this way, researchers noted that those averaging a score of 240 or higher were deemed ready for competitive programs and those students that fell below this threshold were determined to fall into noncompetitive (George, Park, Ip, Gruppuos, & Adashi, 2016).

The second phase of the USMLE includes the Step 2 Clinical Knowledge (CK) and Clinical Skills (CS) examinations, which are typically taken prior to the medical students' fourth year. The Step 2 CK exam measures the student's ability to apply medical knowledge, skills, and understanding as it relates to all aspects of patient care (USMLE Bulletin, 2018). The Step 2 CS exam measures the student's ability to accurately gather relevant information, perform examinations, and communicate findings to standardized patients (USMLE Bulletin, 2018). Similar to the usage of Step 1, there is validity evidence in support of using these results as a selection tool for licensure (Katsufrakis et al., 2016; Norcini et al., 2014). In one study in which the purpose was to determine the external validity of Step 2 CS, scores yielded were positively associated with ratings of the first-year residents; therefore, the researchers determined that Step 2 scores are useful for predicting performance in residency (Cuddy, Winward, Johnston, Lipner, & Clauser, 2016). Comparable to the discussion on Step 1, some have argued against the usage of Step 2 CK and CS in residency selections due to validity issues linked to its intended purpose (McGaghie et al., 2011). However, these standardized exams will likely continue to be used.

The third phase of the USMLE is the Step 3 exam which ensues during the student's residency. The Step 3 exam measures the residents' ability to apply medical knowledge in unsupervised practice for medicine (USMLE Bulletin, 2018). Because this examination occurs after the matching process, it is not used in residency choice decision-making and will not be further discussed. Another instrument often used in residency screening and selections, cited by the Residency Director's Survey is the Medical Students Performance Evaluation (MSPE).

MSPE and letters of recommendation.

The Medical Student Performance Evaluation (MSPE) documents each medical student's performance and professional attributes which is compiled by his/her respective undergraduate medical school (Katsufrakis et al., 2016). The MSPE was introduced to effectively replace the dean's letter and provide a comprehensive assessment of a medical student's academic and nonacademic performance during their time in undergraduate medical education (Andolsek, 2016). It should be noted there is literature that indicates the MSPE can be ineffective due to its objectivity and research showing the evidence provided in the MSPE can be incomplete and vary amongst schools (Katsufrakis et al., 2016). Regardless of these defects, the MSPE is used to rank students internally for residency director decision-making.

Within the MSPE, medical schools provide ranks for each of its students to differentiate top performing with lower performing individuals. It has been recognized in medical education literature that these rankings differ widely causing limitations to the ability of program directors to accurately and systematically compare applicants across undergraduate medical education institutions (Osborn et al., 2016). For example, some medical schools will state that a student is "outstanding," which would be in the highest group/category; whereas this may be in the second highest group/category at a different school after "exceptional" or "superior" (Osborn et al., 2016). Because these are qualitative metrics, researchers have stated that they are not as reliable compared with quantitative methods due to observer bias and the fact that they are not consistently measured across programs (Loh et al., 2013).

While these evaluations do vary by school, there has been research (Brenner, Mathai, Jain & Mohr, 2010) which found that negative comments, even subtle ones, in these recommendations are positively associated with problems during or following residency/graduate medical education. This may be one reason why residency directors continue to cite MSPEs as one of the top screening tools. Other research has indicated that the MSPE has been used more as a screening tool as opposed to making informed evaluations on who to make offers for residency, as they neither predict exam scores nor performance in clinical setting (Andolsek, 2016). Regardless of whether the MSPE can accurately predict future performance during or after residency, it is consistently used. The University of Louisville (UofL) has only recently started the MSPE process; therefore, this variable will not be included in the logistic regression models. Another cited aspect used to screen and provide offers during the residency process is student grades in courses and clerkships or their overall grade point average (GPA) from their time in undergraduate medical education.

Grades/GPA

Grades are commonly used to summarize overall performance of an individual and assure that a student has met the satisfactory level of requirements to advance to the subsequent level of education (Durning & Hemmer, 2012). In one study, grades in clerkships were the highest ranked selection criteria when considering residency applications; however, some argue that they are not as important due to the variability in medical schools leading to poor interpretation of results (Green et al., 2009). Because of this variability, some contend that the Liaison for Committee Medical Education (LCME), which is the accreditation body for medical education institutions, should better define what grading policies and practices should look like across institutions due to the uniqueness of medical education (Durning & Hemmer, 2012). The undergraduate medical education is distinctive from other higher education units as structures of courses, clinical teaching, hours and other facets are different (Kogan & Shea, 2007). Even though there is variability across institutions, in a meta-analysis published in 2013, grades were one of the two strongest measures of doctor performance (Kenny, McInnes, & Singh, 2013). Because grades can measure future performance as a doctor, residency directors will likely continue using these data for future Match® cycles. While the residency director has one perspective of the Match® process and is considering certain academic and non-academic factors, the medical student has a different viewpoint during this rigorous fourth year of medical school.

The Medical Education Student

Medical students seeking a successful match can be immensely stressed because of the high stakes and the seemingly obscure facets (e.g., no one has the answer as to which factors are most important) that are driving the outcomes (Loh et al., 2013). While the great majority of students match, which is especially true for U.S seniors, those who do not match suffer substantial personal and monetary setbacks in their career (Liang et al., 2017). As matching into a residency has become more competitive, medical student residency contenders are increasing the number of applications they are submitting which can cause additional time commitment, crowding in the number of applications that residency directors have to review, as well as an escalation in cost (Weissbart, Kim, Fein, & Stock, 2015).

The number of applications per U.S medical student increased by more than 50% between 2005 and 2015 (Gruppose & Adashi, 2017). Additionally, it should be noted that in a study published by representatives from the NRMP, strong unmatched U.S. fourth year medical students applied to double the number of programs on average than those that matched; however, they received about the same number of interviews (Liang et al., 2017). Research has indicated that there is no improvement in match rate for students submitting an increased number of applications (Weissbart, Kim, Feinn, & Stock 2015). Not only do students have to pay for each application in ERAS, but they also have to pay for travel and lodging during their interview sessions. Applicants applying to residencies spend a range of between $5,000 to $10,000 as they are now ranking more than ten programs to be safe (Ray et al., 2018).

Moreover, in competitive fields such as urology, medical students will do internships away from their medical school to increase their odds of successfully matching. This results in students having to pay for temporary housing, transportation, and other expenses on top of their other permanent rent and additional costs back home (Nikonow, Lyon, Jackman, & Averch, 2015). In the week following the 2015 Match®, a survey was sent to orthopedic surgeon applicants and it was discovered that the average cost per applicant was over $5,000 with a range of $450 to $25,000 (Camp et al., 2016).

In a five-year study on applicants from the NRMP from 2009 to 2014, the average applicant for plastic surgery spent over $6,000 for interviews (Tadisina et al., 2016). In another study, it was estimated that the median applicant in the urology match spent was $7,000 and that the total spent for all applicants in the urology Match was $3,122,000 (Nikonow et al., 2015). Essentially, the Match® can be very expensive. Researchers have offered proposals to amend the current Match® to help with the costs as well as other central factors affecting the students. Despite these findings, the Match® has remained relatively unchanged since its inception in the 1950s (Gruppuso et al., 2017; Ray et al., 2018; Ross & Moore, 2013; Arnold, et al. 2018). Along with the increasingly high cost associated with the Match®, students may be worried about their USMLE scores during the process.

Due to the high-stakes of the Step 1 examination, students are often advised to spend a large amount of time studying for the Step 1 exam as well as considering their total USMLE scores when deciding their specialty application (Gauer & Jackson, 2017). This occurs even if the student has other accomplishments and merits to enter that specialty and would be an outstanding fit (Prober et al., 2016). Students may be genuinely interested in a more competitive specialty and may have the necessary attributes to be effective in that career but may not choose to try it due to an average Step 1 score.

Another critical area of concern for medical programs and students is that because of this intensive process that requires more interviews, applications, and money the medical students' attention is taken away from their fourth-year studies, ultimately hurting their fourth-year education (Arnold, Sullivan, & Okah, 2018). Because of these aforementioned factors, it is important to understand how students are ranking and choosing specialties.

According to the latest published NRMP applicant survey, when considering which factors influence decision-making on where students choose to apply, the top factors were: geographic location, goodness of fit, reputation of program, quality of residents, and academic medical center program (NRMP Applicant Survey, 2017). Four of the top five factors remained the same when the students were asked how they ranked programs after the interview; the interview day experience jumped to number two in the top five most important factors which replaced academic medical center program from the top five (NRMP Applicant Survey, 2017). It has been shown in medical education research, as formerly stated, that medical students still tend to over apply even if the factors mentioned above do not align with where they are ranking residencies because they want to ensure they match. The matching process can be a very stressful time and oftentimes the students are needing leadership and guidance from their respective undergraduate medical education institution to provide the necessary support to ensure they are securing a residency position.

The Undergraduate Medical Education Institution

Similarly, to the medical students, the Match® process is nerve-wracking for medical schools that are trying to ensure they are succeeding in matching their fourth-year students. Medical education programs want to ensure the students who chose to enroll in their undergraduate medical program will be competent and have the skillset to successfully enter residency (Barber, Hammond, Gula, Tithecott, & Chahine, 2018). Because medical students invest a large amount of money and time into their undergraduate medical programs, many believe that the school owes them a career as a physician, which requires graduate medical education training (Bumsted et al., 2017). The debt repayment medical graduates had from their medical education averaged $161,290 in 2011 (Youngclaus, et al., 2013). A common assumption is that this debt plays a key role in determining specialty choice (Youngclaus, et al., 2013). However, based on the latest administered Graduation Questionnaire (GQ), student survey results showed that medical school graduates who note educational debt affecting their medical specialty has decreased over recent years (Graduation Questionnaire, 2018). Due to students wanting to ensure they obtain residency due to their large investment in training, medical schools are get asked about their Match® rates from potential applicants that are wanting to safeguard a smooth transition from undergraduate medical education to graduate medical education (Katsufrakis et al., 2016).

Along with the attentiveness to meet the students' and potential applicants' considerations, the undergraduate medical education institution also desires to have a successful Match® outcome to report to the accreditation body. The Liaison Committee on Medical Education (LCME) requires medical schools to report their success in the Match® as part of the intensive accreditation process. Accreditation aims to ensure that the quality of medical education is optimal for future patient care (Blouin & Tekian, 2018). Failure to be accredited or put on probation can cause significant issues for medical education programs. Medical school leaders desire to report that they are at or exceeding national Match® ratings to ensure that those students interested in attending their school will be reassured to hear that they are entering a successful matching undergraduate medical education while also addressing and meeting the elements within the LCME Standards.

The undergraduate medical education program is also responsible for providing the MSPE. It is important for the program to take accountability of providing accurate assessments of their graduates to residency programs (Sozener et al., 2016). If the program anticipates that a student is not ready for the residency Match®, they should catch this early through an accurate monitoring process and provide the scaffolds the student needs in order to be prepared. Some authors note that advising in undergraduate medical education needs to happen earlier with more precise and honest guidance provided to applicants regarding their qualifications and likelihood of matching (Arnold et al., 2018). There are many different perspectives leading up to and at the conclusion of the Match® process. Moreover, there are many factors that are of critical importance in determining residency applications, interviews and selections. Next, these factors that have not been previously discussed will be outlined which could be used by medical education stakeholders to predict Match® outcomes.

Other Factors

NBME.

Other NLEs taken by medical students during the undergraduate medical education process are the respective National Board of Medical Examiners (NBME) Clinical Subject (“shelf”) Examinations. These are objective, standardized exams designed to evaluate medical student performance on specific specialty content with comparison to the national level (NBME Subject Examination Guide, 2018). These examinations are developed and reviewed by content experts, similarly to the USMLE Step 1 and 2 exams (NBME Subject Examination Guide, 2018).

Oftentimes, medical education program clerkships use the NBME results as part of the student's final grade to determine their learning that occurred during that clerkship (Zahn et al., 2012). Additionally, program faculty report these examination results are valuable for decision-making to determine not only where the student needs improvement but where the program fits across the national scores to determine necessary clerkship modifications (Dong et al., 2014).

MCAT.

The Medical College Admission Test (MCAT) has been used for decisions to get into medical school since 1991 and recently underwent revisions with the new format being introduced in 2015 (Schwartzstein et al., 2013). The MCAT tests student understanding, related to concepts in the natural sciences as well as clinical reasoning (Kroopnick, 2013). The recent revisions in 2015 place more emphasis on the students' ability to recognize the important psychological and behavioral determinants of health for future patient care (George et al., 2016). Research has shown the MCAT can predict future success in medical school and ultimately form the physician future workforce (Schwartzstein et al., 2013); because of this, the MCAT may be useful for decision-making as it relates to student performance in medical training.

Internal exams.

Along with standardized exams such as USMLE and NBME exams, many institutions have their own internal assessments. These can be standardized patient or performance assessments which allow for evaluation of critical facets such as communication and interpersonal skills that cannot be measured using a multiple-choice or written exam (Cuddy et al., 2016). One issue with using internal exams is not all of these assessments are psychometrically-sound which may lead to issues when trying to make inferences or judgments based on the results. This may be due to problems such as latent variables, measurement design, or case specificity (Schauber, Hecht, & Nouns, 2017). The concern is that some of these performance-based assessments require human raters in real-world settings and there are critical steps that must occur such as rater training, test piloting and revisions that are often overlooked (Cuddy et al., 2016). Any time an instrument does not have validity or reliability evidence, the data yielded from them should be used with caution.

Membership in AOA.

Alpha Omega Alpha (AOA) status is consistently ranked as important in candidate selection for residency (Katsufrakis et al., 2016; Loh et al., 2013; Camp et al., 2016). AOA is designed to provide the top achieving portion of a graduating class (i.e., top one-sixth) as it relates to academic standing and other attributes associated with being successful in a career of medicine (i.e. professionalism, commitment to service, etc.) recognition (Tadisina et al., 2016). Membership in AOA was a strong predictor of a successful match in ophthalmology (Loh et al., 2013) and in plastic surgery programs (Tadisina et al., 2016; Sue & Narayan, 2013). Overall, research has shown that resident directors and programs value those medical students that are successful in achieving AOA status during undergraduate medical education (Sue & Narayan, 2013).

Nonacademic factors.

Along with test and other academic measures that are associated with each student, there are nonacademic factors that may be useful in understanding Match® outcomes. Research has shown that gender differences occur across various specialties (van de Horst, Siegrist, Orlow, & Giger, 2010). As previously mentioned, research has shown that females, underrepresented minorities, and those that grew up in areas with underserved populations are more likely to pursue careers in underserved population locations. Additionally, there is evidence that medical students who are more attentive and worrisome than others are more likely to enter person-oriented specialties and those that are more socially dominant are more likely to enter technique-oriented specialties (Taber, Hartung, & Borges, 2011). Another nonacademic factor that has been studied to better understand students' selection of residencies has been the amount of undergraduate medical education and total educational debt (Enoch et al., 2013). By using these nonacademic factors as well as the other previously mentioned academic factors, medical education stakeholders can implement logistic regression to predict the likelihood Match® outcomes. Now that NRMP perspectives and variables associated with medical education students have been provided, next resident specialties will be outlined including recent trends and how researchers define what is a competitive specialty and what is less competitive.

Specialties and Recent Trends

As previously mentioned, the NRMP releases reports that produces data showing test scores and other attributes for applicants that have successfully matched into specific specialties. The number of specialties has risen dramatically over the last twenty-five years. In the 1980s, there were only 51 specialties and subspecialties*,* whereas today there are three times that many (Jolly, Erikson, & Garrison, 2013). In the latest Match® full results published, the top five specialty tracks nationally were: internal medicine, pediatrics, emergency medicine, family medicine, and medicine-preliminary (Match® Results, 2019). As evident in research, there are patterns that reveal there are more competitive specialties compared to others based on test scores and other candidate qualities (Gauer & Jackson, 2017). Additionally, there are patterns of applicant to position ratios presented each year by the NRMP which can indicate the competitiveness of certain specialties (Match® Results, 2019).

In one study published in 2015, the researchers determined that specialty competitiveness should be measured by examining the position per U.S. applicant ratio. The most competitive specialties cited by the authors were: plastic surgery, urology, orthopedic surgery, otolaryngology, neurological surgery, radiation oncology, and dermatology; these researchers determined competitiveness using positions per U.S applicant provided by the NRMP (Chen & Heller, 2014). The Match® results full report from 2017 shows that the most competitive specialties determined this way would be: dermatology, internal medicine/ emergency medicine, adult and child psychiatry, neurological surgery, interventional radiology, orthopedic surgery, physical medicine and rehabilitation, plastic surgery, surgery-general, thoracic surgery, and vascular surgery (Match® Results, 2017).

Other researchers have defined the most competitive specialties as those that fill over 81% of the available positions. In this study, orthopedic surgery, plastic surgery, and otolaryngology had more than 90% of their positions filled which would indicate they were the most competitive (Green, Jones, & Thomas Jr., 2009). In the 2017 Match®

results, the following specialties had filled more than 90% of their positions: dermatology, neurodevelopmental disabilities, orthopedic surgery, otolaryngology, plastic surgery, and radiation oncology (Match® Results, 2017).

Another way to determine competitiveness would be to look at scores for national licensing examinations. Some researchers have deemed competitive specialties are those in which Step 1 scores are averaging greater than 240 (George, et. all, 2016). A review of the Charting Outcomes report shows those that matched into dermatology had the highest Step 1 scores in 2018 (Charting Outcomes, 2018). However, those students that did not match in dermatology still had very high scores on the Step 1; these scores are higher than those that did match in general surgery, which is consistently a very competitive specialty by numerous metrics.

Furthermore, there is research that shows trends of medical students wanting to enter into specialties to allow for more controllable lifestyles outside of primary care (Enoch, Chibnall, Schnidler, & Slavin, 2013). Specialties known as “ROAD” are popular among medical students as they offer a desirable work-life balance and consists of radiology, ophthalmology, anesthesiology, and dermatology; because of work life balance, these specialties are considered competitive by researchers (Chen & Heller, 2014).

It is important to understand that there are differing views in the literature to determine competitiveness as it relates to specialties. Some consider test score averages per specialty, others consider position per applicant, and others consider the percentage of filled positions after the Match®.

Additionally, it is important to note that some medical students may not want to enter certain specialties not because they are do not have necessary test scores or other needed metrics, but for different reasons such as a desire for a more controllable work-life balance or interest in a field that was deemed as less competitive. Medical education stakeholders need to not only understand the trends and specialties that their programs are preparing students for but also recognize the geographic location in which their students are accepting residencies which will be discussed next.

Residency location.

As previously stated in Chapter I, there is a major concern about physician shortage areas. Research has established that students with higher examination scores are more likely to leave the state for residency (Gauer & Jackson, 2017; Loh, Joseph, Keenan, Lietman, & Naseri, 2013). Therefore, if the program is in a state with shortage areas and are wanting to ensure students are matching there, it is imperative to understand these findings in research as well as determine what other factors may help understand why the student is exiting the state. Results of two separate studies that used the American Association of Medical Colleges (AAMC) Graduation Questionnaire (GQ) for analysis, which is a nationwide survey administered to fourth-year medical students ending their undergraduate medical education, revealed that women and those who identified as underrepresented minorities were more likely to enter occupations with underserved populations (Garcia, Kuo, Arangua, & Perez-Stable, 2018; Boscardin et al., 2014).

In a separate national survey, those that were raised in medically underserved locations were more likely to work in an underserved population once training was completed (O'Connell et al., 2018). By having a robust understanding of where their graduates are ending up, medical education programs can consider which students to recruit into their institution. Therefore, if it is part of their mission, the programs can produce physicians likely to become employed in the state. Furthermore, as the students are progressing in the undergraduate medical education program, the program can offer the guidance needed in the Match® process as it relates to geographic regions. Answers to how to better understand some of these concerns are provided in Chapters IV and V of this study. Now that research has been delineated in Chapter II including details on the NRMP, perspectives of the stakeholders involved in the matching process, specialty trends, and matching locations, it is important to understand what details are missing in the review of the literature and how this study aims to alleviate these gaps.

Literature Omission

The literature provides important data and research outcomes that show the significance of adequately preparing for the NRMP. The research shows there are trends and associations between matching outcomes and factors associated with matching into certain specialties; however, there is no clear study that uses logistic regression to determine the matching outcomes using a variety of variables to determine which factors are associated with matching successfully, matching into a competitive specialty, or matching into the state of the institution.

By employing logistic regression, models can be examined by other institutions to see which factors are associated with these outcomes of interest. If they have a physician shortage in their state, they may be interested in developing something to predict which students will stay in the state; if they are simply worried about matching successfully at all, perhaps there is something during admissions into undergraduate medical education that is significantly associated with poorly matching that would help screen out these applicants.

Finally, all medical schools should want to know how to properly advise students as they prepare for the Match®. By knowing that a student is less likely to match into a competitive specialty based on academic factors from admissions or during their time in undergraduate medical education, advising can occur to ensure how to navigate this process through the usage of research-based methods.

Summary

In Chapters I and II, the NRMP process was outlined and the many facets that are associated with matching and the stakeholders involved was discussed. This included the perspectives from the residency director, the medical student, and the undergraduate medical education program. This also included the USMLE examinations, the MSPE, and other metrics used for residency decision-making. Additionally, residency specialties were outlined, including the varying ways in which researchers have determined competitiveness, were covered to show trends in recent cycles. The importance of knowing geographic location was provided to show why this make be an important area to be examined in this work. Finally, what is missing in literature was provided to outline how this work hopes to address these gaps.

Now that these have been discussed, Chapter III will focus on the methods that were used to better understand the outcomes of interest for this study, which are matching successfully, matching into a competitive specialty, matching into the state of Kentucky, matching into primary care, and matching into primary care in the state of Kentucky. This chapter will outline the methodological approach to this study which was a quantitative research design, the sample selection will be discussed, and the data collection and analyses procedures will be provided.

CHAPTER III

METHODS

This study was a quantitative research design using a set of variables to predict binary outcomes. Due to a combination of continuous and categorical variables as predictors and dichotomous variable as outcomes, logistic regression modeling was implemented as oppose to traditional linear regression. Problems with using traditional regression analysis for these types of research questions include a) predicted probabilities may assume negative values or exceed one b) distributional assumptions may not hold in the procedure and/or c) there is an assumed linear function between the two variables which may not hold true (Pituch & Stevens, 2016; Osbourne, 2017; Royston & Altman, 2010).

Logistic regression can be used with a dichotomous outcome variable and a mix of predictor variables with minimal assumptions (Pituch & Stevens, 2016). Logistic regression is often implemented in prognostic studies with binary outcomes to determine or quantify the risk of a future event (e.g., death, cured) (Royston & Altman, 2010). When using binary logistic regression, researchers are interested in determining if a set of variables can predict whether or not an outcome will occur; ultimately finding the best model and understanding the unique effects of each variable while controlling for others is the goal (Osbourne, 2017).

A logistic regression model yields a weighted combination of the variables to determine prediction (Royston & Altman, 2010). A critical difference between logistic regression and standard regression is the odds ratio yielded in logistic regression, which essentially is the odds that the event/outcome will occur (Pituch & Stevens 2016). Logistic regression models have been used to quantify the magnitude of the variables of interest predicting outcomes in medical education research (Dong et al., 2014). Binary logistic regression is often used in other settings such as academia to better identify and monitor students that are of higher risk to achieving a certain outcome to provide scaffolds to help aid their growth in learning (Barber et al., 2018). These models allow for medical school leaders to make informed decisions not only at admissions but during medical school (Barber et al., 2018).

By using logistic regression, medical education institutions can better understand, for each medical student, the odds that they will a) match successfully, b) match into a competitive specialty, c) match into an in-state residency, d) match into primary care, and e) match into primary care in the state of Kentucky. It is because of these reasons that logistic regression was implemented in this study as opposed to traditional regression. Medical education leaders can use the information derived from logistic regression models to better understand match outcomes. By understanding which variables affect outcomes, stakeholders in medical education can monitor progress that are the highest predictors of match outcomes to better prepare students for the residency application process. This chapter will provide information related to the sample of this study, will define competitiveness for this study, discuss and define each of the predictor and outcome variables, provide data on the outcome variables, provide an overview of logistic regression and its usage, and provide information regarding how the data was analyzed.

Sample

The University of Louisville School of Medicine's Undergraduate Medical Education program consists of two years of basic sciences coursework and two years of clinical experiences. The sample for this study was six classes from the University of Louisville's School of Medicine that participated in the Match® process. This study includes all that matched and those that did not match (entire population). The number of medical students that took part in the Match® process in the last seven years is 896; however, two students were removed from analysis as they had incomplete data due to not completing key variables at the time of data analysis which occurred in May 2019. This brings the sample size to 894 for which the researcher collected all variables for all individuals with no missing data for a complete dataset. Below are the specialties that students from the University of Louisville School of Medicine have matched into over the last six years:

- Anesthesiology
- Child Neurology
- Dermatology
- Emergency Medicine
- Family Medicine
- General Surgery
- General Surgery Preliminary
- Internal Medicine
- Interventional Radiology
- Medicine-Preliminary

- Medicine/Emergency Medicine
- Medicine/Pediatrics
- Neurological Surgery
- Neurology
- Obstetrics and Gynecology
- Ob/Gyn Preliminary
- Ophthalmology
- Orthopedic Surgery
- Otolaryngology
- Pathology
- Pediatrics
- Pediatrics/Emergency Medicine
- Pediatrics/Psychiatry / Child Psychiatry
- Physical Medicine & Rehab
- Plastic Surgery
- Psychiatry
- Radiation Oncology
- Radiology-Diagnostic
- Transitional Year
- Urology

Now that the sample of this study has been provided, the definition of competitive specialty for this study will be outlined.

Defining Competitive Specialty

As previously discussed in Chapter II, there are multiple ways to determine if a specialty is competitive. Based on the review of literature, this study will define a specialty by the criteria below.

> *Competitive Specialty – For the last six years (2014-2019), the ratio of the positions per U.S. Senior is less than 1.3 for the specialty in the majority of the six years.*

This criterion was chosen based on the review of literature and an examination of data from the NRMP. Figure 4 shows the competitiveness of all specialties over the last six years as defined by the ratio of position per applicant. These data came from six reports made available by the NRMP and compiled into one visual representation, below by the author of this study.

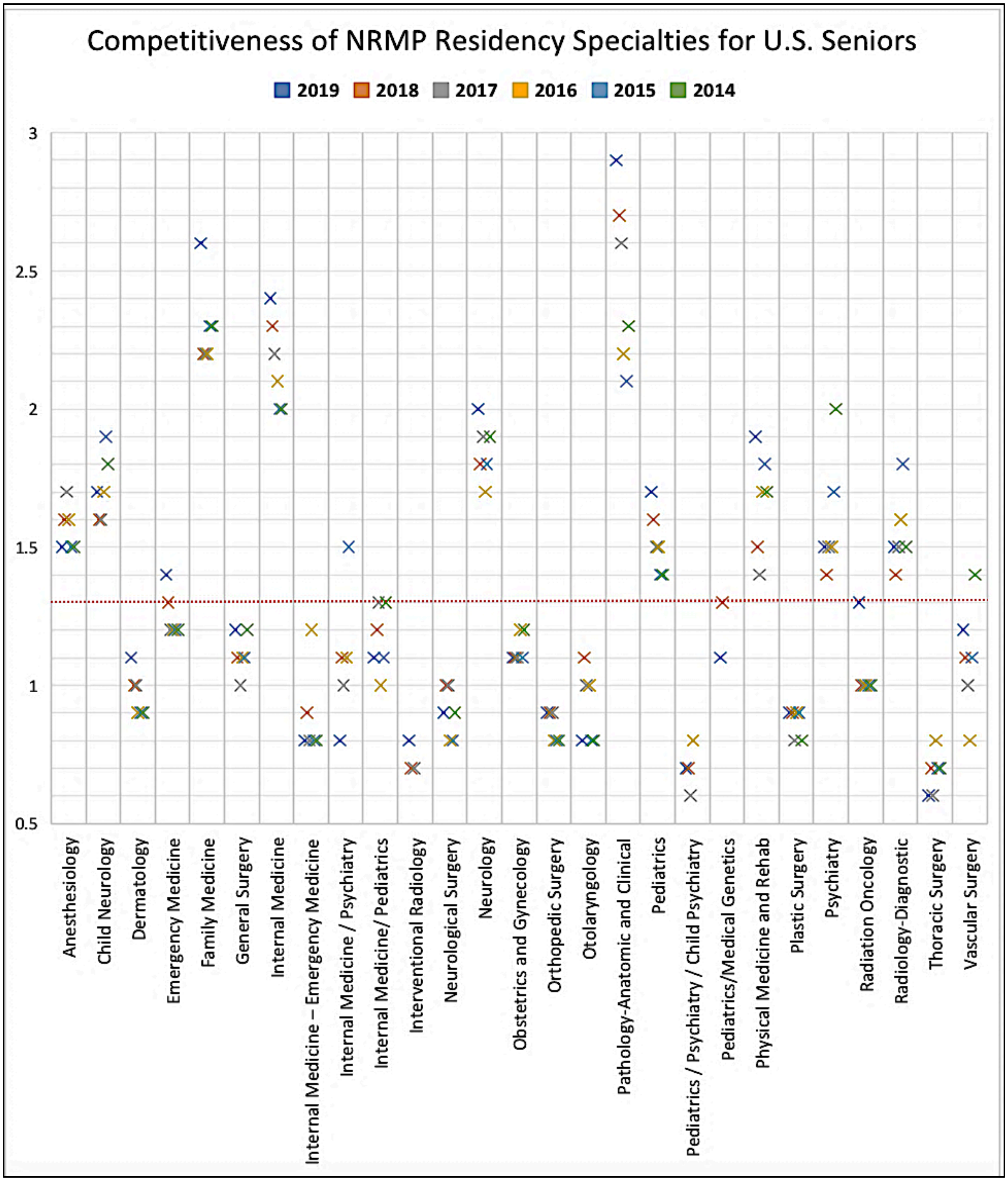

Figure 4. Competitiveness of all Match specialties 2014-2019. Created by Author of this study. Data from NRMP. Red Dotted Line = Ratio of 1.3.

Based on the criterion above and the Match® reports from 2014-2019, the following specialties are competitive for U.S. students in the residency match process:

Table 1

Competitive Specialties Based on Positions Per U.S. Student

Specialty	Position Per U.S. Senior					
	2019	2018	2017	2016	2015	2014
Dermatology	1.1	1.0	1.0	0.9	0.9	0.9
Emergency Medicine	1.4	1.3	1.2	1.2	1.2	1.2
Medicine – Emergency Medicine	0.8	0.9	0.8	1.2	0.8	0.8
General Surgery	1.2	1.1	1	1.1	1.1	1.2
Internal Medicine / Pediatrics	1.1	1.2	1.3	1	1.1	1.3
Internal Medicine / Psychiatry	0.8	1.1	1	1.1	1.5	-
Interventional Radiology	0.8	0.7	0.7	-	-	-
Neurological Surgery	0.9	1	1	0.8	0.8	0.9
Obstetrics and Gynecology	1.1	1.1	1.1	1.2	1.1	1.2
Orthopedic Surgery	0.9	0.9	0.9	0.8	0.8	0.8
Otolaryngology	0.8	1.1	1	1	0.8	0.8
Pediatrics – Medical Genetics	1.1	1.3	-	-	-	-
Pediatrics / Psychiatry / Child Psychiatry	0.7	0.7	0.6	0.8	-	-
Plastic Surgery	0.9	0.9	0.8	0.9	0.9	0.8
Radiation Oncology	1.3	1	1	1	1	1
Thoracic Surgery	0.6	0.7	0.6	0.8	0.7	0.7
Vascular Surgery	1.2	1.1	1	0.8	1.1	1.4

Note. Table includes data from documentation made available by NRMP from 2014-2019.

Additionally, for this study, ophthalmology and urology were also deemed competitive for this study. Both of these specialties do not take place during the NRMP process and a part of the "early match" process. However, both of these specialties have been determined to be competitive in the literature and will be included even though there are no data from the NRMP regarding the ratio of residency position per U.S. Senior (Chen and Heller, 2014; Prober, et al., 2016; Nikonow, et al., 2015; Loh, et al., 2013). This means the specialties outlined in Table 2 below are deemed less competitive based on these criteria.

Table 2

Less Competitive Specialties Based on Position Per U.S. Student

Specialty	2019 Position Per U.S. Senior
Anesthesiology	1.5
Child Neurology	1.7
Family Medicine	2.6
Internal Medicine	2.4
Neurology	2
Pathology - Anatomic and Clinical	2.9
Pediatrics	1.7
Physical Medicine and Rehab	1.9

Psychiatry	1.5
Radiology - Diagnostic	1.5

Note. Table includes data from documentation made available by NRMP from 2014-2019.

It is important to recognize preliminary positions that are noted in the NRMP reports. These positions are less competitive as they are not the same as matching directly into the specialty. These are one-year positions that will hopefully lead to further training in the same field or a different field but require additional training prior matching directly into this specialty. Now that the definition of competitive specialty for this study has been provided, the variables of this study will be defined.

Predictor Variables

This study aimed to better understand which variables predict residency matching outcomes. The variables outlined in Table 3 will be used to determine which set of variables best predict the five outcomes of interest in this study.

Table 3

Predictor Variables in Model

Predictor Variable	Definition
Gender	Gender reported by institution (1 = female, 2 = male)
Age	The age of the student at admissions (range = 19-52)
Parent	Whether or not the student was a parent at the time of admissions (1 = non-parent, 2 = parent)
Disadvantaged	Whether or not the student was noted as having a disadvantaged background at admissions (1 = no, 2 = yes)

MCAT VR	The results on the Verbal Reasoning portion of the Medical College Admissions Test (MCAT). Score provided to admissions during medical school application process (range = 6-15)
MCAT PS	The results on the Physical Sciences portion of the Medical College Admissions Test (MCAT). Score provided to admissions during medical school application process (range = 5-14)
MCAT BS	The results on the Biological Sciences portion of the Medical College Admissions Test (MCAT). Score provided to admissions during medical school application process (range = 6-15)
MCAT	The results of the MCAT. Score provided to admissions during medical school application process (range = 6.7-13.3)
GPA at Admission	The student's cumulative grade point average (GPA) from last enrollment in college or university. Entered as a scale variable (range = 2.18-4.0)
BCPM GPA at Admission	This is the biology, chemistry, physics and mathematics portion of the GPA (range = 1.88-4.0)
AO GPA At Admission	This is the remaining portion of the GPA after the BCPM portion has been removed (range = 2.34-4.0)
BCPM Hours	The number of hours the student had taken in biology, chemistry, physics and mathematics (range = 260-1,560)
AO Hours	The number of hours the student had taken in areas outside of BCPM (range = 110-2,140)
UofL Graduate	Whether or not student earned a degree at UofL prior to medical school (1= yes, 0= no)
In-state at Admission	Whether or not student was from the state of Kentucky or not at the time of admissions (1= yes, 0= no)
Step 1 score	A national examination that students take at the end of their second year of medical school (range = 154-271)
Family Medicine Shelf Examination Score	A national examination that third year students take at the end of the family medicine clerkship (range = 52-98)

Internal Medicine Shelf Examination Score	A national examination that third year students take at the end of the internal medicine clerkship (range = 52-99)
Neurology Shelf Examination Score	A national examination that third year students take at the end of the neurology clerkship (range = 50-94)
OB-GYN Shelf Examination Score	A national examination that third year students take at the end of the OB-GYN clerkship (range = 53-99)
Pediatrics Shelf Examination Clerkship Score	A national examination that third year students take at the end of the pediatrics clerkship (range = 47-99)
Psychiatry Shelf Examination Score	A national examination that third year students take at the end of the psychiatry clerkship (range = 58-99)
Surgery Shelf Examination Score	A national examination that third year students take at the end of the surgery clerkship (range = 48-99)
Step 2 CK Score	A national examination that is taken at the beginning of students fourth year (range = 186-278)
Step 2 CS	A pass/fail examination that is taken at the beginning of students fourth year. In order to pass Step 2 CS, students must pass the three subcomponents: Integrated Clinical Encounter (ICE), Communication & Interpersonal Skills (CIS), and Spoken English Proficiency (SEP) (1 = pass, 2 = fail)
AOA Membership	Alpha Omega Alpha (AOA) is designed to give the top achieving portion (one-sixth) of a graduating class as it relates to academic standing and other attributes associated with being successful in a career of medicine (i.e. professionalism, commitment to service, etc.) recognition (Tadisina et al., 2016) (1= non-member, 2 = member)
Gold Humanism Membership	This is an additional honor society in which members from the UofL School of Medicine are elected to (1= non-member, 2 = member)

Dependent Variables

The variables found in Table 4 are the outcomes of interest of this study, or dependent variables.

Table 4

Outcome Variables in Model

Outcome Variable	Definition
Match Successfully (Y/N)	This means that the student has obtained a residency position during the Match® process (1=Yes, 0=No)
Match into state of Kentucky	Those students matched into a residency position in the state of Kentucky (1=Yes, 0=No)
Match into Competitive Specialty	Those students matched into a competitive specialty (defined later) (1=Yes, 0=No)
Match into Primary Care	The student has matched into primary care (1=Yes, 0=No)
Match into Primary Care in the State of Kentucky	Those students matched into primary care in the state of Kentucky (1=Yes, 0=No)

To better understand matching successfully, the match rate for University of Louisville (UofL) students is provided in Figure 5. This figure shows that in 2014 the match rate was 97% whereas in 2019 the match rate was 95.9% with years 2015-2018 between being below 95%. Historically, the match rates fall between 92-95% according to the NRMP (Match Results, 2018).

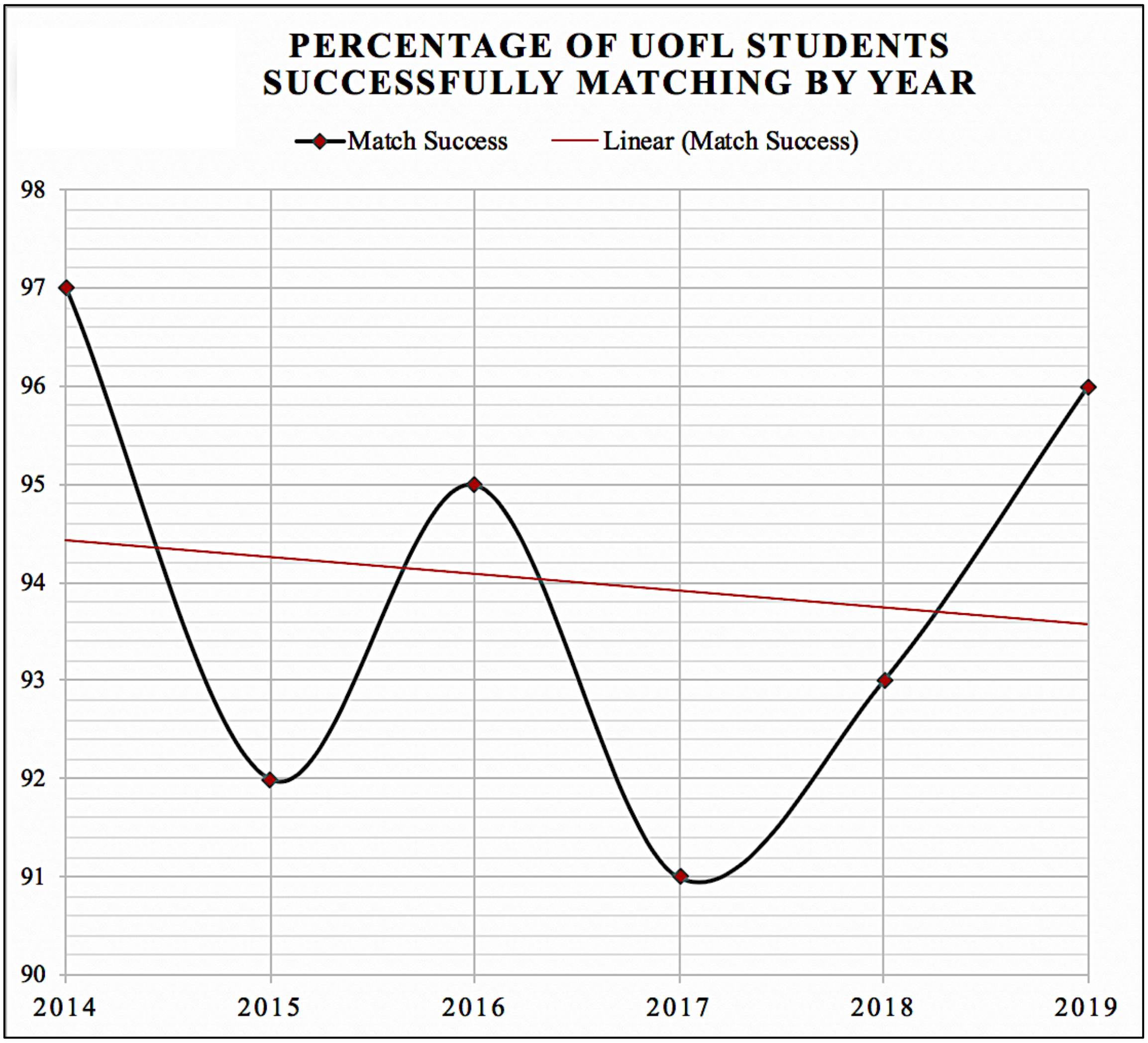

Figure 5. Matching Success for UofL Students from 2014-2019.

It should be noted that this is a slightly negative trend. This is likely due to the aforementioned increase in residency applications. The national match rate is typically around 94%. To further explore the distribution of outcome variables, each matching outcome is provided with frequencies and percentages in Figures 6-10 below.

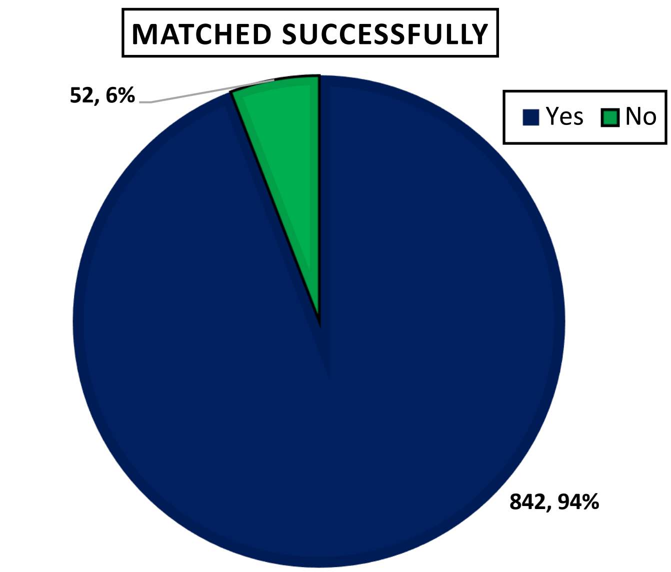

Figure 6. Percentage of Study Participants Matching Successfully

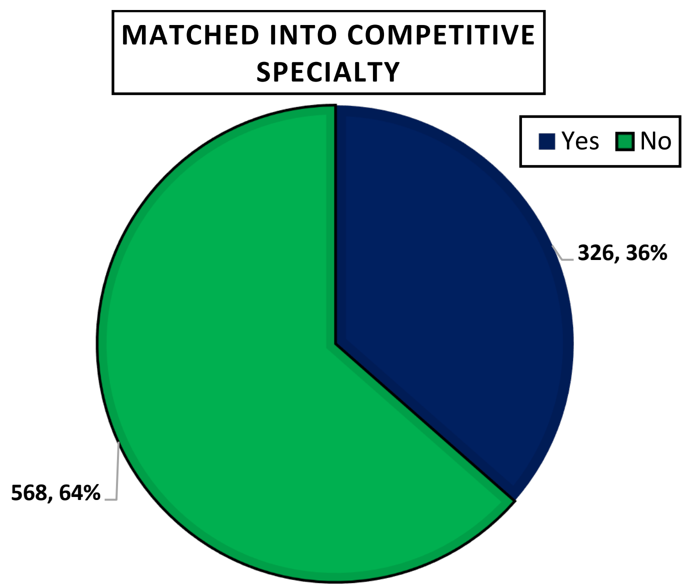

Figure 7. Percentage of Study Participants Matching into Competitive Specialty

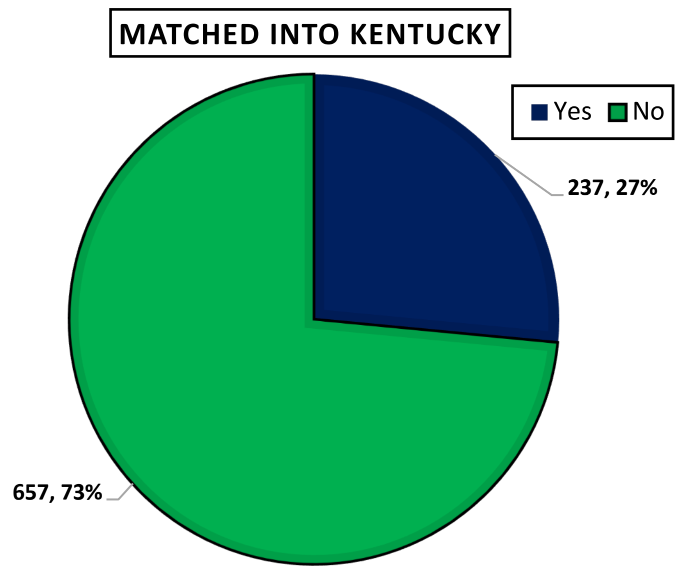

Figure 8. Percentage of Study Participants Matching into Kentucky

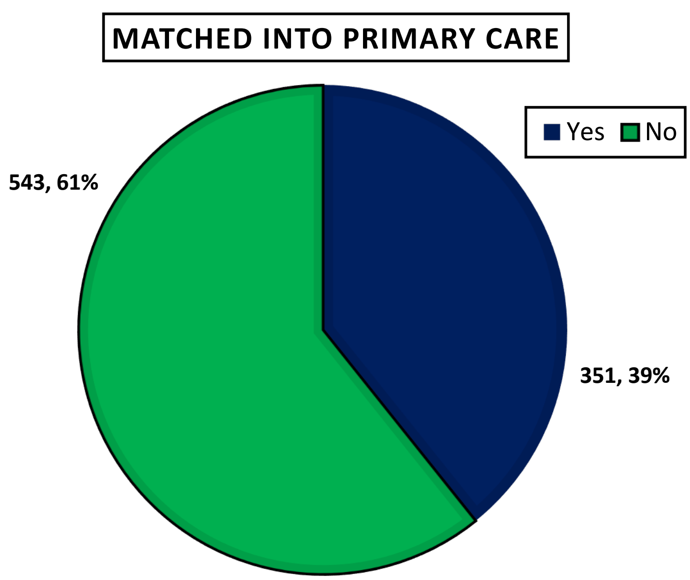

Figure 9. Percentage of Study Participants Matching into Primary Care

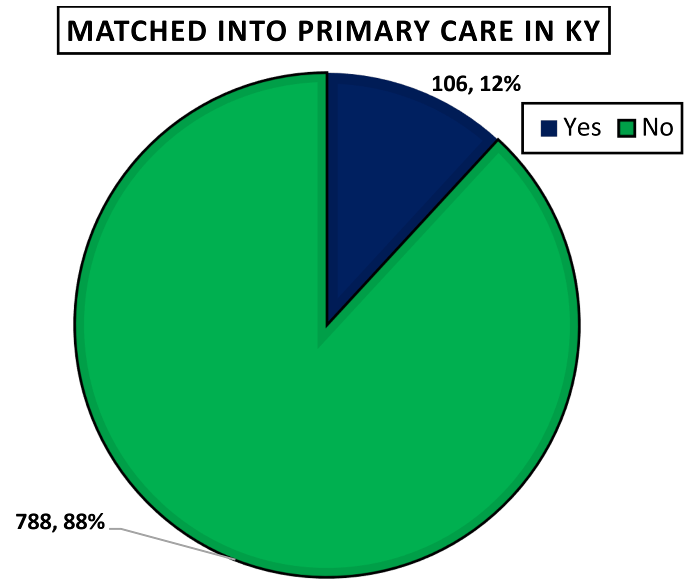

Figure 10. Percentage of Participants that Matched into Primary Care in Kentucky

Logistic Regression

The researcher used logistic regression to answer the research questions. Similar to linear regression, logistic regression uses a set of variables included in a model to better assess the likelihood of a scenario occurring. As previously stated, the major difference between linear (standard) regression and logistic regression is the usage of a binary outcome in logistic regression. Whether this be in clinical trials (e.g., infected/not infected) or higher education (e.g., enrolled, not enrolled), this statistical method is implemented to better understand how different facets affect outcomes of interest; for this study, residency matching outcomes were the interest. The author is using a combination of facets or factors (predictor variables) to determine which combination or set can be used to predict matching outcomes.

Linear Regression Analysis Issues with Binary Outcomes

As previously mentioned, logistic regression will be used to answer the five research questions of this study instead of traditional linear regression as there are several issues with its usage with binary outcomes. Firstly, in linear regression, predicted values can be negative values or exceed 1 which would be invalid; while this does not happen with every data set, it can happen. This means that the closer a value gets to 1, the more likely it is to occur and if that value exceeds 1 it is not interpretable. Second, assumptions of adequate distributions are not upheld using linear regression. This means that each of the predictor variables within this study do not have to be normally distributed, have equal variance within each group, or be linearly related. A third issue with traditional regression would be that, with dichotomous variables, probabilities may not establish valid patterns. The patterns may show that probabilities may change very little at the most extreme values (minimum/maximum) but change extensively with the values closer to the middle of the distribution. These issues can be addressed with logistic regression (Pituch & Stevens, 2016).

Probability and Odds

Probability and odds are two ways to examine binary outcomes. A basic example of this would be to consider a case. There are 200 students in a graduating medical school class. Sixty of these students obtain positions in top 25 residency programs across the nation. Therefore, we can take 60/200 which equals .30. This result (.30) is the probability of a student from this medical class obtaining a position at a top 25 residency program. Probabilities range from 0 to 1; 0 indicating very unlikely to occur and 1 indicating very likely to occur. Using this probability (.30), we can calculate odds as they can be determined by the following equation:

$$Odds\ (Y = 1) = \frac{P(Y = 1)}{1 - P\ (Y = 1)}$$

Both probability and odds can be valuable. Pituch and Stevens (2016) note that odds provide researchers the opportunity to make multiplicative comparisons whereas probability values cannot exceed one so they are limited in that sense; however, because probabilities and odds can be transformed to one another, they are both useful for interpretations in logistic regression. To take odds one step further, we can determine odds ratio which is very valuable in logistic regression and can be used for decision-making as it relates to determining the relative risk or odds for a situation to occur. The odds ratio is the slope in changes from one group to another (Osbourne, 2017). The equation for odds ratio is:

$$Odds\ ratio = Odds \frac{Odds\ (Outcome\ 1)}{Odds\ (Outcome2\ )}$$

To determine how to interpret odds ratio one should consider these rules:

OR = 1 means the odds of the event to occur are the same for both groups

OR > 1 when the probability exceeds .5 which means more likely to occur

OR < 1 when probability is less than .5 which means less likely to occur

Probabilities, odds and odds ratio are all valuable in logistic regression. Additionally, the logit is a central focus on this method.

Logit

The logit is a critical component of logistic regression. Logistic regression computes logits for each individual in a group and logit serves as the dependent variable or outcome variable of the study. These results show the probability of an outcome occurring. It should be noted that natural log of the odds, log of the odds and the logits are all the same; these are interchangeable terms (Pituch & Stevens, 2016). The logit effectively eliminates the lower bound limits that odds have and can produce values that show a normal distribution to determine a more accurate depiction of probability of an event to occur. (Pituch & Stevens, 2016). This figure is the logit of a number *p* between 0 and 1 given by the following formula:

$$logit\ (p) = \ln\ (\frac{p}{1 - p})$$

This value is a central piece of logistic regression and can be transformed into the odds which can then be transformed into probability as previously mentioned to decision-making. When implementing logistic regression, the logit serves as the first part of the logistic regression equation.

Logistic Regression Equation

A logistic regression model provides a prediction based on a weighted combination of the predictor variables. Keeping this context in mind, users of this statistical method are aiming to better understand whether an outcome of interest will occur or not. For this study, the outcomes of interests are matching outcomes. There are multiple predictor variables taken at admission and during the undergraduate medical education program. This work attempted to better understand these predictors effect on dichotomous or binary outcomes. For example, one research question of this study is to understand whether or not students will match into the state of Kentucky (yes/no). The (yes/no) is the binary outcome (Royston & Altman, 2010). The equation below is the logistic regression equation, which is further explained in Table 5.

$$\ln(odds\ Y = 1) = \beta\ +\ B_1X_1\ +\ B_2X_2\ +\ B_3X_3\ \ldots B_kX_k$$

Table 5

Logistic Regression Equation Explained

Portion of Equation	Explanation
$\ln(odds\ Y = 1)$	This is the outcome. This is the logit, the natural log of odds, the log of the odds. This value serves as the dependent variable.
β	This is the regression coefficient. This indicates the amount of change in logit for one-unit change in each predictor.
B	This is the coefficient of the predictor variable. This show the relationship between the predictor and the odds of event occurring. As B increases = Odds Decrease As B decreases = Odds Increase
X	This represents the predictor variables of the study
X_k	This represents the last predictor variable of the equation

Note. Created by Author based on information from Stevens & Pituch, 2016; and class notes from PHST 640 and ELFH 703).

Assumptions of Logistic Regression

There are some assumptions that must be met when using logistic regression. First, the outcome must be discrete. This means that it must be a dichotomous outcome (yes/no; infectious/not infectious). This was not an issue with this study, as all outcome variables were discrete. Next, there must be linearity in the logit. This means that the logistic regression equation should have a linear relationship with the logit form of the outcome variables; essentially irrelevant predictor variables will be thrown out and all possible important predictors in the equation should be included to determine the correct specifications. This will be provided in the results section of this study.

A third assumption that must be met is the absence of multi-collinearity. This means that each variable but must independent from one another. For each of these models there were no issues with multicollinearity which will be discussed with values in Chapter IV showing VIF and tolerance values. While SPSS does not allow collinearity assessment techniques to be used in logistic regression, these values can be obtained using the linear regression option to determine multicollinearity issues which was completed during data analysis.

Another assumption that must be met is that there should be no outliers that influence the model. This means that cases needed to be examined using case summaries and residuals in SPSS to determine if there are outliers affecting the model. There were no outliers that affected the model to be removed from analysis. Finally, the assumption of independence of errors should be met. This means that all predictors should have strong reliability. This was the case for each of the continuous and categorical variables in this study. Along with the assumptions that were met prior to the logistic regression models being developed, additional data screening occurred.

Additional Data Screening Required

As with all analyses, it is important to employ data screening techniques to assess the model. There are a variety of measures that look at overall fit of the model. An important test that was included to examine this was the chi-square test. With the chi-square test, users of logistic regression want this to be significant. A significant value demonstrates there are differences in the probability of an outcome occurring based on the independent variables.

Another important logistic regression screening tool is the usage of the -2log likelihood statistic which informs researchers of the measure of lack of fit or error variation that is in the model. In logistic regression, the smaller this value gets, the better it fits; ultimately it examines the amount of unexplained variance (Pituch & Stevens, 2016). Additionally, as variables are added to the model, this value can be examined to determine if the model is showing better fit. Another test that measures model fit, which is often used in logistic regression with continuous variables is the Hosmer and Lemshow Test for Model Fit. This test looks at the same thing as the chi-square test (differences in predicted probabilities from observed) and researchers would want this result to be non-significant (Osbourne, 2017). These data screening techniques were employed, and results will be provided in Chapter IV. With logistic regression analyses, there are different types of entry method options in SPSS. The author of this work will next provide details as to which was implemented.

Type of Regression: Simple Entry or Stepwise

Due to this study being exploratory and not confirmatory, no hypotheses will be provided as it relates to what best predicts matching outcomes. If many of these variables had been explored before then variables would be entered in the model in blocks using simple entry. However, because many of these variables in this study have not been examined using logistic regression before and some of these outcomes have not been studied previously, variables were entered using stepwise techniques. The variables that were entered in stepwise methods can be found in Figure 11 below with the predictor variables on the left side of the figure and the matching outcome variables on the right side of the figure.

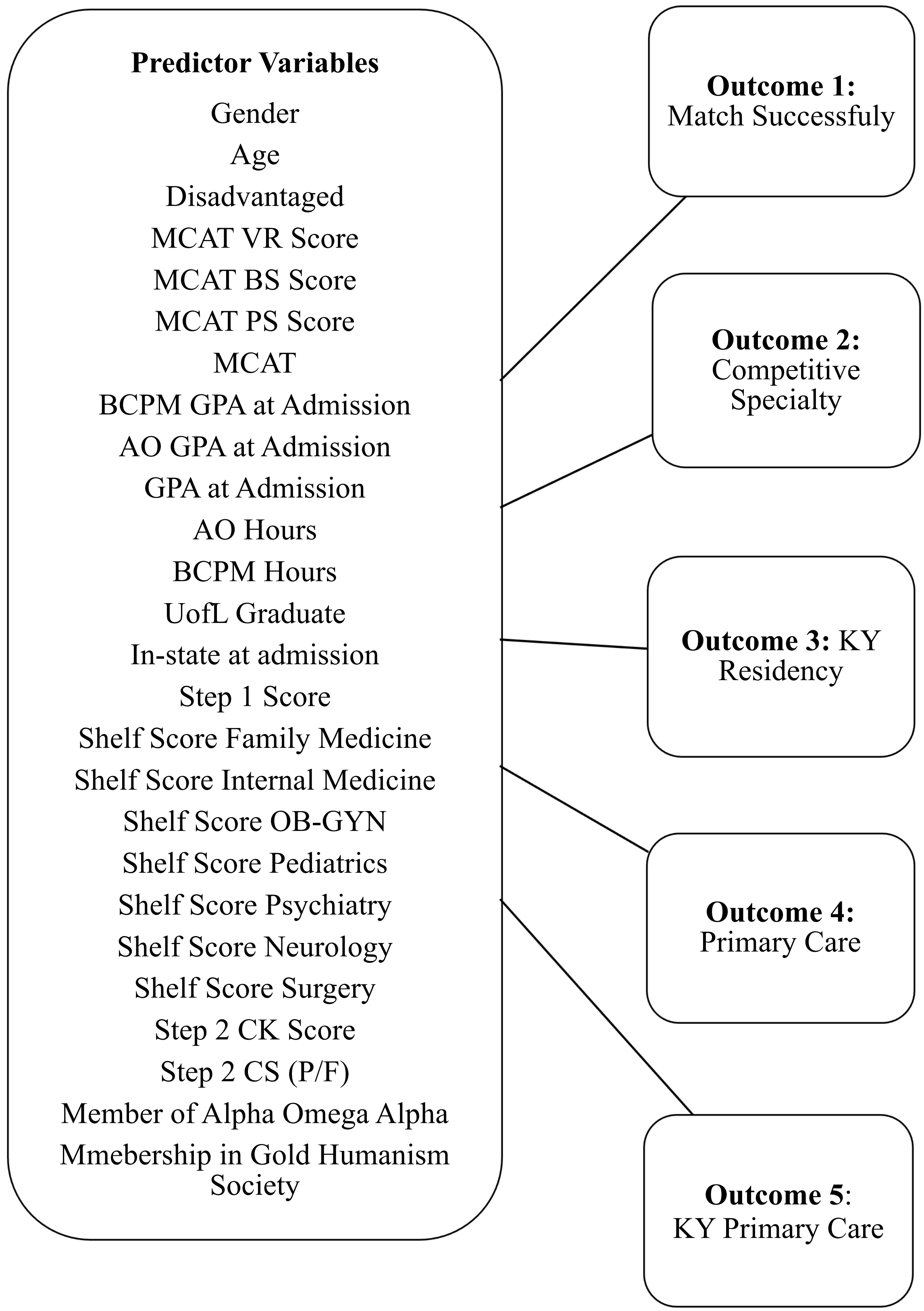

Figure 11. All Variables in Study

Data Collection Procedures

The researcher of this study works for the School of Medicine at the University of Louisville. Because of this, the researcher has access to the data sources previously mentioned for all six classes included in this study. These data were in separate databases (internal spreadsheets, national databases, etc.) The researcher compiled all data into one file and stored the file in a university secured (password protected) drive called CardBox. The researcher ran separate logistic regressions, two-group multivariate analysis of variance (MANOVA), analysis of variance (ANOVA) and chi-square analyses using SPSS software to answer the five research questions of this study. The researcher obtained necessary Institutional Review Board (IRB) approval before data analyses for each of the five research questions occurred. The research questions are outlined below.

Research Questions

RQ_1: Which factors taken at admissions and during the undergraduate medical education program for students at the University of Louisville School of Medicine best predict whether or not a student will match successfully or not?

RQ_2: Which factors taken at admissions and during the undergraduate medical education program best predict whether or not a student will match into a competitive specialty?

RQ_3: Which factors taken at admissions and during the undergraduate medical education program best predict whether or not a student will match into an in-state residency program?

RQ_4: Which factors taken at admissions and during the undergraduate medical education program best predict whether or not a student will match into primary care?

RQ_5*:* Which factors taken at admissions and during the undergraduate medical education program best predict whether or not a student will match into primary care in the state of Kentucky?

All five of these questions were answered using logistic regression. Statistical models determined which factors best predict each of the five residency matching outcomes. Additionally, variables were examined using MANOVA and chi-square tests to provide more information to consumers of this research.

Data Analysis Procedures

Using SPSS software, the researcher determined the predicted probability for each of the five research outcomes. First, it was important to conduct an initial screening of the data to determine the appropriate use of logistic regression for the five research questions; this included the conduction of univariate and bivariate screening and multicollinearity detection tests before deciding if there were any issues with the usage of logistic regression.

Next, residuals, Cook's distance values, and sensitivity analysis were examined to identify if any observations from the 894 cases that poorly fit the model. Then, the logistic regression analysis was conducted to test the associations of the entire set of predictor variables with the outcome variables to determine the strength of association for the entire model. Ultimately all of these data were used for contemplation to determine which variables can be used to best predict outcomes related to the Match®. Now that the sample of this study, the definition of competitive specialty, details on the variables within this study, an overview of logistic regression, and data collection/analyses procedures have been specified, results will be outlined in Chapter IV for each of the five research questions.

CHAPTER IV

RESULTS

Stepwise regression methods were employed to better understand which combination of variables could predict matching outcomes. The matching outcomes served as the dichotomous variables within each of the five research questions which included:

RQ_1: Which factors taken at admissions and during the undergraduate medical education program for students at the University of Louisville School of Medicine best predict whether or not a student will match successfully or not?

RQ_2: Which factors taken at admissions and during the undergraduate medical education program best predict whether or not a student will match into a competitive specialty?

RQ_3: Which factors taken at admissions and during the undergraduate medical education program best predict whether or not a student will match into an in-state residency program?

RQ_4: Which factors taken at admissions and during the undergraduate medical education program best predict whether or not a student will match into primary care?

RQ_5: Which factors taken at admissions and during the undergraduate medical education program best predict whether or not a student will match into primary care in the state of Kentucky?

For the purposes of standardization of variables as well as interpretation of outputs, all continuous variables were converted to z-scores prior to analysis. By using z-scores, it allowed for better interpretation of SPSS outputs as well as the values of odds for drawing inferences based on the findings. For each of the five research questions, results were broken down with goodness of fit and -2 likelihood statistics. These statistics provide information to determine if the model improves with the addition of new predictor variables. Additionally, a logistic regression model is provided for each research question which outlines which of the many variables associated with admissions and the undergraduate medical education program could be used to predict each of the five matching outcomes of interest.

Additionally, further data analysis procedures including multivariate analysis of variance (MANOVA), analysis of variance (ANOVA) and chi-square analysis were conducted to provide additional information to readers of this study; if there was an association, statistical significance was provided. A predictor variable may be significant in a logistic regression model but not using other methodological options.

For example, a regression model may show, when controlling for all variables in the model, that an increase on *exam score A* shows there that the outcome is less likely to occur. Some may interpret this as a direct relationship with the two variables; however, when examining that same variable, (*exam score A*), on its own using ANOVA and the outcome of interest, there may be an opposite effect showing as the exam score increases the odds of the outcome increase.

Ultimately, these additional statistical techniques were conducted to provide more information to medical education stakeholders and consumers of this research to better interpret practical significance of the findings for decision-making as it relates to admissions, the undergraduate medical education program, and the advising of medical students.

Chapter IV will first provide descriptive statistics for each of the categorical and continuous predictor variables as well as outcome variables. Then this chapter will provide results for each of the five research questions. To begin, it is important to understand the distribution of the predictor and outcome variables which can be found in tables 6, 7, and 8 below.

Table 6

Descriptive Statistics for Continuous Predictor Variables

Predictor	N	Mean	Min	Max	SD
Age	894	23.5	19	52	2.9
BCPM GPA	894	3.56	1.88	4.0	.33
CUM AO GPA	894	3.75	2.34	4.0	.26
CUM TOTAL GPA	894	3.64	2.18	4.0	.27
CUM BCPM HOURS	894	663	260	1560	173
CUM AO HOURS	894	567	110	2140	282
MCAT VR SCORE	894	9.8	6	15	1.5
MCAT PS SCORE	894	9.5	5	14	1.6
MCAT BS SCORE	894	10.1	6	15	1.3

MCAT SCORE	894	9.8	6.7	13.3	.9
STEP 1 SCORE	894	227	154	271	18.5
FAM MED SHELF	894	75	52	98	7.4
IM SHELF	894	76	52	99	8
NEUROLOGY SHELF	894	75	50	94	7.3
OB-GYN SHELF	894	77	53	99	8
PEDIATRICS SHELF	894	78	47	99	78
PSYCHIATRY SHELF	894	81	58	99	7.4
SURGERY SHELF	894	75	48	99	8.1
STEP 2 CK	894	241	186	278	15.8

Table 7

Frequencies and Percentages for Categorical Predictor Variables

Predictor	Group	Frequency	Row Percent
Kentucky Resident	Yes	645	72.1
	No	249	27.9
Sex	Female	390	43.6
	Male	504	56.4
UofL Graduate	Yes	185	20.7

	No	709	79.3
Disadvantaged Background	Yes	93	89.6
	No	801	10.4
Step 2 CS	Pass	851	95.2
	Fail	43	4.8
AOA	Yes	143	16
	No	751	84
Gold Humanism	Yes	144	16
	No	750	84

Table 8

Frequencies and Percentages for Outcome Variables

Predictor	Group	Frequency	Row Percent
Match Successfully	Yes	842	94.2
	No	52	5.8
Match into Competitive Specialty	Yes	326	36.5
	No	569	63.5

Match into State of Kentucky	Yes	237	73.5
	No	657	26.5
Match into Primary Care	Yes	351	39.3
	No	543	60.7
Match into Primary Care in State of Kentucky	Yes	106	11.9
	No	788	88.1

The tables above show that there were many predictor variables, both continuous and categorical, that were used to predict the five outcomes of interest through the usage of logistic regression. Now that descriptive statistics have been provided for each variable in this study, detailed results for each of the five research questions will be outlined and final models will be provided.

Matching Successfully

The first outcome of interest for this study was to determine which variables could be used to predict matching successfully (yes/no). As a reminder, the first research question was:

> RQ_1*:* Which factors taken at admissions and during the undergraduate medical education program for students at the University of Louisville School of Medicine best predict whether or not a student will match successfully or not?

To address this research question, all variables were entered as stepwise method to determine what factors would predict matching successfully. Initial data modeling statistics can be examined by looking at Table 9.

Table 9

Step and Model Statistics – Matching Successfully

	Omnibus Test of Model Coefficients			Model Summary		Hosmer and Lemeshow Test			Classification % Correct
	Chi-square	df	Sig	-2 Log likelihood	Nagelkerke R Square	Chi-square	df	Sig	
Step 1	39.5	1	.000	357.2	.121	8.5	8	.387	94.2
Step 2	5.8	1	.016	351.4	.138	6.8	8	.558	94.2
Step 3	6.7	1	.010	344.7	.158	7	8	.534	94.2
Step 4	6.4	1	.012	338.3	.176	4.9	8	.765	94.4

Table 9 shows SPSS output which indicates how much improvement in the model has occurred with the addition of each new predictor variable. The Omnibus Test of Model Coefficients column of the table shows significant values at each step. The first step of this model, which included Step 2 Clinical Knowledge (CK) alone, was significant at the .01 level. This can be interpreted as the addition of Step 2 CK variable to the regression model improved the model from the constant. The constant is what the model consists of before predictors are added. Additionally, at each step within the model, the chi-square value was significant at the .05 level indicating that as Step 2 Clinical Skills (CS) Examination score, the MCAT score, and the Family Medicine Shelf Examination score were added to the logistic regression model with Step 2 CK score, the model to predict matching successfully improved. The chi-square value can be computed by the following formula:

$$x^2 = -2LLreduced - (-2LLfull)$$

The -2LL value assesses the overall model fit. Before predictors were added to the model, the -2LL value was 396.7. The likelihood value in step 1, (included Step 2 CK score), was 357.2. To obtain the initial chi-square value for step 1, we would use the formula above to calculate which is outlined below.

$$x^2 = 396.7 - 357.2 = 39.5$$

The chi-square value can be seen in Table 9, which was significant at the .01 level. This value is similar to the *F* test in multiple linear regression as it shows how well the model fits. The closer -2LL gets to 0 the better the fit; we also want to see the significance of chi-square to remain at each step. Table 9 shows that the value of -2LL decreased at each step indicating that as the predictor variables were added, the more accurately the model predicted. Ultimately -2LL values are difficult to compare across different types of logistic regression models, however, the closer the value gets to zero the better. The Negelkerke values tests the level of variability predicting the outcome variable. The Hosmer and Lemeshow Test for Model Fit looks at the lack of fit and is robust in regression models with continuous variables which encompasses many variables within this study (Osbourne, 2016).

$$Ho: predicted\ probablities = observed\ probabilities$$

$$H\alpha: predicted\ proabilities\ \neq observed\ probabilities$$

Essentially, the Hosmer-Lemeshow goodness-of-fit index tests that the observed data are different from the predicted model, thus we want a non-significant value for each step which we have above. For example, if we had developed a model that predicted 1,500 cases were going to fall in category A, but the observed output showed we only had 450 cases that were observed in category A, this would be an issue with the model; this issue would be discovered by the Hosmer-Lemeshow goodnesss-of-fit index test. Since there was no issue based on the Hosmer-Lemeshow goodness-of-fitness and other model statistics provided in Table 9, next the predictor variables that were included in the final model are provided in Table 10.

Table 10

Variables included in Logistic Regression Model – Matching Successfully

	B	SE	Wald	df	Sig	Exp B	95 CI LB	95 CI UB
Step 2 CS	1.128	.425	7.04	1	.008	3.09	1.343	7.102
MCAT Score	-.384	.146	6.92	1	.009	.681	.511	.907
Family Medicine Shelf	.482	.192	6.34	1	.012	1.62	1.113	2.357
Step 2 CK	.604	.188	10.34	1	.001	1.83	1.266	2.645
Constant	2.211	.429	26.55	1	.000	9.12		

To address multicollinearity, collinearity statistics for the variables, within this model, were examined including tolerance and VIF values. The tolerance values for each of the four predictor variables in this model ranged from .55 to .95 and the VIF values ranged from 1.1 to 1.8 indicating no issues with multicollinearity.

The variables that were shown to predict matching successfully were scores on MCAT, the Family Medicine Shelf Examination scores, the Step 2 Content Knowledge Examination scores, and the Step 2 Clinical Skills Examination scores. The logistic regression model to predict matching successfully is below.

Matching Successfully =

Logit = 2.211 + (1.128 Step 2 CS pass) + (-.384 MCAT ZScore) + (.482 Family Medicine Shelf ZScore) + (.604 Step 2 CK ZScore).

Explanation of the model to predict matching successfully.

As a reminder for each model, the logit serves at the dependent variable, which is the outcome of interest; hence, for this model, the outcome of interest/logit is matching successfully (yes/no). Table 10 shows that the Wald statistic was significant for all variables within the model which indicates that each predictor is significantly different from zero.

The first variable added to this model was the Step 2 Clinical Skills (CS) Examination which reveals, when controlling for other variables in the model, the odds of successfully matching were 3.1 times higher for those that passed the Step 2 CS compared to those that failed. Next the model shows that the higher the MCAT score, the less likely the student would successfully match ($p < .01$), when controlling for Step 2 CS, Family Medicine Shelf, and Step 2 Content Knowledge (CK). It should be noted that the MCAT changed scoring in 2015; however, all persons going through the Match® up to the graduating class of 2019 took the old MCAT.

The third predictor added to the model was the Family Medicine Shelf Examination Score. The model shows that the higher the Family Medicine Shelf Examination Score the more likely the student would successfully match (p < .05), controlling for all variables. Finally, the model shows that as the Step 2 Clinical Knowledge Score increases the more likely the student is to match successfully ($p < .01$). It is important to remember for each of these variables, these results should be interpreted as odds when controlling for the other variables within the model. To further examine these predictor variables within this model above, separate statistical analyses occurred to provide more information to consumers of this work.

Multivariate analysis of variance and chi-square tests.

A two-group multivariate analysis of variance (MANOVA) was conducted on match success and the continuous variables found to predict matching success in the logistic regression model above to examine significance of variables without controlling for other variables. These variables included the Family Medicine Shelf Examination, the MCAT, and the Step 2 Content Knowledge Examination. Using Pillai's trace criterion, the linear combination of Family Medicine Shelf examination, MCAT score, and Step 2 Content Knowledge Examination were significantly associated with match success (Pillai's Trace = .060, F (3, 890) = 19.1, $p < .01$).

Due to the statistically significant multivariate finding, separate ANOVAs were conducted to determine the root of the significant multivariate effect. Results showed significantly different Family Medicine Shelf Examination scores between the two groups, (matching vs not matching), F (1, 892) = 36.7, $p < .01$, partial $\eta^2 = .5$ with those that matched having higher scores (M = 75.6, SD = 7.2) compared to those that did not match (M = 69.3, SD = 6.9). Additionally, results showed significantly different Step 2 CK scores between the two groups, F (1, 892) = 44.2, $p < .01$, partial $\eta^2 = .5$ with those that matched having higher scores (M = 242, SD = 15.1) compared to those that did not match (M = 227, SD = 19.9). There were no significant differences in MCAT scores and match success, F (1, 892) = 0.9, $p > .05$, partial $\eta^2 = .001$, with those matching successfully having a mean score of 9.8 compared to those who did not match successfully having a mean score of 9.9.

To examine differences between the categorical variable found to be a predictor in this model, Step 2 Clinical Skills examination, a chi-square analysis was conducted to understand differences between the two groups.

Table 11

Chi-square Analysis: Matching Successfully and Step 2 CS

Successfully Matched	Passed Step 2 Clinical Skills Examination		Total
	No	Yes	
No	10	42	52
Yes	33	809	842
	43	851	894

Results showed significant differences between match success and passing Step 2 Clinical Skills Examination, $c^2(1) = 25.1$ $p < .01$; Cramer's $V = .167$, $p < .01$. Results showed that those who pass the Step 2 Clinical Skills Examination compared to those that fail are 5.84 times more likely to match successfully. Notice this is a higher odds ratio than provided above in the logistic regression model due this variable, Step 2 CS, being assessed on its own. Now that results have been provided for research question 1, which examined which factors predicted matching successfully (yes/no), the next outcome of interest will be examined, matching into a competitive specialty (yes/no).

Matching into a Competitive Specialty

The second outcome of interest for this study was to determine which variables could be used to predict matching into a competitive specialty (yes/no). As a reminder, the second research question was:

RQ_2: Which factors taken at admissions and during the undergraduate medical education program best predict whether or not a student will match into a competitive specialty?

To address this research question, all predictor variables were entered into SPSS using stepwise methods. As previously stated, the resident positions that were noted as competitive included:

- Dermatology
- Emergency Medicine
- Medicine – Emergency Medicine

- General Surgery
- Internal Medicine – Pediatrics
- Internal Medicine – Psychiatry
- Interventional Radiology
- Neurological Surgery
- Ophthalmology
- Obstetrics and Gynecology
- Orthopedic Surgery
- Pediatrics / Psychiatry / Child Psychiatry
- Plastic Surgery
- Radiation Oncology
- Thoracic Surgery
- Urology
- Vascular Surgery

These specialties were determined competitive by the number of positions per U.S. student ratio as provided by the NRMP and outlined in Chapter III of this study. Similar to the last model, all variables were converted to z-scores for standardization across different scales as well as interpretation. Logistic regression results can be seen in Tables 12 and 13.

Table 12

Step and Model Statistics – Matching into Competitive Specialty

	Omnibus Test of Model Coefficients			Model Summary		Hosmer and Lemeshow Test			Classification % Correct
	Chi-square	df	Sig	-2 Log likelihood	Nagelkerke R Square	Chi-square	df	Sig	
Step 1	97.4	1	.000	1075,7	.141	12.8	8	.119	65.5
Step 2	17.7	1	.000	1058	.165	14.6	8	.068	66.2
Step 3	7.1	1	.008	1050.9	.175	7.7	8	.461	66.9
Step 4	6	1	.014	1044.9	.183	7.9	8	.441	67.9
Step 5	5.7	1	.017	1039.2	.190	10.2	8	.249	67.8

Table 12 shows SPSS output for step statistics. Results show at each step of the model, the chi-square value was significant. The first step of this model, which included Step 2 Clinical Knowledge (CK) alone, was significant at the .01 level; this shows that the presence of Step 2 CK improves the model compared to the constant alone. Additionally, at each step within the model, the chi-square value was significant which indicates that the addition of the Surgery Shelf Examination Score, Membership in Gold Humanism, BCPM GPA, and Step 1 Examination improves the model. Additionally, Table 12 shows that the value for -2LL gets closer to zero with each predictor being added to the model. Finally, the Hosmer and Lemeshow Test for Model Fit showed non-significant findings indicating no issues with what is predicted by the model and the observed values of the outcome of interest, matching into competitive specialty (yes/no). Table 13 provides information on which predictor variables were included in the model to predict matching into a competitive specialty.

Table 13

Variables included in Logistic Regression Model – Matching into Competitive Specialty

	B	SE	Wald	df	Sig	Exp B	95 CI LB	95 CI UB
Gold Humanism	.523	.198	7.014	1	.008	1.687	1.146	2.485
BCPM GPA	-.193	.076	6.415	1	.011	.825	.710	.957
Shelf Surgery	.338	.105	10.375	1	.001	1.402	1.142	1.723
Step 1	.277	.117	5.566	1	.018	1.319	1.048	1.660
Step 2 CK	.379	.115	10.926	1	.001	1.461	1.167	1.829
Constant	-.742	.084	77.897	1	.000	.476		

To examine if there were any issues with multicollinearity, collinearity statistics were inspected including tolerance and VIF values. The tolerance values for each of the five predictor variables in this model ranged from .45 to .96 and the VIF values ranged from 1 to 2.2 indicating no issues with the model.

The variables used to predict matching into a competitive specialty includes: Gold Humanism membership, BCPM GPA, Surgery Shelf Examination, Step 1 Examination, and Step 2 CK Examination. The logistic regression model to predict matching into a competitive specialty is below.

Model to Predict Matching into Competitive Specialty:

$$\text{Logit} = -.742 + (.523 \text{ Gold Humanism Member}) + (-.193 \text{ BCPM GPA ZScore}) + (.338 \text{ Surgery Shelf ZScore}) + (.277 \text{ Step 1 Examination ZScore}) + (.379 \text{ Step 2 CK Examination ZScore})$$

Explanation of the model to predict matching into competitive specialty.

The logit serves as the dependent variable of the study or the outcome of interest; therefore, for this model, the outcome of interest/logit is matching into a competitive specialty (yes/no). Table 13 illustrates the Wald statistic was significant for all variables within the model which shows each predictor is significantly different from zero.

This logistic regression model reveals that being a member of Gold Humanism increases odds of matching into competitive specialty. Specifically, when controlling for other variables in this study, the odds of matching into a competitive specialty are 1.7 times higher for Gold Humanism members compared to non-members ($p < .01$). The second variable in the model is BCPM GPA. This model shows the higher the BCPM GPA, the less likely it is to match into a competitive specialty, ($p < .05$), when controlling for the other variables. The third variable in this study is the Surgery Shelf Score; as the Surgery Shelf Score increases the odds of matching into a competitive specialty increase ($p < .01$). Similarly, to the Surgery Shelf Examination Score, the model shows the higher the Step 1 Examination score the more likely to match into a competitive specialty, ($p < .05$). Finally, the model shows that as the Step 2 Clinical Knowledge scores increases the more likely to match into a competitive specialty, ($p < .01$), controlling for other variables. Remember for each of these variables, it is the case for odds and slope, when controlling for the other variables within the model. To investigate each predictor separately, separate statistical analyses occurred to better understand each variable's relationship with matching into a competitive specialty.

Multivariate analysis of variance and chi-square tests.

To follow up to the logistic regression analyses, a two-group multivariate analysis of variance (MANOVA) was conducted on match success and the continuous variables found to predict those matching into competitive specialty in the model above: BCPM GPA, Surgery Shelf Examination, Step 1 Examination & Step 2 CK Examination. Using Pillai's trace criterion, the linear combination of BCPM GPA, Surgery Shelf Examination, Step 1 Examination & Step 2 CK Examination were significantly associated with match success (Pillai's Trace = .13, F (4, 889) = 33.3, $p < .01$). Due to the significant finding, univariate ANOVAs were conducted to determine the source of the statistically significant finding. Results showed that significant differences were found with Surgery Shelf Examination scores, F (1, 892) = 86.8, $p < .01$, partial $\eta^2 = .089$. Those who matched into competitive specialties had higher Surgery Shelf Examination scores (M = 77.9, SD = 7.6) compared to those that did not match into competitive specialties (M = 72.9, SD = 7.8). Additionally, results showed that significant differences were found with Step 1 examination scores, F (1, 892) = 89.3, $p < .01$, partial $\eta^2 = .091$. Those that matched into competitive specialties had higher Step 1 scores (M = 235, SD = 15) compared to those that did not match into competitive specialties (M = 223, SD = 19). Finally, results showed that significant differences were found with Step 2 CK examination scores F (1, 892) = 99.9 $p < .01$, partial $\eta^2 = .101$. Individuals who matched into competitive specialties had higher Step 2 CK scores (M = 247, SD = 12.8) compared to those that did not match into competitive specialties (M = 237, SD = 16.1). There were no significant differences in BCPM GPA and matching into competitive specialties, F (1, 892) = .31, $p > .05$, partial $\eta^2 = .000$, with those matching into competitive specialties having a mean BCPM GPA of 3.55 compared to those who did not match into competitive specialties having a mean BCPM GPA of 3.56.

To examine differences between the categorical variable found to be a predictor in this model, member of Gold Humanism Society, a chi-square analysis was conducted to determine if there were statistically significant differences between the two groups.

Table 14

Chi-Square Analysis: Matching into Competitive Specialty and Gold Humanism Membership

Matched into Competitive Specialty	Member of Gold Humanism Society		Total
	No	Yes	
No	501	67	568
Yes	249	77	326
Total	750	144	894

Results showed significant differences between matching into a competitive specialty and membership in Gold Humanism Society, $c^2(1) = 21.4$, $p < .01$; Cramer's $V = .155$, $p < .01$. Results showed that members of Gold Humanism Society were 2.3 times more likely than non-members to match into a competitive specialty. This value is different than the logistic regression model due to it being interpreted on its own and not controlling for other variables in the logistic regression model. Now that results have been provided for

RQ_2, which examined which variables could be used to predict matching into a competitive specialty, the next outcome of interest will be examined, matching into the state of Kentucky (yes/no).

Matching into the State of Kentucky

The third outcome of interest for this study was to determine which variables could be used to predict matching into the state of Kentucky (yes/no). As a reminder, the third research question was:

RQ_3*:* Which factors taken at admissions and during the undergraduate medical education program best predict whether or not a student will match into an in-state residency program?

To address this research question, variables were entered in stepwise fashion to determine which factors would predict matching successfully. Initial data modeling statistics can be examined by looking at Table 15.

Table 15

Step and Model Statistics – Matching into Kentucky

	Omnibus Test of Model Coefficients			Model Summary		Hosmer and Lemeshow Test			Classification % Correct
	Chi-square	Df	Sig	-2 Log likelihood	Nagelkerke R Square	Chi-square	df	Sig	
Step 1	19.9	1	.000	1014.1	.032	17.2	8	.029	73.6
Step 2	20.9	1	.000	993.2	.065	8.7	8	.366	73.9
Step 3	8.9	1	.003	984.3	.079	7.2	8	.513	73.9

Step 4	8.2	1	.004	976.1	.092	6.8	8	.557	73.8

Table 15 provides SPSS output which indicate at each step of the model, the chi-square value was significant. At each step within the model, the chi-square value was significant which indicates that the model improves when including the variables of Kentucky resident (yes/no), Gold Humanism membership, Pediatrics Shelf Examination score, and Step 1 examination score. Additionally, Table 15 shows that the -2LL value gets closer to zero with each predictor being added to the model indicating improvement of the model. Finally, the Hosmer and Lemeshow Test for Model Fit showed non-significant findings indicating no issues with what is predicted by the model and observed values of the outcome of interest, matching into the state of Kentucky (yes/no). Table 16 shows which predictor variables were included in the model to predict matching into the state of Kentucky.

Table 16

Variables included in Logistic Regression Model – Matching into Kentucky

	B	SE	Wald	df	Sig	Exp B	95 CI LB	95 CI UB
Kentucky Resident	.821	.196	17.5	1	.000	2.27	1.55	3.35
Gold Humanism	.808	.257	9.9	1	.002	2.242	1.356	3.709
Pediatrics Shelf	.295	.104	8.056	1	.005	1.34	1.096	1.648

Step 1	-.500	.103	23.5	1	.000	.607	.496	.743
Constant	-2.376	.287	68.64	1	.000	.093		

To address multicollinearity, collinearity statistics were examined including tolerance and VIF values. The tolerance values for each of the five predictor variables in this model ranged from .57 to .99 and the VIF values ranged from 1 to 1.8 indicating no issues with multicollinearity.

The variables used to predict matching into the state of Kentucky include: Kentucky resident, Gold Humanism membership, Pediatrics Shelf Examination, Step 1 Examination. The logistic regression model to predict matching into the state of Kentucky is below.

Matching into State of Kentucky =

-2.376 + (.821 Kentucky Resident) + (.808 Non-Gold Humanism Member) + (.295 Pediatric Shelf Examination ZScore) + (-.500 Step 1 Examination ZScore)

Explanation of the model to predict matching into Kentucky.

As a reminder for each model, the logit serves at the dependent variable which is outcome of interest; therefore, for this model, the outcome of interest/logit is matching into the state of Kentucky (yes/no). Table 16 shows that the Wald statistic was significant for all variables within the model which demonstrates each predictor is significantly different from zero.

The results show that Kentucky residents were 2.7 times more likely than non-residents to match into the state of Kentucky, controlling for all variables, which was statistically significant ($p < .01$). The second predictor in this model is membership in Gold Humanism. Results show non-members of Gold Humanism were 2.2 times more likely than members to match into the state of Kentucky, which was statistically significant ($p < .01$). The third variable in this model is the Pediatrics Shelf Examination with results showing higher scores increased the likelihood of matching into the state of Kentucky, ($p < .01$), controlling for other variables. Finally, the model shows students with higher Step 1 Examination scores were less likely to match into the state of Kentucky ($p < .01$), controlling for other variables. To further examine effects of these predictors found to be statistically significant, additional analyses occurred.

Multivariate analysis of variance and chi-square tests

To follow up to the logistic regression analysis, a two-group multivariate analysis of variance (MANOVA) was conducted on matching into the state of Kentucky for residency and the continuous variables found in the model above: Pediatrics Shelf Examination and Step 1 Examination. Using Pillai's trace criterion, the linear combination of the Pediatrics Shelf Examination and Step 1 Examination were significantly associated with matching into the state of Kentucky (Pillai's Trace = .03, F (2, 891) = 13.7, $p < .01$). Due to the statistically significant result, univariate ANOVAs were conducted to determine the cause of the significant multivariate effect. Results showed that significant differences were found with Step 1 Examination scores F (1, 892) = 20.7, $p < .01$, partial $\eta^2 = .023$ with those that matched into the state of Kentucky having lower scores ($M = 222.5$, $SD = 18.8$) compared to those that matched out of state

(M = 228.8, SD = 18.1. There were no significant differences in Pediatric Shelf Examination scores and matching in the state of Kentucky, F (1, 892) = .979, p > .05, partial η^2 .001, with those matching in the state of Kentucky having a mean Pediatric Shelf Examination score of 77.6 compared to those who did not match in the state having a mean of 78.1.

To examine differences between the categorical variables found to be predictors in this model, member of Gold Humanism Society and Kentucky resident, separate chi-square analyses were conducted to examine if there were statistically significant differences between the two groups.

Table 17

Chi-Square Analysis: Matching into Kentucky and Gold Humanism Membership

Matched into State of Kentucky	Member of Gold Humanism Society		Total
	No	Yes	
No	534	123	657
Yes	216	21	237
Total	750	144	894

Results showed significant differences between matching into the state of Kentucky and membership in Gold Humanism Society, $c^2(1) = 12.5$, $p < .01$; Cramer's V = .118, p < .01. Findings show that those who are non-members of Gold Humanism Society were 2.4 times more likely to match into the state of Kentucky than members.

Table 18

Chi-Square Analysis: Matching into Kentucky and Kentucky Resident Comparison

Matched into State of Kentucky	Kentucky Resident in Application		Total
	No	Yes	
No	209	448	657
Yes	40	197	237
Total	249	645	894

Results showed significant differences between matching into state of Kentucky and whether or not the student was a Kentucky resident at admission, $c^2(1) = 19.3$, $p < .01$; Cramer's $V = .147$, $p < .01$. Those who were Kentucky residents at the time of application into medical school were 2.3 times more likely to match into the state of Kentucky for residency. Note that for both this variable and Gold Humanism the odds are different than when these predictors are in the model. This is because these variables in the model are under the method of controlling for all variables whereas with these chi-square analyses, the variables are examined isolated. Now that results have been provided for RQ_3, the next outcome of interest will be examined, matching into primary care (yes/no).

Matching into Primary Care

The fourth outcome of interest for this study was to determine which variables could be used to predict matching into primary care (yes/no). As a reminder, the fourth research question was:

RQ_4: Which factors taken at admissions and during the undergraduate medical education program best predict whether or not a student will match into primary care?

To address this research question, variables were entered in using stepwise method to determine which factors would predict matching into primary care. Initial data modeling statistics can be examined by looking at Table 19.

Table 19

Step and Model Statistics – Matching into Primary Care

	Omnibus Test of Model Coefficients			Model Summary		Hosmer and Lemeshow Test			Classification % Correct
	Chi-square	Df	Sig	-2 Log likelihood	Nagelkerke R Square	Chi-square	df	Sig	
Step 1	35.342	1	.000	1162.447	.053	18.92	8	.015	62.3
Step 2	6.77	1	.009	1155.677	.062	8.16	8	.418	63.6
Step 3	5.08	1	.024	1150.596	.070	9.25	8	.322	63.4

Table 19 shows at each step of the model, the chi-square value was significant. At each step within the model, the chi-square value was significant which shows that with the inclusion of the AO GPA, parental status, and the Step 1 Examination the model improves. Furthermore, Table 19 shows that the -2LL value gets closer to zero with each predictor being added to the model. Lastly, the Hosmer and Lemeshow Test for Model Fit shows non-significant values for steps 2 and 3 indicating no issues with what is predicted by the model and observed values of the outcome of interest, matching into primary care (yes/no). Table 20 illustrates which predictor variables were included in the final model to predict matching into primary care.

Table 20

Variables included in Logistic Regression Model – Matching into Primary Care

	B	SE	Wald	df	Sig	Exp B	95 CI LB	95 CI UB
Parent (Non-Parent)	.978	.469	4.344	1	.037	2.658	1.060	6.665
AO GPA	.166	.074	5.060	1	.024	1.181	1.022	1.365
Step 1	-.432	.073	35.196	1	.000	.649	.563	.749
Constant	-1.404	.463	9.177	1	.002	.246		

To address multicollinearity, collinearity statistics were examined including tolerance and VIF values. The tolerance values for each of the five predictor variables in this model ranged from .977 to .996 and the VIF values ranged from 1 to 1.02 indicating no issues with multicollinearity.

The variables used to predict matching into primary care include: parental status, AO GPA, and Step 1 Examination. The logistic regression model to predict matching into primary care is below.

Matching into Primary Care:

Logit = -1.404 + (.978 for non-parents) + (.166 AO GPA ZScore) + (-.432 Step 1 ZScore)

Explanation of the model to predict matching into primary care.

As a reminder for each model, the logit serves at the dependent variable or the outcome of interest; thus, for this model, the outcome of interest/logit is matching into primary care (yes/no). Table 20 shows that the Wald statistic was significant for all variables within the model.

Results provided in Table 20 show that non-parents were 2.7 times more likely than parents to enter primary care, ($p < .05$), controlling for AO GPA and Step 1 score, which was statistically significant. Next, the model shows those with higher AO GPAs were more likely to enter primary care residencies ($p < .05$). Finally, the model shows those with higher Step 1 scores were less likely to enter primary care residencies ($p < .01$). To examine effects of these predictors found to be statistically significant in isolation, further analyses occurred.

Analysis of variance and chi-square tests.

Due to the continuous variables found to be predictors in this model not being moderately correlated, MANOVA was not conducted. However, separate ANOVAs were analyzed to examine differences between the groups (matching into primary care (yes/no) and the two continuous variables. Results showed significant differences were found with Step 1 Examination scores and primary care choice F (1, 892) = 36.4, $p < .01$, partial $\eta^2 = .039$. Those that that matched into primary care had lower scores (M = 222.6, SD = 18.9) compared to those that matched into other specialties (M = 230.1, SD = 17.6). Furthermore, a separate univariate analysis was conducted to examine differences between primary care choice and GPA on “all other courses” at admissions to medical school. Results showed there were significant differences between AO GPA and primary care choice, F (1, 892) = 4.6, $p < .05$, partial $\eta^2 = .032$ with those that matched into primary care having higher AO GPAS ($M = 3.77$, $SD = .26$) compared to those that matched into other specialties ($M = 3.73$, $SD = .27$).

To examine differences between the categorical variable found to be a predictor in this model, parental status, a chi-square analysis was conducted to see differences between the two groups.

Table 21

Chi-Square Analysis Matching into Primary Care and Parental Status Comparison

Matched into Primary Care	Parent		Total
	No	Yes	
No	517	26	543
Yes	345	6	351
Total	862	32	894

Results showed significant differences between matching into primary care and being a parent, $c^2(1) = 5.9$, $p < .05$; Cramer’s $V = .081$, $p < .05$. Individuals that were not parents at the time of admission were 2.9 times more likely than parents to enter primary care. Now that results have been provided for RQ_4, which examined which variables predict matching into primary care, the next outcome of interest will be examined, matching into primary care in the state of Kentucky (yes/no).

Matching into Primary Care in the State of Kentucky

The final outcome of interest for this study was to determine which variables could be used to predict matching into primary care in the state of Kentucky (yes/no). As a reminder, the fifth research question was:

RQ_5*:* Which factors taken at admissions and during the undergraduate medical education program best predict whether or not a student will match into primary care in the state of Kentucky?

To address this research question, variables were entered in stepwise fashion to determine what factors would predict matching successfully. Initial data modeling statistics can be examined by looking at Table 22.

Table 22

Step and Model Statistics – Matching into Primary Care in Kentucky

	Omnibus Test of Model Coefficients			Model Summary		Hosmer and Lemeshow Test			Classification % Correct
	Chi-square	Df	Sig	-2 Log likelihood	Nagelkerke R Square	Chi-square	df	Sig	Classification
Step 1	43.1	1	.000	607.895	.091	18.510	8	.018	88.3
Step 2	14.9	1	.000	592.925	.121	12.932	8	.114	88.4

Step 3	9.2	1	.002	583.775	.140	12.342	8	.137	88.5
Step 4	5.4	1	.020	578.398	.151	9.288	8	.319	88.3
Step 5	6	1	.014	572.393	.163	3.079	8	.929	88.7

Table 22 shows SPSS output which indicate at each step of the model, the chi-square value was significant. At each step within the model, the chi-square value was significant which shows that the model improves with the inclusion of the variables of Step 1 Examination, Kentucky resident (yes/no), AO GPA, Alpha Omega Alpha Membership, and the Pediatrics Shelf Examination. Additionally, Table 22 shows that the -2LL value gets closer to zero with each predictor being added to the model indicating improvement of the model. Finally, the Hosmer and Lemeshow Test for Model Fit showed non-significant findings for steps 2-5 indicating no issues with what is predicted by the model and observed values of the outcome of interest, matching into primary care in the state of Kentucky (yes/no). Table 23 shows which predictor variables were included in the model to predict matching into primary care in the state of Kentucky.

Table 23

Variables included in Logistic Regression Model – Matching into Primary Care in Kentucky

	B	SE	Wald	df	Sig	Exp B	95 CI LB	95 CI UB
Kentucky Resident	.989	.307	10.37	1	.001	2.69	1.47	4.91

AOA	1.325	.552	5.75	1	.016	3.76	1.27	11.1
AO GPA	.372	.136	7.5	1	.006	1.45	1.11	1.89
Pediatrics Shelf	.354	.146	5.91	1	.015	1.425	1.07	1.9
Step 1	-.783	.140	31.46	1	.000	.457	0.35	0.60
Constant	-4.204	.598	49.37	1	.000	.015		

To address multicollinearity collinearity statistics were examined including tolerance and VIF values. The tolerance values for each of the five predictor variables in this model ranged from .54 to .97 and the VIF values ranged from 1 to 1.9 indicating no issues with multicollinearity.

The variables used to predict matching into primary care in the state of Kentucky included: Kentucky resident, Alpha Omega Alpha (AOA) membership, AO GPA, Pediatrics Shelf Examination, and Step 1 Examination. The logistic regression model to predict matching into primary care in the state of Kentucky is below.

Matching into Primary Care in Kentucky:

-4.204 + (.989 for Kentucky Residents) + (1.325 Non-AOA members) + (.372 AO GPA Zscore) + (.354 Pediatrics Shelf Examination Z Score) + (-.783 Step 1 Examination ZScore)

Explanation of the model to predict matching into primary care in KY.

As a reminder for each model, the logit serves at the dependent variable which for this model is matching into primary care in the state of Kentucky (yes/no). Table 23 shows that the Wald statistic was significant for all variables within the model which shows each predictor is significantly different from zero.

Results show that Kentucky residents were 2.7 times more likely than non-residents to match into primary care in the state of Kentucky, ($p < .01$), controlling for the other variables, which was statistically significant. Additionally, results show non-AOA members were 3.8 times more likely than AOA members to enter into primary care in the state of Kentucky, ($p < .05$), controlling for all variables, which was statistically significant. Next, the model shows that having higher AO GPAs increased the odds of matching into primary care residency in the state of Kentucky ($p < .01$). Furthermore, results show the higher the Pediatrics Shelf Examination score the more likely to enter Kentucky primary care residencies, ($p < .05$), controlling for the other variables in the model. Finally, the model shows that higher Step 1 scores decreased likelihood to match into primary care in the state of Kentucky ($p < .01$). To examine effects of these predictors found to be statistically significant, further analyses occurred.

Multivariate analysis of variance and chi-square tests

A two-group multivariate analysis of variance (MANOVA) was conducted on matching into primary care in the state of Kentucky and the continuous variables found to predict that in the model above: Step 1 examination, Pediatrics Shelf examination, and AO GPA. Due to Step 1 and AO GPA having an insufficient required moderate correlation for MANOVA, AO GPA was pulled from the MANOVA analysis and will be examined using ANOVA.

Using Pillai's trace criterion, the linear combination of the Pediatrics Shelf Examination and Step 1 examination were significantly associated with matching into primary care in the state of Kentucky (Pillai's Trace = .059, F (2, 891) = 28, $p < .01$). Due to the significant finding, univariate ANOVAs were conducted to determine the root of the significant multivariate effect. Results showed that significant differences were found with Step 1 Examination scores and those entering primary care in the state of Kentucky F (1, 892) = 45.2, $p < .01$, partial $\eta^2 = .051$ with those that matched into primary care in Kentucky having lower scores (M = 216, SD = 19.5) compared to those that that did not (M = 229, SD = 17.8).

Additionally, results showed that significant differences were found with Pediatrics Shelf Examination results and primary care choice in the state of Kentucky F(1, 892) = 5.2, $p < .05$, partial $\eta^2 = .006$ with those that matched into primary care in the state of Kentucky having lower scores on the Pediatrics Shelf Examination (M = 76.3, SD = 8) compared to those that matched into other specialties (M = 78.3, SD = 7.9). Notice the different effect here compared to in the logistic regression model.

Further, a separate univariate analysis was conducted to examine differences between primary care choice in the state of Kentucky and GPA on "all other courses" at admissions to medical school. Results showed there were significant differences between AO GPA and primary care choice in the state of Kentucky, F (1, 892) = 8.9, $p < .01$, partial $\eta^2 = .010$ with those matching into primary care in Kentucky having higher AO

GPAS (M = 3.82, SD = .197) compared to those matching into other specialties (M = 3.74, SD = .269).

To examine differences between the categorical variables found to be predictors in this model, Kentucky resident and AOA membership, separate chi-square analyses were examined to see if there were statistically significant differences between the two groups.

Table 24

Chi-Square Analysis: Primary Care in Kentucky and AOA Membership Comparison

Matched into Primary Care in KY	Member of AOA		Total
	No	Yes	
No	649	139	788
Yes	102	4	106
Total	751	143	894

Results showed significant differences between matching into primary care in the state of Kentucky and membership in Alpha Omega Alpha, $c^2(1) = 13.3$, $p < .01$; Cramer's V = .122, $p < .01$. Non-members of Alpha Omega Alpha were 5.5 times more likely than members to enter primary care in the state of Kentucky.

Table 25

Chi-Square Analysis: Primary Care in Kentucky and Kentucky Resident Comparison

Matched into Primary Care in KY	Kentucky Resident		Total
	No	Yes	
No	235	553	788
Yes	14	92	106
Total	249	645	894

Results showed significant differences between matching into primary care in the state of Kentucky and being a Kentucky resident at time of admissions application, $c^2(1) = 12.8$, $p < .01$; Cramer's $V = .120$, $p < .01$. Kentucky residents at the time of application were 2.8 times more likely to enter primary care in the state of Kentucky than non-residents. Now that results have been provided for RQ5, all models are provided in Figure 12 below.

All Models Summary

This work provides logistic regression models, found in Figure 12 below, that can be used to predict matching outcomes. It is important to understand that for each of these predictor variables, it is the case when controlling for the other variables within each model. A discussion of what these models illustrate as to how these models could implicate medical education for students and programs as well as the matching process is provided in Chapter V.

Matching Successfully → Logit = 2.211 + (1.128 Step 2 CS Pass) + (-.384 MCAT ZScore) + (.482 FM Shelf ZScore) + (.604 Step 2 CK ZScore)

Matching into Competitive Specialty → Logit = -.742 + (.523 G.H. Member) + (-.193 BCPM GPA ZScore) + (.338 Surgery Shelf ZScore) + (.277 Step 1 ZScore) + (.379 Step 2 CK ZScore)

Matching into Kentucky → Logit = -2.376 + (.821 KY resident) + (.808 Non-G.H. member) + (.295 Pediatrics Shelf ZScore + (-.500 Step 1 ZScore)

Matching into Primary Care → Logit = -.1404 + (.978 Non – Parents) + (.166 AO GPA ZScore) + (-.432 Step 1 ZScore)

Matching into Primary Care in KY → Logit = -4.204 + (.989 KY Resident) + (1.325 Non – Member AOA) + (.372 AO GPA ZScore) + (.354 Pediatrics Shelf ZScore) + (-.783 Step 1 ZScore)

Figure 12. Logistic Regression Models to Predict Matching Outcomes

CHAPTER V

DISCUSSION

The purpose of this study was to better understand which variables could be used to predict matching outcomes using logistic regression models. The increase of accessible data afforded to medical education stakeholders to improve the understanding of the residency matching outcomes process is critical for decision-making for medical students and undergraduate medical education programs. The models outlined in Figure 12 can be used to guide advisement of students as well as provide opportunities for those medical education stakeholders interested in understanding which variables could predict matching into certain specialties or into geographic regions. There were five outcomes that were explored in depth and multiple variables that were examined to see which variables would predict one of the five outcomes: a) matching successfully, b) matching into a competitive specialty, c) matching into the state of Kentucky, d) matching into primary care, and e) matching into primary care in the state of Kentucky. Chapter V will provide discussion on each of the five research questions, confer how the results of this work contributes to literature, outline how these findings could implicate future practice, discuss limitations, and provide study conclusions.

Matching Successfully

This study examined which predictors could be used to determine if a student would successfully match. Here is the final model to enhance understanding as it relates to which of the factors predicted matching successfully:

$$\text{Logit} = 2.211 + (1.128 \text{ Step 2 CS pass}) + (-.384 \text{ MCAT ZScore}) + (.482 \text{ Family Medicine Shelf ZScore}) + (.604 \text{ Step 2 CK ZScore})$$

Matching successfully predictor: Step 2 clinical skills examination.

As previously discussed, the Step 2 Clinical Skills Examination is a pass/fail examination taken at the start of the fourth year in the undergraduate medical education program. Not surprisingly, there have been studies that show programs that obtain students with higher Step 2 CS scores have higher fill percentages (Green, et al. 2009). As a reminder, fill percentages are one way to determine competitive specialties as outlined in Chapter II of this study. Additionally, a 2016 study showed that the Step 2 CS showed predictive validity in performance in history-taking and physical exam training in residency (Cuddy, et. al., 2016). This is important because program directors want to avoid residents that require repeating residency exams as it can cost resources and scaffolds, they do not want to have to provide.

The Step 2 CS exam tests whether or not the student has the clinical skills that are necessary to advance in the field of medicine. What is interesting is that, according to the latest available Program Director's Survey, released in 2018, only 54% of Program Directors require the Step 2 CS score as part of the application into residency (Program Director's Survey, 2018). However, it is important for students and programs to know that according to this work, students who pass the Step 2 CS examination are 3 times more likely to successfully match then those that fail. This may be due to this exam being the last standardized test taken prior to the Match® process which could be an indicator of the skill level during that time. It also could be that this exam requires communication skills and other attributes outside of content knowledge which are necessary to be an effective physician. A lack of communication skills can be evident in interviews or during the ERAS process which can lead to Match® failures.

As can be seen in review of the results from the latest Program Director's survey, residency program directors want students that have the necessary clinical competence and communication skills (Program Director Survey, 2018). Both of these skills are a central focus of the Step 2 CS. Perhaps the better the undergraduate medical education trains a student for the Step 2 CS examination, the better they are training the students to have the clinical competency and the communication skills for the matching process and residency.

Matching successfully predictor: MCAT

The next predictor in this model is the MCAT score. This exam was modified to be more encompassing of social sciences and to provide a holistic perspective of the skills required to be successful in medical school (Schwartezin, 2013). While this examination has changed, all students that served as cases within this study (graduated 2014-2019) took the old examination. Because of this, results on the MCAT will need to be further examined to see if the model needs modifying with the new scale. The graduating class of 2020 will be the first class that has test-takers on the new exam, likely with some students having scores still on the old examination.

Regardless of the old scale or new scale, it is important to note that this study showed that the MCAT score can be used, when controlling for other variables, to predict match outcomes; however, when examining this variable isolated, it should be known that there were no statistically significant differences between those that matched and those that did not match. Therefore, medical education stakeholders should not interpret the finding from this model as lower MCAT scores increase the odds of matching successfully. They should interpret it as the MCAT score, when controlling for other variables in the logistic regression model, can be used for prediction.

There is an abundance of research that shows MCAT is a valid predictor of USMLE scores (Gauer & Jackson, 2017); however, scores from the MCAT become less of an accurate predictor as a student advances into the medical education program (Barber, et al. 2018). Thus, if admissions committees are wanting to grant access to students in hopes of the students performing well on Step 1, they may use MCAT as a screening tool for this. However, according to this work, MCAT should not be a consideration at admissions as it relates to its prediction related to matching successfully during the fourth year of the program.

Matching successfully predictor: Family medicine shelf examination

The third predictor in this model is the Family Medicine Shelf Examination. This examination is taken at the end of the Family Medicine clerkship during the third year of the program. This clerkship is a six-week clerkship in which students spend time in at least two clinical sites, including one rural area. This study shows that the Family Medicine Shelf Examination score can be used as a measure to predict successfully matching. There were statistically significant differences in univariate analysis results showing those matching successfully had higher Family Medicine Shelf Scores than those that did not match. The Family Medicine Shelf Examination is one of the seven

National Board of Medical Examinations (NBME) that are taken at the University of Louisville (UofL) in the third year.

A 2009 study showed that grades in required clerkships were the most important factors by residency directors; the shelf encompasses a large portion of individuals grades. This examination makes up 30% of a student's clerkship grade at the UofL. Additionally, a 2014 study showed that NBME examinations were a significant predictor of USMLE Step 3 performance (Dong, et al. 2014). The USMLE Step 3 examination is taken during residency and is a required component of gaining licensure.

Recall, as stated in this model discussion, residency directors do not want any failures on licensure examinations or problems with residents. Therefore, if clerkship performance, such as how students do on the Family Medicine Shelf examination, can predict residency exam results, it is important that the medical education stakeholders outlined throughout this study understand why this finding may be a factor in residency decisions. Finally, a 2012 study showed that primary care shelf performance, which would include family medicine, predicted the most variance on Step 2 CK so it can also be useful for that as well (Zahn, et al. 2012). Thus, this examination can provide information to medical education stakeholders as it relates to readiness for the Step 2 CK examination, which is the final predictor in this model.

Matching successfully predictor: Step 2 content knowledge examination.

The final predictor in this model is the Step 2 Clinical Knowledge (CK) Examination. This exam is taken around the same time as the Step 2 CS Examination, at the start of the fourth year of medical school. The model shows that the higher the Step 2 Clinical Knowledge score, the higher the odds of successfully matching are. This finding is similar to other findings in literature that stress the importance of the United States Medical Licensure Examinations (USMLE) which have been discussed throughout this study.

This study showed there was an average 15-point difference in Step 2 Content Knowledge (CK) score between those that matched and those that did not match, which was statistically significant. It should be noted that the Step 2 CK has increased focus on the residency matching process recently and will likely continue to be used as an important screener (Gruppuso & Adashi, 2017). Now that each of the predictor variables in the logistic regression model to predict matching successfully (yes/no) has been outlined, a summary of how this work could impact medical education students and programs will be provided.

Implications for medical students and programs.

Matching successfully is critical for fourth year medical students due to the financial, personal and career commitments they have made to train to get to the matching process. As aforementioned, those that fail to match suffer great setbacks which can lead to career, financial and personal devastation. Students who have a better understanding of which factors predict matching successfully can increase their odds of doing so.

Additionally, undergraduate medical education programs need to show that they are preparing students for residency to the LCME as well as to potential applicants and one way of displaying this is match rate success. The model provided shows that students should not just focus on doing well on Step 1, but that Step 2, CK and CS are very important as it relates to successfully matching. While there has been discussion to move away from standardized examinations towards holistic reviews, these standardized metrics are still being used up to the date of this study. Due to this circumstance, as well as results from the model within this study, students should continue focus on performing well on these standardized examinations. Additionally, the redesigned MCAT should be examined in the future to determine if it is a valid predictor with the medical school graduating class of 2020 or future classes to determine the effect of the new examination and scale.

The results of the Program Director Survey showed there is a little more leniency with the Step 1 examination compared to Step 2 examination as 12% would consider applicants that failed Step 1 examination whereas only 8% would consider students with a failure on Step 2 CK (Program Director's Survey, 2018). This may be due to more time and opportunities for retake and corrections as it relates to Step 1. Because of this, programs can advise students that have lower Step 1 scores/failures that there are other variables that play a role into matching successfully including the preparation for Step 2 examinations which are taken a year later. Now that I have discussed which factors predict matching successfully and how this model could implicate future practice, I will next outline the results from the second research question which was to determine which variables predicted matching into competitive specialties.

Matching into Competitive Specialties

The second model developed in this study was to predict which variables could be used to determine whether or not students matched into competitive specialties. As previously discussed in Chapters II and III, there are multiple ways in literature to define competitive specialties. This work defined it as U.S. Senior per position of 1.3 or less as competitiveness should consider the supply and demand of the specialty positions (Chen & Heller, 2014). This included:

- Dermatology
- Emergency Medicine
- Medicine – Emergency Medicine
- General Surgery
- Internal Medicine – Pediatrics
- Internal Medicine – Psychiatry
- Interventional Radiology
- Neurological Surgery
- Ophthalmology
- Obstetrics and Gynecology
- Orthopedic Surgery
- Pediatrics / Psychiatry / Child Psychiatry
- Plastic Surgery
- Radiation Oncology
- Thoracic Surgery
- Urology
- Vascular Surgery

This study examined if there were any predictors that can be used to determine if the medical student would match into one of these competitive specialties. Here is the final model to better understand which of the factors predicted matching into a competitive specialty:

Logit = -.742 + (.523 Gold Humanism Member) + (-.193 BCPM GPA ZScore) + (.338 Surgery Shelf ZScore) + (.277 Step 1 Examination ZScore) + (.379 Step 2 CK Examination ZScore)

Matching in competitive specialty predictor: Gold Humanism membership.

The first predictor in the model was membership into Gold Humanism Honor Society. This encompasses about 16% of the students in the medical education program. The model shows that members of Gold Humanism were significantly more likely to match into competitive specialties. Thus, those interested in matching into the competitive specialties above, should look at the attributes associated with earning membership into Gold Humanism. This society was established in 2002 and aims to be comprised of medical students, residents and physicians that are have the attributes of integrity, compassion, respect and empathy as it relates to the patient-care process (Gold Humanism Honor Society). The students that gain entrance to this society can also use the projects and initiatives they have worked on as a member as evidence of why they should be admitted into residency during the application process and in interviews with programs. Based on the results of this study, those students interested in matching into competitive specialties should consider what it takes to gain membership in Gold Humanism.

Matching in competitive specialty predictor: BCPM GPA

The second predictor in the model is BCPM ZScore. The BCPM GPA is one variable taken at admissions and examined by committees. This is the portion of the GPA that is composed of coursework in biology, chemistry, physics and mathematics. As this value increases in the model, the likelihood of matching into a competitive specialty decrease. Remember, this only is the case when controlling for other variables. When examining this variable separately using univariate analysis methods there were no significant differences between BCPM GPA for those that matched into competitive specialties compared to those that did not match.

Matching in competitive specialty predictor: Surgery Shelf Examination.

The third predictor included in this model is the Surgery Shelf Examination Score. This is an NBME examination that is taken during the third year at the end of the eight-week surgery clerkship and makes up 30% of the students grade in the Surgery Clerkship at UofL. The logistic regression model, as well as univariate analysis results, showed that those who matched into competitive specialties had higher Surgery Shelf scores compared to those that did not. As previously mentioned, these NBME examinations can predict performance on the Step 2 CK and Step 3 exams which is important for both undergraduate medical education programs as well as residency directors (Dong, et. al. 2014; Zahn, et al. 2012).

Matching in competitive specialty predictor: Step 1 Examination.

The fourth predictor in this model is the Step 1 Examination score. As previously discussed, the Step 1 Examination is an often-cited factor by residency directors of importance in candidate selection. The Step 1 Examination can cause high pressure for the students (Swanson & Roberts, 2016). There are some medical education stakeholders that want to limit the influence of Step 1 scores affecting residency selections as they believe the process should move towards a holistic review (Prober et. al. 2016; McGaghie, et. al., 2011); however, this is still being used as a top screening tool at the time of this study.

As earlier described, this examination is taken at the end of the second year of the undergraduate medical education program. The model to predict matching into a competitive specialty shows those with higher scores are more likely to match into competitive specialties.

The Step 1 score is the number one most cited factor by Program Directors as to who they will interview (Program Directors Survey, 2018). A 2013 study showed that higher Step 1 scores led to more interviews in plastic surgery, a competitive specialty (Sue & Narayan, 2013). This could mean that these students are getting more interviews, thus have better odds of matching into competitive specialties. Results from this work corroborate findings in literature as it relates to the Step 1 Examination's importance in residency outcomes.

Matching in competitive specialty predictor: Step 2 CK Examination.

The final predictor in this model is the Step 2 Clinical Knowledge (CK) score. The model shows an increase in Step 2 CK score means an increase in likelihood to match into competitive specialty. A review of the charting outcomes data provided by the NRMP shows that Step 2 CK scores were higher in competitive specialties such as orthopedic surgery and radiation oncology compared to others such as neurology or physical medicine and rehabilitation (Charting Outcomes, 2018). Results from this study verify what researchers at the University of Minnesota found as it relates to Step 2 CK, the higher the Step 2 CK score the more competitive the specialty (Gauer & Jackson, 2017). A 2008 study showed that Step 2 CK was a better predictor than Step 1 of performing better in residency, thus the authors of the work question why Step 1 is cited as a more important factor by residency directors compared to Step 2 CK (Andriole, et al. 2008).

This study provides evidence that Step 2 CK is a very important factor as it relates to matching success. This study showed that the University of Louisville's 2019 graduating class had the best matching success in five years. Also, this class had a 99% pass rate on the Step 2 CK examination which was the highest of all classes in this study. The relationship between these two findings should be considered as evidence of the Step 2 CK predicting residency matching outcomes. Now that each of the predictor variables in the logistic regression model to predict matching into a competitive specialty (yes/no) has been outlined, a summary of how this work could impact medical education students and programs will be provided.

Implications for medical students and programs.

As previously mentioned, it is important to note that students may not enter competitive specialties for other reasons such as interest in a "less competitive" field or interest in working in primary care. This work does not mean that by choosing less competitive specialties it means they are less competitive applicants. Many competitive applicants choose these fields because the specialty is a better fit and what they are passionate about pursuing a career in.

Results from this study show that for those interested in matching into competitive specialties it is important to perform well on standardized examinations including the Step 1 and 2 CK examinations which adds support to previous findings in literature. For students that do not test as strongly but still want to match into a competitive specialty, they should consider what it takes to gain membership to Gold Humanism and see which attributes can help his or her case in matching into a competitive specialty. Now that I have discussed which factors predict matching successfully and how this model could implicate future practice, I will next outline the results from the third research question which was to determine which variables predicted matching into the state of Kentucky.

Matching into the State of Kentucky

The third model developed in this study was to determine which variables predicted matching into the state of Kentucky. Medical programs would prominently benefit from understanding of what may predict matching locations for students that go into preferred specialties (Gauer & Jackson, 2017). As a reminder, here is the final model to better understand which of the factors predicted matching into the state of Kentucky:

$$\text{Logit} = -2.376 + (.821\ \text{Kentucky Resident}) + (.808\ \text{Non-Gold Humanism Member}) + (.295\ \text{Pediatric Shelf Examination ZScore}) + (-.500\ \text{Step 1 Examination ZScore})$$

Matching in state of Kentucky predictor: Kentucky resident.

The first predictor in this model is whether or not the student is a Kentucky resident. Results from this study showed Kentucky residents were 2.3 times more likely to match into the state, which was significantly different. Considering the issue of shortage areas and other benefits of knowing geographic locations, admissions committees should understand the benefits of recruiting students from the same state if the goal is to employ graduates within the same state to address geographic shortages. Results from this study were similar to a 2017 study that showed residents at the time of admission were significantly more likely to stay in the state in Minnesota (Gauer & Jackson, 2017).

Matching in state of Kentucky predictor: Gold Humanism membership

The second predictor in the model is the membership of Gold Humanism. This variable is also in the model for predicting competitive specialties. Results showed non-members were 2.3 times more likely to enter Kentucky residency than Gold Humanism members. Pairing this finding with the finding that showed Gold Humanism members were significantly more likely to match into competitive specialties, this study shows that these individuals (members of Gold Humanism) are more likely to pursue competitive specialties outside of the state of Kentucky.

Matching in state of Kentucky predictor: Pediatrics Shelf Examination.

The third predictor is the Pediatrics Shelf Examination results. The model shows that there is an increase in likelihood in matching into Kentucky for higher Pediatric Shelf Examination scores. A further examination of this variable alone showed there were no significant differences in the Shelf score using univariate analysis. This should be noted as the importance of understanding that when using logistic regression models, that each variable’s slope/odds is when controlling for the other variables within the model.

Matching in state of Kentucky predictor: Step 1 Examination.

The final predictor in this model is the Step 1 Examination score. This study showed that better performance on the Step 1 showed a less likely chance of matching into the state of Kentucky. This study shows that individuals that perform well are more likely to leave the state to pursue positions elsewhere. Univariate analysis showed significant differences in scores for residency locations as those matching in the state of Kentucky had a mean Step 1 Examination score of 222.5 compared to those leaving the state with a mean score of 228.8. A point of importance is that this study had 645 Kentucky residents at the time of admission but there were only 237 students from this group that matched into the state of Kentucky. While some/many of them may return after residency, future research should examine the odds of returning back to home state by specialty area. Additionally, one could examine those residents at the time of admission that leave as a separate cohort to see what attributes they have compared to those that stay. Now that each of the predictor variables in the logistic regression model to predict matching into the state of Kentucky (yes/no) has been outlined, a summary of how these findings could impact medical education students and programs will be provided.

Implications for medical students and programs.

While this model to predict matching into the same state may not be of concern for medical education students, it should be important for consideration by medical education programs. As previously noted, certain programs within states with significant shortage areas need to better understand which students they can employ in these areas. This is very pertinent in the state of Kentucky as the majority of its counties face physician shortage areas (Crump, et. al., 2013). Therefore, undergraduate medical education programs and policy-makers in medical education should contemplate the value of having students enrolled in medical school from the same state or not in certain states/geographic locations as this variable showed to predict those matching into the same state. Recently, there has been improvement the number of graduates planning to pursue careers with underserved populations as noted by the Graduation Questionnaire (GQ) which shows that 34.7% of respondents noted plans to do this which has grown recently; in 2014, this percentage was 27.3% (Graduation Questionnaire, 2018). Now that I have discussed which factors predict matching into the state of Kentucky and how this model could improve future practice in medical education and the matching process, I will next outline the results from the fourth research question which was to determine what predicted matching into the primary care.

Matching into Primary Care

The fourth model developed in this study was to determine which variables predicted matching into the field of primary care. As discussed in previous chapters, there are shortage areas that need primary care physicians and it would be beneficial for programs to know if they can predict who will go into these fields to alleviate this critical issue. There have been repeated attempts through strategic initiatives to get people to go into primary care (Benbassat & Baumal, 2011); however, the issue still remains at the time of this study. In 2019, the Association of American Medical Colleges (AAMC) released a report that outlined physician supply projections up to 2032. This report shows that there will be an insufficient number of primary care physicians with the shortfall estimated to be between 21,100 and 55,200 (Workforce Data and Reports). This is a significant deficit and more work needs to be done to understand which students will enter primary care specialties. Here is the final model to better understand which of the factors predicted matching into primary care:

Logit = -1.404 + (.978 for non-parents) + (.166 AO GPA ZScore) + (-.432 Step 1 ZScore)

Matching into primary care predictor: parental status.

The first predictor in this model showed that individuals who are not parents at the time of admission were more likely to enter primary care. An examination of parental status alone showed that non-parents were 2.9 times more likely than those individuals who were not parents to match into primary care. This finding needs to be examined further; with a study that encompasses a larger number of parents, the sample could be broken down by an interaction of parental status and gender or parental status and age. Perhaps parents are more interested in discipline-centered areas. Another possibility would be that parents have financial obligations already for their children, on top of educational financial commitments. Additionally, there is a common postulation that debt plays a primary role in fourth year medical students decision-making as it relates to choosing a specialty. A 2013 study showed that all physicians, regardless of specialty, can repay median levels of debt; while this was true it did show that primary care physicians need to be more cognizant of cost of living and other financial decisions as oppose to those in other specialties (Youngclaus, et. al., 2013).

Matching into primary care predictor: AO GPA.

The second predictor in this model was AO GPA. AO GPA, or “all other” GPA, encompasses students grades in coursework outside of science and mathematics. The model shows that as AO GPA increases there is an increase of likelihood in matching into primary care. Examining this variable separately using univariate methods showed significant mean differences in AO GPA with those matching into primary care having a higher mean AO GPA of 3.77 compared to those matching in other specialties with a mean of 3.73. Admissions committees can use this as a central screening factor if they want to employ primary care physicians. While keeping the other important variables in mind, committees could examine AO GPA closely and for applicants that are similar in other metrics give the edge to those performing better in social science coursework.

Matching into primary care predictor: Step 1 score.

The final predictor in this model is the Step 1 Examination score. The results showed that increases in Step 1 scores meant less likely to match into primary care. Additionally, univariate analysis showed those entering primary care had a mean Step 1 score of 222.6 compared to 230.1 for those that matched in other specialties. Now that each of the predictor variables in the logistic regression model to predict matching into primary care (yes/no) has been outlined, a summary of how this work could impact medical education students and programs will be provided.

Implications for medical students and programs.

Employing primary care physicians is an important goal for many undergraduate medical education programs. The results from this model substantiated what research has previously shown as it relates to differences in Step 1 scores and how the results of this heightened-focus exam can predict matching disciplines. This model provides new information as it relates to parental status and AO GPA.

This study shows that those interested in employing primary care physicians should consider student performance on courses in social sciences at admissions to differentiate those more likely to enter the field. Future work should consider the practical significance of parental status and primary care choice to see if a larger sample of parents would result in the same results as this study. Additionally, a qualitative design could lend itself well to a follow-up study with parental status and specialty choice. Now that I have discussed which factors predict matching into primary care and how this model could enhance future practice, I will next outline the results from the final research question which was to determine what predicted matching into primary care in the state of Kentucky.

Matching into Primary Care in the State of Kentucky

The final model developed in this study was to examine whether or not students matched into primary care in the state of Kentucky. As previously mentioned, there are certain programs that are focused on recruiting students to primary care fields in certain geographic locations. Medical education programs, through specific planning including curricular interventions and student recruitment can help address doctor shortages in underserved regions (Boscardin, et. al., 2014). Here is the final model to better understand which of the factors predicted matching into primary care in the state of Kentucky:

Logit = -4.204 + (.989 for Kentucky Residents) + (1.325 Non-AOA members) + (.372 AO GPA Zscore) + (.354 Pediatrics Shelf Examination Z Score) + (-.783 Step 1 Examination ZScore)

Matching into primary care in KY predictor: Kentucky resident.

The first variable is Kentucky resident (yes/no). This study showed that Kentucky residents were 2.8 times more likely than non-residents to match into primary care in the state of Kentucky. Thus, similarly to previous models, residency at the time of admission should be an area of focus during the undergraduate medical education admissions process.

Matching into primary care in KY predictor: AOA membership.

The second variable in this model is Alpha Omega Alpha (AOA) membership. Non-members of AOA were more likely to match into primary care in the state of Kentucky compared to members when controlling for residency, AO GPA, Pediatrics Shelf Examination score, and Step 1 Examination core. An examination of this variable alone, using chi-square analysis, showed that non-members of AOA were 5.5 times more likely than members to match into primary care in the state of Kentucky. An examination of NRMP data shows that non-primary care specialties such as dermatology otolaryngology, and surgery have higher percentages of AOA members for those that matched compared to primary care specialties such as family medicine (Charting Outcomes, 2018).

Matching into primary care in KY predictor: AO GPA.

The next predictor in this model is AO ("all other") GPA. This model showed that higher AO GPAs meant more likely to match into primary care in the state of Kentucky. Univariate results showed those that matched into primary care in the state of Kentucky had significantly higher AO GPAs, (M = 3.82) compared to those that did not (M = 3.74). This finding should be considered for admissions committees as previously discussed for model 4.

Matching into primary care in KY predictor: Pediatrics Shelf Examination.

The fourth predictor in this model is Pediatrics Shelf Examination score. The findings show that higher Pediatrics Shelf scores meant more likely to match into primary care in the state of Kentucky, controlling for other variables in the model. Interestingly, when examining the differences using univariate methods, (not controlling for other variables), those that matched into primary care in Kentucky had statistically significantly lower Pediatrics Shelf Examination scores ($M = 76.3$) than those that did not ($M = 78.3$). This is an important example of why it is critical to understand interpretation of logistic regression models and that each variable within the model should be considered as controlling for other variables in the model.

Matching into primary care in KY predictor: Step 1 Examination.

The final variable in this model is the Step 1 Examination score which shows increase in Step 1 scores meant less likely to match into primary care in the state of Kentucky. Similarly, to other models, those that matched into primary care in the state of Kentucky had lower Step 1 Examination scores ($M = 216$) compared to those that did not ($M = 229$) which was significantly different. As discussed throughout this work, the Step 1 Examination score is often cited as an important factor in predicting matching outcomes and it was found to be significant variable in four out of the five models within this study showing its importance in predicting residency matching outcomes. Now that each of the predictor variables in the logistic regression model to predict matching into primary care in the state of Kentucky (yes/no) has been outlined, a summary of how this work could impact medical education students and programs will be provided.

Implications for medical students and programs.

There are specific reasons for why a program would want to know how to address primary care shortage areas in their state which has been discussed throughout this study. The state of Kentucky ranks 41st, in the bottom 10 nationally, for active primary care physicians per 100,000 populations based on the latest available physician workforce profile provided by the AAMC (Workforce Data and Reports). This report shows that Kentucky ranks 17th for active general surgeons per 100,000 population, ultimately showing that the state may be employing a sufficient number of surgeons but not enough primary care physicians (Workforce Data and Reports). Therefore, medical education decision-makers in Kentucky need to be actively working towards understanding what predicts matching into the primary care in the state to lessen this problem.

The major take-aways from this logistic regression model for programs would be to consider residency at the time of admission and performance in "all-other" courses. If programs are interested in matching students into primary care in their state, a better understanding of these factors and outcomes addressed by this work may help address these shortage areas. Now that I have discussed which factors predict matching outcomes for each of the five research questions, I will next outline this work's contribution to literature, the study limitations, and final conclusions.

Contribution to Literature

This study adds to current research as there is limited research using statistical models to predict matching outcomes. Specifically, there is limited research showing logistic regression and a large number of variables to identify what drives outcomes of the process. Many of the variables used in this work have not been examined in research before, such as AO GPA which was found to be significant in two models. Additionally, not all of these outcome measures have been examined before.

By having a better understanding of not only results from this study but the feasibility of developing regression models to fit each medical education or higher education programs goals, leaders in educational research, assessment or administrational roles can use informative data to drive decision-making and hopefully meet developed internal strategic planning initiatives. Future work could examine individuals that were leaving the state of Kentucky for residency that were in-state residents at the time of admission to see what resulted in them choosing to leave. Additionally, future work could look at parental status and not choosing to enter primary care. Moreover, future research could examine standardized metrics and matching outcomes specific to their own institution's mission. Finally, future studies could examine if any admissions committees are using AO GPA as a tool for granting admission to those they are hoping to enter primary care residencies.

Limitations

There are some limitations for this study. First, this study only encompasses data from one institution; therefore, each of the five models should be validated at separate schools before usage in advising or decision-making. While metrics and outcomes data may look similar, programs and students using these data should proceed with this in mind. Next, as discussed in this study, there are multiple ways to define competitive specialty; others define it differently than the author of this work so future work could consider developing strategies to encompass a broader way to define it or encompass multiple ways into one definition.

Additionally, as previously discussed, there are many reasons for those students choosing to enter a field outside of a "competitive specialty." Therefore, one cannot interpret this model as these are the best or most competitive applicants. This model shows who had success gaining entrance to those competitive specialties. Furthermore, this work examined matching into the state of Kentucky and not specifically shortage areas. While Kentucky has a plethora of shortage areas, not all parts of Kentucky are deemed shortage areas. Finally, as previously discussed, medical education metrics have changed and will continue to evolve so as with any logistic regression model it should be validated and modified as medical education advances.

Conclusions

This study aimed to better understand which factors associated with undergraduate medical graduates can predict whether students a) successfully matched, b) matched into competitive specialties, c) matched into in-state residencies d) matched into primary care, and e) matched into primary care in-state. By having a better understanding of which variables predict these outcomes, medical education students as well as medical education institutions and stakeholders can have a better idea of what drives matching outcomes.

Oftentimes, students are stressed about the unknown aspects associated with the Match® and this is especially relevant in 2019 as the average student is ranking 12.91 programs, the highest ever (Impact of ROL, 2019). It is expensive for students to apply to so many programs, travel to these sites, and rank these programs. While this work will likely not solve this issue, it may give better understanding of odds to matching successfully or into a certain specialty or area which can help students in preparation during the fourth year. Additionally, results from this study can be used within undergraduate medical education programs, specifically as it relates to advising and admissions processes. It is expectant that this study will drive further research in predicting matching outcomes. Additionally, hopefully this work will lead to discussion as it relates medical school admissions processes, the undergraduate medical education program, and the matching process itself.

REFERENCES

American Association of Medical Colleges. Graduation Questionnaire. 2018. Accessed: https://www.aamc.org/download/490454/data/2018gqallschoolssummaryreport.pdf

American Association of Medical Colleges. Workforce Data and Reports. Accessed: https://www.aamc.org/data/workforce/reports/

Andolsek, K. M. (2016). Improving the medical student performance evaluation to facilitate resident selection. *Academic Medicine, 91 (11),* 1475-1479.

Andriole, D. A., Yan, Y., Jeffe, D. B. (2008). Does US medical licensing examination Step 1 scores really matter in surgical residency match outcomes (and should it)? *Journal of American College of Surgeons*, *206*, 533-539.

Arnold, L., Sullivan, C., Okah, F. A. (2018). A free-market approach to the Match: A proposal whose time has not yet come. *Academic Medicine, 93 (1),* 16-19.

Baker, K. (2013). The tip of the iceberg: Improving the quality of rank order lists for the Match. *Academic Medicine, 88 (9),* 1206-1208.

Barber, C., Hammond, R., Gula, L. Tithecott, G., Chahine, S. (2018) In search of black swans: Identifying students at risk of failing licensing examinations. *Academic Medicine, 93 (3)*, 478-485.

Benbassat, J., Baumal, R. (2012). Expected benefits of streamlining undergraduate medical education by early commitment to specific medical specialties. *Advances in Health Sciences Education, 17*, 145-155.

Blouin, D., Tekian, A. (2018). Accreditation of medical education programs: Moving from student outcomes to continuous quality improvement measures. *Academic Medicine, 93 (3),* 377-383.

Boscardin, C. K, Grbic, D., Grumbach, K., O'Sullivan, P. (2014). Educational and individual factors associated with positive change in and reaffirmation. Of medical students' intention to practice in underserved areas. *Academic Medicine, 89 (11),* 1490-1496.

Boysen Osbourne, M., Mattson, J., Yanuck, J., Anderson, C., Tekian, A., Christian Fox, J., Harris, I. B. (2016). Ranking practice variability in the Medical Student Performance Evaluation. Academic Medicine, 91 (11), 1540-1545.

Brenner, A. M., Mathai, S., Jain, S., Mohl, P. C. (2010). Can we predict "problem residents"? *Academic Medicine, 85 (7),* 1147-1151.

Brezinksi, E. A., Harskamp, C. T., Ledo, L., Armstrong, A. W. (2014). Public perceptions of dermatologists and comparison with other medical specialties: Results from a national survey. *Journal of American Academic Dermatology, 71*, 875-881.

Bumsted, T., Schneider, B. N., Deiorio, N. M. (2017). Considerations for medical students and advisors after an unsuccessful match. *Academic Medicine, 92 (7),* 918-922.

Camp, C. L., Sousa, P. L., Hanssen, A. D., Karam, M. D., Haidukewych, G. J., Oakes, D. A., Turner, N. S. (2016). The cost of getting into orthopedic residency: Analysis of applicant demographics, expenditures, and the value of away rotations. *Journal of Surgical Education, 73,* 886-891.

Chen, J. Y. & Heller, M. T. (2014). How competitive is the Match for radiology residency? Present view and historical perspective. *Journal of American Colleges Radiology, 11*, 501-506.

Crump, W. J., Fricker, R. S., Ziegler, C., Wiegman, D. L., Rowland, M. L. (2013). Rural track training based at a small regional campus: Equivalency of training, residency choice, and practice location of graduates. *Academic Medicine, 88 (8),* 1122-1128.

Cuddy, M. M., Winward, M. L., Johnston, M. M., Lipner, R. S., Clauser, B. E. (2016) Evaluating validity evidence for USMLE Step 2 Clinical Skills data gathering and interpretation scores: Does performance predict history-taking and physical examination ratings for first-year internal medicine residents? *Academic Medicine, 91 (1)*, 133-139.

Custers, E. J. F. M., Cate, O. (2018). The history of medical education in Europe and the United States, with respect to time and proficiency. Academic Medicine, 93 (3), S49-S54.

DeVellis, R. (2017). *Scale development: Theory and applications.* Los Angeles: SAGE.

Dong, T., Swygert, K. A., Durning, S. J., Saguil, A., Zahn, C. M., DeZee, K. J., Gilliland, W. R., Cruess, D. F., Balog, E. K., Servey, J. T., Welling, D. R., Ritter, M., Goldenberg, M. N., Ramsay, L. B., Artino, A. R. (2014). Is poor performance on NBME clinical subject examinations associated with a failing score on the USMLE Step 3 Examination? *Academic Medicine, 89 (5),* 762-766.

Durning, S. J., Hemmer, P. A. (2012). Commentary: Grading: What is it good for? *Academic Medicine, 87 (8),* 1002-1004.

Enoch, L., Chibnall, J. T., Schindler, D. L., Slaving, S. J. (2013). Association of medical student burnout with residency specialty choice. *Medical Education*, *47*, 173-181.

Flannery, M. T. (2015). The 2014 United States Residency Match Program data for primary care programs: A review. *European Journal of Internal Medicine, 26 (2015),* 6-8.

Garcia, A. N., Kuo, T., Arangua, L., Perez-Stable, E. J. (2018) Factors associated with medical school graduates' intention to work with underserved populations: Policy implications for advancing workforce diversity. *Academic Medicine, 93 (1),* 82-89.

Gauer, J. & Jackson J. B. (2017). The association of USMLE Step 1 and Step 2 CK scores with residency match specialty and location. *Medical Education Online, 22,* (1358579).

George, P., Soo Park, Y., Ip, J., Gruppuso, P. A., Adashi, E. Y. (2016) The association between premedical curricular and admission requirements and medical school performance and residency placement: A study of two admission routes. *Academic Medicine, 91 (3),* 388-394.

Green, M., Jones, P., Thomas Jr., J. X. (2009). Selection criteria for residency: Results of a national program directors survey. *Academic Medicine, 84 (3),* 362-367.

Grover, A., Orlowski, J. M., Erikson, C. E. (2016). The nation's physician workforce and future challenges. *The American Journal of Medical Sciences, 351 (1),* 11-19.

Gruppuso, P. A. & Adashi, E. Y. (2017). Residency placement fever: Is it time for a reevaluation? *Academic Medicine, 92 (7),* 923-926.

Jena, A. B., Arora, V. M., Hauer, K. E., Durning, S., Borges, N., Oriol, N., Elnicki, M., Fagan, M. J., Harrell, H. E., Torre, D., Prochaska, M., Meltzer, D. O., Reddy, S. (2012). The prevalence and nature of postinterview communications between residency programs and applicants during the Match. *Academic Medicine, 87 (10),* 1434-1442.

Jolly, P. (2012). First-year residents who began their graduate medical education in 2009-2010 and found their positions within and outside the NRMP Match. *Academic Medicine, 87 (5),* 586-591.

Jolly, P., Erikson, C., Garrison, G. (2013). U.S. graduate medical education and physician specialty choice. *Academic Medicine, 88 (4),* 468-474.

Katsufrakis, P. J., Uhler, T. A., Jones, L. D. (2016). The residency application process: Pursuing improved outcomes through better understanding of the issues. *Academic Medicine, 91 (11),* 1483-1487.

Kay, C., Jackson, J. L., Frank, M. (2015). The relationship between internal medicine residency graduate performance on the ABIM Certifying Examination, yearlong in-service training examinations, and the USMLE Step 1 Examination. *Academic Medicine, 90 (1),* 100-104.

Kenny, S., McInnes, M., Singh, V. (2013). Associations between residency selection strategies and doctor performance: A meta-analysis. *Medical Education, 47,* 790-800.

Kogan, J. R., Shea, J. A. (2007). Course evaluation in medical education. *Teaching and Teacher Education, 23 (2007),* 251-264.

Kroopnick, M. (2013). AM Last Page: The MCAT Exam: Comparing the 1991 and 2015 exams. *Academic Medicine, 88 (5),* 737.

Liang, M., Curtin, L. S., Signer, M. M., Savoia, M. C. (2017) Unmatched U.S. allopathic seniors in the 2015 Main Residency Match: A study of applicant behavior, interview selection, and the match outcome. *Academic Medicine, 92 (7)*, 991-991.

Loh, A. R., Joseph, D., Keenan, J. D., Lietman, T. M., Naseri, A. (2013). Predictors of matching in an ophthalmology residency program. *Journal of Ophthalmology, 120 (4),* 865-870.

McGaghie, W. C., Cohen, E. R., Wayne, D. B. (2011). Are United States medical licensing exam Step 1 and 2 scores valid measures for postgraduate medical residency selection decisions? *Academic Medicine, 86 (1),* 48-52.

Morrison, C. A., Ross, L. P., Fogle, T., Butler, A., Miller, J., Dillon, G. F. (2010). Relationship between performance on the NBME Comprehensive Basic Sciences Self-Assessment and USMLE Step 1 for U.S. and Canadian medical school students. *Academic Medicine, 85 (10),* S98-S102.

National Resident Matching Program, Data Release and Research Committee. (2016). Results of the 2016 NRMP Program Director Survey. National Resident Matching Program. Washington, DC.

National Resident Matching Program, Data Release and Research Committee. (2017). Results of the 2017 NRMP Applicant Survey by Preferred Specialty and Applicant Type. National Resident Matching Program. Washington, DC.

National Resident Matching Program, Data Release and Research Committee. (2018). *Match Announcement*. Retrieved from: http://www.nrmp.org/wp-content/uploads/2018/03/Advance-Data-Tables-2018.pdf

National Resident Matching Program, Results and Data: 2017 Main Residency Match®. National Resident Matching Program, Washington, DC.

National Resident Matching Program, Results and Data: 2018 Main Residency Match®. National Resident Matching Program, Washington, DC.

National Resident Matching Program, Results and Data: 2019 Main Residency Match®. National Resident Matching Program, Washington, DC.

National Board of Medical Examiners (2018). *Guide to the subject examination program*. Retrieved from: http://www.nbme.org/pdf/SubjectExams/SubExamInfoGuide.pdf

Nikonow, T. N., Lyon, T. D., Jackman, S. V., Averch, T. D. (2015). Survey of applicant experience and cost in the Urology Match: Opportunities for reform. *The Journal of Urology, 194,* 1063-1067.

Norcini, J. J., Boulet, J. R., Opalek, A., Dauphinee, W. D. (2014). The relationship between licensing examination performance and the outcomes of care by international medical school graduates. *Academic Medicine, 89 (8),* 1157-1162.

O'Connell, T. F., Ham, S. A., Hart, T. G., Curlin, F. A., Yoon, J. D. (2018) A national longitudinal survey of medical students' intentions to practice among the underserved. *Academic Medicine, 93 (1),* 90-97.

Osbourne, Jason W. (2017). *Regression and linear modeling: Best practices and modern methods.* Los Angeles, CA. SAGE Publications, Inc.

Oyler, J., Thompson, K., Arora, V. M., Krishnan, J. A., Woodruff, J. (2015). Faculty characteristics affect interview scores during residency recruitment. *The American Journal of Medicine, 128 (5),* 545-550.

Patterson, F., Knight, A., Dowell, J., Nicholson, S., Cousans, F., Cleland, J. (2016). How effective are selection methods in medical education? A systematic review. *Medical Education, 50*, 36-60.

Peranson, E., Randlett, R. R. (1995). The NRMP matching algorithm revisited: Theory versus practice. *Academic Medicine, 70 (6),* 477-484.

Pituch, K. A., Stevens, J. P. (2016). *Applied multivariate statistics for the social sciences*. New York, NY. Routledge.

Prober, C. G., Kolars, J. C., First, L. R., Melnick, D. E. (2016). A plea to reassess the role of the United States Medical Licensing Examination Step 1 scores in residency selection. *Academic Medicine, 91 (1),* 12-15.

Ray, C., Bishop, S. E., Dow, A. W. (2018) Rethinking the Match: A proposal for modern matchmaking. *Academic Medicine, 93 (1),* 45-47.

Ross, D. A., Moore, E. Z. (2013). A quantitative experimental paradigm to optimize construction of rank order lists in the National Resident Matching Program: The ROSS-MOORE Approach. *Academic Medicine, 88 (9),* 1281-1286.

Royston, P. & Altman, D. G. (2010). Visualizing and assessing discrimination in the logistic regression model. *Statistics in Medicine, 29*, 2508-2520.

Schauber, S. K., Hecht, M., Nouns, Z. M. (2017). Why assessment in medical education needs a solid foundation in modern test theory. *Advances in Health Sciences Education.*

Schwartzstein, R. M., Rosenfeld, G. C., Hilborn, R., Herndon Oyewole, S., Mitchell, K. (2013). Redesigning the MCAT exam: Balancing multiple perspectives. *Academic Medicine, 88 (5),* 560-567.

Sozener, C. B., Lypson, M. L., House, J. B., Hopson, L. R., Dooley-Hash, S. L., Hauff, S., Eddy, M., Fischer, J. P., Santen, S. A. (2016). Reporting achievement of medical student milestones to residency program directors: An educational handover. *Academic Medicine, 91 (5),* 676-684.

Standards for Educational and Psychological Testing. (2014). Washington DC, USA; American Educational Research Association.

Sue, G. R., Narayan, D. (2013). Generation Y and the integrated plastic surgery residency Match: A cross-sectional study of the 2011 Match outcomes. *Plastic Reconstruction Surgery Global Open, 1 (e33*).

Sutton, E., Richardson, J. D., Ziegler, C., Bond, J., Burke-Poole, M., McMasters, K. M. (2014). Is USMLE Step 1 score a valid predictor of success in surgical residency? *The American Journal of Surgery, 208,* 1029-1034.

Swanson, D. B. & Roberts, T. E. (2016). Trends in national licensing examinations in medicine. *Medical Education, 50,* 101-114.

Taber, B. J., Hartung, P. J., Borges, N. J. (2011). Personality and values as predictors of medical specialty choice. *Journal of Vocational Behavior, 78 (2011),* 202-209.

Tadisina, K. K., Orra, S., Gharb, B. B., Kwiecien, G., Bernard, S., Zins, J. E. (). Applying to integrated plastic surgery residency programs: Trends in the past 5 years of the Match. *Journal of Plastic Reconstruction Surgery, 137*, 1344-1353.

United States Medical Licensing Examination (2018). *2018 bulletin of information*. Retrieved from: http://www.usmle.org/pdfs/bulletin/2018bulletin.pdf

University of Louisville School of Medicine Student Affairs. Gold Humanism Honor Society. Retrieved from: http://louisville.edu/medicine/studentaffairs/student-involvement/ghhs

van de Horst, K. V., Siegrist, M., Orlow, P., Giger, M. (2010). Residents' reasons for specialty choice: Influence of gender, time, patient and career. *Medical Education, 44,* 595-602

Weissbart, S. J., Kim, S. J., Feinn, R. S., Stock, J. A. (2015). Relationship between the number of residency applications and the yearly match rate: Time to start thinking about an application limit? *Journal of Graduate Medical Education, (March),* 81-85.

Youngclaus, J. A., Koehler, P. A., Kotlikoff, L. J., Weicha, J. M. (2013). Can medical students afford to choose primary care? An economic analysis of physician education debt repayment. *Academic Medicine, 88 (1)*, 16-25.

Zahn, C. M., Saguil, A., Artino, A. R., Dong, T., Ming, G., Servey, J. T., Balog, E., Goldenberg, M., Durning, S. J. (2012). Correlation of National Board of Medical Examiners scores with United States Medical Licensing Examination Step 1 and 2 scores. *Academic Medicine, 87 (10)*, 1348-1354.

CURRICULUM VITAE

Jacob Shreffler
Program Manager, Evaluation & Assessment
University of Louisville School of Medicine
Email: jrshre01@louisville.edu

Degrees

M.S. University of Louisville 2016

B.S. Illinois College 2012

Higher Education Experience

University of Louisville, Louisville, KY (August 2014 - present)

Program Manager for Evaluation & Assessment, School of Medicine (promoted from Coordinator in same unit) (October 2018 – present)

Coordinator, Evaluation & Assessment, School of Medicine (December 2017 - September 2018)

Assessment Coordinator, College of Education and Human Development (December 2015 - December 2017)

Accreditation Site Visitor and Assessment Reviewer, (June 2015 – December 2017)

Graduate Assistant, University of Louisville, Louisville, KY (August 2014 - December 2015)

Peer-Reviewed Publications

Shreffler, M.B., & Cocco, A.R., **Shreffler, J.,** (2019). An examination of the relationship between instruction type and learning outcomes in Sport Management courses. *Sport Management Education Journal, 13*(2), 1-10

Ferguson, B., Shoff, H., **Shreffler, J.,** McGowan, J., Huecker, M. (2019). Does my ER Doctor Sleep? The Trouble with Recovery from Night Shift. *The Journal of Emergency Medicine*, *Vol. 57 (2),* 162–167.