ARTIFICIAL INTELLIGENCE-DRIVEN POPULATION HEALTH MANAGEMENT IMPROVING HEALTHCARE VALUE & EQUITY: CULINARY MEDICINE & ITS MULTI-SITE COHORT STUDY WITH NESTED BAYESIAN ADAPTIVE RANDOMIZED TRIAL OF 3,785 MEDICAL TRAINEES/PROFESSIONALS & PATIENTS

A DISSERTATION

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BY

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Abstract

Health systems globally are faced with failed ethical commitment to their patients and financial extinction if they fail to consistently provide clinically efficacious, societally equitable, cost-effective healthcare. Despite the known causal link between the nutrition-related chronic disease epidemics and the world’s top morbidity cause, cardiovascular disease, there is no evidence-based, cost effective, scalable model of nutrition education intervention for and with medical trainees and professionals and their patients. Similarly, there is no known demonstrated case successfully applying artificial intelligence (AI)-driven Big Data within a population health management framework for such an intervention to optimally refine it. Therefore, the medical school-based teaching kitchen, The Goldring Center for Culinary Medicine (GCCM) at Tulane University School of Medicine, launched the largest known multi-site cohort study with nested Bayesian adaptive randomized controlled trial (BA-RCTs) across 30 medical centers and 3,785 medical trainees/professionals. Cooking for Health Optimization with Patients (CHOP) with its four sub-studies features not only the first known systematic review and meta-analysis on this subject to determine best practices. CHOP also serves as the first known nutrition education study utilizing the latest AI-based machine learning (ML) techniques to complement the traditional statistical approaches to provide real-time, precise treatment estimates for causal inference and assessment of hands-on cooking and nutrition education for medical professionals and trainees’ patient counseling competencies, and improved patient psychometric and biometric outcomes. (1) The first sub-study, CHOP-Meta-analysis, demonstrated that though the average effect size (ES) across the 10 eligible nutrition education studies among medical trainees was 0.36 (95%CI 6.87-13.85; p<0.001), the only study meeting the STROBE criteria for high quality, the phase I sub-study of CHOP-Medical Students below, had significantly triple the ES (31.67; 95%CI 29.91-33.43). (2) CHOP-Medical Students demonstrated in inverse variance-weighted fixed effects meta-analysis of propensity score-adjusted fixed effects multivariable regression across 2,982 students that GCCM versus traditional clinical education significantly improved trainees’ total mastery counseling patients in 25 nutrition topics (OR 1.64; 95%CI 1.53-1.76; p<0.001). (3) CHOP-CME demonstrated that among 230 medical professionals, GCCM education significantly increased these odds, but by 159% more than the trainees’ improvement (OR 2.66; 95%CI 2.26-3.14; p<0.001) in addition to significantly increasing the odds of counseling most patients on nutrition in their clinical practices (OR 5.56; 95%CI 2.12-14.18; p<0.001). (4) CHOP-Community demonstrated that GCCM education versus the standard of care significantly increased patient adherence to the Mediterranean diet (MedDiet) (OR 1.94; 95%CI 1.04-3.60; p=0.038) and greater connectedness in their social networks (p=0.007). The pilot RCT for diabetes patients, CHOP-Diabetes, nested in this sub-study demonstrated superior improvements in diastolic blood pressure (-4 versus 7 mmHg, p=0.037) and cholesterol (-
14 versus 17 mg/dL, p=0.044) for patients randomized to GCCM versus the standard of care. The nested Phase II BA-RCT, CHOP-Family, demonstrated that GCCM versus standard of care had significantly greater MedDiet adherence based on their grocery receipts (OR 4.92; 95%CI 1.78-13.56; p=0.002). Using the Random Forest Multiple Imputation ML algorithm, the simulated Phase III BA-RCT predicted 93 hospital admissions and $3.9 million would be saved providing GCCM versus standard of care for congestive heart failure (CHF) exacerbation-risk patients primarily from underserved communities. Among 41 tested ML algorithms, the top performing Iterative Classifier Optimizer was comparable to the estimated traditional statistical model for the trainees’ primary endpoint for (1) (RMSE 0.314 versus 0.282), and the top performing Kstar was superior to the traditional model for the professionals’ primary endpoint (RMSE 0.431 versus 0.414). The four sub-studies within CHOP taken together provide the first known multi-site cohort and BA-RCT evidence for superiority of hands-on cooking and nutrition education compared to the standard of education and medical care for improved trainee/professional nutrition counseling competencies and patient outcomes. CHOP utilized the state-of-the-art in causal inference-based statistics, randomized trials for causal assessment, and ML to provide robust, precise estimates of comparative treatment effectiveness. This research infrastructure was scaled up to meet GCCM’s growing programmatic needs as it has since grown over 5 years to 30+ medical centers providing 53,674+ teaching hours to 4,171+ medical trainees/professionals and patients. CHOP has utilized the latest rigorous study design and analysis methodologies to provide a blueprint to optimize health systems through sustainable improvements as population health management that is clinically and cost effective, reducing health inequities while improving individual outcomes.
1. Introduction

1.1. Background

Chronic diseases are responsible for over half of global mortality and the majority of United States health expenditures, despite being driven largely by such modifiable behaviors as inadequate diet and exercise and abuse of alcohol and tobacco.\(^1\) Among these, nutrition factors have been identified by a recent *Journal of the American Medical Association* report as the leading risk factor for morbidity and premature mortality.\(^2\) This nutrition-related chronic disease epidemic is gaining increased public attention not only for its substantive health and financial impacts, but also for its related health disparities affecting food insecure lower income populations.\(^3\)

Diabetes as just one such chronic disease is the seventh leading cause of mortality in the United States,\(^4\) resulting in $245 billion annually or 1 of every 5 health care dollars.\(^5\) This situation is worsened by the negative impact of reduced access to healthy foods and underlying health disparities in the lower income minority food deserts, as noted by the American Diabetes Association.\(^6\) Delays in eliminating such racial and ethnic health inequities results in an additional $308 billion annual costs.\(^7\) Improved diet is a promising approach that has been shown to result in significant reductions in disease incidence and burden, chiefly with the Mediterranean diet (MedDiet).\(^8\)–\(^11\) Currently, first line therapy for
90% of diabetes cases\textsuperscript{12,13} features diet modification aimed at reducing patients’ serum glucose levels to an optimal range.\textsuperscript{14} The standard for nutrition education for patients with documented patient diet improvements is registered dietitian (RD)-led medical nutrition therapy (MNT) which typically includes a nutrition and lifestyle assessment, nutrition counseling and goal setting, and follow-up sessions for goal modification and behavior maintenance.\textsuperscript{15,16} However, MNT programs have several key challenges including limited physician referral and RD availability, decreasing insurance reimbursements for MNT, and patient attrition rates of 79%.\textsuperscript{17}

Inadequate response from health systems is associated with this shared medical and public health challenge, as only a minority of primary care physicians regularly counsel their patients in nutrition or monitor their body mass index (BMI).\textsuperscript{18} This is in contrast to the United States Preventive Services Task Force (USPSTF) recommendations (Grade B) that patients should be screened for obesity as measured by BMI, and be offered or referred to intensive, multicomponent behavioral interventions that include: behavioral management activities, improving diet and physical activity, addressing barriers to change, self-monitoring, and lifestyle maintenance.\textsuperscript{19} Insufficient training is associated with this under-performance by health professionals in chronic disease management and prevention.\textsuperscript{20} A recent report demonstrates that nearly 1 in 2 pediatricians and internists report inadequate proficiency for discussing basic nutrition treatment options.\textsuperscript{21} These
deficits arise earlier in training as just one in four medical schools in the United States meet the minimum 25 nutrition education hours recommended by the National Academy of Sciences.\textsuperscript{22} It is thus not surprising that 81\% of graduating medical students believe they are unprepared to provide their patients nutrition counseling.\textsuperscript{23} The importance of integrated, comprehensive, and inter-professional nutrition education throughout medical education is increasingly clear.\textsuperscript{24,25} Yet despite the medical community increasingly calling internally for reform,\textsuperscript{26} existing education interventions in residencies and medical schools share several features that limit their generalizability, feasibility, sustainability, and thus role in health policy.\textsuperscript{27,28} These challenges, along with reality of rising clinical and financial costs of nutrition-related chronic diseases with the associated health inequities, are met with the concurrent emergence of the Big Data era, heralded as the new frontier of unprecedented innovation productivity.\textsuperscript{29} Artificial intelligence (AI)-based machine learning (ML) algorithms are gaining prominence in medicine and public health through healthcare informatics by translating large, rapidly growing, high-dimensional, and heterogeneous datasets into effective health management and policies decisions, with a high-profile example being the recent Mayo Clinic and United Healthcare partnership through Optum Labs analyzing clinical and claims data for 150 million patients.\textsuperscript{30,31}

1.2. Research Challenges
Such pressing societal health challenges necessitate historic accelerations in the successful collaboration between the medical and public health sectors. Such an approach is promoted by the Centers for Disease Control and Prevention (CDC) as the intersection of four interrelated strategies: integrated clinical and community resources for chronic disease management, health system interventions that facilitate this integration, environmental considerations rooting such interventions that empower healthy behaviors in the context of a patient’s community, and rigorous epidemiological methodology to assess program effectiveness.\textsuperscript{32} Despite this promising conceptual map, there persists a paucity of rigorous studies to demonstrate evidence-based interventions that can thus be adapted at a broader national and global health policy level.

Past studies in this field of nutrition counseling in and through medical education face weaknesses both in term of theoretical and methodological foundations. The internal and external validity of these studies are limited by a lack control comparison,\textsuperscript{33–39} validated survey metrics,\textsuperscript{26,33,35,37,40,41} multi-year longitudinal follow-up,\textsuperscript{26,34,35,37–40} deliberate practice counseling patients,\textsuperscript{33,35–40} adequately powered sample sizes,\textsuperscript{26,33–36,38–40} and randomized study design or statistical methodologies allowing causal inference.\textsuperscript{26,33–41} The absent or limited description of robust theoretical foundations also limit these studies’ contributions to the field’s evidence-base. However, there does exist promising theoretical frameworks in neighboring fields of nutrition, medical education, and clinical
outcomes research whose intersection allows a more comprehensive critique of this field, while pointing to a promising common ground foundation. From the perspective of nutrition research, the above studies omit the emerging standard in evidence-based nutrition, the MedDiet. This is despite a growing body of evidence indicating the MedDiet provides the greatest health benefit and chance of adoption and maintenance among current diets, including a recent systematic review indicating MedDiet ranks first among protective diet patterns against coronary heart disease, the leading mortality cause globally claiming the lives of 17.9 million people every year. Recent nutrition guidelines are increasingly demonstrating a shift towards the MedDiet such as the United States Department of Health and Human Services and U.S. Department of Agriculture’s 2015-2020 Dietary Guidelines for Americans. These guidelines define nutrition standards for federal and state programs including food stamps and school lunches. The absence of the MedDiet in these studies geared ultimately toward clinical outcomes makes them particularly vulnerable to the nutrition field’s critique given the well-documented causal link in both randomized controlled trials (RCTs) and large population-based cohort studies between MedDiet and improved chronic disease management.

Best practices in education are also lacking for these studies, as they also did not capture the two emerging hallmarks of evidence-based medical education: simulation-based
medical education with deliberate practice (SMBE-DP) and comparative effectiveness research (CER). Their reliance on traditional clinical education without both simulation and deliberate practice has been shown to be inferior for skill acquisition in mastery learning, compared to the experiential learning approach of SBME-DP. From the outcomes research standpoint, these studies fall outside of the Institute of Medicine (IOM) 2009 CER recommendations for national research funding priorities. These previous nutrition studies emphasize efficacy of their intervention rather than the CER focus on effectiveness comparing a new treatment to existing standards. They also have reduced or absent coverage of two leading CER priorities, health care delivery systems and racial and ethnic disparities, which are becoming increasingly central to national health system reform. Nutrition education interventions are prohibitively narrow in these studies to address trainee competencies, while being largely silent on the system and health equity implications of the nutrition education interventions.

The above research hurdles undermine the sustainability of the American healthcare system, as outlined by the Triple Aim developed by the Institute for Healthcare to fill needed system gaps to improve (1) the individual patient’s care experience, (2) the per capita cost of that care, and (3) so the population health. Greater clinical and cost effectiveness for the individual and the distribution of equitable improvements across individuals generate improved population health management (PHM). CER and
associated tools such as high-dimensional electronic health record (EHR) data--containing extensive epidemiologic, clinical, laboratory, and genetic information--can thus enhance PHM by providing clinical and cost effective answers to defining or refining standards of care.\textsuperscript{50} The growing prominence of PHM is assisted by the growth of accountable care organizations (ACOs), which are projected to manage the health of nearly 1 in 3 Americans by 2020,\textsuperscript{51} according to Leavitt Partners under former Health and Human Services (HHS) secretary, Mike Leavitt. A promising approach to PHM thus can entail CERs in medical education with nutrition SBME-DP, yet trials are limited in number and programmatically unproven to work outside small pilot studies. Emerging evidence supports Bayesian adaptive (BA) trials to help CER overcome its prohibitively time consuming or restrictive limitations by increasing trial efficiency, without sacrificing reliable and valid study conclusions.\textsuperscript{52} Yet no known programs to date test SBME-DP hands-on cooking and nutrition education for medical students, let alone with BAT trial designs for CER.

1.3. Intervention

Tulane University School of Medicine responded by launching the disruptive innovation sub-field of culinary medicine (CM), at the intersection of the fields of medicine, public health, nutrition, and education. The concrete realization of CM is the world’s first known medical school-based teaching kitchen and research laboratory: The Goldring
Center for Culinary Medicine (GCCM), founded in 2011. The Center under the leadership of a physician and chef recruited the author as a data scientist and public health researcher to create and lead their research program in February 2013. GCCM 1.5 years later moved from its temporary semi-portable kitchens into its own fully equipped kitchen in a former food desert, in collaboration (and in the same building) with an urban grocery store and garden. Over the stove and dinner table, doctors and future medical professionals share clinical pearls on nutrition, exercise, and risk avoidance behavior-based chronic disease management with lower income families, who in turn share their community insights which contribute to professional and trainee education. By deploying versatile analytic methods that incorporate traditional biostatistics, health economic, social network analysis, and AI-based ML, GCCM sharpens its education programming for medical trainees and professionals learning how to better counsel patients and thus indirectly improve patient outcomes, and clinical programs for patients to directly improve their own health. From the program’s birth to May 2016, GCCM has provided over 24,680 hours of hands-on cooking and nutrition education to 444 medical students and 3,728 patients nationally across its 30+ partner sites that stretch across 15+ states in this scalable, population health model.

Toward this surveillance, GCCM implemented Cooking for Health Optimization with Patients (CHOP) as the first known multicenter prospective cohort study with nested BA-
RCTs, assessing superiority of hands-on cooking and nutrition education compared to the standards of education and care respectively for medical trainees/professionals and patients. CHOP also serves as the first known trial to assess through CER SBME-DP hands-on cooking and nutrition education for medical trainees, professionals, and patients; first to incorporate ML and social network analyses (SNAs); and first to expand nationally with other academic and medical centers to demonstrate scalability and sustainability. Long-term GCCM education is provided at the medical student, resident, and practicing physician stages of training. Trainees and physicians’ own diets, attitudes, and competencies in providing patients nutrition counseling are assessed relative to their peers receiving traditional clinical education. Community members through a sub-cohort study and patients through an RCT have their diets, health behaviors, and competencies in healthy shopping, cooking, and eating compared relative to their peers receiving respectively no GCCM classes and registered dietician (RD)-led medical nutrition therapy (MNT).

1.4. Hypotheses

The author formulated and tested three hypotheses by creating and directing the three associated studies and papers that would be the first of their kind to allow future studies from other study teams: (1) CHOP-Meta-Analysis, a regularly updated systematic review and meta-analysis of nutrition education curricula for medical trainees that would
demonstrate GCCM produces superior improvements in nutrition counseling competencies than prior interventions; (2) CHOP-Medical Students, a longitudinal cohort study for medical trainees across 15+ medical schools and (3) practicing medical professionals through CHOP-CME covering multiple continuous medical education (CME) meetings nationally that would demonstrate superior competency improvements versus traditional clinical education; and (4) CHOP-Community, a Phase I to 3 BA-RCT that would provide proof of concept for GCCM versus RD-led MNT by producing preliminary results of superior improvements in hemoglobin A1c (HbA1c), lipids, and blood pressure (Figure 1) for Phase I (CHOP-Diabetes RCT), leaving Phase II (CHOP-Family RCT) and III (CHOP-CHF RCT) to respectively demonstrate 20% greater MedDiet adherence and 9% reduced hospitalizations respectively compared to controls.

These studies were meant to create the sustainable, scalable research and data infrastructure model to stimulate development of similar models able to inform national and global policy in nutrition-related chronic disease management, particularly as it relates to associated clinical, cost and health equity outcomes. Such outcomes are of particular interest given how the greatest health and financial tolls of chronic diseases are in late-term complications and unequally affect certain socioeconomic and racial groups, often treated with costly hospitalization and surgical interventions both to manage complications and prevent them.53 However, the growing complexity of healthcare data
and resource limitations require more real-time, accurate, and robust analytic techniques to provide actionable results to drive health policy aimed at improving health outcomes and disparities of chronic disease.\textsuperscript{54} AI-based techniques are increasingly prominent approaches to address these challenges. Pilot AI products have already begun to demonstrate efficacy in patient outcomes and potentially financial savings as well with continual method refinement.\textsuperscript{55–58} Such approaches are part of a growing field of health informatics driving interventions at an earlier stage for patients by better predicting health events and thus how to prevent them.\textsuperscript{45,46} These CHOP studies are thus meant to provide the theoretical and methodological framework including traditional biostatistics and AI, and preliminary results to inform a scalable research model for later research groups with implicated health policy changes.

2. Materials and Methods

2.1. CHOP-Meta-Analysis

2.1.1. Systematic search. Papers were identified through searching the literature published between January 1, 1994 and July 1, 2016 on PubMed, Web of Science, and Embase databases (Figure 2). Search terms used included: “nutrition education”, “diet education”, “classes”, “curriculum”, “online”, “modules”, “problem-based learning”, or “learning”; and “medical students”, “medical schools”, “students”, “residents”,
“physicians”, “health professionals”, or “medical professionals”. Textbooks and articles identified also were searched in their reference section to generate additional sources.

The meta-analysis was performed according to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines.59

2.1.2. Inclusion and Exclusion Criteria. Inclusion criteria included: (1) pre-post studies investigating the association between nutrition education and medical student competencies providing patient nutrition counseling, (2) and published in the last 22 years. Due to the absence of widespread consensus on education models and evaluation metrics, only pre-post studies were included in order to allow comparison of competency improvements across studies. This time frame was chosen due to the nutrition curricula advances in American medical school (beginning with the National Institutes of Health-funded Nutrition in Medicine Program launched in 1995),60 with no nation-wide nutrition guideline or program changes in medical schools until the creation of GCCM in 2011.

Exclusion criteria included: (1) studies lacking pre-post data investigating the association between nutrition education and medical trainee competencies providing patient nutrition counseling, (2) insufficient data for treatment effect and standard error, (3) duplicated publication, (4) editorial articles, reviews, letters, or meta-analyses. If multiple studies were published by the same author with the same case series, the study with the larger sample size or more recent publication date was used.
2.1.3. **Data Coding Information.** The extraction was conducted by the author. The outcome of interest was the trainee competencies providing patient nutrition counseling. The following characteristics were extracted from the original papers, in duplicate, using a standardized data extraction form: design of the study (e.g., clinical-trial, cross-sectional, case-control or prospective cohort), lead author, year of publication, country of origin, sample size, data to estimate uncertainty (i.e., number of events with diabetes), follow-up duration, effect size (ES) measurements corresponding 95% confidence intervals (CIs) and variables that entered into the model as potential confounding factors.

2.1.4. **Study Quality Scoring Criteria.** Paper quality was scored using the 40-point STrengthening the Reporting of OBservational studies in Epidemiology (STROBE) scoring system.\(^6\) Included studies were assigned to one of three corresponding levels of quality: low (0-19), moderate (20-29), and high (30-40).

2.1.5. **Statistical Methods.** ES was calculated for each study and then combined across studies by dividing the mean difference between post and pretest percentage competency by the pretest standard deviation. For studies using a Likert scale for competency improvement, the pre-post change was divided by the number of scale points and multiplied by 100 to convert the change to a percentage. For studies lacking sufficient
information initially, we used t-test values and degrees of freedom to calculate ES correlation.\textsuperscript{62} Sample size was used to correct the estimates for ES, which were then used to calculate correlation coefficients.

Pooled estimates and 95\% confidence intervals (CIs) of the correlations were calculated for each outcome using an inverse-variance weighted fixed or DerSimonian & Laird random effects meta-analysis models.\textsuperscript{62} Random effects were chosen as the final models over fixed effects models if there was significant overall heterogeneity across the individual studies, indicated by Cochran's Q-test (p<0.10) and the I\(^2\) statistic (≥75\%).\textsuperscript{63,64} These tests were used due to the suspicion for study heterogeneity from study teams in different nations and time periods using different types of education interventions for varying study durations.\textsuperscript{62} Sub-group analysis was conducted according to study quality given the wide variation in intervention types and quality. Sub-group differences across the quality strata were assessed by Cochran's Q-test and the I\(^2\) statistic. A p-value less than 0.10 indicated significant heterogeneity.\textsuperscript{63} Due to concerns the overall ES would be skewed by publication bias (studies with larger sample sizes and/or smaller p-values being more likely to be published), the bias was evaluated graphically by funnel plot and quantitatively with the Harbord-Egger and Begg-Mazumdar statistical tests.\textsuperscript{65,66} However, asymmetrical funnel plots are due to small study effects (with fewer studies included in meta-analyses) generated not just by publication bias, but also by heterogeneity across
individual studies. Therefore, random effects meta-analysis was used to account for heterogeneity, and the Duval and Tweedie nonparametric "trim and fill" method was used to account for publication bias. This technique uses rank-based data augmentation to adjust the meta-analysis by potential missing studies (both their number and ES) that may have been excluded due to publication bias. Trim and fill estimates the missing studies by the following formula:

\[ R_0 = \gamma^* - 1 \]

\[ L_0 = \{4S_{rank}^* - n (n + 1)\} / (2n - 1) \]

\[ Q_0 = n - \frac{1}{2} - \sqrt{2n^2 - 4T_n + 1/4} \]

when the meta-analysis studies are ranked by their distance to the pooled effect, with \( \gamma^* \) denoting the length of the rightmost run of ranks, \( S_{rank} \) denoting the Wilcoxon statistic, and \( n \) denoting the number of studies. Trim and fill was chosen given its popularity as a meta-analysis adjustment method, its consistent and efficient performance reducing publication bias with up to mild study heterogeneity, its applicability for smaller datasets, the arbitrary nature of the alternative methods of selection functions, and the paucity of quantitative evidence for the performance of selection models or superiority of such models (i.e. Copas) over such funnel plot measures as trim and fill. The above traditional statistical analyses were conducted with Stata 14.2 (StataCorp, College Station, Texas, United States of America), with the
significance level set at the alpha value of 0.05 in two-sided tests except as otherwise noted.

2.1.6. Machine learning methods. Traditional biostatistics enjoys a long evidence-based role in nutrition education, public health, and clinical medicine research. But the growing complexity, rapid publication rate, and varying research quality of these fields have contributed to the increasing emphasis placed on the techniques of ML, as a subdiscipline of AI. ML has been consistently shown to optimize the speed, precision, and validity of conclusions drawn from existing knowledge and personalize them to the individual patient within a PHM paradigm. Its advantages over traditional statistics include the processing of high dimensional data (i.e. large aggregate data from population health management EHR and omics data) and its real-time speed automating updated conclusions based on a continual stream of new studies. But recent research demonstrates that ML techniques have an additional superior edge in the handling of missing data, which can undermine valid meta-analyses. Multiple imputation (MI) is a well-accepted statistical technique of addressing this, but it may be impossible for traditional MI to address missing values in high-dimensional data that could require imputation models with all the dataset’s variables. Further, ML-based MI has been shown to be superior to traditional statistics-based MI by producing more narrow confidence intervals with greater efficiency.
One of the leading theoretical and practical frameworks for ML is probabilistic modelling. This approach describes how to represent and handle model uncertainty, with a key foundation for this framework being Bayesian optimization. Practically speaking, ML algorithms are generally divided into supervised and unsupervised learning techniques based on whether the underlying data structures, inputs (i.e. predictors), and outputs (i.e. outcomes) are respectively known, or unknown. Supervised learning is thus well suited to filling in missing data as the data structure and parameters are already known. This learning category is further subdivided into whether the desired outcome is continuous (and thus require regression methods including linear regression) or is categorical (and require classification methods including artificial neural networks [ANNs], decision trees, Naïve Bayes, or support vector machines [SVMs]).

ML was thus used in this study using R package 3.3.2 (R Foundation for Statistical Computing, Vienna, Austria) to optimize performance of traditional biostatistical models of meta-analysis that otherwise may not produce reliable and valid results given the wide variety in education intervention and study quality (including missing data vital to meta-analysis computing). ML was specifically used to first strengthen MI using the random forest algorithm (RF-MI), due to the data structure and this technique’s greater efficiency, less biased estimates, and narrower confidence intervals than the popular
traditional MI technique of MI by chained equations (MICE). ML was then used to assess model performance of the traditional fixed and random effects meta-analysis. This assessment was based on the highest performing ML algorithm, chosen among 26 algorithms systematically tested, after first being selected for testing based on their appropriateness for the dataset given its continuous outcome (ES). Algorithm performance was evaluated with values >100% for root relative squared error (RRSE) being considered sub-optimal as they indicate the model does little better than predicting the outcome mean.

2.2. CHOP-Medical Students and CHOP-CME

2.2.1. Intervention. The GCCM classes adapted for this collaboration adapt the evidence-based medical education model of simulation-based medical education with deliberate practice (SBME-DP) into training for patient nutrition counseling. A recent meta-analysis established the superiority of this model versus more lecture-based models, as seen prominently in traditional clinical education curricula in medical schools. The competency-based GCCM elective classes were adopted from prior evidence-based curricula as part of a larger curriculum extending from medical school to residency and into continuing medical education (CME) credits for longitudinal training for current and future physicians. To meet the 25 contact hours of nutrition education recommended by the National Academy of Sciences, the GCCM elective spans 28
hours comprising eight classes, each including 0.5 hour pre-class lecture videos, 1.5 hours of hands-on cooking, and 0.75 hour of problem-based learning covering the clinical application of the lecture content based on national board exam questions, while participants share the prepared meal. In addition to the elective mostly provided for first and second students, there are five 3-hour disease specific modules for upperclassmen amid their clinical rotation duties. These seminars focus on such topics as nutrition in congestive heart failure, celiac disease, and HIV management. Programming aimed at pediatric and family medicine residents is also available to partner sites. This GCCM curriculum was translated into five 2-hour CME modules for practicing physicians by incorporating more advanced clinical teaching points. Modules were advertised through Tulane University School of Medicine on behalf of GCCM, and a separate annual clinical conference. This intervention was compared to the control of non-GCCM nutrition education, specifically that provided in traditional clinical education as part of the individual medical schools’ curricula. The nutrition education in these curricula were treated as a homogenous control due to schools adhering to similar curricula requirements as mandated through the common accreditation body, the Liaison Committee on Medical Education (LCME) recognized by the United States Department of Education.91

2.2.2. Data. The first multicenter student analysis evaluated student responses to a validated 59-question panel survey distributed throughout the study bodies of fifteen
academic medical centers and schools including:

- University of Chicago Pritzker School of Medicine
- Rutgers Robert Wood Johnson Medical School
- Meharry Medical College
- Texas College of Osteopathic Medicine
- Lake Erie College of Osteopathic Medicine
- University of Colorado–Denver School of Medicine
- University of Texas Health Science Center–San Antonio
- University of Illinois-Chicago College of Medicine
- University of Tennessee-Memphis College of Medicine
- AT Still University Kirksville College of Osteopathic Medicine
- University of Utah School of Medicine
- University of Texas Health Science Center at Houston McGovern Medical School
- Mississippi Gulf Coast Community College
- Church Health Center
- Tulane University School of Medicine.

The survey (Appendix 1) was adapted from prior validated surveys\textsuperscript{34,36,38,39} following the 2013-2015 qualitative assessments of the CHOP target demographic, and quantitative testing of its Fall 2012-2015 survey with the first three years of student responders (Appendix 2). The physician analysis assessed responses from any GCCM or clinical
conference CME modules. The current survey utilizes a five-point Likert scale for student diets, attitudes toward nutrition counseling, and competencies in counseling. Study inclusion criteria were survey completion during the study period of August 2012 to March 2016 and enrollment at one of the collaborating schools for students, and participation in any of the GCCM or clinical conferences for physicians. Exclusion criteria included more than one response per site during a given semester, and failure to note participation or nonparticipation in the GCCM elective (students) or CME modules (physicians). To ease interpretation, dietary intake of various foods was translated into the MedDiet validated 9-point score system based on intake frequency. Responses were also dichotomized for dietary responses into daily intake of not, attitudinal questions about the role of nutrition counseling in healthcare as strongly agree versus not, and for competencies counseling patients as totally competent versus not. The Tulane Institutional Review Board approved this study.

2.2.3. Statistical Methods. The primary endpoint was total mastery averaged over the 25 counseling topics; the secondary endpoints were strong agreement that nutrition counseling should be routine, and high or medium versus low MedDiet adherence. In place of the attitudinal question, the additional secondary endpoint for medical professionals was providing nutrition counseling for patients on most visits with the main predictor being post versus pre-GCCM participation. The primary analysis featured
multivariable fixed effects regression with propensity score (PS) adjustment to allow causal inference (Stata “xtlogit, fe” command). The PS (Stata “pscore” command) was estimated using a probit model and then divided subjects into the optimal number of blocks to achieve balance (6 in this study). This statistical technique for the students controlled for known confounders of gender, age, race, prior nutrition education, special diet, school year, and medical school, in addition to unobserved time invariant traits (i.e., region-specific culture trends through the fixed effects approach), and the likelihood of receiving GCCM classes (through the PS adjustment). For the professionals’ analysis, the same variables were controlled for with the exception of school year and medical school year being omitted, and the following variables added: type of medical professional, primary care specialty, and number of practice years based upon prior research into known confounders.

2.2.4. Machine Learning Algorithms. Secondary analysis compared model performance from traditional statistics and 41 ML algorithms, given the rapid growth in data volume and complexity in clinical outcomes research which lends itself to ML, and the rising role of ML across nearly all research fields including education research. Along with similar classification techniques such as Bayesian classifiers and artificial neural network (ANN), support vector machine (SVM) algorithms attempt to organize data into predefined classes to accurately predict the destination class for each data point in a
Such classification techniques are widely utilized examples of data mining techniques, which along with traditional statistical techniques, are increasingly used in a complementary fashion to increase the predictive power of models and the interventions and policies they inform. The SVM models were generated for regression with 10-fold cross validation following MI of missing values in the original dataset using multivariable normal regression and Bayesian Markov chain Monte Carlo procedure. STATA 14.2 (StataCorp, College Station, Texas, United States of America) was used to analyze traditional statistical results using the imputed dataset. Adjusted ORs are reported with 95% CIs. Statistical significance was set at a two-tailed p-value of <0.05.

The major supervised ML algorithms (regression or classification) were deployed with the final algorithm, which was determined based on model accuracy, training time, linearity, and parameters. SVM is a classification technique proposed by Vapnik and Chervonenkis that fits an optimal decision boundary among other possible decision boundaries by maximizing the margin separating two classes. The simplest of the Bayesian methods and one of the leading efficient and accurate ML algorithms, Naïve Bayes has been shown to outperform SVM and other ML algorithms including Decision Tree and k-Nearest Neighbor. Yet modifications to SVM allow it to supersede the performance of Naïve Bayes, such as when Principal Component Analysis (PCA) is utilized to decrease the feature or attribute number. Naïve Bayes identifies
and applies features or labels to a given class with the high accuracy, efficiency, and simplicity. More complex Bayesian networks with their conditional probabilities of variables in relation to each other (and implementation as classification or regression) can model more advanced real-world relationships, such as differentiating depression syndromes. Based on the brain’s neuronal connections that are strengthened or inhibited based on increasing input, ANN is a popular classification technique particularly with parallel processes given its speed and accuracy to model complex non-linear relationships which can confound traditional statistics. Yet all these techniques risk overfitting, or amplifying minor data variations by model fitting to random noise. Comparing model and method performance therefore is accomplished by first creating a model on an initial or training dataset and then assessing its performance on an independent external or testing dataset.

For this analysis, popular ML algorithms above among others were run based on their appropriateness to the data structure using the same variables from the traditional statistics model of PS-adjusted fixed effects multivariable regression. Though exclusion of certain variables could boost ML model performance, keeping all variables in the ML models allowed better comparison to the traditional statistical models. ML algorithm performance was compared among themselves with the RRSE, with 100% serving as the threshold for unacceptable models, and then compared to the traditional statistical models.
with the RMSE.

2.2.4. Sample Size Calculations. Sample size calculations were derived based on the reported treatment effect of nutrition education on diets, attitude, and competencies (DACs) of medical trainees.\textsuperscript{33–41,89} Calculations indicated that 94 responses were needed to detect a 25% greater DAC improvement versus control with a power of 80% (Stata “power twoproportions” command for two-sample proportions test using Pearson’s chi-squared test).

2.3. CHOP-Community

2.3.1. Summary. Inclusion criteria was \( \geq 7 \) years of age and availability to participate in at least one GCCM class from August 2012 – February 2017. The study design is a longitudinal cohort study accepting patients who identify themselves to GCCM through its website, on-site presence at its inner-city grocery store location, or via its phone given the national interest for GCCM classes generated through aggressive social media, news media, and community outreach. Its data, metrics, and protocols are detailed below as per its three sub-studies corresponding to its three phase BA-RCT: CHOP-Diabetes RCT, CHOP-Family RCT, and CHOP-CHF RCT for its Phase I-III respectively. Patients willing at the time of recruitment to be randomized (with the associated requirement to enter a control arm should they be randomized to it rather than the treatment arm) are
then directed to one of the three sub-studies; otherwise, they remain in the cohort study without randomization as the free classes cannot by GCCM policy be limited to only randomized subjects. All three RCTs feature a cross-over design so that subjects initially randomized to the control arm can enter the treatment arm at least 6 months after being on the control arm and completing the required pre-post surveys should they wish. Descriptive statistics of demographic factors and their inclusion in multivariable regression models and AI-algorithms could not be done as initial IRB approval did not include access to these variables.

2.3.2. CHOP-Diabetes BA-RCT. 2.3.2.1. Subjects. Inclusion criterion was patients with diagnosed type 2 diabetes (T2D) presenting to Tulane University Hospital and Clinics from June 2014-June 2015. Exclusion criterion was pre-existing enrollment in another study involving interventions for diabetes. Institutional Review Board approval was granted through Tulane University for this study, and informed patient consent was collected.

2.3.2.2. Design. This study uses a pilot RCT design to compare RD-led MNT with chef, physician, and medical student-led hands-on cooking and nutrition classes. The six-module cooking and nutrition curriculum translates the MedDiet for culture-specific kitchens across different socioeconomic levels. The control group received the standard
of nutrition education, RD-led MNT, consisting of a one-time RD counseling visit with a referral opportunity to an American Diabetes Association-certified diabetes education class. The treatment group participated in the GCCM modules over 1.5 months as part of an evidence-based GCCM curriculum. Each two-hour cooking class consisted of 30 minutes of didactic lessons and 90 minutes of cooking time. The design and endpoints for this pilot study were adopted from a recent RCT which provided evidence of MedDiet improving HbA1c for patients with T2D, including keeping the study non-blinded due to logistical concerns.

2.3.2.3. Data. Biometric data were collected through chart reviews from baseline to 6 months after participation in the intervention or control groups according to regularly scheduled primary care clinic visits. Reviewers had to have knowledge of subjects’ study groups in order to collect biometric data at the correct 6 month time point following their completion of the last cooking class or their MNT session. Biometric data points included: HbA1c, systolic and diastolic blood pressures (SBP and DBP), total cholesterol, triglycerides, low density lipoproteins (LDL), high density lipoproteins (HDL), heart rate (HR), body mass index (BMI), and hypoglycemic agents and insulin. Psychometric data were collected through a survey developed from validated tools at baseline and again at 1.5 months following the MNT session for control patients or the last GCCM class for intervention patients. These data points included: DACs for healthy shopping,
meal-preparation, eating, and storage. Food desert residence was defined by the United States Food and Drug Administration (USDA) as a subject claiming a permanent home address in a low-income census tract where a significant number or share of residents are more than 1 mile (urban) or 10 miles (rural) from the nearest supermarket.\textsuperscript{116}

Survey responses (psychometrics) used a multi-point Likert scale for dietary habits with different foods (9-point scale ranging from never per month to over 3 times daily), attitudes (5 points ranging from very unconfident to very confident), and competencies as frequencies of healthy eating actions (5 points ranging from never to always). Survey responses were dichotomized to aid in interpretation into: most times for dietary habits (over 4 times weekly versus less), mostly confident for attitudes (confident and very confident versus neither), and competencies (most of the times or always versus neither).

2.3.2.4. Endpoints. A permuted block design randomization scheme was used. The primary endpoint over six months of follow-up was HbA1c reduction of -0.3\% (-27 mmol/mol) from baseline to follow-up within each group, with secondary endpoints including DBP reduction of 10 points and a 25\% improved response in the DAC sections from baseline to follow-up, based on the existing literature for such nutrition education interventions for this patient population.\textsuperscript{15,16,45,46,117}
2.3.2.5. **Statistical Methods.** This intention-to-treat statistical analysis used the mean biometric values with 95% CI, which were calculated after verifying that continuous variables do not significantly deviate from normal distribution with the Shapiro-Wilk and Shapiro-Francia tests (Stata “swilk” command),\textsuperscript{118} and skewness and kurtosis tests for normality (Stata “sum, detail” command). Multilevel mixed effects linear regression with repeated time measures were used to investigate biometric and psychometric changes from baseline to 6 months for the GCCM compared to control groups (Stata “xtmixed” and “contrast” commands).\textsuperscript{119} An increase in a metric over the study period was represented as a positive value, and a decrease was represented as a negative value. This regression was used in place of ANOVA with repeated measures due to that the regression method produces correct standard errors for each effect automatically while handling unequal observations within subjects. These unequal observations from missing values were affected by the sample including lower socioeconomic patients with less reliable transportation and communication capacities, with their subsequent irregular attendances at scheduled clinic visits or responses to study staff attempts to contact them. Since this was a pilot clinical trial, it was powered to assess safety and proof-of-principle, not clinical effectiveness. Analyses were conducted using STATA 14.2(StataCorp, College Station, Texas, United States of America).\textsuperscript{75} A p-value <0.05 was considered statistically significant.
2.3.3. CHOP-Family BA-RCT. CHOP-Diabetes RCT was necessary to run as a pilot study to first determine safety, program feasibility, and informing of priors in order to launch the first known Bayesian adaptive (BA) trial in hands-on cooking and nutrition education for patients, CHOP-Family BA-RCT as a Phase II and III seamless trial. BA study design was selected over traditional clinical designs due to a growing health system pressure (to demonstrate superior comparative effectiveness for systems to offer such GCCM programming amid tight budgets for PHM), data complexity (increasingly high-dimensional biometric, genetic, and social network data) and velocity (from the same CHOP-Medical Students sites and a steadily growing number wishing to launch GCCM clinical trials at their sites), and lack of extensive priors. There was only known previous RCT in hands-on cooking and nutrition education for patients (Monlezun et al. 2015) to inform sample size, duration, endpoints, and treatments arms. BA design detailed CHOP-Family BA-RCT would recruit any child ≥7 years of age with their accompanying parent or guardian; enroll 128 adult-child pairs (256 subjects total); test the primary endpoint of 20% improved MedDiet adherence (high/medium versus low) with GCCM versus control based on food receipt-documented purchases; test the secondary endpoints of 1 point MedDiet improvement, 20% increased weekly frequency in self-reported cooking, and 5% decreased likelihood of hospitalization; test the tertiary endpoints of the biometric and psychometric endpoints from CHOP-Diabetes RCT using the biometric data collection tools and validated surveys adapted from that trial (Appendix 3); require
152 total weekly food receipts be collected from GCCM versus control subjects to assess the primary endpoint with 80% power; randomize each adult-child pair 1:1:2 to one of three study arms (Control 1: No intervention; Control 1: GCCM-provided healthy diet educational pamphlets [similar to what healthcare providers distribute in their clinics, in lieu of adequate time for nutrition counseling]; Treatment 1: 6 GCCM classes provided to adult-child pairs); include interim analyses every 6 months; have stoppage rules including closure of the trial once the primary endpoint is achieved; include revision of the inclusion criteria be restricted to patients with congestive heart failure (CHF) admitted to Tulane Medical Center or other medical center (including other CHOP partner sites) with approved data sharing (Phase III), elevate the hospitalization secondary endpoint to be the primary endpoint (Phase III), and add the secondary endpoints of gross charges and length of stay (Phase III), if the primary endpoint was met (Phase II) along with adequate simulation results indicating the new primary endpoint would be met.

Given the RCT design, traditional statistical analyses of the endpoints would include Pearson chi-square (Stata “tab, chi2” command) for categorical dependent variables, and independent sample t-test (Stata “ttest” command)\textsuperscript{121,122} or Wilcoxon rank sum test (Stata “ranksum” command)\textsuperscript{123,124} for interval dependent variables as appropriate, based on the presence or absence respectively of normal distribution. SNAs through network plotting (Stata “nwplot” command) were conducted based upon GCCM’s unique intervention
advantage of having suspected dynamic, exponentiated improvements in patient health due to their social network members taking part in the intervention as well. If a parent takes a hands-on cooking and nutrition class with his or her child, it is plausible that both will eat better than if just one or the other participated in the course. Further, GCCM has the theorized cost-effectiveness of having diffusion of its innovation throughout underserved, food desert communities by having GCCM-trained community members teaching their friends, neighbors, etc. by virtue of shared meals. This theoretical work is built upon social cognitive theory, \(^{125}\) social contagion and network theory, \(^{126-133}\) and complex adaptive system theory, \(^{134-137}\) in addition to the empirical evidence of Christakis and Fowler who demonstrated that obesity spreads up to 3 degrees of separation through 32 years of the Framingham Cohort Study. \(^{138}\)

This study’s SNA was opened to include CHOP-Family adult-child pairs and all community members who voluntarily signed up for GCCM classes from 2012-2017 following provider referral, former GCCM participant referrals, or personal searches in-person at the food desert-based GCCM or its social media, website presence, or media appearances. Greater analysis inclusion for the SNA allowed assessment of organic and study design-related associations of subject participation and diffusion of innovation through their communities. Pearson chi-square test (Stata “tab, chi2” command) was used to compare social networks by GCCM versus control. PS (Stata “pscore” command)\(^ {94,95}\)
adjusted fixed effects multivariable regression (Stata “xtlogit, fe” command) was used to assess self-reported MedDiet adherence among all community members, controlling for prior nutrition education, primary care physician (PCP) nutrition counseling provided, the likelihood of receiving GCCM classes, and time invariant unobserved traits. The fixed effects regression results for all community members was compared to those just for CHOP-Family subjects, and to the above statistics outlined just for this sub-set.

Simulated future trials would be run at each interim analysis to guide a priori-defined design revision. Simulations would be conducted according to the multiplication rule in statistical independence theory, in which the increased probability of MedDiet adherence (30%) for GCCM versus control subjects would be multiplied by the decreased probability (30%) of CHF-related hospitalizations. The latter probability was formulated based on the 30% reduced rate of myocardial infarction, stroke, and cardiovascular (CV)-related mortality from MedDiet adherence, demonstrated in the large, multi-center RCT (Prevención con Dieta Mediterránea, PREDIMED) of 7,447 subjects. Based on the PREDIMED results, it was plausible that a stricter assumption could be made (i.e. that MedDiet would at least reduce by 30% the rate of CV-related admissions). This joint probability of event A and B occurring together (A = GCCM-driven improvements in MedDiet; B = MedDiet-related reduction in CHF-related hospital admissions) could be expressed with the statistical theory of independence:
P(AB) = P(A) P(B)

The ML algorithm, RF-MI, was used to fill in missing values, with values close to 0 for the normalized root mean squared error (NRMSE) considered adequate performance of the imputation. The Kaplan-Meier curve (Stata “sts” command), proportions of admission and readmission, and sums of gross charges and length of stays were performed in STATA 14.2 (StataCorp, College Station, Texas, United States of America). ML calculations were conducted in R package 3.3.2 (R Foundation for Statistical Computing, Vienna, Austria)

3. Results

3.1. CHOP-Meta-Analysis

Of the 172 citations identified using the search protocol, 10 studies met inclusion and exclusion criteria (Table 1, Figure 2). RF-MI produced imputed values with a RMSE of 0.103. Using traditional statistics, significant overall heterogeneity was detected (Q-test p<0.001; I² 99.4%). Random effects meta-analysis was thus used to demonstrate an overall ES across 1 high, 3 moderate, and 6 low quality studies of 10.36 (95%CI 6.87-13.85; p<0.001) (Figure 3). The only high quality study rated by STROBE quality, had a significantly higher ES (31.67; 95%CI 29.91-33.43) than moderate quality (ES 7.72; 95%CI 1.72-13.72) and low quality studies (ES 8.02; 95%CI 5.18-10.86) (Q-
test p<0.001; I² 98.6%). High, moderate, and low quality studies demonstrated that the nutrition education interventions they assessed improved medical student competencies (%, pooled standard deviation) respectively by 72% (2%), 18% (13%), and 21 (14%).

The asymmetrical funnel plot (Figure 4) and the Harbord-Egger (p=0.014) and Begg-Mazumdar (p=0.020) statistical tests indicated significant small study effects, possibly due to publication bias. Trim and fill was thus used to produce an adjusted overall ES in random effects meta-analysis of 4.05 (95%CI 0.28-7.83; p=0.035) (Figure 5), and an adjusted funnel plot that added 5 studies suspected to be missing secondary to publication bias (Figure 6). ML was then used to compare the above unadjusted and adjusted random effects meta-analysis results. Because of the continuous variable of ES, ML-linear regression (ML-LR) with 10-fold cross validation was the first algorithm used, demonstrating an overall ES of 10.35 (95%CI 9.95-10.75). The RRSE was improved from 97.99% to 81.31% by switching from simple ML-LR to ML-LR with locally weighted learning (LWL). LWL utilized an instance-based algorithm to allot instance weights and thus use them to produce the final estimate through a specified weighted instances handler in ML-LR. This ML method outperformed the remaining 24 tested algorithms: Gaussian regression, multilayer perceptron with backward propagation, SVM with regression, K-nearest neighbors, additive regression, attribute selected classifier, bagging, cross validation parameter selection, multi-scheme, random committee,
randomizable filtered classifier, random sub-space, regression by discretization, stacking, vote, weighted instances handler wrapper, input mapped classifier, decision table, M5 model tree, zero-R, decision stump, random forest, random tree, and reduced error pruning tree with backfitting.

3.2. CHOP-Medical Students and CHOP-CME

Of the 13,175 eligible trainees across 15 study sites, 2,982 (22.63%) students met study criteria and generated 3,593 survey responses from Fall 2012 to Spring 2017. Among those meeting criteria, 624 (20.93%) subjects participated in the GCCM classes; 1,706 (57.21%) were female; 1,035 (34.71%) were non-white; and 830 (27.83%) were third or fourth year upperclassmen with clinical experience. Subjects receiving GCCM versus traditional clinical education had significantly greater odds meeting the primary endpoint of total mastery averaged over 25 counseling topics using inverse variance-weighted fixed effects meta-analysis (OR 1.64; 95%CI 1.53-1.76; p<0.001) (Figure 7), and the secondary endpoint of strong agreement that nutrition assessment should be part of a routine medical visit (OR 1.91; 95%CI 1.49-2.45; p<0.001). Improvement in total mastery was non-significant with GCCM versus control in the first year at the first pilot site at Tulane University School of Medicine (OR 0.98; 95%CI 0.81-1.19; p=0.859) (Figure 8). The improvement peaked with GCCM curriculum improvements by the second year (OR 2.52; 95%CI 2.06-3.08; p<0.001), and then declined though still
remaining significant with the scaling up of the program to an additional 9 sites up until Spring 2016 (OR 1.69; 95%CI 1.34-2.13; p<0.001). Five additional sites from Spring 2016 - Spring 2017 similarly was associated with reduced though still significant total mastery for the full study duration of Fall 2012 - Spring 2017 (OR 1.64; 95%CI 1.53-1.76; p<0.001), with significantly greater mastery odds for 20 of the 25 topics. GCCM versus control subjects from Fall 2012 - Spring 2016 had significantly greater odds of high/medium versus low MedDiet adherence (OR 1.32; 95%CI 1.00-1.73; p=0.048), but significance was lost when an additional 5 sites joined the study with their first year deploying the GCCM curriculum (OR 1.11; 95%CI 0.87-1.41).

The logistic algorithm (RRSE 98.16%) produced an OR (1.60) and RMSE (0.316) less than the estimated traditional statistical model of PS-adjusted fixed effects multivariable regression for the primary endpoint across the full study duration (RMSE 0.282). This algorithm outperformed the following 41 algorithms by their classes: Bayesian (Bayes Net, Naive Bayes, Naive Bayes Multinomial Text, and Naive Bayes Updateable), Functions (Multilayer perceptron, SGD, SGD Text, Simple Logistic, SMO, and Voted Perceptron), Lazy (IBK, KStar, and LWL), Meta (AdaBoostM1, Attribute Selected Classifier, Bagging, Classification via Regression, CV Parameter Selection, Logit Boost, Multiclass Classifier, Multiclass Classifier Updateable, Multischeme, Random Committee, Randomizable Filtered Classifier, Random Sub-space, Stacking, Vote, and
Weighted Instances Handler Wrapper), Miscellaneous (Input Mapped Classifier), Rules (Decision Table, JRip, OneR, Part, and ZeroR), and Trees (Decision Stump, Hoeffding Tree, J48, LMT, Random Forest, Random Tree, and REP Tree). Model performance was boosted when shifted to an Iterative Classifier Optimizer algorithm (RMSE 0.314).

Of the 230 medical professionals who generated 308 completed surveys, 64 (27.83%) were repeat responders and 40 (17.39%) completed post-GCCM class surveys. Of the overall completed surveys, 54 (17.53%) were post-GCCM surveys. Among responders, the mean (SD) age was 45.10 (15.72), 162 (70.43%) were female, 175 (76.09%) were white, 67 (29.13%) followed a special diet, 76 (33.04%) had prior nutrition education, 156 (67.83%) were physicians (with the remaining 74 being registered nurses, physician assistants, occupational therapists, registered dieticians, nurse practitioners, and other medical professionals), on average had practiced 10-19 years after training, and 132 (57.39%) specialized in primary care.

In fully adjusted multivariable fixed effects regression with PS adjustment for the primary endpoint, GCCM significantly doubled health professionals’ total mastery in the 25 competency topics averaged together (OR 2.66; 95%CI 2.26-3.14; p<0.001), and improved but non-significantly their own Mediterranean diet adherence on the 9-point scale (Beta 0.03; 95%CI -0.54-0.60; p=0.097). GCCM improved professional
competency counseling patients in all the topics, and significantly in the majority (17 of 25) including in: Mediterranean diet, Dash diet, low fat diet, high protein diet, serving size, moderate alcohol intake, eating disorders, cholesterol, diabetes diet, obesity weight loss, omega fats, dietary fats, antioxidants, calories, hydration, food allergies, fiber, and body mass index (BMI). For the secondary endpoint, GCCM significantly increased professionals’ odds of actually counseling their own patients in nutrition (OR 5.56; 95%CI 2.14-14.48; p<0.001).

The top performing ML algorithm was Kstar (RRSE 88.11%) compared to the other algorithms (RRSE): Gaussian Processes (97.88%), linear regression (96.97%), multi-layer perceptron (140.89%), SMOreg (122.25%), IBk (106.17%), LWL (96.71%), additive regression (98.86%), bagging (93.36%), CV parameter selection (100.00%), multi-scheme (100.00%), random committee (95.96%), randomizable filtered classifier (134.62%), random sub-space (92.73%), regression by discretization (101.69%), stacking (100.00%), vote (100.00%), weighted instances handler wrapper (100.00%), input mapped classifier (100.00%), decision table (97.95%), M5 rules (98.01%), zero R (100.00%), decision stump (100.16%), M5P (97.89%), random forest (90.52%), random tree (112.03%), REP tree (98.27%). Compared to the traditional statistical fully adjusted regression model for the primary endpoint (OR 5.56 with propensity score-adjusted multivariable fixed effects regression RMSE of 0.431), the ML logistic regression
algorithm produced similar OR and RMSE (5.24; 0.459), but ML algorithm performance became superior to the traditional model by using the KStar algorithm (RMSE 0.414).

3.3. CHOP-Community

3.3.1. CHOP-Community. Among the total sample size of 558 patients, 303 (54.30%) participated in the GCCM treatment. In PS-adjusted fixed effects multivariable regression controlling for prior nutrition education, PCP nutrition counseling provided, the likelihood of receiving GCCM classes, and time invariant unobserved traits, patients receiving GCCM versus not significantly increased their adherence to the MedDiet (OR 1.94; 1.04-3.60; p=0.038), and in unadjusted SNA with Pearson chi square test, also their connectedness in their social networks (p=0.007) with friends and medical professionals being the most central social network members of GCCM versus control subjects.

3.3.2. CHOP-Diabetes BA-RCT. In this study randomizing 27 subjects either to GCCM or the control arm, 18 (67%) participated in the GCCM intervention with an average age of 62 years, 75% being African American, 67% female, and 46% residing in a USDA-defined food desert, all comparable to the control group. In contrast to the control group, the GCCM group had superior mean HbA1c reduction from baseline to 6 months, -0.4% (-28 mmol/mol) versus -0.3% (-27 mmol/mol) p=0.575, that was not statistically significant (Table 3). There were significantly greater reductions in the GCCM versus
control group for DBP (-4 versus 7 mmHg, p=0.037) and total cholesterol (-14 versus 17 mg/dL, p=0.044). The control group had a transient negative HbA1c improvement one month after the intervention; whereas, the improvement was sustained at 6 months for the GCCM group after the intervention lasted 1.5 months. GCCM subjects either had greater reductions or a slower rise in all negative risk factor biometrics compared to the control group, which instead worsened in these biometrics (SBP, DBP, total cholesterol, and LDL) with the exception of triglycerides and HR. Both the GCCM and controls groups had similar pre-post BMI measurements.

The largest biometric difference for both groups was total cholesterol as the GCCM group decreased by 14 mg/dL (-0.4 mmol/L), compared to the control group increasing by 17 mg/dL (0.4 mmol/L). This inverse relationship is similar for LDL, as the GCCM group decreased by 6 mg/dL (-0.2 mmol/L) while the control group increased by 13 mg/dL (0.3 mmol/L). The control group did have a -20 mg/dL (-0.2 mmol/L) greater drop in triglycerides than the GCCM group and 15 mg/dL (0.4 mmol/L) greater increase in HDL. Lipid lowering medications and insulin were similar for both groups at baseline, though there were two GCCM patients who ceased use of hypoglycemic agents, compared to no control patients coming off their medications during the study period. Metformin 1000mg and Lantus (15-50 units) respectively were the most common hypoglycemic agent and insulin used for both groups.
GCCM patients’ psychometrics improved but without statistical significance compared to the control group in their attitudes and competencies in healthy food shopping and eating. The two largest differences in DAC changes between the groups were in competencies. There was a greater proportion increase of GCCM subjects compared to controls who mostly believed they could eat correct portions (18% versus -11%, p=0.124), and who used nutrition panels to make food choices (34% versus 0%, p=0.745) (Table 4). The GCCM group lagged behind the control group in the proportion increasing their vegetable consumption (16% versus 23%, p=0.736) and fruits (0% versus 22%, p=0.255). Though both the GCCM and control subjects met the primary endpoint for HbA1c and missed the secondary endpoint for DBP, only the GCCM group met the 25% endpoint for DAC improvement, specifically in competencies for using nutrition panels in food choices.

3.3.3. CHOP-Family BA-RCT. The primary endpoint was met after the second interim analysis with 155 food receipts from the adult-child pairs within 15 families. GCCM versus control produced 4 times the high/medium versus low MedDiet adherence (40.00% versus 10.00%, p<0.001). SNAs of the 561 subjects including CHOP-Family subjects indicated that significantly greater social network connectedness occurred after at least one GCCM class (p=0.007) (Figure 9 and 10). The four most centrally located
network members for GCCM subjects were friends (38.64%), medical professionals (17.61%), children (17.05%), colleagues/classmates (14.20%). The four most centrally located members for control subjects were medical professionals (36.36%), children (29.55%), friends (25.00%), and siblings (4.55%). Among all community members, fixed effects models indicated that GCCM versus control significantly increased the odds of high/medium versus low self-reported MedDiet adherence (OR 1.94; 95%CI 1.04-3.60; p=0.038) (Figure 11). Among only the CHOP-Family subjects, the significantly increased odds were 2.5 times the overall community sample (OR 4.92; 95%CI 1.78-13.56; p=0.002). The over four-fold increased odds of higher self-reported MedDiet adherence were comparable to the RCT (Pearson chi-square statistics) for the CHOP-Family subjects of 4-fold increased likelihood of MedDiet adherence based on food receipts.

Before proceeding to enrolling CHF patients in GCCM versus control arms, the simulated Phase III was conducted beginning with RF-MI for 1,031 admissions from 682 patients presenting to Tulane Medical Center from 2012-2015 with the primary diagnosis of CHF exacerbation. RF-MI showed adequate imputing performance (RMSE 0.001). Kaplan-Meier curves were then constructed based on readmission reason (Figure 12). Based on the CHOP-Family BA-RCT and PREDIMED RCT data, providing GCCM to patients at risk for CHF exacerbations as a PHM adjunct treatment would have resulted in reductions of: 93 hospital admissions; $3,903,706.40; 323.29 days length of stay; and 12
<30 day readmissions.

4. Discussion

4.1. CHOP-Meta-Analysis

This novel systematic review and meta-analysis not only was the first known to demonstrate a statistically significant ES of nutrition education on medical trainees’ competencies in patient nutrition counseling, but also did so by featuring an innovative bridge between traditional statistics and AI-based ML. The present meta-analysis has several strengths: (i) it was based on a systematic review in the acquisition of studies, following international PRISMA standards; (ii) the data analysis was performed using the latest evidence-based statistical methods (iii) by pooling multiple studies, the effective sample size was greatly increased; (iv) an adjustment to account for heterogeneity and publication bias was performed to strengthen result validity; and (v) a novel integration of traditional statistics and newer AI-based ML was completed to produce more precise results. This study demonstrated satisfactory performance of ML with random forests MI for missing values, and produced more precise results for the ES compared to the traditional statistical approach. ML-linear regression with locally weighted learning and 10-fold cross validation closely approximated ES results from the unadjusted random effects meta-analysis, but with tighter confidence intervals (10.36, 95% CI 6.87-13.85;
versus 10.35, 95\%CI 9.95-10.75).

ML with memory-based locally weighted regression is expressed by the following formulas:

\[
\begin{align*}
\omega_{ii} &= \exp\left[\frac{-1}{2} (x_i - x_q)^T D (x_i - x_q)\right] \\
X &= (\tilde{x}_1, \tilde{x}_2, ..., \tilde{x}_p)^T X = (\tilde{x}_1, \tilde{x}_2, ..., \tilde{x}_p)^T \\
\tilde{x}_i &= [(x_i - x_q)^T 1]^T \\
y &= (y_1, y_2, ..., y_p)^T \\
\beta &= (X^T W X)^{-1} X^T W y \\
\hat{y}_q &= \beta_{n+1}
\end{align*}
\]

with query point \( x_p \) having \( p \) training points \( (x_i, y_i) \) and \( W \) denoting the diagonal weight matrix; \( X \) denoting the matrix with vector \( y \); and \( \beta_{n+1} \) representing for regression vector \( \beta \) the \( (n + 1)\text{th} \) element.\(^\text{142} \) This algorithm contrasts the traditional statistical technique used in this study of DerSimonian & Laird non-iterative random effects meta-analysis. This random effects model was chosen as it is a well-established random effects technique\(^\text{143} \) with demonstrated non-inferiority in most situations to more computationally intensive techniques for meta-analysis of heterogeneous studies.\(^\text{144–147} \)

This method is expressed by the following formulas:

\[
E (Y_i) = \mu
\]
\[ \text{var}(Y_i) = \sigma^2 + s_i^2 \]
\[ w_i = (\sigma^2 + s_i^2)^{-1} \]
\[ \bar{w}_i = (\delta^2 + s_i^2)^{-1} \]
\[ \bar{\mu} = \sum \bar{w}_j Y_j / \sum \bar{w}_j \]
\[ \text{var}(\bar{\mu}) = (\sum \bar{w}_j)^{-1} \]

for \( K \) studies with \( i \) denoting 1, \ldots, \( K \); \( Y_i \) denoting the ES and \( s_i^2 \) its variance for each study.

These above methodological advances in analytic techniques (with the hybrid of traditional statistics concurrently with ML) in addition to the rigorous STROBE-based study quality assessment are coupled with this study’s strength of detailing the theoretical underpinnings of nutrition education for medical trainees at the collaborative intersection of public health and clinical medicine. But despite the strengths of the present meta-analysis, overall heterogeneity was not negligible and could be attributed to various sources, like differences in methodology, duration of studies, or different types of interventions across a limited number of available studies. Publication bias seemed to be evident and therefore the results of this meta-analysis should be interpreted with caution. The trim and fill traditional statistical technique and ML algorithms represent novel approaches to accounting for these phenomena to produce more valid and precise meta-
analysis results, but the threat of biased results cannot be completely eliminated.

4.2. CHOP-Medical Students and CHOP-CME

This study serves as the largest known multi-site cohort study of SBME-DP hands-on cooking and nutrition education compared to traditional clinical education for 2,982 medical students across 4 years and 15 academic medical centers and schools, and for 230 medical professionals across CME programming in multiple states. The rigorous statistical analysis notably allows causal inference that hands-on cooking and nutrition education can not only be successfully scaled and adapted to diverse student and professional communities throughout the United States, but also such an approach is superior to traditional clinical education for improving trainee/professionals’ diets, counseling attitudes, and competencies in patient nutrition counseling. This study also demonstrates that such results can be generated through the combined utility of traditional biostatistics and the newer AI-based ML techniques able to handle larger amounts and more complex data to improve speed and prediction accuracy, producing comparable results to the statistical models and evidence of ultimately superior results.

Such a scalable intervention with robust monitoring techniques may suggest a promising approach to the documented insufficient training in nutrition counseling during medical school. CHOP-Medical Students and -CME shows that trainees/professionals not only
learn the clinically relevant techniques in nutrition counseling that can concurrently improve their own diets, but also they directly practice these methods by subsequently leading classes for patients after their own classes are complete. Lessons learned from one site can be transferable for the national GCCM network as partner schools participate in continuous quality improvement (QI) programming with the moderated open source curriculum. Partner sites participate in curriculum development for steady program enhancement, as evidenced by CHOP-Medical Students showing the odds of competency mastery increasing twofold at the end of the second year (with the addition of three partner sites), and holding steady even with 15 total sites currently and quality diversity in how each site deploys the standardized GCCM curriculum. Ongoing QI is underway annually at the national GCCM submit for school deans, physicians, allied health professionals, researchers, chefs, industry partners, and students from partner sites that are approaching 50 total.

Against these results, important limitations of this study must be considered. This study still faces the challenge of selection bias as ethical considerations require the GCCM classes and associated survey to be voluntary. The large sample, PS-adjusted fixed effects multivariable regression, and ML techniques can attempt to reduce the effect of such bias on the results, but it cannot eliminate it or the reduced response rate from responders. And despite controlling for the medical school and using a standardized moderated open
source curriculum, subjects can receive varying quality of GCCM classes depending on the experience of the instructor and the resources available in their teaching kitchen.

While considering these important limitations, this study may still suggest one promising approach to integrating the public health and medical sectors. GCCM’s hands-on cooking and nutrition classes may indicate a scalable model of reducing the chronic disease epidemics and associated health disparities by improving medical professional competencies and diets. Instead of just teaching a man to fish, the GCCM intervention may offer a possible sustainable method of showing him or her how to cook it, and the researcher how to study it.

4.3. CHOP-Community

4.3.1. CHOP-Diabetes BA-RCT. This is the first known BA-RCT that demonstrates improved blood pressure and lipid panels using a novel MedDiet-based hands on cooking and nutrition curriculum for patients with type II diabetes (T2D), including subjects from lower income food deserts. This study also demonstrates non-significant HbA1c and healthy eating competency improvements for the cooking versus control subjects. This intervention may thus provide evidence for a novel clinical education model able to operationalize the validated MedDiet into a scalable competency and attitude modification model, particularly for patients burdened by healthy food disparities. These results suggest that subsequent clinical trial phases are warranted on the grounds of
documented feasibility and clinical efficacy to confirm these findings. Global health system implications for this model include a potentially rapid diffusion of this education innovation through medical schools and hospitals to improve patients’ health in the short-term as 28 medical schools and institutions in the past four years have partnered with GCCM to provide this curriculum for their communities. The long-term implication is building workforce capacity of medical students and physicians better trained in nutrition counseling as they teach these classes for health disparity reduction and improved PHM.

The results should be considered against the study limitations. First, this is a smaller single-site pilot study investigating feasibility and early signs of clinical efficacy. Secondly, though rigorous 1:1 randomization was utilized with follow-up communication connecting subjects to their respective treatment or control exposures, there were a lower number of control subjects compared to treatment who completed their study exposure. The potential greater appeal of cooking classes or recruiter bias may have contributed to this, though control subjects were informed they could participate in the cooking classes six months after their MNT session. Medication changes by treating physicians may have also contributed to biometric changes, though this treatment bias was addressed by randomization, blinding of treating physicians to study group assignment, and medication comparison showing no notable differences between treatment and control groups.
The only systematic review and meta-analysis of different dietary interventions on T2D glycemic levels, lipids, and weight representing 20 RCTs (n=3073 subjects) failed to show any other trails achieving improved health metrics with hands-on cooking and nutrition education.\textsuperscript{117} Rather than simply mirroring previous trials included in this large meta-analysis assessing the impact of MedDiet foods on patients’ biometric health, this trial actually taught patients with T2D what to do with the foods they enjoy. Further, this study demonstrated superior HbA1c reduction with its MedDiet-based intervention group compared to the MedDiet groups in the meta-analysis, -0.4\% (-28 mmol/mol) versus -0.1\% (-25 mmol/mol) that was sustained even after the intervention, including blood pressure and cholesterol improvements. Larger RCTs are needed to determine if the HbA1c impact is statistically significant. Yet this current study still suggests that subjects can improve their competencies in healthy eating with the MedDiet even without ongoing education or provision of healthy MedDiet foods. Superiority testing compared to the standard of care is proper to later clinical trial phases, but it is noteworthy that the GCCM treatment effect superiority may be an underestimate in diet-based supplemental management for diabetes, considering the majority of primary care physicians fail to provide any substantive nutrition counseling to their patients, let alone a RD referral.\textsuperscript{149,150} As the GCCM curriculum targets not only patients but also their current and future physicians, this intervention provides evidence for a capacity-building, clinically effective intervention that is implementable at medical schools and health
centers nationally. Future RCTs and their derivative AI-simulated trials are needed to test the optimal dose and timing of GCCM education for health outcomes among patients with diabetes, heart, and other nutrition-related chronic diseases, in addition to the optimal diffusion of this GCCM innovation through patients’ social networks to determine if such networks can help sustain the health improvements.

4.3.2. CHOP-Family BA-RCT. This is the first known BA-RCT to assess hands-on cooking and nutrition education compared to the standard of care for patient nutrition education, which typically is a nutrition hand-out or little to no specific nutrition counseling provided during patient visits by providers. The trial notably was able to conclude its Phase II clinical trial period early and allowed seamless transition into its Phase III period after producing a 30% improved MedDiet adherence with GCCM versus control. This improvement based on the PREDIMED trial confers a 30% reduced risk of myocardial infarction, stroke, and cardiovascular (CV)-related mortality. The SNA notably allowed demonstration of diffusion of this healthy eating innovation through participants’ communities as they became more strongly interconnected in their social networks and related incentives, which have documented RCT benefit improving patients’ diets. And finally, this study allowed rapid simulation of its Phase III period and revision of the study design based on improved priors from the CHOP-Family Phase II BA-RCT, CHOP-Diabetes RCT, and PREDIMED trials, using ML to validate
the traditional statistical results. Thus the GCCM not only indicates improved adult and child adherence to the MedDiet. It also suggests using a large hospital dataset this improvement can be translated into substantive reduction in patient hospitalizations with its associated high clinical and financial cost exceeding $3.9 million through this low-cost intervention (requiring only food costs and kitchen access, as medical students donate their time running the classes).

5. Conclusion

Rising clinical and financial costs of the obesity and nutrition-related chronic disease global epidemics with their resultant health inequities continue, along with world-wide health system pressures to provide higher value care to patients and populations, with greater clinical effectiveness and health equity for lower cost to share the societal improvements fairly. Yet along with these challenges comes the growing utility of health informatics tapping the strengths of AI to turn Big Data into Big Intelligence for healthcare management and policy decisions to optimize health system performance for patients, payers, and providers. Such recent innovations include the rapidly improving data collection via widespread EHR adoption, storage, and analysis--a surging number of informatics teams are harnessing the historical strengths of these Big Data high-dimensional datasets, defined as such by International Business Machines (IBM) as the 4
V’s (volume, variety, velocity, and veracity),\textsuperscript{154} to optimize health systems by optimizing healthcare outcomes.\textsuperscript{155} Most immediately, AI-based ML methods within Big Data are helping drive the rapid advances in precision medicine\textsuperscript{156,157} within higher value PHM provided by health systems.\textsuperscript{158} The four CHOP sub-stories were designed to demonstrate proof of principle for the promise of AI-driven Big Data in precision medicine and PHM through the test case of culinary medicine, while seeking to establish the evidence-based foundation for hands-on cooking and nutrition education for medical professionals and patients. The cohort and RCT findings from these four sub-studies covering 3,785 subjects--CHOP-Meta-Analysis, CHOP-Medical Students, CHOP-CME, and CHOP-Community--provide a substantive theoretical and analytical grounding (both statistically and ML-wise) for continually assessing and sharpening culinary medicine, as a cost-effective, scalable, and sustainable program within a PHM framework particularly for underserved communities.

CHOP-Meta-Analysis explored the strengths and weaknesses of past studies in the academic and practical intersection of medicine, public health, nutrition, and education, confirming that GCCM’s methodological approach was superior to past approaches. CHOP-Medical Students and -CME showed that culinary medicine training was superior to traditional clinical education across a large multi-site cohort study for 3,212 medical trainees and professionals at 15 medical centers and schools and CME programs over 5
years, including allowing for center-level adaptation to fit the local program needs. And
CHOP-Community translated the BA trial designs, increasingly used by the National
Institutes of Health and Federal Drug Administration, to provide faster, more accurate
results demonstrating GCCM produces superior MedDiet adherence. This improvement
confers not only a 30% reduction in CV-related morbidity and mortality, but can produce
nearly 100 fewer hospitalizations and $3.9 million for a tertiary medical center over 3
years.

CHOP has innovative and significant implications for healthcare management and policy:
(1) large cohort and RCT evidence support health systems and medical schools adopting
GCCM-produced culinary medicine curricula as hands-on cooking and nutrition
education over other nutrition programs due to GCCM’s superior trainee, professional,
and patient outcomes; (2) such an intervention provides proof of principle for a cost-
effective, scalable, and sustainable program uniting community members and health
organizations preferentially benefiting lower income communities to reduce health
inequities; (3) health systems through Accountable Care Organizations (ACOs) and
insurance corporations can have significant cost savings through health care reform
incentives to provide cost effective population health management through such an
intervention targeting multiple social determinants of health, with a notable element
diffusing the intervention’s impact through participants’ social networks; and (4) AI-
based Big Data now has proof of principle for such an intervention to ensure an agile and accurate research infrastructure can concurrently grow with and drive growth for such a clinically and cost effective intervention as a component of an effective population health management strategy for learning health systems. These implications are demonstrated by the above analytics results, and the following programmatic results: from Fall 2012 - 2016, GCCM expanded from one 1 site to 15 medical centers and schools nationally, providing 4,171+ medical students/professionals and patients over 53,674+ free hours of evidence-based nutrition education into which they can sink their teeth, by training medical professionals able to train their classmates, colleagues, and patients in effective health improvement. If healthcare systems globally are to be worthy to serve the patients of this and future generations, such an intervention as culinary medicine among similar interventions which is clinically efficacious, cost-effective, quickly adaptive, and equitable suggest a promising AI-based approach forward to deliver true value care, that has not lost its human touch or compassion for the individual patient as a person.

References


14. Testa MA, Simonson DC. Health economic benefits and quality of life during improved glycemic control in patients with type 2 diabetes mellitus: a randomized,


32. Chronic Disease Prevention And. CDC’s Chronic Disease Prevention System [Internet]. [cited 2016 May 16];Available from: http://www.cdc.gov/chronicdisease/about/prevention.htm


37. Lebensohn P, Kligler B, Dodds S, et al. Integrative medicine in residency education:


58. Piette JD, Krein SL, Striplin D, et al. Patient-Centered Pain Care Using Artificial
Intelligence and Mobile Health Tools: Protocol for a Randomized Study Funded by the US Department of Veterans Affairs Health Services Research and Development Program. JMIR Res Protoc 2016;5(2):e53.


82. Deng Y, Chang C, Ido MS, Long Q. Multiple Imputation for General Missing Data


91. Liaison Committee on Medical Education. Functions and structure of a medical school: standards for accreditation of medical education programs leading to the MD degree [Internet]. [cited 2016 Dec 2];Available from: http://lcme.org/publications/


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142. Schaal S, Atkeson CG, Vijayakumar S. Scalable Techniques from Nonparametric


Table 1. Studies meeting criteria for meta-analysis of nutrition education for medical trainees (1994-2015)*

<table>
<thead>
<tr>
<th>Study</th>
<th>Nation</th>
<th>Sample Size</th>
<th>Study Quality by STROBE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Afaghi et al. 2012</td>
<td>Iran</td>
<td>46</td>
<td>Moderate</td>
</tr>
<tr>
<td>Barss et al. 2008</td>
<td>UAE</td>
<td>43</td>
<td>Low</td>
</tr>
<tr>
<td>Conroy et al. 2004</td>
<td>USA</td>
<td>110</td>
<td>Moderate</td>
</tr>
<tr>
<td>Crowley et al. 2014</td>
<td>NZ</td>
<td>61</td>
<td>Low</td>
</tr>
<tr>
<td>Kohlmeier et al. 2003</td>
<td>USA</td>
<td>117</td>
<td>Low</td>
</tr>
<tr>
<td>Lebensohn et al. 2012</td>
<td>USA</td>
<td>61</td>
<td>Low</td>
</tr>
<tr>
<td>Lewis et al. 2014</td>
<td>USA</td>
<td>332</td>
<td>Low</td>
</tr>
<tr>
<td>Monlezun et al. 2015</td>
<td>USA</td>
<td>627</td>
<td>High</td>
</tr>
<tr>
<td>Ray et al. 2012</td>
<td>UK</td>
<td>98</td>
<td>Moderate</td>
</tr>
<tr>
<td>Schlair et al. 2012</td>
<td>USA</td>
<td>111</td>
<td>Low</td>
</tr>
</tbody>
</table>

*Abbreviations: Hrs, hours; STROBE, STrengthening the Reporting of OBservational studies in Epidemiology; UAE, United Arab Emirates; USA, United States of America; New Zealand; UK, United Kingdom. Studies arranged in alphabetical order.
Figure 1. CHOP study flow chart

CHOP-Studies

Meta-analysis + Students + CME + Community

Treatment Effect (CHOP Dataset)

Statistics

Machine Learning

Predicted Effect (Hospital Dataset)

Statistics

Machine Learning
Figure 2. CHOP-Meta-Analysis data extraction flow chart

Potential papers identified from databases searches (n=172)

Review of title and keywords. Excluded studies included:
- Meta-analyses, reviews, letters (n=28)
- Abstract and full text not available (n=7)

Further evaluation by abstract (n=137)

Excluded studies included:
- No intervention (n=30)
- Not pre-post study (n=54)
- No students, residents, or fellows (n=1)
- Before 1994 (n=23)

Detailed evaluation by full-text (n=10)

Excluded studies included:
- Not adequate data for additional analysis (n=2)
- No competencies (n=0)

Studies finalized for meta-analysis (n=10)
Figure 3. ML-based meta-analysis results for competency improvement with nutrition education stratified by STROBE study quality*
Figure 4. Funnel plot (pseudo 95% CI) suggesting publication bias*

*Asymmetrical plot indicates notable small study effects, possibly due to publication bias and/or heterogeneity across individual studies.
Figure 5. Trim and fill adjustment of meta-analysis accounting for publication bias*

*Filled squares, estimated number of missing studies with their associated effect sizes to adjust the overall meta-analysis effect size.
Figure 6. Trim and fill funnel plot (pseudo 95% CI) suggesting resolved publication bias.

*Abbreviations: CI, confidence interval; Filled squares, estimated number of missing studies with their associated effect sizes; symmetrical plot suggests no small study effects from publication bias and/or heterogeneity across individual studies.
Figure 7. Fixed effects inverse-variance weighted meta-analysis of propensity score-adjusted multivariable fixed effects regression of GCCM versus control: (N=2,982 medical students, 15 sites) Fall 2012-Spring 2017

<table>
<thead>
<tr>
<th>Competency</th>
<th>OR (95% CI)</th>
<th>Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mediterranean Diet</td>
<td>2.87 (1.95, 4.23)</td>
<td>3.11</td>
</tr>
<tr>
<td>Dash Diet</td>
<td>2.48 (1.52, 4.04)</td>
<td>1.95</td>
</tr>
<tr>
<td>Vegetarian Diet</td>
<td>2.42 (1.61, 3.62)</td>
<td>2.84</td>
</tr>
<tr>
<td>Low Fat Diet</td>
<td>2.73 (1.70, 4.40)</td>
<td>2.06</td>
</tr>
<tr>
<td>High Protein Diet</td>
<td>1.45 (0.90, 2.34)</td>
<td>2.04</td>
</tr>
<tr>
<td>Serving Size</td>
<td>2.00 (1.37, 2.92)</td>
<td>3.26</td>
</tr>
<tr>
<td>Moderate Alcohol</td>
<td>1.19 (0.86, 1.64)</td>
<td>4.48</td>
</tr>
<tr>
<td>Eating Disorders</td>
<td>1.43 (1.04, 1.96)</td>
<td>4.66</td>
</tr>
<tr>
<td>Cholesterol</td>
<td>1.46 (0.94, 2.27)</td>
<td>2.40</td>
</tr>
<tr>
<td>Diabetes Diet</td>
<td>1.76 (1.19, 2.56)</td>
<td>3.18</td>
</tr>
<tr>
<td>Diabetes Weight Loss</td>
<td>1.56 (1.14, 2.14)</td>
<td>4.71</td>
</tr>
<tr>
<td>Obesity Weight Loss</td>
<td>1.80 (1.32, 2.44)</td>
<td>4.95</td>
</tr>
<tr>
<td>Omega Fats</td>
<td>1.76 (1.21, 2.56)</td>
<td>3.32</td>
</tr>
<tr>
<td>Dietary Fats</td>
<td>1.61 (1.07, 2.42)</td>
<td>2.80</td>
</tr>
<tr>
<td>Antioxidants</td>
<td>1.45 (1.00, 2.09)</td>
<td>3.44</td>
</tr>
<tr>
<td>Calories</td>
<td>1.81 (1.36, 2.41)</td>
<td>5.70</td>
</tr>
<tr>
<td>Hydration</td>
<td>1.54 (1.17, 2.04)</td>
<td>6.04</td>
</tr>
<tr>
<td>Celiac</td>
<td>1.72 (1.19, 2.49)</td>
<td>3.42</td>
</tr>
<tr>
<td>Food Allergies</td>
<td>2.04 (1.39, 2.98)</td>
<td>3.21</td>
</tr>
<tr>
<td>Glycemic Index</td>
<td>1.59 (1.04, 2.43)</td>
<td>2.59</td>
</tr>
<tr>
<td>Fiber</td>
<td>2.07 (1.48, 2.88)</td>
<td>4.21</td>
</tr>
<tr>
<td>Food Label</td>
<td>1.50 (1.17, 1.91)</td>
<td>7.77</td>
</tr>
<tr>
<td>Osteoporosis</td>
<td>1.29 (0.88, 1.87)</td>
<td>3.29</td>
</tr>
<tr>
<td>BMI</td>
<td>1.33 (1.02, 1.76)</td>
<td>6.41</td>
</tr>
<tr>
<td>Exercise</td>
<td>1.28 (1.01, 1.63)</td>
<td>8.15</td>
</tr>
<tr>
<td>Overall (I-squared = 37.4%, p = 0.032)</td>
<td>1.64 (1.53, 1.76)</td>
<td>100.00</td>
</tr>
</tbody>
</table>
Figure 8. Random effects inverse-variance weighted meta-analysis of multivariable logistic regression of GCCM versus control: (N=627 medical students, 1 site) Fall 2012-Spring 2014

<table>
<thead>
<tr>
<th>Competency</th>
<th>OR (95% CI)</th>
<th>Weight (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Year 1 original</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Osteoporosis</td>
<td>0.51 (0.17, 1.55)</td>
<td>0.97</td>
</tr>
<tr>
<td>Folic acid label</td>
<td>1.04 (0.54, 2.02)</td>
<td>2.72</td>
</tr>
<tr>
<td>Diabetes weight</td>
<td>0.93 (0.45, 1.91)</td>
<td>2.26</td>
</tr>
<tr>
<td>Calories</td>
<td>1.89 (0.95, 3.37)</td>
<td>2.54</td>
</tr>
<tr>
<td>Antioxidants</td>
<td>1.04 (0.49, 2.19)</td>
<td>2.14</td>
</tr>
<tr>
<td>Exercise</td>
<td>0.77 (0.39, 1.50)</td>
<td>2.65</td>
</tr>
<tr>
<td>Hydration</td>
<td>0.37 (0.16, 0.83)</td>
<td>1.80</td>
</tr>
<tr>
<td>Body mass index (BMI)</td>
<td>1.15 (0.55, 2.37)</td>
<td>2.25</td>
</tr>
<tr>
<td>Omega</td>
<td>0.58 (0.24, 1.39)</td>
<td>1.55</td>
</tr>
<tr>
<td>High protein</td>
<td>1.47 (0.56, 3.87)</td>
<td>1.27</td>
</tr>
<tr>
<td>My plate</td>
<td>1.82 (0.79, 4.16)</td>
<td>1.73</td>
</tr>
<tr>
<td>Alcohol</td>
<td>0.95 (0.44, 2.04)</td>
<td>2.03</td>
</tr>
<tr>
<td>Eating disorders</td>
<td>0.68 (0.29, 1.63)</td>
<td>1.81</td>
</tr>
<tr>
<td>Cholesterol</td>
<td>1.21 (0.59, 2.54)</td>
<td>2.34</td>
</tr>
<tr>
<td>Diabetes diet</td>
<td>0.79 (0.30, 2.06)</td>
<td>1.29</td>
</tr>
<tr>
<td>Obesity weight loss</td>
<td>1.64 (0.65, 4.15)</td>
<td>1.38</td>
</tr>
<tr>
<td>Low fat diet</td>
<td>0.93 (0.34, 2.62)</td>
<td>1.15</td>
</tr>
<tr>
<td>Subtotal (I² squared = 30.3%,  p = 0.333)</td>
<td>0.98 (0.81, 1.21)</td>
<td>23.01</td>
</tr>
</tbody>
</table>

| Year 2 (original)            |             |            |
| Osteoporosis                 | 1.71 (0.90, 3.25) | 2.89       |
| Folic acid label             | 1.18 (0.64, 2.21) | 5.20       |
| Diabetes weight              | 1.71 (0.92, 3.12) | 3.01       |
| Calories                     | 1.53 (0.84, 2.79) | 3.29       |
| Antioxidants                 | 1.92 (0.98, 3.70) | 2.62       |
| Exercise                     | 2.78 (1.37, 5.33) | 2.50       |
| Hydration                    | 1.89 (1.03, 3.46) | 3.24       |
| Body mass index (BMI)        | 1.29 (0.71, 2.33) | 3.38       |
| Omega                        | 2.56 (1.20, 5.1)  | 2.79       |
| High protein                 | 3.14 (1.42, 6.97) | 1.87       |
| My plate                     | 2.99 (1.55, 5.47) | 2.75       |
| Alcohol                      | 2.64 (1.45, 4.83) | 3.28       |
| Eating disorders             | 0.80 (0.41, 1.57) | 2.67       |
| Cholesterol                  | 1.24 (0.67, 2.32) | 3.14       |
| Diabetes diet                | 2.99 (1.53, 5.50) | 2.90       |
| Obesity weight loss          | 3.03 (1.69, 5.52) | 2.94       |
| Low fat diet                 | 1.79 (0.78, 4.10) | 1.73       |
| Subtotal (I² squared = 29.4%,  p = 0.123) | 1.88 (1.40, 2.49) | 48.28     |

| Year 2 supplemental          |             |            |
| Mediterranean diet            | 7.40 (3.78, 14.49) | 2.62       |
| DASH diet                     | 6.43 (3.69, 11.80) | 2.02       |
| Veggie diet                   | 3.65 (1.91, 6.98) | 2.81       |
| Fats                          | 3.06 (1.56, 6.00) | 2.64       |
| Celluc                        | 1.77 (0.92, 3.30) | 2.79       |
| Food allergies                | 2.18 (1.16, 4.13) | 2.32       |
| Glycemic index                | 3.22 (1.37, 7.47) | 1.63       |
| Fiber                         | 3.07 (1.65, 5.70) | 3.10       |
| Subtotal (I² squared = 47.8%,  p = 0.063) | 2.08 (2.06, 4.20) | 19.94     |

Heterogeneity between groups:  p = 0.000
Overall (I² squared = 65.3%,  p = 0.000)  1.72 (1.54, 1.95)  100.00
Figure 9. CHOP-Community social network analysis: Increased social network interconnectedness following GCCM training (p=0.007)*

*Abbreviations: CHOP, Cooking for Health Optimization for Patients; GCCM, Goldring Center for Culinary Medicine; PCP, primary care provider. Methods: propensity-score adjusted fixed effects multivariable multinomial regression for causal inference via controlling for prior nutrition education, PCP nutrition counseling provided, the likelihood of receiving GCCM classes, and time invariant unobserved traits. Statistical significance set at two-tailed p-value <0.05. All analyses performed in STATA 14.2 (STATACorp, College Station, Texas, United States of America). Results: greater social network connectedness occurs after at least one GCCM class was taken.
Figure 10. CHOP-Community social network analysis: Increased social network interconnectedness following GCCM classes*

*Abbreviations: CHOP, Cooking for Health Optimization for Patients; GCCM, Goldring Center for Culinary Medicine; PCP, primary care provider. Methods: propensity-score adjusted fixed effects multivariable multinomial regression for causal inference via controlling for prior nutrition education, PCP nutrition counseling provided, the likelihood of receiving GCCM classes, and time invariant unobserved traits. Statistical significance set at two-tailed p-value <0.05. All analyses performed in STATA 14.2 (STATACorp, College Station, Texas, United States of America). Results: greater social network connectedness and support occurs after at least one GCCM class was taken, particularly with subjects' friends being the most significant supportive network member.
Figure 11. CHOP-Community social network analysis: GCCM classes independently increase MedDiet score (p<0.021)*

*Abbreviations: CHOP, Cooking for Health Optimization for Patients; GCCM, Goldring Center for Culinary Medicine; MedDiet, Mediterranean Diet; PCP, primary care provider. Methods: propensity-score adjusted fixed effects multivariable regression for causal inference via controlling for prior nutrition education, PCP nutrition counseling provided, the likelihood of receiving GCCM classes, and time invariant unobserved traits. Statistical significance set at two-tailed p-value <0.05. All analyses performed in STATA 14.2 (STATACorp, College Station, Texas, United States of America). Results: greater number of GCCM classes independently increases MedDiet adherence (larger sphere), as PCP nutrition education (red) and social interconnectedness increases with classes. This analysis also identifies friends and medical professionals as the most interconnected members of study subjects' supportive social networks, suggesting they could be the most efficient members to focus future interventions to maximize GCCM class impact on subjects.
Figure 12. CHF hospitalizations clinical & cost savings with GCCM based on RCT-backed machine learning-based models*

*Abbreviations: CHF, congestive heart failure; GCCM, Goldring Center for Culinary Medicine; MedDiet, Mediterranean Diet; BA-RCT, Bayesian adaptive randomized controlled trial; MI, myocardial infarction; CV, cardiovascular; PREDIMED, Prevención con Dieta Mediterránea; NEJM, New England Journal of Medicine; RF-MI, random forest multiple imputation; ML, machine learning; RMSE, root mean squared error. Methods: The multiplication rule in statistical independence theory was used to multiply the increased probability of MedDiet adherence (30%) for GCCM versus control subjects from the CHOP-Family BA-RCT, and the decreased probability (30%) of MI, stroke, and CV-related mortality from the PREDIMED trial (Estruch et al. 2013 NEJM). The ML algorithm, RF-MI, was used to fill in missing values, with values close to 0 for the RMSE considered adequate performance. The Kaplan-Meier curve, proportions of admission and readmission, and sums of gross charges and length of stays were performed in STATA 14.2 (STATACorp, College Station, Texas, United States of America). ML calculations were conducted in R package 3.3.2 (R
Foundation for Statistical Computing, Vienna, Austria). Results: RF-MI had adequate imputing performance (RMSE 0.001). Values are shown in bold.
Appendix 1. CHOP-Medical Students Survey (current)

CODE: To ensure anonymity, please use the following 6-letter/digit code: First 2 letters of your mother’s first name, then the month you were born (2 digits), and the first 2 letters of the town where you were born. For example, if your mother's name is Judy, you are born in August and you are from Altoona, the code would be JU08AL.

Part 1 of 4: Attitudes

Q1 In general, I believe that..

<table>
<thead>
<tr>
<th>Nutritional counseling should be included in any routine appointment, just like diagnosis and treatment. Specific advice about how to make dietary changes could help patients improve their eating habits. Physicians can have an effect on a patient’s dietary behavior if they take the time to discuss the problem.</th>
<th>Strongly disagree</th>
<th>Disagree</th>
<th>Neither Agree nor Disagree</th>
<th>Agree</th>
<th>Strongly Agree</th>
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</table>
Part 2 of 4: Dietary Habits

Q2 On average over the last 6 months, how often did you consume..?

<table>
<thead>
<tr>
<th>Food Category</th>
<th>Never</th>
<th>1-2 times per week</th>
<th>3-5 times per week</th>
<th>1 time daily</th>
<th>2 or more times daily</th>
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</thead>
<tbody>
<tr>
<td>Vegetables (e.g. carrots, spinach, tomatoes, but NOT potatoes or French fries)</td>
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<td>Legumes (e.g. beans, split peas, peanuts, or lentils)</td>
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<td>Fruits (e.g. oranges, apples, bananas)</td>
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<td>Nuts or nut butters (e.g. peanuts, almonds, cashews)</td>
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<td>Cheese or fermented dairy (e.g. yogurt)</td>
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<td>Red and processed meat (e.g. hamburgers, steak, hotdogs)</td>
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<td>Non-fried fish or seafood (e.g. canned, baked, grilled)</td>
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<td>Whole grains (e.g. whole wheat bread or pasta, oats, brown rice, corn tortilla)</td>
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<td>Monosaturated fats (e.g. avocado, olive or canola oils)</td>
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<td>1 alcohol serving (e.g. 1 can of 12 oz beer = 1 glass of wine = 1 shot of spirits)</td>
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<td>Baked products (e.g. muffins, doughnuts, pastries)</td>
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<td>Calorie-containing beverages (e.g. coke/soda, non-black coffee drinks, energy drinks)</td>
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<td>Saturated fats (e.g. butter, 2% or whole milk, margarine)</td>
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Part 3 of 4: Competencies

Q3.1 For me educating patients independently of support from other medical
professionals on the following topics, I feel..
<table>
<thead>
<tr>
<th>Mediterranean Diet and its health effects.</th>
<th>Not at all confident</th>
<th>Somewhat confident</th>
<th>Neither not at all confident, or totally confident</th>
<th>Mostly confident</th>
<th>Totally confident</th>
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<tr>
<td>DASH diet and its health effects.</td>
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<tr>
<td>Vegetarian diet and its health effects</td>
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<tr>
<td>Very low fat diet and its health effects.</td>
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<td>High protein/high fat diet (e.g. Atkins) and its health effects.</td>
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<td>Examples of a serving size from the 2011 “My Plate” guidelines.</td>
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<tr>
<td>Definition of moderate alcohol consumption and its health effects.</td>
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<tr>
<td>Recognizing warning signs and symptoms of patients with eating disorders.</td>
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<tr>
<td>Role of dietary cholesterol and saturated fat in blood lipids.</td>
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<tr>
<td>Recommended dietary patterns for type 2 diabetes.</td>
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<tr>
<td>Significance of modest weight loss for type 2 diabetes.</td>
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<td>Weight loss strategies in overweight patients.</td>
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<tr>
<td>Role of Omega-3 and -6 fatty acids in heart health and their food examples.</td>
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</tbody>
</table>
Q3.2 For me educating patients on the following topics independently off support from
other medical professionals, I feel..

<table>
<thead>
<tr>
<th>Role of dietary fat types (e.g. saturated vs. other) and their food examples.</th>
<th>Not at all confident</th>
<th>Somewhat confident</th>
<th>Neither not at all confident, or totally confident</th>
<th>Mostly confident</th>
<th>Totally confident</th>
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<tr>
<td>Identifying antioxidant-rich grocery produce.</td>
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<td>Calories per gram of protein, carbohydrate and fat, and their basic metabolic roles.</td>
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<td>Role of hydration in health, and fluid needs based on activity and age.</td>
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<td>Celiac disease and management strategies for patient’s diet and lifestyle.</td>
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<tr>
<td>Food allergies and management strategies for patient’s diet and lifestyle.</td>
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<td>The role of glycemic index and load in dietary management.</td>
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<td>Fiber in disease prevention, and example ingredients.</td>
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<td>Assessing the total calories, saturated fat, and sodium using the food label.</td>
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<td>Osteoporosis and prevention and treatment strategies for patient’s diet and lifestyle.</td>
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<td>Calculation of body mass index (BMI) and waist-to-hip ratio based on gender.</td>
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<td>Overall benefits of aerobic exercise on health and well-being.</td>
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Q3.3 In the majority of my patient visits, I:

<table>
<thead>
<tr>
<th>Provide nutrition assessment and counseling.</th>
<th>No</th>
<th>Yes</th>
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<tbody>
<tr>
<td>Track the most recent Body Mass Index (BMI).</td>
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</table>

Part 4 of 4: Demographics

Q4.1 Please select your current institution if a student, resident, or fellow.
Tulane University School of Medicine, New Orleans, LA
University of TX-Southwestern Medical School: Montcrief Cancer Institute, Dallas, TX
UNTHSC Texas College of Osteopathic Medicine, Dallas, TX
Texas Christian University, Dallas, TX
University of Illinois-Chicago College of Medicine, Chicago, IL
University of Colorado-Denver School of Medicine, Denver, CO
Charles R. Drew/UCLA Medical Education Program, Los Angeles, CA
Western University of Health Sciences College of Osteopathic Medicine of the Pacific/Pacific-Northwest, Pomona, CA/Lebanon, OR
University of Texas School of Medicine in San Antonio, San Antonio, TX
Lake Erie College of Osteopathic Medicine Arnot Ogden Medical Center, Elmira, PA
Rutgers Robert Wood Johnson Medical School, New Brunswick, NJ
Meharry Medical College, Nashville, TN
University of Chicago Pritzker School of Medicine, Chicago, IL
Michigan State University College of Human Medicine, East Lansing, MI
Penn State Hershey College of Medicine, Hershey, PA
Mercer University School of Medicine, Columbus/Macon/Savannah, GA
West Virginia University School of Medicine, Morgantown/Martinsburg, WV
University of Alabama School of Medicine, Tuscaloosa, AL
University of Tennessee College of Medicine, Memphis, TN
University of Mississippi School of Medicine, Jackson, MS
University of Central Florida College of Medicine, Orlando, FL
University of South Alabama College of Medicine, Mobile, AL
AT Still University Kirksville College of Osteopathic Medicine, Kirksville, MO
University of Utah School of Medicine, Salt Lake City, UT
University of California-Irvine School of Medicine, Irvine, CA
University of South Carolina School of Medicine, Columbia, SC
University of Texas McGovern Medical School, Houston, TX
Children’s Hospital of San Antonio, San Antonio, TX
Sky Lakes Medical Center, Klamath Falls, OR
Swedish Medical Center, Seattle, WA
Northwest Arkansas Community College, Bentonville, AK
Mississippi Gulf Coast Community College, Biloxi, MS
George Washington University, Washington, D.C.
John Peter Smith (JPS) Health Center, Forth Worth, TX
Nationwide Children’s Hospital, Columbus, OH
Church Health Center, Memphis, TN
Duke University, Durham, NC
Emory University, Atlanta, GA
Florida Atlantic University, Boca Raton, FL
Georgetown University, Washington, D.C.
University of Maryland, Baltimore, MD
University of North Carolina, Chapel Hill, NC
University of Southern California, Los Angeles, CA
University of Vermont, Burlington, VT
University of Kentucky, Louisville, KY
University of South Florida, Tampa, FL
Thomas Jefferson University, Philadelphia, PA
Temple University, Philadelphia, PA
Philadelphia College of Osteopathic Medicine, Philadelphia, PA
Drexel University, Philadelphia, PA
Other __________________________
Q4.2 Please select the month/year you are taking the survey.

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Q4.3 Please select the month/year you took your last Culinary Medicine class if you took one.

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</table>
Q4.4 In what year of schooling are you for your respective track if you are a student?

<table>
<thead>
<tr>
<th>Track</th>
<th>1\textsuperscript{st} Year</th>
<th>2\textsuperscript{nd} Year</th>
<th>3\textsuperscript{rd} Year</th>
<th>4\textsuperscript{th} or &gt;4\textsuperscript{th} Year</th>
</tr>
</thead>
<tbody>
<tr>
<td>MD (Medical Doctor) or DO (Doctor of Osteopathic Medicine) Nurse (ADN/LPN/BSN/RN/MSN) PA (Physician Assistant) OT (Occupational Therapist) RD (Registered Dietician) NP (Nurse Practitioner) R.Ph (Pharmacist) PT (Physical Therapist) Other (please specify):</td>
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</table>

Q4.5 How many years ago did you complete your respective health sciences education degree if you are no longer a student?
<table>
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<tr>
<th>MedDiet (Medical Doctor) or DO (Doctor of Osteopathic Medicine) Nurse (ADN/LPN/BSN/RN/M SN) PA (Physician Assistant) OT (Occupational Therapist) RD (Registered Dietician) NP (Nurse Practitioner) R.Ph (Pharmacist) PT (Physical Therapist) Other (please specify):</th>
<th>Less than 10 years (but still a Resident/Fellow)</th>
<th>Less than 10 (after Residency/Fellowship)</th>
<th>10-19</th>
<th>20-29</th>
<th>30 or over</th>
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<tr>
<td>Q4.6 What is your age? ______________</td>
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<td>Q4.7 Are you male or female? Male Female</td>
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<td>Q4.8 With what race or ethnicity do you primarily identify? Non-Hispanic White Non-Hispanic Black Native American Non-Hispanic Asian Mexican American or Other Hispanic Other ________________</td>
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</table>
Q4.9 Do you follow any specific dietary practices? (e.g. gluten-free, vegetarian, weight watchers, kosher, etc.)?
No
Yes
Q4.10 Did you have any nutrition training prior to your current schooling?
No
College major or minor
Graduate classes (e.g. MPH, RD, etc.)
Other (please specify) ____________________

Q4.11 For medical students, what is your intended specialty?
Anesthesiology
Dermatology
Emergency Medicine
Family Medicine
General Surgery
Internal Medicine
Neurology
Obstetrics and Gynecology
Ophthalmology
Orthopedic Surgery
Pathology
Psychiatry
Radiology
Biotech/ Pharmaceutical Research
ENT
Immunology
Internal Medicine/ Pediatrics
Neurosurgery or Cardiothoracic Surgery
Otolaryngology
Pediatrics
Physical Medicine & Rehabilitation
Reproductive Endocrinology (Fertility)
Sports Medicine
Undecided
Urology
Not applicable
Q4.12 Please select your involvement in Culinary Medicine opportunities if applicable.

<table>
<thead>
<tr>
<th>Elective or culinary medicine class</th>
<th>No</th>
<th>Yes</th>
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<tbody>
<tr>
<td>Community service (at least 4 hours)</td>
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<tr>
<td>3rd or 4th year medical student seminars</td>
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<tr>
<td>Medical student rotation at Johnson and Wales</td>
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<tr>
<td>Additional community service (5-10 hours)</td>
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<tr>
<td>Additional community service (more than 10 hours)</td>
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Q4.13 Please select the number of Culinary Medicine classes you have taken.

0
1
2
3
4
5
6
Over 6

Q4.14 Are you satisfied with the quality and quantity of your nutrition education?

No
Yes

Q4.15 Do you have any recommendations or critiques for curriculum topics or opportunities?

Q4.16 If you participated in any Goldring Center for Culinary Medicine (GCCM)
cooking classes, who was most influential in your choice to participate?
Co-worker/classmate
Child
Extended family (i.e., aunt, cousin, etc.)
Friend
Grandparent
Parent
Neighbor
Sibling (i.e., brother or sister)
Medical professional (i.e., doctor, nurse, RD, etc.)

Q4.17 If you are student, how often do you provide nutrition counseling to patients when you are allowed by your attending and clinical schedule? (i.e., suggesting to patients wheat instead of white pasta on 3rd/4th year medical school rotations in an outpatient clinic).
Almost never (0 out of every 10 patients)
Rarely (1-3 out of every 10 patients)
Sometimes (4-6 out of every 10 patients)
Often (7-8 out of every 10 patients)
Almost every time (9-10 out of every 10 patients)

Q4.18 Please write your email address. ________________________________
Appendix 2. CHOP-Medical Students Survey (original)

Part 1 of 3

Each statement below finishes the sentence, "In general, I believe that..." Please choose the response that is closest to your opinion about each statement.

Q1 Nutritional assessment and counseling should be included in any routine appointment, just like diagnosis and treatment.
   strongly disagree  
   disagree  
   uncertain  
   agree  
   strongly agree

Q2 Patients need specific instructions about how to change their eating behavior.
   strongly disagree  
   disagree  
   uncertain  
   agree  
   strongly agree

Q3 Specific advice about how to make dietary changes could help some patients improve their eating habits.
   strongly disagree  
   disagree  
   uncertain  
   agree  
   strongly agree

Q4 Patients need ongoing counseling following the initial instruction to maintain behavior changes consistent with a healthier diet.
   strongly disagree
Q5 Physicians can have an effect on a patient’s dietary behavior if they take the time to discuss the problem.

Part 2 of 3

Q6 Over THE LAST 6 MONTHS, how often did you eat: Dark green, leafy vegetables (e.g. spinach, romaine lettuce, mesclun mix, kale, turnip greens, bok choy, swiss chard, broccoli, broccoli rabe, cauliflower, cabbage, brussel sprouts)

Never
Less than once a week
Once per week
2-4 times per week
Nearly daily or daily
Twice or more per day

Q7 Over THE LAST 6 MONTHS, how often did you eat: Other vegetables (e.g. carrots, peas, corn, green beans, tomatoes, squash)

Never
Less than once a week
Once per week
2-4 times per week
Nearly daily or daily
Twice or more per day
Q8 Over THE LAST 6 MONTHS, how often did you eat: Beans, split peas, or lentils
Never
Less than once a week
Once per week
2-4 times per week
Nearly daily or daily
Twice or more per day

Q9 Over THE LAST 6 MONTHS, how often did you eat: Fruits (e.g. oranges, grapefruits, fresh apples or pears, bananas, berries, grapes, melons)
Never
Less than once a week
Once per week
2-4 times per week
Nearly daily or daily
Twice or more per day

Q10 Over THE LAST 6 MONTHS, how often did you eat: Whole milk dairy foods (e.g. whole milk, hard cheese, butter, ice cream)
Never
Less than once a week
Once per week
2-4 times per week
Nearly daily or daily
Twice or more per day

Q11 Over THE LAST 6 MONTHS, how often did you eat: Low-fat milk products (e.g. low-fat/skim milk, yogurt, cottage cheese)
Never
Less than once a week
Once per week
2-4 times per week
Nearly daily or daily
Twice or more per day

Q12 Over THE LAST 6 MONTHS, how often did you eat Whole eggs
Never
Less than once a week
Once per week
2-4 times per week
Nearly daily or daily
Twice or more per day

Q13 Over THE LAST 6 MONTHS, how often did you eat: Nuts or nut butters (e.g. peanuts, almonds, walnuts, pine nuts, cashews)
Never
Less than once a week
Once per week
2-4 times per week
Nearly daily or daily
Twice or more per day

Q14 Over THE LAST 6 MONTHS, how often did you eat: Red meats (e.g. beef, lamb, bison, or venison)
Never
Less than once a week
Once per week
2-4 times per week
Nearly daily or daily
Twice or more per day

Q15 Over THE LAST 6 MONTHS, how often did you eat: Pork
Never
Less than once a week
Once per week
2-4 times per week
Nearly daily or daily
Twice or more per day

Q16 Over THE LAST 6 MONTHS, how often did you eat: Processed meats (e.g. sausages, salami, bologna, hot dogs, bacon)
Never
Less than once a week
Once per week
2-4 times per week
Nearly daily or daily
Twice or more per day

Q17 Over THE LAST 6 MONTHS, how often did you eat: Turkey, chicken, poultry
Never
Less than once a week
Once per week
2-4 times per week
Nearly daily or daily
Twice or more per day

Q18 Over THE LAST 6 MONTHS, how often did you eat: Shrimp or other crustaceans, shellfish (e.g. oysters, clams, mussels, lobster, crawfish)
Never
Less than once a week
Once per week
2-4 times per week
Nearly daily or daily
Twice or more per day

Q19 Over THE LAST 6 MONTHS, how often did you eat: Fish, seafood (not fried, but broiled, baked, poached, or canned)
Never
Less than once a week
Once per week
2-4 times per week
Nearly daily or daily
Twice or more per day

Q20 Over THE LAST 6 MONTHS, how often did you eat: Stick margarine
Never
Less than once a week
Once per week
2-4 times per week
Nearly daily or daily
Twice or more per day

Q21 Over THE LAST 6 MONTHS, how often did you eat: Refined grains (e.g. white bread, white rice)
Never
Less than once a week
Once per week
2-4 times per week
Nearly daily or daily
Twice or more per day

Q22 Over THE LAST 6 MONTHS, how often did you eat: Whole grain breads and cereals (e.g. whole wheat, oatmeal, brown rice, barley)
Never
Less than once a week
Once per week
2-4 times per week
Nearly daily or daily
Twice or more per day

Q23 Over THE LAST 6 MONTHS, how often did you eat: Baked products (e.g. muffins, doughnuts, cookies, cake, pastries)
Never
Less than once a week
Once per week
2-4 times per week
Nearly daily or daily
Twice or more per day

Q24 Over THE LAST 6 MONTHS, how often did you drink Calorie-containing beverages (e.g. Regular soda, Snapple, Nestea, Gatorade, Energy Drinks)
Never
Less than once a week
Once per week
2-4 times per week
Nearly daily or daily
Twice or more per day

Q25 Over THE LAST 6 MONTHS, how often did you drink: Diet or "zero-calorie" drinks (e.g. Diet coke/Coke Zero, 5-hour energy, sugar-free energy or sports drinks)
Never
Less than once a week
Once per week
2-4 times per week
Nearly daily or daily
Twice or more per day

Q26 Over THE LAST 6 MONTHS, how often did you drink: Alcohol (1 can of 12 oz beer = 1 glass of wine = 1 shot of spirits)
Never
Less than once a week
Once per week
2-4 times per week
Nearly daily or daily
Twice or more per day

Q27 Over THE LAST 6 MONTHS, how often did you eat: Deep fried foods
Never
Less than once a week
Once per week
2-4 times per week
Nearly daily or daily
Twice or more per day

Q28 Over the LAST 6 MONTHS: How often did you add salt to food at the table
Never
Less than once a week
Once per week
2-4 times per week
Nearly daily or daily
Twice or more per day

Part 3 of 3

Q29 Strategies for osteoporosis prevention and treatment, including nutrition and lifestyle.
Yes, totally proficient
Somewhat proficient
No, not proficient
Not Applicable

Q30 Assessing the total calories and saturated fat per portion of food by using the food label.
Yes, totally proficient
Somewhat proficient
No, not proficient
Not Applicable

Q31 Significance of modest weight loss for patients with insulin resistance syndrome (diabetes).
Yes, totally proficient
Somewhat proficient
No, not proficient
Not Applicable

Q32 Calories per gram of protein,
carbohydrate and fat, and their basic metabolic roles.
Yes, totally proficient
Somewhat proficient
No, not proficient
Not Applicable

Q33 Means of identifying antioxidant-rich produce while grocery shopping.
Yes, totally proficient
Somewhat proficient
No, not proficient
Not Applicable

Q34 Overall benefits of aerobic exercise on health and well-being.
Yes, totally proficient
Somewhat proficient
No, not proficient
Not Applicable

Q35 Role of water and hydration in health, and fluid needs based on activity and age.
Yes, totally proficient
Somewhat proficient
No, not proficient
Not Applicable

Q36 Calculation of body mass index (BMI) and waist-to-hip ratio based on gender.
Yes, totally proficient
Somewhat proficient
No, not proficient
Not Applicable

Q37 Role of Omega-3 and Omega-6 fatty acids in heart health.
Yes, totally proficient
Somewhat proficient
No, not proficient
Q38 Reported health risks of high protein/high fat diets, such as the Atkins diet.
   Yes, totally proficient
   Somewhat proficient
   No, not proficient
   Not Applicable

Q39 Examples of a serving size of meat or dairy from the 2011 “My Plate” guidelines.
   m Yes, totally proficient
   m Somewhat proficient
   m No, not proficient
   m Not Applicable

Q40 Definition of moderate alcohol consumption and its role in health and disease.
   Yes, totally proficient
   Somewhat proficient
   No, not proficient
   Not Applicable

Q41 Recognizing warning signs and symptoms of patients with eating disorders.
   Yes, totally proficient
   Somewhat proficient
   No, not proficient
   Not Applicable

Q42 Role of dietary cholesterol and saturated fat in elevating blood lipids.
   Yes, totally proficient
   Somewhat proficient
   No, not proficient
   Not Applicable

Q43 Recommended dietary patterns for non-
insulin dependent (Type 2) diabetes mellitus.
Yes, totally proficient
Somewhat proficient
No, not proficient
Not Applicable

Q44 Reported information on health impact of a very low fat diet.
Yes, totally proficient
Somewhat proficient
No, not proficient
Not Applicable

Q45 Optimal strategy for weight loss in overweight or obese patients.
Yes, totally proficient
Somewhat proficient
No, not proficient
Not Applicable

Part 4. The following contains demographic information.

Q46 In what year of medical school are you?
Pre-medical
T1
T2
T3
T4

Q47 Which category below includes your age?
17 or younger
18-20
21-24
25-29
30-39
40-49
50-59
60 or older
Q48 Are you male or female?
Male
Female

Q49 Are you White, Black or African-American, American Indian or Alaskan Native, Asian, Native Hawaiian or other Pacific Islander, or other ethnicity?
White
Black or African-American
American Indian or Alaskan Native
Asian
Native Hawaiian or other Pacific Islander
Other (please specify)

Q50 Which of these dietary practices do you follow?
Diet Program (e.g. Weight watchers, Jenny Craig)
Gluten-free
Halal
Kosher diet
Vegetarian
Vegan
No restrictions
Other (please specify)

Q51 Did you have any nutrition training prior to medical school? Please select all that apply.
No
College coursework (1 course)
College coursework (2 or more courses)
RD
PhD
Other (please specify)

Q52 What is your intended specialty?
Anesthesiology
Dermatology
Emergency Medicine
Family Medicine
General Surgery
Internal Medicine
Neurology
Obstetrics and gynecology
Ophthalmology
Orthopedic Surgery
Pathology
Pediatrics
Psychiatry
Radiology
Other (please specify)
Appendix 3. CHOP-Community Survey

CODE: To ensure anonymity, please use the following 6-letter/digit code: First 2 letters of your mother’s first name, then the month you were born (2 digits), and the first 2 letters of the town where you were born. For example, if your mother's name is Judy, you are born in August and you are from Altoona, the code would be JU08AL.

How many times in a usual week do you:

<table>
<thead>
<tr>
<th>Activity</th>
<th>0</th>
<th>1-2</th>
<th>3-4</th>
<th>5-6</th>
<th>7 (daily)</th>
<th>Over 7 (more than once daily)</th>
</tr>
</thead>
<tbody>
<tr>
<td>cook or help to cook a meal?</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>eat left-overs from home-cooked meals?</td>
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<td></td>
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</tr>
<tr>
<td>plan meals ahead of time?</td>
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<td></td>
<td></td>
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<tr>
<td>go grocery shopping?</td>
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</tr>
<tr>
<td>use a nutrition label (found on the back/side of food packages) to help you make food choices?</td>
<td></td>
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</tr>
<tr>
<td>use MyPlate to help make sure you have the suggested food groups and portion sizes?</td>
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<td></td>
</tr>
</tbody>
</table>

In general, do you believe that:

<table>
<thead>
<tr>
<th>Activity</th>
<th>Strongly disagree</th>
<th>Some-what disagree</th>
<th>Not sure</th>
<th>Some-what agree</th>
<th>Strongly agree</th>
</tr>
</thead>
<tbody>
<tr>
<td>preparing healthy home-cooked</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

116
<table>
<thead>
<tr>
<th>Meals take too much time or money?</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Eating healthier may help prevent or improve symptoms for diseases (such as high blood pressure, diabetes or heart disease)?</td>
<td></td>
</tr>
<tr>
<td>Cooking classes would help you learn how to shop for and use ingredients to make healthy meals?</td>
<td></td>
</tr>
<tr>
<td>You can easily find and purchase foods to eat healthy?</td>
<td></td>
</tr>
</tbody>
</table>
Over the last week, how often do you:

<table>
<thead>
<tr>
<th></th>
<th>0</th>
<th>1-2</th>
<th>3-4</th>
<th>5-6</th>
<th>7 (daily)</th>
<th>Over 7 (more than once daily)</th>
</tr>
</thead>
<tbody>
<tr>
<td>drink soft drinks or sugar sweetened drinks (such as coke, sweetened coffee drinks, sweet teas and energy drinks)?</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>drink fruit juice or smoothies?</td>
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<td></td>
</tr>
<tr>
<td>eat sweet snack foods (such as candy bars or doughnuts)?</td>
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<td></td>
</tr>
<tr>
<td>eat salty or savory snack foods (such as chips or pretzels)?</td>
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<td></td>
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<tr>
<td>eat frozen or pre-packed meals (such as frozen dinners, canned soups, deli salads, etc.)</td>
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<td></td>
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<td></td>
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<tr>
<td>prepare breakfast at home?</td>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>eat breakfast that is pre-packaged, store-bought, or restaurant-bought?</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>eat vegetables (such as spinach, carrots, or tomatoes)?</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
</tr>
</tbody>
</table>

Over the last week, how often do you:

<table>
<thead>
<tr>
<th></th>
<th>0</th>
<th>1-2</th>
<th>3-4</th>
<th>5-6</th>
<th>7 (daily)</th>
<th>Over 7 (more than once daily)</th>
</tr>
</thead>
<tbody>
<tr>
<td>use vegetable-based oils (such as</td>
<td></td>
<td></td>
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<tr>
<td></td>
<td>olive, canola, or soybean)?</td>
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<td></td>
</tr>
<tr>
<td></td>
<td>eat legumes (such as beans, peanuts, split peas, or lentils)?</td>
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<td></td>
</tr>
<tr>
<td></td>
<td>eat fresh or frozen fruits? (such as apples and bananas)?</td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>use dairy products (such as butter, milk, cream, or ice cream)?</td>
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<td></td>
</tr>
<tr>
<td></td>
<td>eat nuts or nut butters (such as almonds or peanut butter)?</td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>eat red meats (such as beef, pork or lamb)?</td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>eat seafood (such as fish, crawfish, or shrimp)?</td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>eat whole grain breads and cereals (such as whole wheat bread or pasta, brown rice, or oatmeal)?</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>drink a serving of alcohol (1 serving is 1 can of 12 oz beer, 1 glass of wine, 1 shot of spirits)?</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

How would you rate your healthy eating habits?

<table>
<thead>
<tr>
<th></th>
<th>1 (Poor)</th>
<th>2</th>
<th>3 (Good)</th>
<th>4</th>
<th>5 (Great)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rating</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

How many times do you exercise for at least 30 minutes a week?

<table>
<thead>
<tr>
<th></th>
<th>0</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>Over 6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Times</td>
<td></td>
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<td></td>
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<td></td>
</tr>
</tbody>
</table>

How many cooking classes have you participated in with The Goldring Center for Culinary Medicine?
<table>
<thead>
<tr>
<th>Classes</th>
<th>0</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>Over 6</th>
</tr>
</thead>
</table>

My highest education level finished is:

<table>
<thead>
<tr>
<th>Level</th>
<th>None</th>
<th>Elementary or middle school</th>
<th>High school or GED</th>
<th>College</th>
<th>Graduate school</th>
</tr>
</thead>
</table>

I am part of this survey group:
- Beginner cooking class: START of my class series
- Beginner cooking class: END of my class series
- Intermediate cooking class: END of my class series
- No cooking class: my FIRST survey
- No cooking class: my SECOND survey

I am participating in the class because:
- I am a Laitram employee.
- I am a family member or guest of a Laitram employee.
- I have a chronic health condition (i.e. diabetes, hypertension, hyperlipidemia, etc.) in a randomized trial with GCCM (The "Teaching Kitchen").
- I am a family member or guest of someone with a chronic health condition (i.e. diabetes, hypertension, hyperlipidemia, etc.) in a randomized trial with GCCM (The "Teaching Kitchen").
- I have another reason (i.e. not Laitram or diabetes).

What are the types of medical professionals or sources and where you talked with them that gave you the most nutrition counseling this past year, such as ways to change your meals so they have less sugar? (You can choose more than one).

<table>
<thead>
<tr>
<th>Doctor clinic or ambulatory surgical center</th>
<th>Home</th>
<th>Hospital (including Emergency Room, ER)</th>
<th>Mobile health center or health fair</th>
<th>Urgent care clinic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Certified Diabetes Educator</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Who are the people you talk most with during a usual week, and where do you talk with them? (You can choose more than one).

<table>
<thead>
<tr>
<th></th>
<th>Home</th>
<th>Public places (i.e. church/mosque/synagogue, parks, restaurants, etc.)</th>
<th>Work</th>
</tr>
</thead>
<tbody>
<tr>
<td>Co-worker/classmate</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Child</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Extended family</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(i.e. aunt, cousin, etc.)</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
If you participated in any Goldring Center for Culinary Medicine (GCCM) cooking classes, who was most influential in your choice to participate?

<table>
<thead>
<tr>
<th>Relation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Friend</td>
</tr>
<tr>
<td>Grandparent</td>
</tr>
<tr>
<td>Parent</td>
</tr>
<tr>
<td>Neighbor</td>
</tr>
<tr>
<td>Sibling (i.e. brother or sister)</td>
</tr>
</tbody>
</table>

Co-worker/classmate
Child
Extended family (i.e. aunt, cousin, etc.)
Friend
Grandparent
Parent
Neighbor
Sibling (i.e. brother or sister)
Medical professional (i.e. doctor, nurse, RD, etc.)

What is your email?

Thank you for your time!