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RESEARCH ARTICLE

Interprofessional Team Diagnostics Consultation Improves Health Professions' Practice Outcomes and Clinical Research

Elizabeth Kenimer Leibach[1], Professor Emerita[2]

[1]HMES Healthcare Management and Education Services, LLC
[2]College of Allied Health Sciences, Department of Medical Laboratory, Imaging, and Radiologic Sciences, Augusta University, Augusta, Georgia USA
[2]School of Health Professions, Department of Clinical Laboratory and Medical Imaging Sciences, Rutgers University, Newark, New Jersey USA

*eleibach@comcast.net

ABSTRACT

Background: Communication gaps in health services delivery significantly compromise quality in clinical decision making. Information generated by diagnostics professionals' accounts for much of the objective data in the clinical record and therefore is foundational in clinical decision support. This work describes the Diagnostics Consultation Model©, a diagnostics communications portal, which supports communications among interprofessional teams, providers, and institutions.

Aims: Study aims were to develop and validate a workflow prediction index (the complexity index) to assign resolution of consultation requests to diagnostics practitioners with requisite competencies based on an algorithm comprised of characteristics available at the point of consultation initiation. The complexity index functions as the entry into a workflow process directing consultation requests, first, to diagnostics practitioners for investigation and then into communication processes for tracking medical history, patient/consumer clinical information, resolution logic, conclusions, and next step recommendations among all healthcare providers.

Methods: Data to develop the complexity index (N = 325 consultation cases) were collected during daily activities in the clinical diagnostics laboratory and describe consultation characteristics important in clinical decision making and available at the point of consultation initiation. The complexity index was developed and validated by comparison of regression analyses using consultation characteristics, i.e., clinical outcomes, available at the point of consultation initiation (development) and after consultation completion (validation).

Results: Diagnostics Consultation Model© methodology links communication processes among all providers in all care settings, i.e., community, institutional, and referral, involved in the care paths of individual patient/consumers. This methodology also provides the capability to follow individuals' medical histories longitudinally and, through regular consultations and practice-based clinical research, to address issues of medical effectiveness, cost efficiency, access, equity, timeliness, safety, and compliance.

Conclusion: Implementation of Diagnostics Consultation Model© methods and curriculum in health professions' daily practice has the potential to change health services delivery by the redistribution of care through interprofessional teams coordinated by standardized communication processes. Employed as a systems approach to individualized patient/consumer care, the Diagnostics Consultation Model© could provide the communications technology and methodology structure for value-based healthcare continuously optimized to address the needs of individuals, populations, and health systems throughout the continuum of care.

Introduction

Options for ordering and utilizing clinical diagnostics testing are burgeoning. In a 2017 World Health Organization Bulletin, it was estimated that more than 40,000 screening, diagnostic, monitoring, and prognostic tests, performed in the clinical and imaging laboratories and via point of care testing in multiple venues, are available to providers to aid in disease treatment.[1]

In 2021, the *in vitro* diagnostics (IVD) global market exceeded $91.7 billion and is projected to grow at a compound annual growth rate of 3.1% to $128.9 billion from 2022 to 2030 (Global Market Insights, November 11, 2021, https://www.gminsights.com/industry-analysis/in-vitro-diagnostics-market). With an increase in genomic testing capability, a changing regulatory environment encouraged by the rapid SARS-CoV-2 response, rising incidence of infectious and chronic disease, incorporation of artificial intelligence (AI)-assisted IVD evaluation enabling personalized medicine, and the proliferation of direct-to-consumer diagnostics, numbers of tests available and their costs are increasing daily.[2-5]

Concurrently, the services delivery gap between analytic accuracy (valid, actionable diagnostics results) and medical meaningfulness (providers' understanding of results) is growing larger, as well.[6-7] Issues related to re-interpretation of diagnostics information produced by older generations of technology vis-à-vis information from new, more sensitive and specific generations are increasing, also, because of the rapid advancement of technology and computerization.[8-9] Rapid advancements in diagnostics technologies coupled with similar expansion in testing options and choices mandate the development of evidence based testing algorithms linked to the care paths of the major chronic diseases and health challenges encountered most frequently.[10-12] Developing, also, is an equally compelling mandate to provide these evidence based algorithms to both providers and patient/consumers for their use in shared clinical decision making (CDM).[7,12,13-16]

In 2015, the U.S. National Academy of Medicine (NAM) published a landmark report, "Improving Diagnosis in Health Care," identifying failures in the diagnostic process as a major contributor to overall medical errors.[17] The NAM report describes the diagnostic process as a series of activities engaging patient/consumers with healthcare throughout their lifetimes embedded in work systems comprised of structures, processes, and outcomes.[18] The report presents corroborating evidence from multiple sources that most patient/consumers will experience at least one diagnostics error with associated negative outcomes in their lifetimes.

Diagnostics information is clearly foundational to efficiency and effectiveness of health service delivery. It is estimated that as much as 93% of the objective data in the clinical record is comprised of diagnostics information, much of which impacts CDM.[12,19-21] Errors, delays, and misinterpretation involving the generation of orders (pre-analytical processing) and utilization of

diagnostics data (post-analytical processing) also increase the probability of inappropriate resource utilization.[22] As many as 50-60% of all clinical laboratory orders may be inadequately justified[23]; and most clinical laboratory errors (68-87%), including inappropriate/unjustified orders, have been shown to be non-analytic.[24-25] Even more significant, the ordering of diagnostics studies is rarely based on evidence of comparative effectiveness over the entire cycle of care after evaluating associated health outcomes in similar index cases.[7,17,26-29]

These communication gaps in health services delivery negatively impact healthcare quality.[17,30-31] Frequently reported is the disproportionate contribution of incomplete, inadequate, and conflicting communications to errors in CDM[22,26,32]; and medical errors are not just the result of miscommunications by individual practitioners but are also predicated by systems, processes, and conditions that have failed.[17,22,31,33-36]

Communication failures occur at multiple junctures within the care path. To address the outcomes of handoff communication failures, standardized communication tools have been structured for use during care transitions involving unit to unit transfers, e.g., surgery to ICU, anesthesia to surgery; within unit transfers, e.g., nursing shift report, within radiology communications; or during inpatient rounding.[22,25,37-38]

Universal implementation of the electronic health record (EHR) has also been implicated in healthcare communications failures.[39] Lapses in clinical reasoning leading to inadequate CDM have been attributed to EHR structure as primarily transactional data repositories, i.e., EHRs simultaneously provide a glut of data and dearth of organized, actionable information.[12,28] EHRs lack meaningful organization schemes, e.g., a library of care plans and designated sections for interprofessional team synopses to guide CDM throughout the care continuum.[12,40] Difficulties involved in following complex treatment plans and formulating evidence based next steps have led to patient/consumer-related safety incidents as well as practitioner burnout.[35.39,41-42] As a result of these system design flaws, application program interfaces (APIs) connecting EHR frameworks to middleware providing expanded clinical decision support (CDS) capability are being envisioned and developed.[12,36,43-46]

An additional contributor to the communication gap in continuity of care is the lack of an evidence-based method for determining interprofessional team (IPT) member roles and functions. An international review of IPT rounding practices in intensive care units summarizes the wide variation in IPT composition and lack of evidence related to impact of IPT practices on patient/consumers' clinical outcomes.[47] In North America, according to Amaral et al[47], both handoff (sending) and receiving physicians and nurses are consistently included as IPT members, clinical pharmacists are common IPT

members, and other health professions (HP) are included *ad hoc* according to the identified clinical problem. However, the diagnostics professions were not reported as either designated or *ad hoc* IPT members.

Though the need for more closely controlled communications among healthcare providers is being addressed in various ways, this brief review reveals continuing communication gaps related to handoffs in care transitions, EHR integration of summaries of care activities after handoffs, and codification of IPT roles and functions. And these communication process gaps in integration of clinical information across treatment silos represent significant threats to effective and efficient health services delivery.[12,28,39,43]

Study Problem

Diagnostics information should be delivered by specialized diagnostics professionals in the context of best evidence and risk assessment tailored to patient/consumers' medical circumstances. Communication of diagnostics information by diagnostics professionals within the patient/consumer-centered team expands IPT effectiveness and efficiency and significantly facilitates, substantiates, and improves the shared decision-making process among healthcare professionals and patient/consumers participating in IPT health services delivery.[10,32,46,48-50]

Therefore, the emerging role for diagnostics professionals, e.g., medical laboratory and imaging professionals, is to design and conduct clinical research to generate evidence for development of testing and treatment algorithms positively impacting patient safety and health outcomes as part of clinical laboratory, imaging, and institutional quality improvement programs.[10,14-15,26-27,25,46,49-52]

Information thus generated would be tailored specifically to the needs of providers and patient/consumers for CDS through the provision of summarized, documented, and reported best evidence for evaluation of treatment and other care options.[32,53]

Study Aim

This report describes the development of the Diagnostics Consultation Model© (DCM©), a clinical diagnostics service communications portal, designed to support CDM within IPT, providers, and institutions.[12,15] The DCM© was developed from a retrospective review of records of medical laboratory professionals' (MLP) consultations with other healthcare providers and characterized the consultation elements occurring in these various clinical settings. This information was then used to design methods describing workflow processes occurring throughout each consultation scenario based on elements (variables) extracted along the consultation care path. These methods optimize consultation resolution as assessed by improvement in clinical and quality outcomes.

Also, a typology of practice competencies attributable to each MLP practice level

involved in consultation resolution was developed from an analysis of types of consultations comfortably handled by each MLP practice level. From the synthesis of these findings, i.e., consultation characteristics and practitioner competencies, a workflow process algorithm was investigated that forwards consultation requests directly to appropriately educated and experienced MLP practice levels and communicates diagnostics findings and recommendations to designated IPT members.[12]

Study Questions

Using data from consultation events occurring in the clinical diagnostics laboratory (CDL), consultation characteristics documented at the time of initiation as well as those available only after consultation completion were associated with MLP practice level resolving the consultation. Three MLP practice levels defined are: (a) MLP Level 1, MLT (medical laboratory technician)/MLS (medical laboratory scientist); (b) MLP Level 2, MLS Specialist/Manager; and (c) MLP Level 3, DCLS (Doctor of Clinical Laboratory Science)/PhD (Specialty Scientist Doctor of Philosophy)/MD (Medical Doctor). These MLP practice level descriptions define a typology of increasing complexity, i.e., scope of knowledge and professional responsibilities, in MLP practice.

Consultation characteristics (variables) available at the point of consultation initiation that proved significant in prediction of MLP most appropriate for consultation resolution are test cycle phase (i.e., pre-analytic, analytic, post-analytic), and medical service/hospital location. Significant predictors available only after consultation completion are handoffs/logic steps required for resolution, and medical subject.

A diagnostics workflow prediction model, the complexity index (CI), was developed from consultation case data using test cycle phase and medical service/hospital location as predictor variables and MLP practice level as the dependent variable. Next, the predictor variables available only after consultation completion, i.e., number of handoffs/logic steps and consultation medical subject, were regressed against MLP practice levels, the dependent variable. The CI predicted similar MLP practice levels from both the independent variables available at the point of consultation initiation and those available after consultation completion.

Study question 1

The first research question for the study was: Can the MLP practice levels resolving consultations be predicted by an index, the CI, derived from the variables test cycle phase and medical service/hospital location? The first descriptor, test cycle phase, is defined as the point in the testing process soliciting the consultation, i.e., pre-analytic (test selection, order placement, specimen collection), analytic (obtain results), and/or post-analytic (results interpretation, analytic test sequencing). Both these variables, test cycle phase and medical service/hospital location, can be

documented at the point of consultation initiation.

Study question 2

The second research question for the study was: Can MLP practice levels resolving consultations be predicted by number of handoffs/logic steps and medical subject associated with consultation cases? The number of handoffs/logic steps and medical subject are available only after consultation completion and were used to evaluate the predictive performance of the CI.

Research Design and Methods

Study Design

Neither methods for characterization of MLP consultations nor attribution of MLP consultations to significant diagnoses or health outcomes have been reported. To address these gaps regarding the role of MLP consultations in CDS, this exploratory study was conducted to document and characterize MLP involvement in consultation with other health providers regarding questions they have about access to and utilization of diagnostics information. Being able to predict the pathway and direction of questions about diagnostics information would not only provide the methodology to monitor for and mitigate patient safety concerns but would also significantly inform efforts to staff diagnostics laboratories and educate practitioners appropriately for consultation practice.[12,16]

The study design is a retrospective review of consultations occurring during a four-month period in the Fall season at a tertiary care healthcare system associated with an U.S. academic medical center. The research was approved by the medical center's institutional review board (Augusta University, IRB #10-12-126/IRBNet #611273-2). The focused research questions address the probability of developing an accurate diagnostics workflow prediction algorithm, i.e., CI, to direct consultation requests within the DCM© to MLP practice levels and IPT members. The data involved in developing and evaluating the CI were gathered from real world consultation experiences of various levels of MLP practitioners in the CDL. Data describing consultation characteristics as well as workflow processes and MLP involved in consultation resolution were collected.

Consultation definition and sample characteristics

The study consultation population was defined as all documented interventions (consultations) between MLP and other healthcare providers (hospital-based users of laboratory information) in a U.S. 600-bed, tertiary care hospital affiliated with an academic medical center. Both electronic and face-to-face interactions were considered as consultations. Data on 325 consultation events, i.e., N=325 consultation cases, were recorded during a 24-hour per day, 11-week data collection period.

Consultation data collection tool (DCT) development

MLP managers and clinical pathology section chiefs were asked to participate in

study instrument design, piloting, implementation, analysis, and evaluation. Over a four-month period, four meetings were conducted. The first meeting (month 1) was dedicated to a project overview and design of the DCT. During the second month, the DCT was piloted, and a second meeting was conducted with participating MLP to refine the initial DCT draft, and the DCT was finalized. Instructions regarding completion of the DCT, results reporting, as well as information regarding goals and objectives of the project were shared with MLP participants during the remaining two educational sessions conducted prior to the beginning of data collection.

The DCT, reduced from an Excel file for this format and shown as Figure 1, was completed by participating MLP during the normal workday as consultations occurred. MLP consultations were described demographically by CDL area, date/time, medical service/hospital location, urgency status, type of provider initiating the consultation intervention, number of handoffs/logic steps, and testing cycle phase, i.e., pre-, post-, and analytic, to which they related. Cumulative DCTs were submitted electronically to the principal investigator every two weeks; an email reminder prompt was sent before each submission was due. Data tables were then created in statistical software for manual entry of variable values and subsequent data analysis.

Pathologist/Manager/Designee: Inclusive Dates: Submitted By, CL Area, and Date:	_____ _____ _____

Date	Time	Service/ Location	Urgent		Healthcare Provider							Consultation Category							Consultation Summary	Forward		Review Comments	Reviewer	Review Date
			Y	N	AD	AT	HS	MT	RN	CP	OT	Test Select	Place Order	Collect/ ID/Tran	Obtain Result	Results Logic	Test	Other		YES	NO			

Legend: AD = Administrator; AT = Attending Physician; HS = House Staff; MT = Medical; Technologist / Clinical Laboratory Scientist; RN = Nurse: CP = Pathologist; OT = Other; Health Care Provider (define in space provided below); Test Select = Test Selection; Query (Check); Place Order = Order Placement Clarification (Check); Collect / ID / Tran = Specimen ID, Collection, Transport Details (Check); Obtain Result = Preliminary or Final; Results Inquiry (Check); Results Logic = Interpretation and / or Reflex Logic (Check); Test = Analytic Query (Check); Other = Miscellaneous requests, e.g., billing information; (check); Forward = Forward to Manager's / Pathologist's Attention (Check).

Figure 1. The Consultation Data Collection Tool (DCT)

Study Methods

Methods for continuous clinical and quality improvement of CDS consultation services through the DCM© are described in this study. Methods were developed that, first, describe processes for documentation of characteristics of consultation events occurring in CDL operations. Then methods are described to develop processes, directing workflow (i.e., consultation requests) to appropriately prepared MLP, derived from analyses of these consultation characteristics.

Data abstraction procedure

All descriptive and inferential statistical analyses were performed using IBM SPSS® Statistics, v. 29; standard formatting conventions, as well as default thresholds and significance levels for regression modeling, were used. In preparation for descriptive characterization of consultations, data were initially collected into multiple levels of categorical measurements to preserve granularity. However, total number of consultations was insufficient to allow for analysis on all independent variables (IV) at all levels, and for some analyses, granular data were recoded according to the algorithms given in Table 1.

In addition, data abstraction tables (data not shown) were created for recording additional assessments derived from the statistics data table. These additional assessments, i.e., number of handoffs/logic steps, MLP practice level disposition, and medical subject categories, were qualitatively derived from "consultation summary," "forward," and "reviewer comments" entries for each consultation in the DCT. Resultant definitions of handoffs/logic steps and MLP practice level disposition categories are also given in Table 1.

Table 1. Summary of Category Transformation Algorithms

Variable	Initial Number of Levels	Transformed (Recoded) Number of Levels
CL Area	12	0 = Professional Knowledge (non-specimen receiving areas)
		1 = General Knowledge (specimen receiving area)
Provider Type	7	0 = Non-RN
		1 = RN
Test Cycle Phase	7	1 = Pre-analytic (test select, place order, collect / ID / transport)
		2 = Analytic (specimen analysis)
		3 = Post-analytic (obtain result, results logic, other)
Handoffs/logic steps	5	1 = One logic step, no handoffs
		2 = Two hand-offs/logic steps
		3 = Three or greater handoffs/logic steps
MLP Practice Level Consultation Disposition	6	1 = MLP Level 1 (MLT/MLS complete, one logic step and no handoff)
		2 = MLP Level 2 (Referred to MLS Specialist/Manager)
		3 = MLP Level 3 (Referred to DCLS/PhD/MD)

Each of the 325 recorded consultation events was assigned to a medical subject category defined in Table 2. The original and/or non-recoded categories are also shown in Table 2. The "comments" field was used to record free-form comments related to issues arising from the consultation CDS process itself, or documentation from it.

Table 2. Original Categories and/or Non-recoded Consultation Characteristics Summary

Original Categories and/or Non-recoded Consultation Characteristics (IV) N = 325	IV Frequency	IV Percent
Clinical Laboratory Area Involved	n = 278	100
Chemistry	63	23
Clinical Pathologists/ Residents	42	15
Immunology/Send Outs	35	13
Outpatient (Medical Office Building)	3	1
Point of Care Testing	40	14
Receiving	95	34
Missing Data: % = (1.00 – n/N) x 100	47	14
Time of Day Initiated	n = 182	100
8 a.m. – 12 p.m.	37	37
1 p.m. – 4 p.m.	37	37
Other	26	26
Missing Data: % = (1.00 – n/N) x 100	143	44
Medical Service/Location Origin	n = 270	100
Emergency Department	28	10
Chemistry (Clinical Laboratory)	23	9
Other	219	81
Missing Data: % = (1.00 – n/N) x 100	55	17
Urgency	n = 278	100
Routine	191	69
STAT	87	31
Missing Data: % = (1.00 – n/N) x 100	47	14
Healthcare Provider Type	n = 289	100
RN	143	51
Other (administrators, MLP, medical students, pharmacists, physicians, respiratory therapists)	135	49
Missing Data: % = (1.00 – n/N) x 100	47	14
Consultation Type (Test Cycle Phase Involved)	n = 278	100
Pre-analytic: Test Select, Place Order, Collect/ID/Transport	137	49
Analytic: Test Parameters	86	31
Post-analytic: Obtain Result, Results Logic, Other	55	20
Missing Data: % = (1.00 – n/N) x 100	47	14
Medical Subject	n = 278	100
Education	3	1
Genetics/Molecular	6	2
Technology Decisions	16	6
IT Ordering	96	35
Pediatric Genetics/Molecular	5	2
Results Resolution	75	27
Patient Safety/Identification	36	13
Test Integration/Evaluation	19	7
Proficiency Testing	3	1
Specimen Referral/Send Out	19	7
Missing Data: % = (1.00 – n/N) x 100	47	14

Study analyses

Study analyses were guided by these steps:

1. The consultation cases sample size (N=325) was considered large enough to power analyses supporting the research questions of the study. Data were cleaned by evaluating missing data, outliers, normality, and linearity. In preparation for regression analyses, homoscedasticity and independence of residuals were also assessed. Power analyses were performed from the determination of the ratio of cases to IVs. Detailed procedures and results of these analyses have been reported previously.[12]

2. MLP practice levels were defined by analyses of position descriptions of staff responsible for final consultation disposition/resolution. MLP practice levels resolving consultations are defined as (a) MLP Level 1, MLT/MLS; (b) MLP Level 2, MLS Specialist/Manager; and (c) MLP Level 3, DCLS/PhD/MD.

3. A diagnostics workflow prediction model, the CI, was developed using the IVs, test cycle phase and medical service/hospital location, and dependent variable (DV), MLP practice level. The predictive performance of the CI was then evaluated against variable values available after consultation completion, i.e., numbers of handoffs/logic steps and medical subject, that also correlated with MLP practice levels involved in consultation final disposition, i.e., MLP Levels 1-3. The CI predicted similar MLP practice levels from both datasets, i.e., the independent variables available at the point of consultation initiation and those available after consultation completion.

4. These findings formed the basis of methodology to identify work processes optimizing workflow through the DCM© communication portal. The methodology described is intended to function at the point of consultation initiation to direct work orders to the MLP practice level with the competencies and experience skill set most closely aligned with the resources required for resolution of the consultation case.

Study question 1: Study analyses

The first research question was: Can the MLP practice level resolving consultations be predicted by an index derived from the variables test cycle phase and medical service/hospital location? IVs, test cycle phase and medical service area, were modeled with the MLP practice level involved in final consultation disposition, i.e., DV, to create the composite predictor variable, CI. All the regression models were evaluated using Multiple R^2 and its associated p value along with standardized beta weights for each of the IVs in the models.

1. Study question 1, analysis 1

Analysis 1 defined the CI by predicting the relationship among the predictor variables, test cycle phase and medical service/hospital location, and the outcome variable, MLP practice level (levels 1-3) involved in consultation disposition. There were two IVs for this analysis: (1) test cycle phase (3 levels: pre-analytic, analytic, post-analytic) and (2) medical service area (11 levels, see Table 3 for medical service/hospital location categories). These IVs entered the regression model together to distinguish the DV, MLP level involved in consultation disposition. The

regression equations follow:

a. Modeling with Test Cycle Phase: MLP practice level = Test Cycle Phase (cyclic phases treated as continuous variables).

b. Modeling with Medical Service / Hospital Location: MLP practice level = Test Cycle Phase + Medical Service / Hospital Location (add each service, one by one).

Table 3. Summary of Medical Service Algorithms

Original Medical Service Areas	Consultation Number (Original Areas)	Medical Service Area Transformations	Transformed Medical Service Areas	Consultation Number (Transformed Areas)
1, Allergy	1	37, Other		
2, Cardiology	14		1, Cardiology	14
3, Cardiac CCU	0			
4, Dermatology	0			
5, Endocrinology	0			
6, ENT (Otolaryngology)	0			
7, Emergency/ Trauma	58		2, Emergency/ Trauma	58
8, Family Medicine	9		3, Family Medicine	9
9, Gastroenterology	0			
10, Geriatrics	0			
11, Gynecology	0			
12, Hematology	1	10, Oncology		
13, Infectious Disease	0			
14, Medicine (Gen)	0			
15, Medicine (Other)	0			
16, Med ICU	3		4, ICU:	30
			3 (Medicine)	
			6 (Neurology)	
			4 (Nursery)	
			10 (Pediatrics)	
			7 (Surgery)	
17, Nephrology	0			
18, Neurology	2	37, Other		
19, Neuro ICU	6	16, Med ICU		
20, Nursery	0			
21, Nursery ICU	4	16, Med ICU		
22, Obstetrics (L&D)	34		5, Obstetrics	34
23, Oncology	10		6, Oncology	10
24, Ophthalmology	0			
25, Orthopaedics	0			
26, Pediatrics	24		7, Pediatrics	24
27, Pediatrics ICU	10	16, Med ICU		
28, Pulmonology	1	37, Other		
29, Rheumatology	0			
30, Surgery (Gen)	18		8, Surg Gen	18

2. Study question 1, analysis 2

The full regression model defined the CI candidate IVs and included those categories of test cycle phase and medical service/hospital location found to be statistically significant with 95% confidence in the last step of the analysis. The model is: MLP practice level = Test Cycle Phase + Medical Service/Hospital Location (best predictors).

Study question 2: Study analyses

The second research question is:

Can MLP practice levels resolving consultations be predicted by number of handoffs/logic steps and medical subject associated with consultation cases? Handoffs/logic steps and medical subject were the variables documented after consultation completion that correlate with MLP practice level.

These variables were tested to develop a model predicting the level of human resources required to resolve consultation queries (i.e., MLP practice level) using the variable values available after consultation completion. All of the regression models were evaluated using Multiple R^2 and its associated p value along with standardized beta weights for each of the IVs in the models.

1. Study question 2, analysis 1:

Define the post-consultation completion predictive model by testing the relationship among the IVs, i.e., handoffs/logic steps and medical subject, and the DV, MLP practice level (levels 1-3) involved in consultation disposition.

There were two IVs for this analysis: (1) handoffs/logic steps with 3 levels (completed with one logic step, no handoff; two handoffs/logic steps; ≥3 handoffs/logic steps) and (2) medical subject (10 levels). See Table 2 for medical subject categories. These IVs entered the regression model together to distinguish the DV, MLP level involved in consultation disposition. The regression equations follow.

a. Modeling with Handoffs/Logic Steps: MLP practice level = Handoffs/Logic Steps (add each level, one by one).
b. Modeling with Medical Subject: MLP practice level = Medical Subject (add each level, one by one).

2. Study question 2: Analysis 2:

The full regression model defined the post-completion candidate IVs and included those categories of number of handoffs/logic steps and medical subject found to be statistically significant with 95% confidence in the last step of the analysis. The model is:

MLP practice level = Handoffs/Logic Steps (best predictors) + Medical Subject (best predictors).

Results

Characterization of Consultation Requests

Data were collected on seven consultation characteristics reported in Table 2. Initial analyses indicated that MLP practice level consultation disposition can be predicted by four of the seven IVs: test cycle phase, medical subject, medical service, and number of handoffs/logic steps required to resolve the consultation clinical question. These initial analyses are shown in Table 4.

Table 4. Statistical Inferences Among Variables Predicting MLP Practice Level Consultation Disposition

Crosstabulation	Inferential Statistics							
MLP Practice Level Disposition (3 Levels) by:	Pearson Chi-Square			Likelihood Ratio			Cramer's V	
	Value	df	Sig[a]	Value	df	Sig[a]	Value	Sig[a]
Test Cycle Phase[b]	32.387	4	≤ .01	28.533	4	≤ .01	.227	≤ .01
Medical Subject[c]	98.390	18	≤ .01	74.838	18	≤ .01	.396	≤ .01
Medical Service[d]	30.733	20	.059	39.479	20	.006	.218	.059
Handoffs/Logic Steps[e]	97.166	4	≤ .01	122.713	4	≤ .01	.393	≤ .01

a. Asymptotic significance

b. Test cycle phase = Consultation type, 3 levels (Pre-analytic, Analytic, Post-analytic)

c. Medical Subject = 10 levels (Education, Genetics/Molecular, Technology Decisions, IT Ordering, Peds Genetics/Molecular, Results Resolution, Safety/ID, Test Integration/Evaluation, Proficiency Testing, Specimen Referral/Transport)

d. Medical Service/Hospital Location = 11 Levels (Cardiology; Emergency/Trauma; Family Medicine; ICUs; Obstetrics; Oncology; Pediatric; Surgery, General; Surgery, Other; Clinical Laboratory; Other)

e. Handoffs/Logic Steps = 3 levels (completed with one logic step, no handoff; two handoffs/logic steps; ≥3 handoffs/logic steps)

The hypothesis was that the direction of resources to the appropriately prepared MLP practice level for consultation disposition could be based on some combination of these four predictor variables correlated with MLP practice level disposition.

Assessments of overall data fitness

The appraisal of findings included an evaluation of the fitness of the data to support conclusions from analyses addressing the study questions. The dataset was prepared by evaluating accuracy/coding errors, missing data, normality, linearity, and outliers. In

preparation for regression analyses, homoscedasticity (homogeneity of variance) and independence of residuals (multivariate normality) were also assessed when appropriate. Power was evaluated *post hoc* by the determination of the ratio of cases on each variable to each IV or DV, also, to further assess statistical conclusion validity. The analytic variables assessed are test cycle phase, medical service/hospital location, medical subject, handoffs/logic steps, and MLP practice level. Medical service/hospital location and medical subject are categorical variables and were analyzed as such through a binary transformation of each level of the variable. Test cycle phase, handoffs/logic steps, and MLP practice level are ordinal level measurements but were analyzed as interval level justified by the relatively large number of cases (N=325) and the assumptions of the central limit theorem.[54] Assessments of homogeneity of variance and normality on some variables were improved by log, inverse, and/or square root transformations. Detailed procedures and results of these analyses have been reported previously.[12]

Analysis of Consultation Requests

Study question (SQ) 1. SQ 1 was: Can the MLP practice level resolving consultations be predicted by an index derived from the variables test cycle phase and medical service/hospital location? The two variable categories tested in the prediction model, i.e., CI, were test cycle phase (pre-analytic, analytic, and post-analytic levels) and 10 medical service/hospital locations. Crosstabulations and regression modeling were undertaken to determine the contribution of each of these variables and/or variable levels to the MLP practice level ultimately resolving the consultation case. The final regression model for SQ 1 was: invMLP3LevelDisposition = sqrTestCycle3Levels + srvSurgeryOth + srvClinLab. Test cycle phase as well as two medical service locations, "surgery other" (than general) and "clinical laboratory," were significant determinants of MLP practice level consultation resolution. The CI thus created from this discovery provided a numerical value indexed to one of the three MLP practice levels most appropriate for consultation resolution.

Study question 1 regression analyses assumptions testing

For assumptions testing of the categorical variable, medical service/hospital location, each of the 10 category levels was transformed into a binary variable with a code of 1 if the case fit into that category and a code of 0 otherwise. These variables, by definition, are distributed binomially (bimodally) and were used in subsequent analyses.

Study question 1 regression variables assessment: frequencies

Frequencies for cases in each of the SQ 1 analytic variables and variable levels are summarized in Table 5. Consultation requests from family medicine and oncology services did not meet minimum numbers for analysis against each level of the DV MLP practice level and were not included in further regression analyses.

Table 5. Study Question 1 Analytic Variables: Frequencies (N = 306, Missing = 0 Cases)

Variable	Variable Levels	N (Cases)	Percent (%)
MLP (3 Levels)[a]	MLP 1	231	75.5%
	MLP 2	53	17.3%
	MLP 3	22	7.2%
Test Cycle Phase (3 Levels)	Pre-analytic	70	22.9%
	Analytic	54	17.6%
	Post-analytic	182	59.5%
Cardiology	Cardiology (No = 0)	292	95.4%
	Cardiology (Yes = 1)	14	4.6%
Emergency Medicine	Emerg Med (No = 0)	248	81.0%
	Emerg Med (Yes = 1)	58	19.0%
Family Medicine[b]	Fam Med ((No = 0)	306	97.1%
	Fam Med (Yes = 1)	9	2.9%
Intensive Care Units (ICUs)	ICUs (No = 0)	276	90.2%
	ICUs (Yes = 1)	30	9.8%
Obstetrics	Obstet (No = 0)	272	88.9%
	Obstet (Yes = 1)	34	11.1%
Oncology[c]	Oncol (No = 0)	306	96.7%
	Oncol (Yes = 1)	10	3.3%
Pediatrics	Peds (No = 0)	282	92.2%
	Peds (Yes = 1)	24	7.8%
Surgery, General	Surg Gen (No = 0)	288	94.1%
	Surg Gen (Yes = 1)	18	5.9%
Surgery, Other	Surg Oth (No = 0)	284	92.8%
	Surg Oth (Yes = 1)	22	7.2%
Clinical Laboratory	Clin Lab (No = 0)	244	79.7%
	Clin Lab (Yes = 1)	62	20.3%

[a.] Dependent (outcome) variable = MLP (3 Levels)

[b.] All Family Medicine cases were multivariate outliers and deleted from the dataset for further analysis.

[c.] All Oncology cases were multivariate outliers and deleted from the dataset for further analysis.

Study question 1 regression variables assessment: descriptive statistics

Standard skew and kurtosis analyses for the categorical regression variable, medical service/hospital location, indicate significant non-normal distributions on all variable categories. Binary transformations were undertaken on all variable levels to improve normality and were used in subsequent regression analysis. Detailed procedures and results of these assessments have been reported elsewhere.[12]

Descriptive statistics for the ordinal/interval regression variables, i.e., MLP, 3 levels, and test cycle phase, 3 levels, are shown in Table 5, also. Both measures were significantly skewed and kurtotic as compared to the standard parameters for a normal distribution, 3.3 at p=.001. Though inverse transformation for the MLP variable and square root transformation for the test cycle phase variable were undertaken to improve normality, the transformed distributions of both these variables remained non-normal. Analysis of regression residuals (error in the model) was used to test for multivariate normality and equality of variance (homoscedasticity).[54] Shapiro-Wilk's test and the statistic also suggest a statistically significant difference from multivariate normal (S =.795, df = 306, p =.000).

In the SQ 1 model, there are 10 potential predictors, derived from the 10 levels of the medical service/hospital location variable, that entered into the model with test cycle phase and were regressed against the MLP practice level DV. The regression variables were examined for multivariate outliers using the Mahalanobis D statistic and the chi square critical value of 31.2 (p=.001). Using this statistic, 19 cases, 5.8% of the dataset (19/325 cases), had Mahalanobis D statistics greater than the chi square critical value 31.2 (p=.001) and were removed from further analysis. Deletion of these 19 cases resulted in 306 cases for SQ 1 analysis, a large enough sample size remaining to conform to the assumptions of the central limit theorem.[54]

For all 10 medical service/hospital location predictors and test cycle phase, Levene's test for equality of error variances is statistically significant (F = 9.14, df = 26/279, p<.001); therefore, the assumption of equality of variance is not satisfied. Inverse, square root, and log transformations for these ordinal/interval level variables were undertaken to improve the distributions of these variables in order to better meet central limit theorem assumptions, decrease the chance of type 1 error, and therefore, improve statistical conclusion validity. Detailed procedures and results of these assessments have been reported elsewhere.[12]

Study question 1 regression model testing

The full regression model for SQ 1 is: inverseMLP3LevelDisposition = sqrTestCycle3Levels + 10 binary medical service/hospital location levels entered one by one against the DV MLP level. The inverse value for the MLP DV and the square root value for the test cycle IV were used in regression analysis. Binary values for each of the categories of the medical service/hospital location IV were entered into the model one at a time. Test cycle phase and the medical service area "surgery, other" were predicted by the test of means differences. One additional medical service area, "clinical laboratory," emerged as a significant predictor in the regression, explaining variance in the MLP DV not already accounted for by test cycle phase. All remaining medical service/hospital location predictors were eliminated from further analyses since they resulted in no change to the model. Detailed

procedures and results of these assessments have been reported elsewhere.[12]

The final regression model, testing IV contributions to MLP level disposition, is: invMLP3LevelDisposition = sqrTestCycle3Levels + srvSurgeryOther + srvClinLab. Table 6 summarizes the coefficients for the final model. A positive beta weight for an inverse scale measure for MLP means that the predictor is associated with a lower practice level of MLP; likewise, a negative beta weight is interpreted as indicating a higher level of MLP practice.

Table 6. Study Question 1 Regression Variables: Final Model Coefficients (N = 306, Missing = 0 Cases)

Final Model[a]		Coefficients					
		Beta	t	Significance	Zero Order	Partial	Part
1	Test Cycle Phase Sqr.[b]	.185	3.277	.001	.185	.185	.185
	Test Cycle Phase Sqr.[b]	.178	3.178	.002	.185	.180	.177
2	Surgery, Other	.148	2.650	.008	.157	.151	.148
	Test Cycle Phase Sqr.[b]	.156	2.758	.006	.185	.157	.153
	Surgery, Other	.133	2.369	.018	.157	.135	.132
3	Clinical Laboratory	-.115	-2.020	.044	-.164	-.115	-.112

[a] Final model is: invMLP3LevelDisposition = sqrTestCycle3Levels+ srvSurgeryOth+ srvClinLab

[b] Model 1 is: invMLP3LevelDisposition = sqrTestCycle3Levels

[c] Model 2 is: invMLP3LevelDisposition = sqrTestCycle3Levels + srvSurgeryOth

[d] Model 3 is: invMLP3LevelDisposition = sqrTestCycle3Levels + srvSurgeryOth + srvClinLab

[e] Predictor: Square root value of variable Test Cycle Phase, 3 levels = sqrTestCycle3Levels

[f] Predictor: Surgery, Other = srvSurgeryOth

[g] Predictor: Clinical Laboratory = srvClinLab

[h] Dependent Variable: inverse value of variable MLP, 3 levels = invMLP3LevelDisposition

Study question 1 regression model testing summary

Table 7 summarizes important statistical descriptors of the final regression model. The predictor influencing MLP practice level disposition the most is test cycle phase, explaining 3.4% of variance (R square change=.034, p=.001). Test cycle beta weight is also significant at .178, p=.008; the positive beta weight, for an inverse scale, indicates that the test cycle phase (1-3) is inversely associated with MLP practice level (1-3); as the test cycle phase level measure increases, the MLP practice level (1-3) decreases.

The interpretation of SQ 1 regression findings was limited by these small explained variances and the violations of

regression assumptions which have been discussed previously. As a consequence, these limitations should be considered when interpreting study findings. However, a *post hoc* power calculation, where N=306, R Square Δ=.069, and number of predictors is 3, returned a power estimate of .987 which mitigates, to some extent, the violation of regression assumptions.

Table 7. Study Question 1 Regression Variables: Final Model Summary (N = 306, Missing = 0 Cases)

Model[a]	R	R Square Δ	F	df1	df2	Sig. of F
1[b] Test Cycle Phase Sqr.[e]	.185	.034	10.740	1	304	.001
Test Cycle Phase Sqr.[e]	.185	.034	10.740	1	304	.001
2[c] Surgery, Other	.237	.056	7.022	1	303	.008
Test Cycle Phase Sqr.[e]	.185	.034	10.740	1	304	.001
Surgery, Other[f]	.237	.056	7.022	1	303	.008
3[d] Clinical Laboratory[g]	.262	.069	4.082	1	302	.044

[a] Final model is: invMLP3LevelDisposition = sqrTestCycle3Levels+ srvSurgeryOth+ srvClinLab

[b] Model 1 is: invMLP3LevelDisposition = sqrTestCycle3Levels

[c] Model 2 is: invMLP3LevelDisposition = sqrTestCycle3Levels + srvSurgeryOth

[d] Model 3 is: invMLP3LevelDisposition = sqrTestCycle3Levels + srvSurgeryOth + srvClinLab

[e] Predictor: Square root value of variable Test Cycle Phase, 3 levels = sqrTestCycle3Levels

[f] Predictor: Surgery, Other = srvSurgeryOth

[g] Predictor: Clinical Laboratory = srvClinLab

[h] Dependent Variable: inverse value of variable MLP, 3 levels = invMLP3LevelDisposition

Study question 1 pre-consultation CI structure

SQ 1 regression modeling against the MLP practice level outcome variable confirmed that a workflow prediction index, the CI, can be constructed from the values of three predictor characteristics collected at the point of consultation initiation, i.e., test cycle phase and two medical services, "surgery, other" and "clinical laboratory." Using the beta weights from the final regression model (see Table 6), a simple matrix was constructed to explain the logic for predicting the most appropriate MLP practice level for consultation resolution. Positive beta weights for test cycle phase (.156, p=.006) and surgery, other (.133, p=.018) indicated that these measures vary inversely with an inverse MLP practice level. The negative beta weight (-.115, p=.044) of the clinical laboratory predictor for an inverse MLP3LevelDisposition scale, indicated that the srvClinLab measure varies directly with MLP practice level (1-3); as the srvClinLab measure increases becoming more negative, the MLP practice level (1-3) increases. The matrix conceptualizing the logic in the use of the CI for workflow

prediction is shown in Table 8.

Table 8. Study Question 1 Complexity Index Definition Matrix

MLP Practice Level	Consultation Point of Initiation Predictors		
	Test Cycle Phase	Surgery, Other	Clinical Laboratory
1[a]	3	3	1
2[b]	2	2	2
3[c]	1	1	3

[a] MLP practice level 1 = test cycle phase beta weight highest >.156 + surgery, other beta weight highest >.133+ clinical laboratory beta weight lowest >-.115

[b] MLP practice level 2 = test cycle phase beta weight high but <.156 + surgery, other beta weight high but <.133 + clinical laboratory beta weight low but >-.115

[c] MLP practice level 3 = test cycle phase beta weight lowest <.156 + surgery, other beta weight lowest <.133+ clinical laboratory beta weight highest >-.115

In order to operationalize the CI in the future, the logic of the conceptual changes in beta weights as presented in Table 8 were translated into values associated with predictor variables that can enter into an algorithm describing the logic of the beta weight changes. The algorithm would take the general form of the regression model: MLP practice level predicted = test cycle phase + surgery, other + clinical laboratory. More specifically, the MLP practice level to receive the presenting consultation request would be indicated by a combination of values related to test cycle level (pre-analytic, analytic, or post-analytic), presence/absence of "surgery, other" origin, and presence/absence of "clinical laboratory" origin. The values entered into this algorithm were a combination of beta weights of each of the variable levels calculated from the SQ 1 dataset (N=306 cases) and the associated intercept value. This more specific algorithm, using the actual beta weights from the regression equations, is: MLP practice level (predicted) = beta weight (test cycle 1, 2, or 3) + 0 or beta weight (surgery, other) + 0 or beta weight (clinical laboratory) + intercept (i.e., variance not explained by predictors). The MLP practice level values derived from this algorithm can then be used to predict the MLP practice level assigned for consultation resolution from the trendline plotted using the means for each MLP practice level in the SQ 1 dataset. Figure 2 displays the practice levels means trendline plot for the SQ 1 dataset.

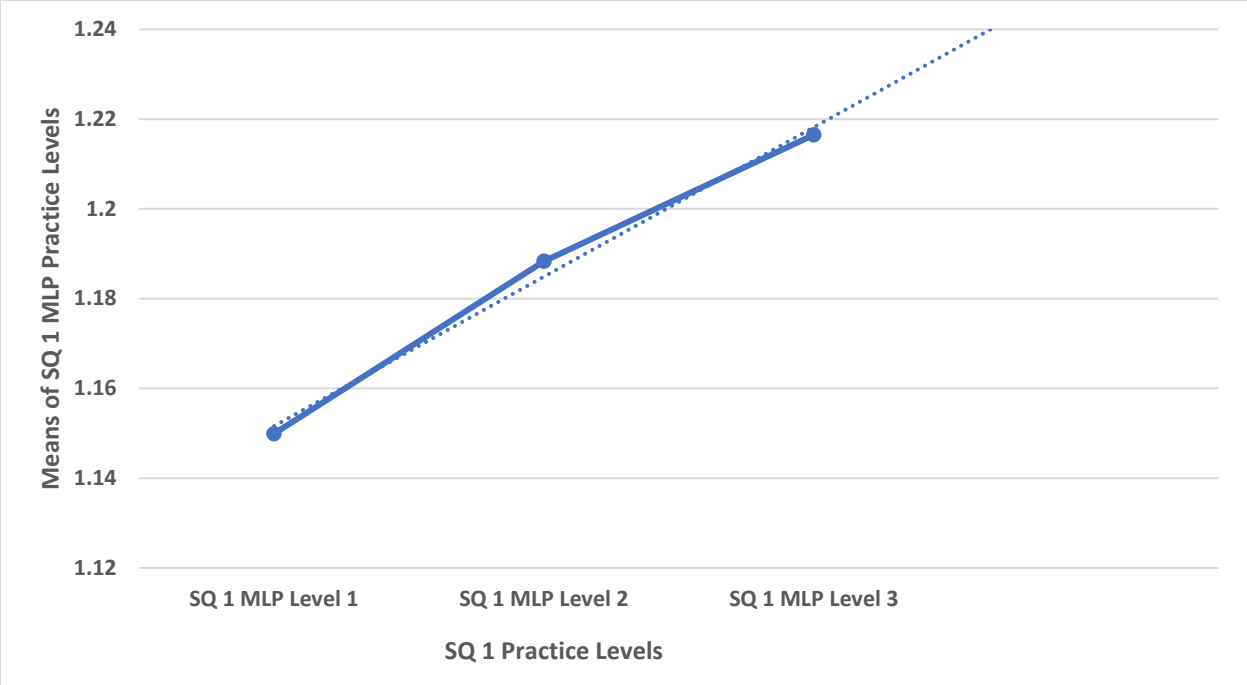

Figure 2. Study Question 1 MLP practice level means trendline plot

Means for each MLP practice level in the SQ 1 dataset represent the average number of consultation cases resolved by each practice level. In practice, ideally, the value generated from the predicted MLP practice level algorithm would fall on the trendline within the confidence limits of the mean of one of the MLP practice levels. Thus, the consultation request would be directed to the MLP practice level with associated mean value closest to that predicted by the algorithm.

Study question 2

SQ 2 was: Can MLP practice levels resolving consultations be predicted by number of handoffs/logic steps and medical subject associated with consultation cases? To address this question, a different dataset of consultation characteristics was analyzed for the significance of their contributions to the choice of MLP practitioner resolving consultation cases; the characteristics analyzed for this question were available only after consultation completion. The MLP practice level thus generated by the post-completion workflow predictive model serves as a validation method for the CI developed for prospective application. The variable categories tested in the full post-completion prediction model were handoffs/logic steps (3 levels) and 10 medical subject categories shown in Table 2. ANOVA and regression modeling were undertaken to determine the contribution of each of these variables and/or variable levels to the MLP practice level ultimately resolving the consultation case. The final regression model for SQ 2 was:

invMLP3LevelDisposition = sbjITOrdering + logHandoffsLS3LevelsTOT + sbjSafetyID.

Handoffs/logic steps as well as two medical subjects, IT ordering and safety/ID, were significant determinants of MLP practice

level consultation resolution. The post-completion workflow prediction model thus created from these analyses also provided a numerical value indexed to one of the three MLP practice levels most appropriate for consultation resolution.

Study question 2 analyses assumptions testing

For assumptions testing of the categorical variable, medical subject, each of the 10 category levels was transformed into a binary variable with a code of 1 if the case fit into that category and a code of 0 otherwise. These variables are distributed binomially (bimodally), linear by definition and, with a sample size of 308 for SQ 2, can be assumed to meet the multivariate normality and homoscedasticity assumptions invoked in the central limit theorem.[54] These binary variables were used in preliminary regression analyses.

In the SQ 2 model, there are 10 potential predictors, derived from the 10 levels of the medical subject variable, that entered into the model with handoffs/logic steps and were regressed against the DV MLP practice level. SQ 2 regression variables were examined for multivariate outliers using the Mahalanobis D statistic and the chi square critical value of 29.6 (p=.001). Using this statistic, 17 cases, 5.2% of the dataset (17/325 cases), had Mahalanobis D statistics greater than the chi square critical value 29.6 (p=.001) and were removed from further analysis. Deletion of these 17 cases resulted in 308 cases for SQ 2 analysis, a large enough sample size remaining to conform to the assumptions of the central limit theorem.[54]

Study question 2 regression variables: frequencies

Frequencies for cases in each of the SQ 2 analytic variables and variable levels are summarized in Table 9. Consultation requests related to the subjects of education, genetics/molecular, pediatrics genetics/molecular, and proficiency testing did not meet minimum case numbers for analysis against each level of the dependent variable MLP practice level and were not included in further regression analyses.

Table 9. Study Question 2 Analytic Variables: Frequencies (N = 308 Missing = 0 Cases)

Variable	Variable Level	N (Cases)	Percent (%)
MLP (3 Levels)	MLP 1	237	76.9
	MLP 2	56	18.2
	MLP 3	15	4.9
Handoffs/Logic Steps (3 Levels)	1 Logic Step; No Handoffs	151	49.0
	2 Handoffs/Logic Steps	102	33.1
	≥3 Handoffs/Logic Steps	55	17.9
Education[a]	(No = 0)	308	
	(Yes = 1)	0	
Genetics/Molecular[a]	(No = 0)	308	
	(Yes = 1)	0	
Technology Decisions	(No = 0)	292	94.8
	(Yes = 1)	16	5.2
IT Ordering	(No = 0)	192	62.3
	(Yes = 1)	116	37.7
Peds Genetics/Molecular[a]	(No = 0)	308	
	(Yes = 1)	0	
Results Resolution	(No = 0)	206	66.9
	(Yes = 1)	102	33.1
Safety ID	(No = 0)	272	88.3
	(Yes = 1)	36	11.7
Test Integration/Evaluation	(No = 0)	289	93.8
	(Yes = 1)	19	6.2
Proficiency Testing[a]	(No = 0)	308	
	(Yes = 1)	0	
Specimen Referral/Transport	(No = 0)	289	93.8
	(Yes = 1)	19	6.2

[a] All cases from each subject category were multivariate outliers and deleted from the dataset for regression testing.

Study question 2 regression variables: descriptive statistics

Descriptive statistics for the categorical regression variable, medical subject, and for the ordinal/interval variables MLP level and handoffs/logic steps are summarized in Table 9. Both the standard skew and standard kurtosis statistics indicate significant non-normal distributions on all variable levels except test integration/evaluation which can be considered normally distributed (skew=3.662; kurtosis=3.662). All other variable levels were skewed, i.e., positive

skew greater than or negative skew less than 3.3, p=.001. Seven of the eight variable levels showed platykurtic (negative) distributions (kurtosis statistic less than 3.3, p=.001).

Analysis of regression residuals was used to test for multivariate normality and equality of variance (homoscedasticity).[54] Shapiro-Wilk's test and the statistic suggests a statistically significant difference from multivariate normal (S=.825, df=308, p=.000). For all 10 medical subject predictors and handoffs/logic steps, Levene's test for equality of error variances is statistically significant (F=11.846, df=17/290, p<.001); therefore, the assumption of equality of variance is not satisfied. The lack of equality of variance usually results from small sample sizes in some or all variable categories which increases the chance of type 1 error. Detailed procedures and results of these assessments have been reported elsewhere.[12]

Study question 2 regression model testing

The full regression model for SQ 2 is: inverseMLP3LevelDisposition=logHandoffsLS3LevelsTOT + 10 binary medical subject levels entered one by one against the DV MLP level. The inverse value for the MLP DV and the log value for the handoffs/logic steps independent variable (IV) were used in regression analysis. Binary values for each of the levels of the medical subject IV were entered into the model one at a time.

A preliminary test of mean differences was undertaken to suggest the direction of the regression findings. (Data not shown.) This preliminary analysis indicated that mean values of six of the 10 potential medical subject predictors differed significantly among MLP levels and, therefore, portend adding significantly to the predictive value of the regression model. The four variable levels that were excluded from further regression analysis are:

1. sbjEducation
2. sbjGeneticsMolecular
3. sbjPedsGeneticsMolecular, and
4. sbjProficiencyTesting.

The t statistic values indicated that four variables/variable levels in the full model were significant predictors of MLP level disposition (DV variable = invMLP3LevelDisposition) at p≤.016: logHandoffsLS3LevelsTOT (p=.000); sbjITOrdering (p=.000); sbjSafetyID (p=.016); and sbjResultsResolution (p=.000). The Eta squared values (i.e., percent variance explained) from the test of means differences suggested the significance of these variables, also. Detailed procedures and results of these analyses have been reported elsewhere.[12]

The final SQ 2 regression model is: invMLP3LevelDisposition = sbjITOrdering + logHandoffsLS3LevelsTOT + sbjSafetyID + sbjResultsResolution. Table 10 summarizes the coefficients for this final model. Even though the medical subject level, results resolution, was a significant predictor by itself and explained 4.0% of the variance in the MLP DV, it did not significantly add to the prediction model after adjusting for IT

ordering, handoffs/logic steps, and safety/ID (p=.540). The final model was thus reduced to three predictors of MLP practice level: IT ordering, handoffs/logic steps, and safety/ID.

Table 10. Study Question 2 Regression Variables: Final Model Coefficients (N = 308, Missing = 0 Cases)

Final Model[a]	Coefficients					
	Beta	t	Significance	Zero Order	Partial	Part
1[b] sbjITOrdering[e]	.225	4.038	.000	.225	.225	.225
sbjITOrdering	.185	3.258	.001	.225	.183	.180
2[c] logHandoffsLS3LevelsTOT[f]	-.157	-2.752	.006	-.203	-.156	-.152
sbjITOrdering	.226	3.937	.000	.225	.220	.214
logHandoffsLS3LevelsTOT	-.212	-3.623	.000	-.203	-.203	-.197
3[d] sbjSafetyID[g]	.193	3.263	.001	.057	.184	.177

[a.] Aim 2 final model is: invMLP3LevelDisposition = sbjITOrdering + logHandoffsLS3LevelsTOT + sbjSafetyID

[b.] Model 1 is: invMLP3LevelDisposition = sbjITOrdering

[c.] Model 2 is: invMLP3LevelDisposition = sbjITOrdering + logHandoffsLS3LevelsTOT

[d.] Model 3 is: invMLP3LevelDisposition = sbjITOrdering + logHandoffsLS3LevelsTOT + sbjSafetyID

[e.] Predictor: Medical subject level IT Ordering = sbjITOrdering

[f.] Predictor: Handoffs/Logic Steps, 3 levels = logHandoffsLS3LevelsTOT

[g.] Predictor: Medical subject level Safety/ID = sbjSafetyID

[h.] Dependent Variable: inverse value of variable MLP, 3 levels = invMLP3LevelDisposition

Study question 2 regression model testing summary

Table 11 summarizes important statistical descriptors of the final regression model. The predictor influencing MLP practice level disposition the most was medical subject IT ordering, explaining 5.1% of variance (R square change=.051, p=.000). Handoffs/logic steps was also significant with 4.1% variance explained (R square change=.041, p=.000) after adjusting for the contribution of IT ordering. The third significant predictor in the model was medical subject safety/ID explaining 1.8% (R square change=.018, p=.016) of the variance in MLP practice level after adjusting for the contributions of both IT ordering and handoffs/logic steps variables. Positive beta weights for an inverse MLP3LevelDisposition scale indicate that the associated measure is inversely associated with MLP practice level (1-3); as the measure increases, the MLP practice level (1-3) decreases.

Table 11. Study Question 2 Regression Variables: Final Model Summary (N = 308, Missing = 0 Cases)

Model[a]	R	R Square Δ	F Δ	df1	df2	Sig. of F Δ
1[b] sbjITOrderingf	.225	.051	16.304	1	306	.000
sbjITOrdering	.225	.051	16.304	1	306	.000
2[c] logHandoffsLS3LevelsTOTg	.271	.023	7.573	1	305	.006
sbjITOrdering	.225	.051	16.304	1	306	.000
logHandoffsLS3LevelsTOT	.271	.023	7.573	1	305	.006
3[d] sbjSafetyIDh	.324	.031	10.647	1	304	.001

[a.] Study question 2 final model is:
[b.] invMLP3LevelDisposition = sbjITOrdering + logHandoffsLS3LevelsTOT + sbjSafetyID
[c.] Model 1 is: invMLP3LevelDisposition = sbjITOrdering
[d.] Model 2 is: invMLP3LevelDisposition = sbjITOrdering + logHandoffsLS3LevelsTOT
[e.] Model 3 is: invMLP3LevelDisposition = sbjITOrdering + logHandoffsLS3LevelsTOT + sbjSafetyID
[f.] Predictor: Medical subject level IT Ordering = sbjITOrdering
[g.] Predictor: Handoffs/Logic Steps, 3 levels = logHandoffsLS3LevelsTOT
[h.] Predictor: Medical subject level Safety/ID = sbjSafetyID
[i.] Dependent Variable: inverse value of variable MLP, 3 levels = invMLP3LevelDisposition

The three significant predictors of MLP practice level, logHandoffsLS3LevelsTOT, sbjITOrdering and sbjSafetyID, together explained 10.5% of the variance in the invMLP3LevelDisposition DV. The predictor accounting for the most variance was sbjITOrdering at 5.1%, followed by logHandoffsLS3LevelsTOT at 2.3%, and sbjSafetyID at 3.1%. The model was statistically significant at p =.001. The medical subject level sbjResultsResolution dropped from the final model because the predictor did not significantly contribute to the model after adjustment for the other predictors accounting for more variance. Beta weights of the three predictors varied as the model grew in complexity suggesting that explained variance in invMLP3LevelDisposition was shared among the predictors. The beta weight for sbjITOrdering was .225 by itself, .185 when considering handoffs, and .226 in the final model. Similarly, the beta weight of handoffs increased from -.157 to -.212 when sbjSafetyID was added to the model. The beta weight for sbjSafetyID alone was .193. A Bonferroni correction applied to revise the alpha level to account for the simultaneous testing of three models, did not change the interpretation of significance, i.e., critical value of p<.05/3 tests = .017, for any of the test models.

As with SQ 1, the interpretation of SQ 2 regression findings is limited by the small explained variances and the violations of regression assumptions which have been discussed previously.[12] As a consequence, these limitations should be considered when interpreting study findings. However, a post-

hoc power calculation, where N=308, R Square Δ=.105, p=.05, and number of predictors is 3, returned a power estimate of .9996 which mitigates, to some extent, the violation of regression assumptions for both SQ 1 and SQ 2.

Study question 2 post-consultation prediction index structure

SQ 2 regression modeling against the MLP practice level outcome variable confirmed that a workflow prediction index can also be constructed from the values of three post-consultation predictor characteristics only available after consultation completion, i.e., handoffs/logic steps and two medical subject level variables, IT ordering and safetyID. Using the beta weights from the final regression model, a simple matrix was constructed to predict the most appropriate MLP practice level for consultation resolution. Positive beta weights for IT ordering (.226 p=.000) and safetyID (.196, p=.001) indicate that these measures vary inversely with an inverse MLP practice level.

MLP3LevelDisposition scale, indicates that the handoffs/logic steps measure varies directly with MLP practice level (1-3); as the handoffs/logic steps measure increases becoming more negative, the MLP practice level (1-3) increases. A preliminary matrix defining the logic in the use of the post-consultation workflow prediction index is shown in Table 12.

Table 12. Study Question 2 Post-Consultation Workflow Predictive Index Definition Matrix

MLP Practice Level	Post-Consultation Workflow Predictors		
	IT Ordering	SafetyID	Handoffs/Logic Steps
1[a]	3	3	1
2[b]	2	2	2
3[c]	1	1	3

[a] MLP practice level 1 = IT ordering beta weight highest >.226+ safetyID beta weight highest >.196+ handoffs/logic steps beta weight lowest <-.212

[b] MLP practice level 2 = IT ordering beta weight high but <.226 + safetyID beta weight high but <.196 + clinical laboratory beta weight low but >-.212

[c] MLP practice level 3 = IT ordering beta weight lowest <.226+ safetyID beta weight lowest <.196+ clinical laboratory beta weight highest >-.212

Study question 1 and study question 2 regression models comparison

Both workflow prediction indices, i.e., the SQ 1 CI and the SQ 2 post-consultation completion index, categorize the same DV, MLP practice level, into one of three levels. The models were covaried against each other to validate the predictive performance of the CI using measures available only after consultation completion, i.e., two competing predictor datasets were utilized to categorize levels of MLP practice, and the

results compared.

Covariance analysis measures and removes the influence of joint variability of predictors on the DV MLP measure. The analysis identified the variance in model SQ1 after adjusting for model SQ 2 and the variance in model SQ 2 after adjusting for model SQ 1. In preparation for these regressions, the multivariate outliers were eliminated from both the SQ 1 model and the SQ 2 model leaving 290 (N=308-18) cases for the analysis. Next the final models of each study question were analyzed using the shared dataset. The final model comparison summaries for each SQ are given in Table 13.

Table 13. Study Question 1 and Study Question 2 Final Model Comparison Summary (N=290 Cases)

Comparison Models[a]	R	R Square Δ	F Δ	df1	df2	Sig. of F Δ
1 Aim 1[b] (added first)	.259	.067	6.883	3	286	.000
Aim 2[c]	.384	.147	8.859	3	283	.000
2 Aim 2[c] (added first)	.353	.124	13.540	3	286	.000
Aim 1[b]	.384	.023	2.550	3	283	.056

[a] Dependent Variable: inverse value of variable MLP, 3 levels = invMLP3LevelDisposition

[b] Aim 1 Predictors: srvClinLab + srvSurgOth + sqrTestCycle3LevelsTOT

[c] Aim 2 Predictors: srvClinLab + srvSurgOth + sqrTestCycle3LevelsTOT + logHandoffsJS3LevelsTOT +sbjSafetyID + sbjITOrdering

Interpreting the summary, the SQ 1 model alone was statistically significant with R square of .067 (p=.000). Also, the SQ 2 model alone was statistically significant with R square of .124 (p=.000). Adding SQ 2 predictors' variances to SQ 1, the R square changes from .067 to .147. This .08 R square change (119% = .08/.067; p=.000) indicated the addition of a significant contribution to the variance explained in SQ 1. On the other hand, adding SQ 1 predictors' variances to SQ 2 resulted in a statistically insignificant R square change of .023 (.124 to .147, p=.056). A Bonferroni correction applied to revise the alpha level to account for the simultaneous performance of two tests (SQ 1 and SQ 2 regressors), did not change the interpretation of significance, i.e., critical value of p<.05/2 tests = .025, for either test model or the comparison.

It can be concluded from the comparison analysis that both the CI (SQ 1 pre-consultation completion workflow predictive model) and the SQ 2 post-consultation completion workflow predictive model were statistically significant and different from one another yet predicted, in general, similar MLP practice levels. Both the pre-consultation (SQ1, CI) and post-consultation (SQ 2) workflow prediction models provided similar numerical values indexed to one of the three MLP practice levels most appropriate for consultation resolution.

When comparing regression models that use the same dependent variable and the same

estimation period, as is the case with SQ 1 and SQ 2, R square change was used as the criterion for comparing them. Figure 3 graphically demonstrates the similarity of the practice level means trendlines for SQ 1 and 2 as well as the linearity of their mean plots.

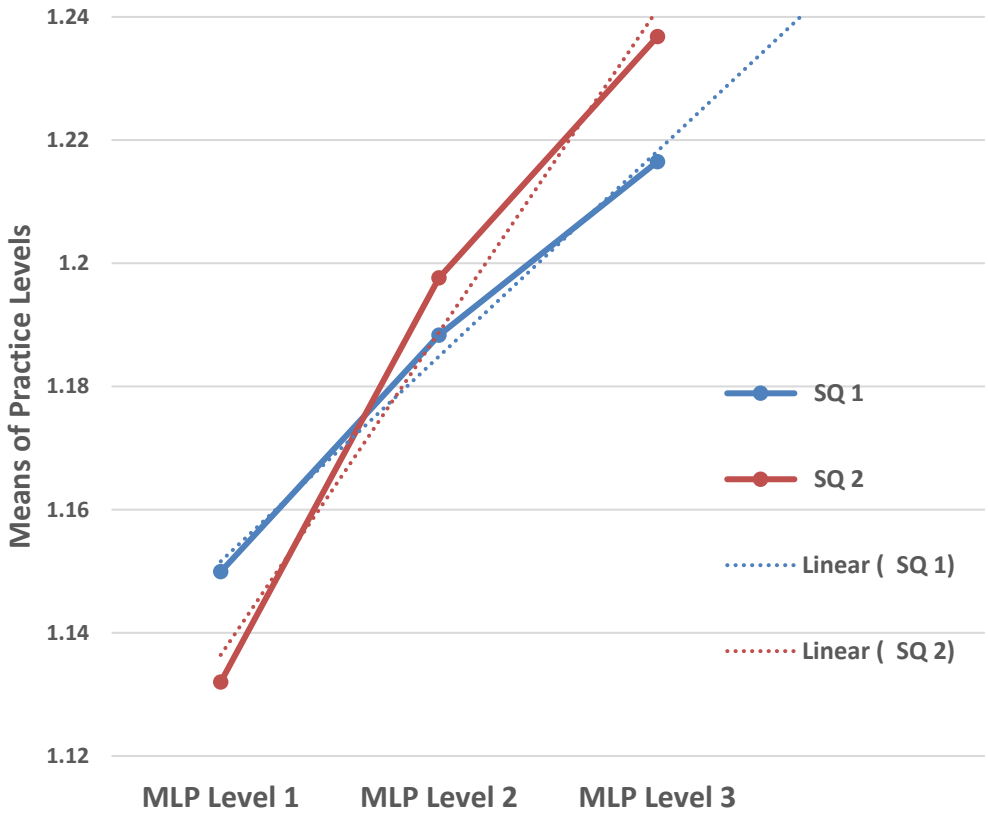

Figure 3. Study Question 1 and Study Question 2 MLP practice level means trendlines comparison

Discussion

Study Results Redux and Significance

The purpose of this work is to describe the DCM©, a clinical diagnostics service communications portal, designed to support CDM among IPT, providers, and institutions.[12,16] Specific study questions guided the design, development, and evaluation of a workflow prediction index, the CI, that could assign consultation requests for resolution based on an algorithm comprised of consultation characteristics available at the point of consultation initiation. The CI is intended to function as the entry point into a workflow process, first, directed to the appropriately qualified MLP for investigation and then branching into processes for tracking medical history and clinical information accumulation, documenting resolution logic and detail, verifying conclusions, and communicating recommendations to all HP involved in the care path and the health record.

Pre-consultation completion elements determined to be significant predictors of the MLP practice level best prepared to resolve particular consultations were test cycle phase and medical service of consultation origin. Post-consultation completion elements determined to be significant predictors of the MLP practice level best prepared to resolve particular consultations were number of handoffs/logic steps and medical subject. Both pre-completion and post-completion models predicted one of three MLP levels of practice defined by education, experience, and position responsibilities and were both determined to be statistically significant predictors of MLP practice level appropriate for consultation resolution. Findings from the post-consultation model were employed to assess the predictive performance of the CI.

Study significance for healthcare delivery

The impact of communications errors on quality of health services delivery is well documented, nearly two-thirds of all sentinel events continue to be related to communication failures, and handoffs/handovers are implicated in more than half these errors.[25,55] Diagnostics information, as the primary source of objective medical data, is implicated in many of these errors.[17] This study addresses the gap in communications among MLP and other HP within and among healthcare delivery systems.

Codifying methodology for development of the CI was the first step in actualization of the DCM© communications portal, i.e., appropriately prepared MLP are identified by the CI and engaged to begin consultation resolution work. Using methods similar to these reported, models could be developed predicting workflow in an ever-expanding communications system related to consultation resolution, e.g., number and level of practice of other HP involved in handoffs, practice competencies utilized in resolution, databases searched for CDM/CDS, number and scope of communication tools employed. This scope expansion would become the foundation for the design of the next steps in actualization of the DCM©.

Figure 4 is a diagram of work process steps to be investigated in order to supply the evidence base for completion of the DCM© communications system. Direction of each workflow step would require analyses similar to those described in this study to identify significant afferent and efferent predictors guiding sequential steps in the consultation communications processes among providers involved in consultation resolution. Once predictors are identified at each step, workflow direction could be automated by AI/machine learning algorithms completed with predictors found to be significant at each step.

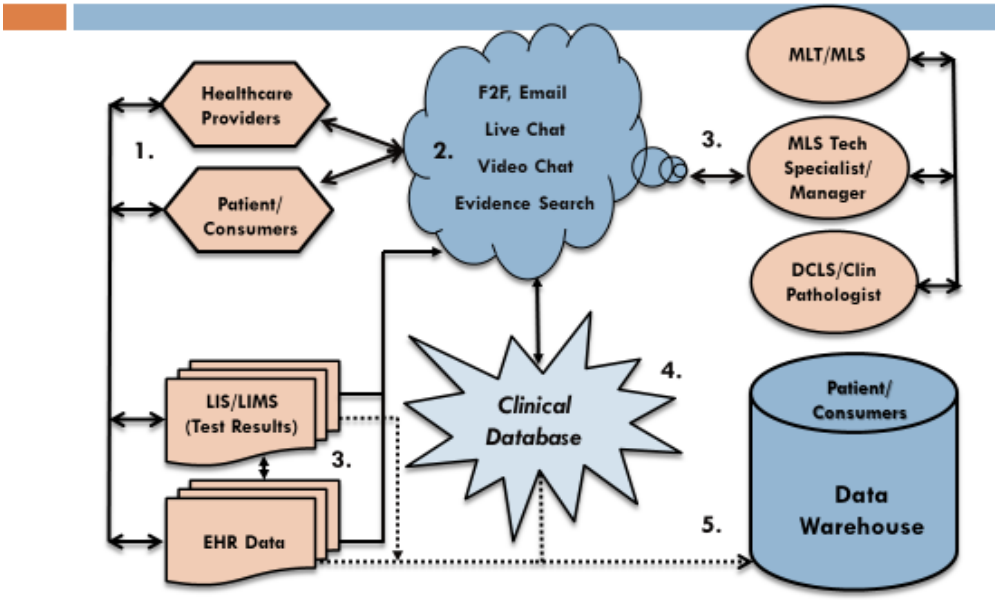

Figure 4. Diagnostics Consultation Model© (DCM©) Work Processes Flow:

1. Consultations are requested by providers as well as patient/consumers.
2. MLP Diagnostics consultants review applicable evidence from curated databases, e.g., PubMed, through the lens of individuals' health information (i.e., precision medicine).
3. Diagnostics consultants draw on the expertise and knowledge of other healthcare providers as well as historical diagnostics information from the CDL information systems and business systems in the consultation process.
4. Consultation summaries along with demographic and other PHI (protected health Information) are documented in local clinical databases.
5. With patient/consumer consent, all health record data are sent to the patient/consumer-controlled electronic data warehouse. Continuing workflow beyond this follows from practitioner communications, practitioners' competences, databases involved in handoffs/logic steps, and the consultation medical subject.

The potential significance of this work for healthcare delivery relates to improvement in CDM/CDS not only within departments but also throughout health systems. At the unit level, work can be distributed based on medical complexity directly to practitioners with commensurate competencies. Verification rules establishing release of results and recommendations for further clinical interventions can be designed based on the complexity of the cases and number and types of practitioners and services required beyond the unit level. Further, stepwise and summary documentation of all CDM and evidence supporting them would be maintained in the EHR for review by all

authorized IPT members to assure continuity of care. Because data from consultations would be evaluated continuously for impact on health outcomes and maintained in one record, patient/consumers could be brought into care plan planning, evaluation, and CDM even as care environments proceed from community to institution and back to community for post-event follow-up.

Study significance for clinical and quality research

Prior to the widespread adoption of electronic health records (EHR) in health systems and provider practices, clinical data were available only for clinical trials through strict experimental protocols approved by institutional review boards. Data generated through patient care were generally considered to be only for internal quality improvement analysis, examined only in the aggregate, and not to be published outside the institution where gathered.[74,77] Often studies involving clinical data generated through healthcare services delivery were not considered to be research, but rather quality improvement.[12,74]

EHRs have provided improved and more standardized access to patient/consumer and delivery processes data while regulations protecting patent/consumer privacy and confidentiality have better defined circumstances under which clinical data may be studied and communicated.[15,17,49,52,56,74]
However, despite these access improvements, understanding of the informatics techniques required to extract data elements and build the requisite dashboard data displays for clinical research studies are limited in most institutions to information technology (IT) specialists in institutional level quality and utilization review roles.[41-42,57] On the other side of the clinical and quality research equation, most HP who understand the relationship between clinical and diagnostics interventions and health outcomes lack the IT skills to build EHR-based clinical studies at the same time IT specialists lack clinical knowledge and experience.

Health informatics methodology, designed to identify, capture, and analyze relevant data from the EHR, is needed to compare medical effectiveness of algorithm variations and generate evidence on which to base recommendations regarding best practices in communications.[28,43-44,78] Much developmental work is needed in codifying interoperability among databases and standardization in IT methodology before the integration of clinical outcomes with the transactional record to create digital, searchable clinical summaries for care continuity becomes feasible.[40,28,79]

The potential significance of this work in forwarding clinical and quality research lies in the development of a structured framework to serve as a guide for these evidence-based practice (EBP) quality improvement studies linking diagnostics and clinical information to patient/consumer health outcomes. This framework, the A6 Method for Healthcare Clinical and Quality Research (A6 HCQR), describes

methodology for building an evidence base for efficient and effective delivery of patient/consumer-centered care through work processes of the DCM©.[12] The A6 HCQR integrates the rigor of the well-characterized literature synthesis process into the classic Quality Theoretical Framework developed and first reported in 1988 by Donabedian and detailed more thoroughly in the SEIPS Model.[6-7,12,18,80] The A6 HCQR is a clinical and quality research structure that not only allows for, but requires, the design, development, implementation, and evaluation of clinical studies utilizing clinical outcomes data (evidence of impact) generated through analyses of health services delivery care paths.[12]

This study applies A6 HCQR methodology for building an evidence base for efficient and effective delivery of patient/consumer-centered care through work processes of the DCM© by integrating the rigor of the well-characterized literature synthesis process, classical quality theory, and outcomes research applied in practice.

The A6 HCQR method is comprised of six steps (ASK, ACQUIRE, APPRAISE, ANALYZE, APPLY, ASSESS) guiding the design, implementation, evaluation, and communication of findings of clinical and quality research studies.[12] Table 14 summarizes the constructs in each step and offers the steps in the progression of this study as exemplars. The A6 HCQR methodology, with adaptations for specific clinical questions, could guide clinical and quality studies in all healthcare settings as illustrated by its application in the study described here.

Table 14. A6 Method for Healthcare Clinical and Quality Research: Steps A1-A6 Definitions and Examples

A6 Method for Healthcare Clinical and Quality Research (A6 HCQR)		
A6 HCQR Step	A6 HCQR Step Definition	A6 HCQR Step Example
A1 ASK	Topic area (EBI, evidence-based initiative) is identified that is considered to contribute significantly in performance related to failure, achievement, and/or maintenance of a quality goal.	Data were presented that justify the selection and evaluation of consultation characteristics as predictors of MLP practice level consultation resolution.
A2 ACQUIRE	A1 topic is distilled into a specific and measurable clinical question. Preliminary review of the literature is conducted to determine the strength of the body of evidence supporting the clinical impact of the question and to discover seminal reports that could inform further, more extensive literature search strategies.	Literature related to major theories influencing the construction of the communications portal of the DCM©, the evidence-based initiative (EBI) to be investigated, was accumulated
A3 APPRAISE	A pool of candidate practices is generated from the extensive, if not exhaustive, review of literature evaluated on strength of reported evidence as well as relevancy to the clinical situation for which the EBI is being designed. Also, a pool of variables, i.e., measures reported to vary with changes in the EBI-related practice, is accumulated. Literature identified previously will be analyzed in two processes, article abstraction and variable extraction to compile the candidate practices and variable pools.	Literature from theories supporting DCM© design as well as pilot study data were presented that justified the selection and evaluation of test cycle phase, medical service/hospital location, medical subject, and handoffs/logic steps as predictors of MLP practice level consultation resolution. Research questions were refined.
A4 ANALYZE	All the products of previous planning steps are synthesized into an EBI implementation protocol. Details of protocol implementation and variable analysis are identified and described to include IRB and administrative permissions and approvals, personnel participation secured, preparation of training materials, design of data collection tools, schedule of educational sessions, timeline for accomplishment of major milestones, and evaluation methods.	Datasets were evaluated for accuracy and fitness. Analyses were planned to determine if models predicting MLP practice level resolution could be constructed from pre-consultation (research question 1) and post-consultation (research question 2) characteristics. IRB approval was obtained for the study. Evaluation methods were planned.
A5 APPLY	Training, data collection, and analysis begins. Implementation barriers and hurdles are documented and their impacts on study findings considered. Adaptations are considered by the research team and, if feasible, work-arounds developed, documented, and implemented.	Analyses were conducted to determine the significance of contributions of both pre-consultation characteristics (test cycle phase and medical service area) and post-consultation characteristics (handoffs/logic steps and medical subject) to the choice of MLP practitioner resolving the consultation case.
A6 ASSESS	EBI evaluation strategies are conducted. Analysts prepare data for assessment to include pooling of indicators from different collection sources and by different variable types, missing data analyses, sensitivity analyses, and power determinations. Data are then analyzed descriptively by individual variables as well as variable groups. These analyses are then used to assess significant differences between baseline and EBI performance on specific indicators and to perform inferential analyses to determine the contribution of variable combinations to overall EBI path effectiveness.	Pre-consultation and post-consultation predictive models were evaluated quantitatively and qualitatively. Statistical inferences were drawn regarding the strength of evidence predicting MLP practice level in both pre-consultation and post-consultation datasets. Study design and data collection limitations were identified, documented, and assessed for their impact on the internal validity and generalizability of study findings.

Study significance for education in quality

Tracking measures of quality performance and the achievement of quality goals are priorities in health services delivery.[58-59] Not only do licensing and accrediting bodies monitor closely and publish institutional performance metrics but federal payments to providers and reimbursements to institutions are often linked to performance against quality standards. [29,52,60-64] Donabedian,[18] Carayon et al.,[6-7], J. O. Westgard,[67] S. Westgard,[68] Christenson et al.,[27] Leibach and Russell,[75] and Leibach,[12,16] have provided robust theoretical frames for the design and operationalization of substantive CDL quality improvement (i.e., clinical and quality research) programs. Historically, quality measures have focused on error rates (failures) in process steps or slippage in patient/consumer satisfaction.[65-68] With increased focus on value-based care (highest quality/lowest cost), measures are being developed that include health outcomes that can be objectively documented through audits of patient/consumer records.

The evidence-based practice (EBP) paradigm represents a new direction in education as well as quality improvement for the CDL and other health system units.[16,69-70,71-73,75] Clinical and quality researchers will need different skills sets to assess quality issues impacting the total diagnostics testing and care process. Practitioners will be required to integrate evidence with practice outside the experimental, statistical model of analytic phase quality control.[65] Education in clinical and quality research methodology must be directed to practitioners as well as student learners.[87] Didactic coursework, clinical internships, and continuing professional education must be designed to inform practice and expose students and practitioners alike to clinical experiences providing the greatest opportunity to develop research skills necessary not only to utilize evidence in CDM but also to generate and communicate data-supported practice guidelines, to monitor patient/consumers' clinical paths, to evaluate and introduce new technology, to develop quality indicators, and to create and analyze testing algorithms. Not only will health outcomes evidence be used in CDM, but these utilization data can be analyzed to support evidence for practice improvement across all healthcare delivery systems, public and private.[14-15,69-70,88-90]

Implementation of DCM© methodology would serve to educate practitioners in quality tenets and link them into the institution-wide delivery, measurement, evaluation, and reporting of quality services. The A6 Method for Healthcare Quality and Clinical Research (A6 HCQR), providing the structure for the DCM© quality studies applied in this work and described in more detail elsewhere,[12] would serve as the educational framework for implementation of homologous studies in medical service areas beyond the CDL. Following the A6 HCQR steps, medical services would collect data related to daily unit activities to analyze, set priorities, and assign workflow on the basis of resources, both material and human, required to resolve consultations most effectively within their scopes of practice. The establishment of these initial

data collection and analysis work processes is analogous to development of the CDL CI and would follow the same methodology. Past the establishment of this first step in workflow direction, the medical service unit would then become the next step in DCM© actualization, if CDL consultation resolution required participation of an IPT member from that medical service. Or if the consultation request were not primarily dependent on diagnostics information for resolution, the CDL would become a process step, and a MLP IPT member, in the medical service unit's consultation resolution workflow process. Providers from medical services other than CDL would enter the DCM© at step one in Figure 4.

Prior to DCM© implementation, practitioners in all medical and support services and administrative units would be educated as to its institutional structure, related work processes in their areas, and functions required to fulfill their roles in documenting, analyzing, and/or reporting outcomes. The integration of all these DCM© quality functions would be the foundation of an institutional or system-wide value based quality initiative that would meet and exceed all current reporting requirements; that is, the fully actualized DCM© would provide the evidence for a learning health system based on the measurement and evaluation of health outcomes for both individuals and populations served by the provider system.[76] In addition, a curriculum based on DCM© methodology and A6 HCQR clinical and quality research constructs, i.e., health services science, could be developed as a guideline for continuing or formal education certification in health services science earned through participation in quality activities in the learning health system or after completion of formal programs to be developed in health services science.[12,14-16,73,75-76,91]

Study limitations. The limitations of the study relate to potential bias in the collection and interpretation of data elements, i.e. consultation characteristics. First, the complete and accurate recording of all data cannot be assured. In addition, no attempt was made to standardize individual research participants' perceptions of consultation questions through interrater comparisons. Although interpretations of research participants were guided by commonly held practice understandings, there was also no strict control on the interpretation of categories into which primary data were assigned; in some instances, data were placed in categories, e.g., test cycle phase assignment, without clear support and documentation for the choice by the research participant.

In addition, the statistically significant CI predictors derived from the SQ 1 and SQ 2 datasets in this study represent very small variances in the MLP practice level DV. Therefore, the predictive performance of both the pre-consultation completion CI and the post-consultation completion model are subject to increased type 1 error. In addition, generalizability to other clinical settings is limited; findings from data collection and

analyses in different clinical settings is expected to vary seasonally, with specific catchment populations, and with clinical and diagnostics services provided. However, given the goal of methodology development, it can be concluded that the study adequately addressed the SQs posed. In future studies, limitations of this study defining the CI can be overcome by improved data collection practices, the evaluation of more specific predictors for the CI, greater participation of practitioners throughout the various sections of the CDL and automating the DCM© workflow processes.

Conclusions

The purpose of this study was to describe the Diagnostics Consultation Model© (DCM©), a CDL communications portal. To that end, methodology was developed for establishing DCM© processes to (1) streamline workflow and improve CDM for MLP and other health professionals throughout the health system and (2) for use in the design of data collection processes and collection tools for implementation of the DCM© in multiple clinical settings. Developing methodology to describe the CI was the first step in actualizing this purpose.

Datasets and analyses described in this study are intended to be the foundation of continuous, evidence based CDL and enterprise clinical and quality improvement studies. Because implementation of DCM© methodology is predicated on the collection of data (evidence) related to work processes, findings can also support internal CDL job analysis and workflow process improvements as operational structures evolve. Larger studies, in multiple health system settings, to refine data collection platforms along with continuous analyses of findings at all practice levels will contribute to the refinement of setting-specific algorithms derived from this methodology.

Implementation of DCM© methods and curriculum in health professions' daily practice and formal and continuing education venues has the potential to change health services delivery by the redistribution of care through interprofessional teams (IPT) coordinated by standardized workflow and communication processes.[6,12,76] IPT membership would be determined by developments necessitating changes in care paths and would follow patient/consumers through all care environments and levels of care. In addition, this care delivery structure portends the capability to follow individuals' medical histories longitudinally and, through regular consultations, to address issues of access, equity, and compliance for the purpose of development of an evidence based, individualized care plan for every patient/consumer.

Future directions

Future studies to refine the DCM© CI should focus, then, on identifying CI predictors explaining more variance in MLP practice level. Identification of more specific CI predictors could be accomplished by collection of more consultation data and reestablishing priority of predictor

significance through regression analysis. For instance, diagnosis (ICD) codes are projected to explain significant variance in the CI model because they describe diagnosis acuity and complexity. However, theses codes were not available at the time of data collection for this study. The collection of ICD codes, including co-morbidities, could be added to the study protocol to increase specificity in consultation characteristics definition and thus increased CI specificity. In addition, only some levels of the medical service variable were significant predictors. If consultation requests originate from a medical service area found to be statistically non-significant, then a value would not be entered into the CI prediction algorithm resulting in compromised MLP level assignment due to the omission of explained variance, albeit small. Future studies should focus on the identification of more "forced choice" predictors, e.g., test cycle phase, that add significantly to the variance in MLP practice level. These "forced choice" variables would fit into one mutually exclusive variable category and would, therefore, always enter a value into the algorithm.

To summarize continuing DCM© expansion, future studies should focus on three critical next steps: (1) identification of more specific predictors for the CI (the point of entry into the portal) (2) systematic, unbiased collection of afferent and efferent workflow characteristics (i.e., number and types of practitioners, handoffs/logic steps, practice competencies, and databases) as well as communications involved in CDM at each work process step, and (3) DCM© automation.

Results from studies implementing DCM© communications processes among all providers involved in consultation resolution would then become the basis of expansion of the DCM© throughout the healthcare system. With this expansion, the DCM© would grow into full potential as the standardized conduit for patient/consumer information in all levels of care, i.e., primary, secondary, tertiary, and referral. Results from studies in DCM© automation should focus on development of AI algorithms to increase the feasibility of implementation. The capabilities of the current transactional and interoperable structure of electronic health records inhibits auditing of statistically valid numbers of cases to support evidence-based care path design.[57,65,83-88]

Data collection for study analyses is labor intensive and subject to significant collection bias. Also, workflow processes are manually initiated and dependent on practitioner priority for initiation and follow through. Automation of collection, workflow direction, IPT and EHR communications, and continuous evaluation would increase both the quality and value of DCM© processes through the improvement of process efficiency and assessment of medical effectiveness. Continuing studies in healthcare education and clinical and quality research should focus on conducting and reporting findings from services delivery and clinical outcomes quality improvement

investigations. A6 HCQR methods should be applied, and findings reported for the purpose of objectifying a standardized, reproducible, consistently communicated approach to the generation and incorporation of clinical research findings into daily practice to improve quality and value of services. A6 HCQR-guided curriculum should also be implemented in doctoral and post-doctoral programs and incorporated into position responsibilities of all HP practitioners with quality and utilization review responsibilities to increase the integration of clinical and quality research methods into practice, focus patient/consumer care on communication of clinical and quality study findings, and promote EHR research methods innovation to codify approaches to algorithm development guiding individualized patient/consumer care.

The significance of future studies should be evaluated by the extent to which STEEEP healthcare quality aims (i.e., safe, timely, efficient, effective, equitable, patient-centered) are improved by the direction of consultations and consultation information summaries to appropriate MLP at the point of consultation initiation and, subsequently, to all IPT members involved in consultation resolution (AHRQ, https://www.ahrq.gov/talkingquality/measures/six-domains.html; PSQH, https://www.psqh.com/analysis/improvement-interventions-and-the-iom-aims-for-quality-steep-7/2/).[76]

Future studies employing DCM© methodology could be structured to identify outcomes measures related to STEEEP aims in all healthcare practices, in all modes of health communications, and in diagnostics algorithm and treatment guideline development and evaluation. DCM© curriculum could be employed in formal and continuing education programs to educate healthcare providers in quality and clinical research tenets as the basis for continuous quality improvement. In this way, the DCM©, employed as a health system approach to evidence-based practice, quality improvement, and individualized patient/consumer care (i.e., health services science), could provide the foundation for value-based healthcare continuously optimized to address the needs of individuals, populations, and health systems throughout the continuum of care.[12]

Conflicts of Interest Statement

The author has no conflicts of interest to declare.

Author and Affiliations

Elizabeth Kenimer Leibach, Ph.D., Ed.D., M.S., MLSCM, SBBCM
Principal Officer
HMES Healthcare Management and Education Services, LLC
706 Summergate Court
Augusta, GA 30909-3159 USA
Voice: (706)951-2883
Email: eleibach@comcast.net

Professor Emerita
Department of Medical Laboratory, Imaging, and Radiologic Sciences
College of Allied Health Sciences
Department of Pathology
Medical College of Georgia
Augusta University
Augusta, GA 30912 USA
Voice: (706)951-2883
Email: eleibach@augusta.edu

Professor Emerita
Health Sciences
Department of Clinical Laboratory and Medical Imaging Sciences
School of Health Professions
Rutgers University
Newark, NJ 07101 USA
Voice: (706)951-2883
Email: elizabeth.leibach@rutgers.edu

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