An Individualized Approach to Remediating Skill Decay: Framework and Applications

Roberto K. Champney, Erin G. Baker, Tarah N. Schmidt-Daly, Kay M. Stanney, Kelly Hale, Richard Long, George Chadderdon
Design Interactive
Oviedo, FL
Roberto| Erin.Goodrich| Tarah.Daly| Kay| Kelly| Richard.Long| George.Chadderdon@designinteractive.net

Julie Jacko, François Sainfort, Jit Chan, Andrew Nelson
BioMedical Metrics, LLC
Golden Valley, MN
jitchan@gmail.com,JJacko|FSainfort|ANelson@ Biomedicalmetrics.com

ABSTRACT

Physicians predominantly use self-monitoring to assess and maintain skill proficiency, and to determine when refresher training is required. However, strikingly low correlations exist between physician self-assessments and observer-expert ratings. In addition, in many military and civilian positions, training and education schedules are often standardized and rigid, potentially leading to wasted resources on training that is not needed for those that remain proficient at needed skills. In order to optimize training, there is a critical need for adaptive learning systems that can objectively measure, and preemptively or timely refresh knowledge and support skill maintenance. This paper outlines challenges associated with objectively quantifying skill decay within the medical domain. Requirements for a skill decay framework are summarized based on identified challenges, and a preliminary Skill-DETECT (Degradation Evaluation Toolkit for Eliminating Competency-loss Trends) framework is presented. This Skill-DETECT framework uses objective data to tailor an education and training program to a user's specific needs. The current application of the Skill-DETECT framework is developed within a medical environment, and utilizes electronic medical records generated by a physician, as well as real-time cognitive assessment data to suggest recommendations on individualized, optimized retraining regimens to reduce the likelihood of skill decay.

ABOUT THE AUTHORS

Dr. Roberto Champney is a Senior Research Associate II at Design Interactive, Inc. His work focuses on field analysis, design and evaluation of interactive and training systems, and emotion in design. Dr. Champney holds a Ph.D. degree in Industrial Engineering and Management Systems from the University of Central Florida.

Erin G. Baker is a Research Associate at Design Interactive, Inc. Her work focuses on human- computer interaction, training development and interaction, and medical research and applications for the military with experience working to support the Army, Air Force, Navy, and Veteran's Benefit Administration. She holds a M.S. degree in Industrial Organizational Psychology from the University of Central Florida.

Tarah N. Schmidt-Daly is a Research Associate at Design Interactive, Inc. Her work focuses on psychology, human-factors, and modeling and simulation with focus on vigilance, game based environments, and the detection of improvised explosive devices. She holds a M.S. degree in Modeling and Simulation from the University of Central Florida.

Kay M. Stanney is President of Design Interactive, Inc., and has over 20 years' experience in the design, development, and evaluation of human-interactive systems. Her research and development in the areas of multimodal interaction, augmented cognition, and virtual environments has been funded by the National Science Foundation (NSF), Office of Naval Research (ONR), Defense Advanced Research Projects Agency (DARPA), Distributive Technology Office (DTO), and National Aeronautics and Space Administration (NASA), as well as other sources. She received a B.S. in Industrial Engineering from the State University of New York at Buffalo in 1986, her Masters and Ph.D. in Industrial Engineering, with a focus on Human Factors Engineering, from Purdue University in 1990 and 1992, respectively, after which time she spent 15 years as an Industrial Engineering professor at the University of Central Florida.

Dr. Kelly Hale is Sr. Vice President of Technical Operations at Design Interactive, Inc., and has over 12 years experience in human systems integration research and development. Her R&D efforts are focused in augmented cognition, adaptive, personalized systems, multimodal interaction, training sciences, and virtual environments. Through these efforts, Kelly and her team have developed advanced neurophysiological measurement techniques and have advanced real-time mitigation strategy framework and induction techniques to optimize training, situation awareness, and operational performance through optimization of user cognitive and physical state. She received her BSc in Kinesiology/Ergonomics Option from the University of Waterloo in Ontario, Canada, and her Masters and PhD in Industrial Engineering, with a focus on Human Factors Engineering, from the University of Central Florida.

Richard Long is a Senior Modeling and AI Specialist at Design Interactive with over 25 years' experience in innovative and successful application of Artificial Intelligence, Data Mining and Expert Systems technologies to diverse solutions in both the public and private sector. Mr. Long is named inventor or co-inventor in two US Patents and has published numerous papers in the fields of Neural Networks , Cognitive Neuroscience and Emotional/Cognitive modeling.

Dr. George Chadderdon is a Senior Systems Modeler at Design Interactive, Inc. and has 10 years of computational neuroscience research experience in the area of dopaminergic mechanisms of reinforcement learning and working memory, as well as over 5 years of software industry R&D experience in pattern recognition and artificial intelligence technology. Dr. Chadderdon holds a B.S. in Computer Engineering from the University of Illinois, Urbana-Champaign.

Julie A. Jacko is the President and CEO of BioMedical Metrics, LLC and holds an adjunct faculty appointment with the School of Public Health at the University of Minnesota. She holds a Ph.D. in Industrial Engineering from Purdue University and is an expert in Human Factors Engineering. She is a world-renowned academician and researcher in human-computer interaction and health informatics.

François Sainfort is a Senior Partner with BioMedical Metrics, LLC and holds an adjunct faculty appointment with the School of Public Health at the University of Minnesota. He holds a Ph.D. in Industrial Engineering from Ecole Centrale Paris in France and is an expert in Health Systems Engineering. He is a world-renowned academician and researcher in the fields of medical decision making, healthcare simulation and operations research.

Daniel Chan is a Project Manager for BioMedical Metrics, LLC and a Program Coordinator for the School of Public Health at the University of Minnesota. He holds a Master's degree in Health Intelligence and Analytics from the University of Minnesota. He has extensive IT project management experience and is an expert in health analytics and health informatics.

Andrew Nelson is a Senior Partner with BioMedical Metrics, LLC; the Executive Director of the HealthPartners Institute for Education and Research; and the Vice President Research for HealthPartners. He has extensive experience in managing healthcare education and research projects and is world-renowned expert in human research ethics and protection of human subjects.

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jitchan@gmail.com,JJacko|FSainfort|ANelson@ Biomedicalmetrics.com

INTRODUCTION

Training and retraining have long been an important priority in the clinical domain (Lundberg and Lamm, 1993). However, rapid advances in medical technology, new treatments, new drugs and new medical knowledge in general make it extremely difficult for clinicians to keep up with these changes, while keeping busy practice schedules. This is exacerbated for primary care physicians who have seen the scope and depth of their work increase, and are seeing increasingly more complex and severe patients presenting with multiple conditions (St. Peter et al., 1999). Further, there are really no objective mechanisms in place for these physicians to detect any potential degradation in their skills. Without objective guidance, ongoing training may not be targeted at the skills that are most needed. Further the *rate* of skill decay can be affected by various moderating factors such as conditions of retrieval, individual differences, task characteristics, and training conditions, which further complicates the concerns with self-assessment and remediation. One possible means of identifying skill decay and prescribing training is via the direct assessment of skills, yet this approach may quickly become cumbersome and complicated given the breadth of skills and the busy schedules of practicing physicians. Thus, operationally feasible, yet objective, alternate approaches are necessary to mitigate for skill decay and optimize sustainment of training. This paper presents the groundwork necessary to uncover the requirements and potential options to guide the development of a skill degradation evaluation framework for eliminating competency-loss trends, which could be integrated in training management systems. What follows is a review of two types of challenges that may influence the design of such a framework: Operational Challenges and Skill Decay Challenges.

CHALLENGES IN QUANTIFYING SKILL DECAY

Types of Skill Decay

In order to understand how to operationalize a framework that supports addressing and mitigating for skill decay, it is first necessary to understand the nature of skill degradation. While skill decay may assume numerous operational definitions, a commonly accepted definition proposes that skill decay is a decline or deterioration of trained or acquired skills after a period of nonuse (Arthur, Bennett, Stanush, & McNelly 1998; Wang et al, 2013). In a similar vein, work by the Army Research Institute refers to skill decay as its interchangeable counterpart—skill retention (or the problem of). Skill retention refers to the ability to retain skills, which have been trained or acquired, after a period of nonuse. The period of nonuse, in this sense, would be referred to as the retention interval (Wisher et al, 1999). Factors contributing to the rapid decay of skill will also contribute to an individual's *inability* to retain said skill, and as such, both of these terms shall be used synonymously in this paper. When the human performance literature defines skill decay, it is generally referring to a loss of skills from a prior baseline (i.e., absolute cognitive skill decay; Norman and Eva, 2005; Weaver et al., 2012). This interpretation describes a situation where the necessary clinical knowledge and skills have already been formally trained and acquired, yet factors within that clinical context contribute to an individual's inability to retain said knowledge and/or skills. Relative skill decay refers to a diagnosis of outdated skills in the face of changing scientific knowledge and diagnostic standards over time (Norman and Eva, 2005; Weaver et al., 2012). This distinction takes on a more unorthodox, theoretical standpoint on what exactly can be classified as cognitive skill decay in a clinical setting. Since the academic formation of medical instruction, the progressive fluidity of medical knowledge has been well recognized and established as a volatile, yet inherent, element of the field, and should be considered when assessing clinical skill decay.

Experts affiliated with medical colleges and teaching hospitals emphasize that in order for health practitioners to advance their knowledge and stay abreast of developments in this ever-changing, ever-advancing field, they have to invest in a continuing education (Ahmed & Ashrafian, 2009). Thus, due to the specific standards of clinical settings, cognitive skill decay also implicates deviations from the latest knowledge/skills in the field (relative skill decay). This emphasizes the need for a skill decay framework to support the tracking of both absolute skill decay and skill obsolesce (relative skill decay). While cognitive decline is also important, this decline is not specific skill dependent but a more generalized decay that would be outside of the scope of this effort.

Characteristics

Many factors can contribute to skill decay, including skill and task characteristics, methodical characteristics (i.e., training and testing characteristics), and individual differences.

<u>Skill & Task Characteristics:</u>

The characteristics of the skills and tasks being trained or learned have an impact on decay patterns. Some of these characteristics are related to a task's complexity, cognitive demands, and physical demands. As shown in Table 1, meta-analytic findings have shown that decay occurs most in tasks with moderate cognitive demands and little or no physical demands (Wang et al, 2013).

		Cognitive Load		
		Low	***Moderate***	***High***
Physical Demands	***Low***	No Decay	**<u>High Decay</u>**	Low Decay
	Moderate	No Decay	Low Decay	Low Decay
	High	Low Decay	Low Decay	Low Decay

Table 1: Wang et al, 2013 Meta-analytic Skill Decay Results

Within cognitive load, task complexity has been conceptualized along 4 components: closed versus open-looped, discretion, dynamic complexity, and component complexity, with the highest levels of skill decay associated with tasks that were closed looped, high discretion, and of low dynamic and component complexity, suggesting that decay for complex tasks may be less influenced by other moderating factors compared to decay for simpler tasks (Wang et al., 2013; Wisher et al., 1999). Types of skills or tasks may have varied degrees of decay and thus a one-size-fits-all decay scheme is unlikely to exist. Different characteristics will influence the time course of decay and thus the skill decay framework must accommodate for such variability and characterization.

<u>Methodological Characteristics:</u>

Similarly, the manner in which a skill is learned or trained (training characteristics), as well as how a skill is assessed (testing characteristics), has an impact on skill decay. Meta-analytic findings show that skill decay occurs more rapidly when training to criterion, when there is little or no structure in the learning or training environment, when feedback or performance reviews are not utilized, or when the similarities between the training and the transfer environment are poor (Arthur, Bennett, Stanush, & McNelly 1998; Wang et al., 2013; Wisher et al., 1999). These characteristics imply a relationship with the quality of learning that took place, and thus the higher quality of learning (e.g., more opportunities for learning, better feedback, etc.) appears to influence the likelihood of decay. From another perspective, there are factors that influence the likelihood of observing errors interpreted as skill decay, such as the retention interval or dissimilarities between the training and testing environment (Arthur et al., 1998; Wang et al., 2013; Wisher et al., 1999). This highlights the challenge that is faced when attempting to determine or predict skill decay as there are independent variables that have an impact in skill decay yet may be out of the control of the Skill-DETECT framework (e.g., quality of training). This implies that the framework cannot simply predict skill decay based on a pre-determined decay curve and thus must make use of additional data that may provide insight as to the current level of skill proficiency for each physician.

<u>Individual Differences:</u>

Individual difference characteristics relate to the innate differences among individuals (i.e. age, sex, personality, learning style, intelligence, etc.). Research has highlighted how some of these characteristics (e.g., age, innate ability or intelligence) influence skill decay (Glendon, McKenna, Hunt, & Blaylock, 1988; see also Arthur, Bennett, Stanush, & McNelly 1998; and Wang et al. 2013 for a review). Age plays a role in the eventual decay of cognitive faculties, therefore affecting the performance of physicians (Blasier, 2009). Not only do physical skills decay, but cognitive skills decline as well; with physical skills decaying more rapidly with age than cognitive skills. This implies that physicians who still know how to perform well might not possess the physical strength or stamina to engage in lengthy procedures or attend to a high load of patients. Innate ability or intelligence has been studied at great length and is also claimed to affect skill decay. Higher ability individuals retain knowledge over longer periods of time than lower ability individuals (Arthur, Bennett, Stanush, & McNelly 1998; Oberlander et al, 2007; Nembhard & Uzumeri et al., 2000; Wisher et al., 1999). Individuals with higher innate ability or intelligence are more likely to willingly partake in opportunities to overlearn, memorize and retain knowledge in a more meaningful and decay resistant way, and/or schedule refresher training during times of skill nonuse to attenuate skill decay (Arthur, Bennett, Stanush, & McNelly 1998; Johnson & Sagae, 2012; Weaver, Newman-Toker, & Rosen, 2012; Wisher et al., 1999). While physicians may be considered high-performance individuals who could perhaps be categorized as both having a higher innate ability and practice requirements, it is difficult to make inferences without providing some kind of assessment for traits that may influence skill decay.

In addition to age and human traits such as innate intelligence, skill decay may also be impacted by an individual's level of expertise. The differences in the cognitive pathways of novices vs. experts have implications for the distinct ways in which the cognitive skills of these two groups may decline. An expert's typical naturalistic/dual-process model of cognitive reasoning, for example, would vary substantially from a novice's typical rational information processing model (Weaver, Newman-Toker, and Rosen, 2012). The cognitive shortcuts so often utilized by experts, such as heuristics and pattern recognition and interpretation, prove to be a double edged sword, as experts are able to more efficiently draw conclusions and free up other cognitive resources to attend to other presenting factors, but at the same time may prematurely come to conclusions without considering all possible courses of action. Within a highly trained workforce such as physicians, there are still variations in expertize that may influence the decay curves. This implies that a skill decay framework should incorporate parameters that characterize individual differences as factors that may impact the rate of skill decay for individuals being tracked within it, yet at the same time, will need confirmatory measures to determine if indeed skill decay has taken place.

Assessment of Skill Decay

Skill decay has been reported to follow a pattern of rapid degradation followed by slower decrements in performance in relation with time (Hicks, Marsh, and Russell, 2000). This forms a 'forgetting curve' similar to the one illustrated in Figure 1.

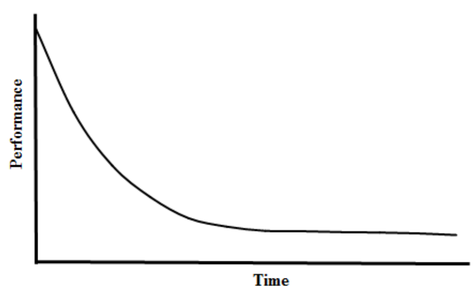

Figure 1: Representative Forgetting Curve

This performance change represents skill decay, and can be captured by detecting errors in performance. Errors may occur for many reasons as illustrated by the multiple challenges outlined earlier. Generally, research of skill decay and reacquisition will report performance trends in terms of percent correct responses. The amount or quantity of errors can be stipulated by this overall percent correct score (Oberlander et al, 2007; Johnson & Sagae, 2012; Pavlik & Anderson, 2005; Pugh & DaRosa, 2013). Skill decay is marked by an increase in errors over time. However, given the variability in complexity and content of most clinical tasks and skills, the cause of deterioration in task performance is not usually obvious. To identify when and why the degradation of skills occurred, it is necessary to gain a better understanding of the underlying cognitive mechanisms involved in skill decay and in order to do so, one must dissect the process of a task – in this case, clinical care, that often times involves classifying the unobservable (Zhang et al. 2004). This implies that in order to identify skill decay, a skill decay framework must not only incorporate mechanisms to track and measure errors rates but at the same time but also have a library of pre-established performance thresholds that indicate that a skill has reached an undesirable level of performance.

OPERATIONAL CHALLENGES

Within the operational clinical environment, there are a number of challenges that deserve consideration such as: Self-Assessment, Friction Points, and Clinical Judgment.

Self-Assessment

Today, physicians in outpatient clinical settings are expected to be competent in self-assessment and self-monitoring of diagnosis knowledge and skills, and to have the metacognition to determine how best to maintain proficiency through lifelong learning and skills development (Mann, 2011). Without ongoing practice, skill loss occurs (Stefanidis et al., 2006). However, self-assessments and expert independent assessments are not always highly correlated (Pandey et al., 2008), thus leading to potential gaps in voluntary selection of most applicable practice or training sessions to maintain proficiency (Chang et al., 2007). Training and retraining have long been an important priority in the clinical domain (Lundberg and Lamm, 1993). However, rapid advances in medical technology, new treatments, new drugs and new medical knowledge in general make it extremely difficult for clinicians to keep up with these changes, while keeping busy practice schedules. This is exacerbated for primary care physicians who have seen the scope and depth of their work increase, and are seeing increasingly more complex and severe patients presenting with multiple conditions (St. Peter et al., 1999). In a study of over 12,000 physicians, St. Peter and colleagues found that 30% of primary care physicians and 50% of specialists reported that the scope of care provided by primary care physicians had increased during the previous two years. As a result, primary care physicians are concerned about current expectations and feel a need to prepare to fulfill their expanding roles effectively and maintain their skills. This highlights the need for tools that are able to measure and track the learning and potential decay of physician knowledge, skills and attitudes (KSAs). It also implies that a skill decay framework must support the tracking of a broad range of KSAs and maintain a type of user profile (e.g., a learner model) that can track physicians' KSAs and associated decay.

Friction Points

Within any domain there may be a number of areas where conflict or difficulties may arise. In the clinical domain, there are a number of areas where error may occur. Zhang et al. (2004) describe the complexity of the overall medical system in which medical errors can occur and organize it in a hierarchy of six different levels: 1) individuals; 2) individual-technology interaction; 3) distributed systems including teams and groups of people and technology; 4) organizational structures; 5) institutional functions; and 6) national regulatory environment. As changes at all levels of the health care system occur and push primary care physicians to take a more prominent role in caring for patients, particularly those with complex medical conditions, it is increasingly important to assist physicians in acquiring and maintaining critical skills and monitor the quality of care they provide. This has two key implications that may impact a skill decay framework: 1) in addition to medical procedure related skill decay, there are other types of KSAs that may be involved at each of the six levels of the medical system hierarchy, 2) in addition to skill decay, skill obsolesce must also be monitored, as it can contribute to errors if the physician is not practicing according to the latest standards of care.

Clinical Judgments

Cognitive skills are at the core of clinical judgment and reasoning, and are difficult to elicit and observe. Montgomery (2006) emphasizes that practical reasoning - a flexible, interpretive capacity to determine the best action to take when knowledge depends on circumstance - is required to take care of patients. That interpretive capacity is what is commonly referred to as “clinical judgment”. While clinical judgment is neither a science nor a technical skill, it puts both to use. Objective assessment on a frequent basis of this complex cognitive skill is challenging due to the time and resources required (e.g., limits in simulation-based programs readily available to physicians; resources required to evaluate standardized patients and live observers).

A key operational challenge for the development and implementation of a skill degradation system is to find ways of using and mining readily available information in order to evaluate current clinical judgment proficiency.

GAPS IN CURRENT METHODS

Undoubtedly, efforts at standardizing physicians’ continuous learning have been effective in ensuring a bare minimum of updated knowledge in the healthcare community (Ahmed & Ashrafian, 2009). Yet medical education, residency and fellowship training, and technology evolve at a rapid pace (Kahol, Vankipuram, and Smith, 2009) such that the longer a physician has been practicing independently, the more remote they are from their initial education. Current approaches that identify skill decay are limited to the identification of past medical errors (e.g. pointing out adverse drug events and/or misdiagnoses from electronic health records [EHR] data or litigation and determining that the physician needs to follow up with some re-training) (Singh, Thomas, Khan, and Petersen, 2007). Alternative skill decay approaches other than error identification rely on a broad, one-size-fits-all approach that utilizes procedure practice frequency as a measure of skill capability (State Medical Licensure Requirements and Statistics, National Registry of Certified CME Professionals, American Medical Association). These approaches are limited in that they do not adapt across the expected variability of conditions and characteristics that apply to individual physicians, nor do they specify nor prescribe training regimens contingent upon diagnosed or predictive areas of skill decay (Myers & Greenson, 2012). As mentioned earlier, physicians in outpatient clinical settings are expected to be competent in self-assessment and self-monitoring. Further, relying on third party interventions (e.g., when a colleague or subordinate identifies a skill decay issue) are not a suitable approach given that there is no guarantee that such observations would be noted or reported before a catastrophic failure occurs.

SKILL DECAY FRAMEWORK REQUIREMENTS

The preceding review summarizes operational and skill decay challenges, which provide the foundation for a preliminary set of requirements for a framework that seeks to identify and mitigate skill decay (Table 2). The goal of such a framework within the military medical domain is to predict and assess the onset of cognitive clinical skill degradation, and determine with specificity which knowledge or skills have degraded or will be likely to degrade. This is particularly applicable for physicians returning to clinical practice within the US after deployment, where traditional clinical skills were not actively practiced during deployment.

Development of a framework that meets requirements outlined in Table 2 promises to provide exceptional value to military physicians who, during deployment, must be knowledgeable in military-unique medical requirements including procedures rarely seen in primary care. Upon return, these physicians are expected to continue to see patients as they did before interruption, maintaining competency in their primary care field. Having a system to support identification of skill decay across cognitive skills could be used to tailor training, resulting in substantial improvements in readiness to practice clinical skills.

Table 2: Skill Decay Framework Requirements
1. Support tracking of a broad range of KSAs for each individual participant being tracked 2. Support tracking of KSAs related to individual skills, interaction with technology, team interactions, organizational structures, institutional functions, and regulations 3. Support tracking of different types of both absolute and relative skill decay 4. Support use of existing data for mining patterns of skill decay in order to reduce physician workload and buy-in 5. Support existing organizational processes to support seamless integration and reduce physician workload

6. Support the use of categorization and characterization of KSAs to provide individual KSA skill decay models
7. Support use of multiple types of data to predict likelihood of skill decay (e.g., retention intervals) while supporting direct assessment to confirm skill decay (e.g., direct measures of performance).
8. Support characterization of individual participants on variables that may influence skill decay
9. Support integration of measures of performance and thresholds to identify levels of skill proficiency

SKILL-DETECT FRAMEWORK

Utilizing the requirements outlined in Table 2, the Skill Degradation Evaluation Toolkit for Eliminating Competency-loss Trends framework has been conceptualized to assess decay in cognitive skills for family practice physicians (Figure 2). The proposed framework is designed to (1) identify when degradation of cognitive clinical skills occurs, (2) predict probable and confirm onset of cognitive skills degradation through the analysis of EHR data or other data sources, and (3) prescribe retraining regimens which enable physicians to preemptively refresh knowledge and maintain proficiency. In order to accomplish this, the framework will utilize existing sources of data where possible and infer from them the possible onset of skill decay. Specifically, the framework is designed to utilize information gleaned from electronic health records (EHR) to evaluate task complexity and frequency. EHR data has the potential to be a critical source of information on physician delivery of care and proficiency, and is already being used in the United Kingdom to measure providers' performance for a small subset of chronic diseases, organization of care, and patient experience (Baker et. al, 2007). What has not been explored to date is the potential to leverage EHRs to preemptively identify and remediate cognitive clinical skill gaps, ultimately improving performance and preventing clinical errors. The Skill-DETECT framework is designed to scan copious historical EHRs for a provider within a specified timeframe, flagging skills that show potential for cognitive clinical decay. In order to make this possible, it is necessary to make inferences from this data. A hybrid modeling approach is utilized to assess skill decay, wherein a power law model is utilized as a first pass filter. Additional filters utilize rule-based and statistical modeling methods to further refine decay prediction based on patterns of performance compared to standards of care.

Because EHR data can only be used to evaluate KSAs at a high level, a secondary evaluation approach is designed into the Skill-DETECT framework which utilizes a real-time assessment component. This allows physicians who are flagged as potential decay candidates to complete a specific simulated scenario designed to target specific KSAs identified. For example, if EHR data reveals a physician has not assessed or treated a patient with asthma within a specific period of time, they may be alerted to complete an assessment that would guide them through a simulated patient-doctor interaction for that condition to assess KSAs such as their diagnostic skills, communication skills, and knowledge of current medications to determine their current level of proficiency.

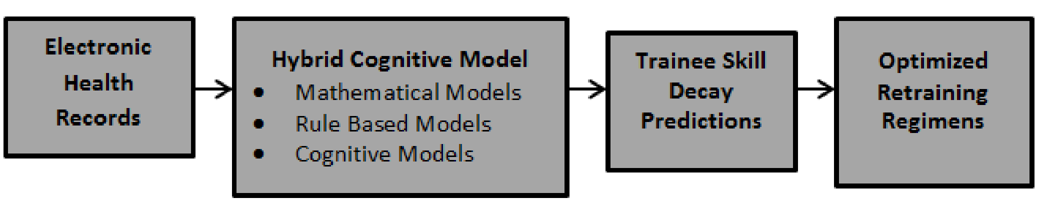

Figure 2: Skill-DETECT Framework

DISCUSSION

The development of a framework to objectively assess skill decay utilizing available, existing data sets across cognitive skills related to clinical medical tasks is challenging due to the variety of skills involved, the numerous factors that can impact decay parameters, and the complexity in existing data records As was discussed in the overview of the different challenges, the development of such a framework is not trivial. In particular, it is evident that skill decay is influenced differently by a broad range of variables. Thus, it is not possible to create a one-size-fits-all approach that would be able to integrate all possible variables. Every procedure or sub-procedure in a physician skillset is bound to have its own skill decay curve that is influenced differently by the variables discussed. This challenge is further complicated by the operational constraints that exist in an outpatient clinical environment. In the operational environment, the likelihood of obtaining all the data needed to make objective and direct assessments of skill decay is limited for a number of reasons. Among them is physician workload, which limits the ability to make direct assessments via tests or other observation methods. Other constraints include the available data that may be utilized to assess proficiency which is likely to be limited in detail such that only partial assessments may be possible.

While challenges do exist, the value promised by the Skill-DETECT framework is worth pursuing. If successful, it promises to support the identification of skills that are in higher likelihood of requiring remediation allowing both physician and medical organizations to fine tune training efforts. Next steps will include validation of the Skill-DETECT framework, comparing the model output based on EHR data to subject matter expert (SME) performance ratings. It is expected that the predictive model will correlate with SME ratings, thus demonstrating the utility in objectively evaluating and flagging skill decay on a continual basis through EHR data assessment.

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