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Work in Progress: Leveraging Technology Trends to Develop a Skills-Based Approach to Engineering Design

Dr. Shiny Abraham, Seattle University

Shiny Abraham is an Assistant Professor of Electrical and Computer Engineering at Seattle University. She received the B.E. degree in Telecommunication Engineering from Visveswaraiah Technological University (VTU), India in 2007 and Ph.D. from Old Dominion University, Norfolk, VA in 2012. Her research interests span the areas of Wireless Communication, Internet of Things (IoT), Optimization using Game Theory, and Engineering Education Research. She is a member of the IEEE and ASEE, a technical program committee member for IEEE Globecom, ICC, ICCCN and VTC conferences, and a reviewer for several international journals and conferences.

Dr. Kenneth A Connor, Rensselaer Polytechnic Institute

Kenneth Connor is an emeritus professor in the Department of Electrical, Computer, and Systems Engineering (ECSE) at Rensselaer Polytechnic Institute (RPI) where he taught courses on electromagnetics, electronics and instrumentation, plasma physics, electric power, and general engineering. His research involves plasma physics, electromagnetics, photonics, biomedical sensors, engineering education, diversity in the engineering workforce, and technology enhanced learning. He learned problem solving from his father (who ran a gray iron foundry), his mother (a nurse) and grandparents (dairy farmers). He has had the great good fortune to always work with amazing people, most recently the members and leadership of the Inclusive Engineering Consortium (IEC) from HBCU and HSI ECE programs and the faculty, staff and students of the Lighting Enabled Systems and Applications (LESA) ERC, where he was Education Director until his retirement in 2018. He was RPI ECSE Department Head from 2001 to 2008 and served on the board of the ECE Department Heads Association (ECEDHA) from 2003 to 2008. He is a Life Fellow of the IEEE.

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Abstract

The past decade has seen pedagogical transformations that are changing the landscape of engineering education. The emphasis on active learning, critical thinking, and problem-solving has permeated engineering programs world-wide. However, with the rapid adoption of new technologies and applications, there is an alarming skills gap in the engineering workforce. Traditional engineering education tends to be more knowledge-based, and often task-oriented. In order to bridge the gap between theory and practice, it is crucial that students are provided the opportunity to develop, practice, and test technical skills and competencies that are transferable to the workforce.

In this work, the authors will explore the feasibility of integrating design-oriented modular experiences related to trending technologies, within the undergraduate ECE curriculum. In particular, a framework based on Simpson's Psychomotor Domain will be used to design learning experiences for skills related to Connectivity, Data Analytics, and Visualization (CAV). While the choice of CAV is geared towards preparing students for a data-driven world, the framework could be adapted to include other technology trends that are pervasive and ubiquitous. Assessment strategies will be identified to gauge the impact of these interventions on students' perception of competence. The underlying goal of this work is to combine the traditional knowledge-based curriculum with skills-based experiences to broaden students' horizons, while helping them develop transferable knowledge and skills. Skills-based learning also opens up opportunities for hands-on learning in which experimentation plays a key role – also known as Experiment Centric Pedagogy. This is based on the idea that engineering education should have plenty of activities that enable students to act like engineers.

Introduction

Emerging technologies such as Artificial Intelligence (AI), Internet of Things (IoT), Augmented and Virtual Reality (AR and VR), and Autonomous Vehicles, among many others, have increased the global demand for skilled workers **[1]**. However, recent graduates often lack the preparation and experience to fill those roles. In a 2019 survey of 600 human resource leaders **[2]**, 64% believe there is a significant gap between their organization's skill needs and the current capabilities of its workforce, up from 52% in 2018. Among the top barriers to filling open positions, the pace of technology changes ranks highest at 37%, followed by lack of available talent at 30%. Surprisingly, 90% of employers stated that they would be willing to hire candidates who validate their knowledge using a certification, digital badge, or coursework instead of a college degree. Less than half of employers (46%) believe college prepares students to join the workforce, which may explain why 64% of employers belong to organizations that have collaborated with educational institutions to make curriculum more responsive to workforce needs. The technology trends listed above are further enabled by industries such as the semiconductor **[3]** and wireless **[4]**, both of which are facing acute shortage of new talent. Hence, in addition to employer-specific training, it is imperative that engineering programs update their curricula and pedagogy to include experiential learning experiences that would better prepare graduates to meet industry expectations. Building the workforce of tomorrow is the shared responsibility of industry and higher education establishments.

As part of the National Science Foundation (NSF) and the American Society for Engineering Education (ASEE)'s joint initiative called Transforming Undergraduate Education in Engineering (TUEE), a framework for developing Knowledge, Skills, and Abilities/Attitudes (KSAs) was proposed. In Phase I of the project **[5]**, industry participants shared that they found current training of graduates to be inadequate to meet present industry needs and out of sync with future requirements. They identified core competencies and an array of skills and professional qualities needed in a "*T-shaped engineering graduate—one who brings broad knowledge across domains, deep expertise within a single domain, and the ability to collaborate with others in a diverse workforce*." Among the 36 KSAs that were identified, 9 correspond to knowledge, 14 to skills, and 13 to abilities. Besides non-technical and interpersonal skills such as communication, mentoring, project management, leadership, effective prioritization, and ability to create a vision, eight technical skills that are key to engineering design were identified:

KSA 3: Ability to identify, formulate, and solve engineering problems (skill)
KSA 10: Critical thinking (skill)
KSA 16: Ability to use new technology and modern engineering tools necessary for engineering practice (skill)
KSA 19: Applied knowledge of engineering core sciences and implementation skills to apply them in the real world (skill)
KSA 20: Data interpretation and visualization (skill)
KSA 24: Systems thinking (skill)
KSA 26: Application-based research and evaluation skills (skill)
KSA 31: Ability to deal with ambiguity and complexity (skill)

While most of the skills listed above are satisfied, either directly or indirectly, through ABET criteria, some are emphasized more than others. Bloom's taxonomy of educational objectives (1956) is widely used in curriculum design to plan learning experiences and prepare evaluation tools **[6]**. The original taxonomy was organized into three domains: Cognitive, Affective, and Psychomotor, although only the cognitive domain was developed initially, followed by work on the affective domain by **[7]**. The cognitive domain includes objectives which deal with the recall or recognition of knowledge and the development of intellectual abilities and skills. The affective domain includes objectives which describe changes in interest, attitudes, and values, and the development of appreciations and adequate adjustment. The psychomotor (or motor-skills) domain includes objectives which involve physical movement, coordination, and use of motor-skills. Bloom et.al recognized the existence of the psychomotor domain but indicated that no procedures existed for ordering or classifying them due to the lack of related work in schools and colleges at that time. In fact, the revised Bloom's taxonomy (2001) that was designed to incorporate new knowledge and thought into the framework, focused on the cognitive domain **[8]**. Not surprisingly, exercises and assessments that develop and test cognitive skills are directly integrated in program curricula, while skills related to psychomotor and affective domains are often overlooked. Although the intention behind the separation of domains was to facilitate a better understanding of the learning process, an unfortunate consequence was that most of the work in curriculum development has taken place exclusively in the cognitive domain, except for some compelling research support for the inseparability of the domains, especially between cognitive and affective components **[9]**. The body of knowledge related to neuroscience, cognitive science, the social and behavioral sciences, and psychology shows that emotion and cognition interact to facilitate focused attention and decision making **[10] [11] [12]** and that cognitive knowledge directs the execution of our movements or performances (motor-skills), and vice versa **[12]**. However, the psychomotor domain is comparatively underexplored and under-applied in ECE.

The proposed work builds on the first author's experience with a pilot curriculum enhancement project that focused on incorporating IoT-based hardware and software platforms in relevant core and elective ECE courses at Seattle University **[13] [14]**. A unique attribute of this project was that the integration of chosen skills was not limited to a stand-alone course on IoT; rather, it was a holistic approach wherein IoT-based skills and related technologies are spread throughout the undergraduate program. While the pilot project focused on the design and implementation of smart+connected devices for IoT applications, the work proposed in this paper will explore a convergence of three aspects of IoT, i.e., CAV, and its seamless integration in the undergraduate ECE curriculum through structured activities focusing on psychomotor skills. In order to understand, explain, and extend this knowledge beyond the confines of a specific institution, or an academic discipline, it has to be grounded in core concepts and key theoretical principles. Hence, this work proposes a conceptual model based on a psychomotor domain framework to frame three guiding research questions.

Research Questions

Drawing on the abundance of existing knowledge in the cognitive domain and its inseparability from the affective and psychomotor domains, the proposed work will focus on expanding the knowledge base on the impact of psychomotor skills on engineering education. Our overarching hypothesis is that engineering educators can create better engineers if the affective and psychomotor domains are given as much importance as the cognitive domain. Through a holistic integration of design-oriented, psychomotor skills-based, modular learning experiences related to trending technologies within the undergraduate ECE curriculum, we seek answers to the following research questions.

1 – What impact do these interventions have on student learning and their ability to communicate and demonstrate learned skills?

2 – Does an early introduction to these interventions lead students to persist through gateway or "barrier" courses?

3 – What impact do these interventions have on students' perceptions of competence and increased engagement of underrepresented students in ECE programs?

Theoretical Background

Based on the original taxonomy of educational objectives, frameworks for the psychomotor domain were developed by Simpson **[15]**, Dave **[16]**, and Harrow **[17]** to address the need for a classification system in fields that require a high degree of manual dexterity and sensory skills. As illustrated in Figure 1, Simpson's framework includes seven stages of learning -- *perception, set, guided response, mechanism, complex overt response, adaptation, and origination.* This hierarchical learning model begins with the initial, but complex, process of selecting, organizing, and interpreting sensory stimulation. It gradually progresses to the learner's ability to carry out a specific sequence of guided activities and ends with the learner's ability to improvise appropriate sets of complex behavior. Dave's (1970) framework includes five stages of learning; imitation (ability to replicate the actions of others following observations), manipulation (ability to replicate actions from memory or instructions), precision (ability to perform actions with expertise and without interventions), articulation (ability to adapt existing psychomotor skills to meet requirements), and naturalization (ability to perform actions in an automatic, intuitive or unconscious way). This framework has been considered the simplest of the three, and the easiest to apply. Harrow's (1972) framework is typically associated with development of physical fitness, dexterity, agility, and body control. It includes six degrees of coordination namely reflex movement, fundamental movements, perceptual abilities, physical abilities, skilled movements, and non-discursive communication.

A review of existing literature in the psychomotor domain shows that teaching models have been developed to promote critical thinking in the psychomotor setting **[18]**. Contemporary motor-skill learning theory **[19]** clearly supports the interaction of cognitive and neuromuscular processes as being necessary for the efficient execution of motor programs, which in turn utilizes cognitive functions such as comparing, evaluating, memory, and imagery. The fundamental objectives of engineering instructional laboratories include psychomotor (demonstrate competence in selection, modification, and operation of appropriate engineering tools and resources) and sensory awareness (use the human senses to gather information and to make sound engineering judgements in formulating conclusions about real-world problems) **[20]**. A case study details the process of using a structured computer-aided instructions methodology

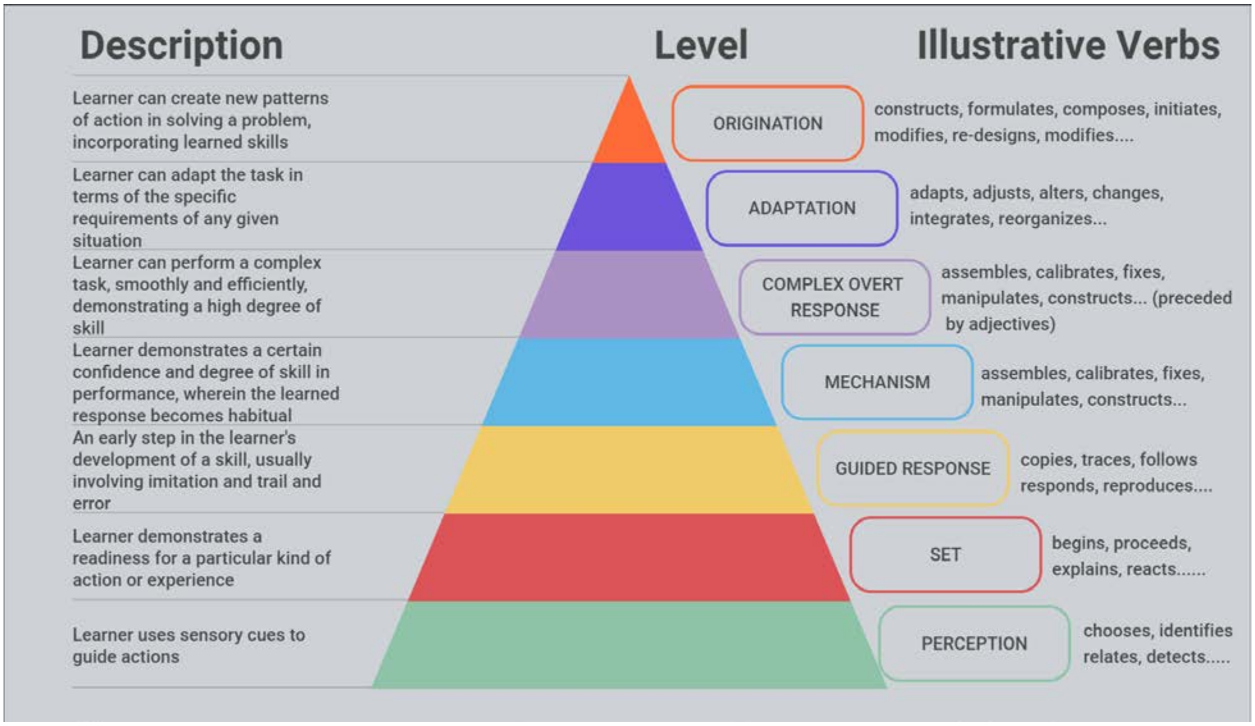

Figure 1. Adapted and simplified representation of Simpson's Psychomotor Domain **[15]**

to improve psychomotor skills in teaching and learning of turbo-machines, specifically to develop characteristic operating curves for a typical centrifugal pump **[21]**. Using Dave's framework in conjunction with annotated video recordings, students were asked to memorize and imitate the steps required in the experimentation, followed by manipulating valve settings to understand the relationship between the change in flow rate and the head developed, as well as the efficiency of the pump. Students were then asked to precisely change various parameters to analyze the range of operating conditions to obtain the optimal efficiency point at a given pump speed. Finally, learned skills were reinforced by repeating the above procedures at different speeds. It was observed that the new teaching-learning strategy resulted in considerable improvement in students' performance within one year. The feasibility of immersive technologies such as AR and VR, and body sensory technologies such as Microsoft Kinect **[12]** in developing a sense of presence, or the extent and likelihood that a learner feels connected to the learning intervention is being explored.

Research Design - Adaptation to the CAV(Connect-Analyze-Visualize)

IoT technology is often associated with smart+connected devices that transform the way we live and work. While connectivity is undoubtedly the core of IoT, this technology has evolved from just a collection of sensors communicating over the internet to a massive ecosystem that interconnects people, environments, businesses, infrastructures, and more. The ability to visualize data from hundreds of sensors simultaneously, while enhancing the viewer's current perception of reality is the essence of AR technology. Looking to the future, the estimated 50 billion IoT devices will generate massive amounts of data that need to be harnessed and analyzed for decision-making purposes. Sophisticated machine learning algorithms can analyze billions of data points to develop predictive models, and identify patterns of interest, be it opportunities for growth, or undesirable threats. Connectivity, Data Analytics, and Visualization, can be thought of as the Holy Trinity of IoT, its brawn, brains, and beauty, respectively. Although this work explores a convergence of CAV and its seamless integration in the undergraduate ECE curriculum, educators could design learning experiences based on emerging technologies from any given area of interest.

An example of a quarter/semester-long project for junior or senior undergraduate ECE students in an Embedded Systems or IoT course would be a voice-controlled smart light. Although the idea of creating a prototype of a popular commercial device may seem intimidating, scaffolding strategies can be used to design exercises that allow students to gradually build on skills. The level of complexity increases as they progress up the learning pyramid, as shown in Table 1. The hardware toolkit would include a Raspberry Pi, Matrix Creator (microphone array), NodeMCU IoT development board based on ESP8266, MOSFET, 12V LED lamp, electrical outlet, camera, and a wide range of resistors, LEDs, and circuit building tools. The software suite would include access to Amazon Web Services (Alexa Skills Kit, Amazon Voice Services (AVS), Lambda), ngrok tunnel, and OpenCV. In a guided version of the activity, the instructor would introduce the available tools, describe their capabilities, and demonstrate a simple exercise of turning an LED on and off using a basic program. In an unguided version of the activity, students would take initiative in assessing the available resources, creating a design for the experimental setup, and implementing the design. By the end of this exercise, students would have a working knowledge of some powerful tools that are highly valued in the technology industry.

Table 1: Adaptation of Simpson's Psychomotor Domain learning objectives to the CAV model **[15]**

Level of Expertise	**Description of Level**	**Example of Measurable Student Outcome**
Perception	*Learner uses sensory cues to guide actions*	Based on the available hardware and software resources, determine what you would need to design a voice-controlled smart light
Set	*Learner demonstrates a readiness for a particular kind of action or experience*	Design a flowchart to illustrate your design process. List the software packages you will need to implement this design

Guided Response	*An early step in the learner's development of a skill, usually involving imitation and trial and error*	Build a simple circuit that can turn an LED on and off using an Arduino code
Mechanism	*Learner demonstrates a certain confidence and degree of skill in performance, wherein the learned response becomes habitual*	Now use a photoresistor to control the brightness of the LED based on ambient light in the room. Upload this data
Complex Overt Response	*Learner can perform a complex task, smoothly and efficiently, demonstrating a high degree of skill*	Test your design with a 12V LED lamp instead. Does it work? If your answer is no, how would you redesign the circuit to make it work?
Adaptation	*Learner can adapt the task in terms of the specific requirements of any given situation*	Using the Raspberry Pi, Matrix Creator and Alexa Skills Kit, control the light using voice commands. How would you create a secure URL to the localhost?
Origination	*Learner can create new patterns of action in solving a problem, incorporating learned skills*	Replace voice commands with facial, gesture, or object detection to control the Smart Light. Upload energy consumption data to the cloud and use visualization tools to present data in an interactive visual format

Beginner-level activities that leverage built-in data acquisition systems, for example, sensors on a smart phone or on a Bluetooth Low Energy (BLE) sensor tag are well-suited for pre-engineering FTIC students who may lack the prerequisite knowledge necessary to comprehend and execute a hardware or software task. With proper scaffolding strategies, ECE students in their mid-freshman and sophomore years may be well-equipped to perform intermediate-level tasks that involve microcomputers or IoT development boards and peripheral sensors, an example of which is the Raspberry Pi-based Temperature and Humidity sensor. These activities coupled with simple data analysis and visualization exercises complete the IoT cycle. As an example, analysis of the vibration intensity data recorded from a smartphone mounted on a bike could provide insight into terrain conditions. A web application platform could then be configured to display real-time vibration intensity on a gauge, terrain elevation on a 3D graph, traversed route on a Google maps widget, and threshold notifications via email, SMS, or other cloud communication services. Similarly, temperature and relative humidity data could be analyzed to examine the relationship between mean and standard deviation of daily measurements, or to calculate dew point measurements. Temporal data could be represented using line charts or bar graphs, and location of sensors could be displayed on a Google maps widget. AR enhancements on web application platforms could provide an exciting and interactive interface to view sensor data.

The overarching goal of the proposed idea is to combine the traditional knowledge-based curriculum with skills-based psychomotor experiences. While developing transferable knowledge and experiential skills, students are also engaging in courses in a way that enhances their learning, consequently being better prepared to meet ABET and industry expectations. The research goal of this work is to investigate the impact of these interventions on students' learning, persistence, and perceptions of their competence, especially for women and underrepresented minority students. As part of ongoing work, the authors will use the CAV-adapted framework for the psychomotor domain, to answer the three research questions.

Mixed Methods Skills Assessment

Quantitative methods within engineering education often use one of the following three approaches: 1) descriptive statistics that report the situation without addressing any relationships between variables or groups. For example, using a longitudinal design to examine students' growth in cognitive abilities and retention, in response to certain interventions; 2) using pre-existing theory to guide the formation of hypotheses about relationships that might exist between groups or variables. For example, a study investigating a hypothesis that spatial reasoning and visualization contribute to success in engineering by comparing pre- and post-test scores of students; 3) using statistical analyses to examine how different groups perform in relation to a given theory. For example, using constructivist learning theory to examine the impact of instructional software on the conceptual and problem-solving knowledge of engineering students [22]. While quantitative methods are considered reliable because they are deeply rooted in statistical analysis, providing numerical data, they provide less elaborate accounts of human perceptions or motivations. Research studies indicate that solely focusing on statistical analysis can bury the voices of underrepresented groups [23] [24] [25]. As stated by Foor et.al. [25]: "Using surveys with large sample sizes, null hypotheses, and the expectation of statistical significance cannot meaningfully describe marginalized individual's experiences".

On the other hand, qualitative methods are characterized by the collection and analysis of textual data, and by its emphasis on the 'human factor', and context within which the study occurs [26]

[27]. Commonly used data collection strategies for qualitative studies include 1) observations of performances and behaviors of individuals or groups; 2) structured or unstructured interviews or focus groups; and 3) documents written or read by participants in a study [26]. While qualitative methods provide a holistic and contextual perspective of the study, they are often based on small sample sizes.

There has been growing interest in the adoption of mixed methods research to harness the strengths and counterbalance the weaknesses of quantitative and qualitative methods. The sequence in which these methods are employed is often motivated by the research questions. For example, when there is a need to explore a research setting before attempting to find answers, qualitative studies would precede quantitative studies. On the other hand, when statistical analyses display patterns or trends that warrant a closer look, qualitative investigations can follow a quantitative study. Alternately, qualitative methods can be embedded in a large quantitative study, or quantitative data can support a primarily qualitative study **[28]**.

The authors hope to refine a mixed methods approach for assessment of qualitative and quantitative measures of outcomes related to the implemented interventions, to provide broader and in-depth perspectives of the problem being addressed. Individual assessment and development will be performed using a conscious-competence model that classifies learning into four stages: unconscious incompetence, conscious incompetence, conscious competence, and unconscious competence [29]. Learners progress through these four stages as they develop the skill sets required to move up the pyramid in Figure 1. Responses to self-assessment questions that gauge learners' confidence in their solutions or designs will be mapped to the four stages. The underlying goal of this method would be for learners to progress along the learning continuum from "unconsciously incompetent" to "consciously competent" or higher.

Conclusion

The exponential growth and adoption of certain emerging technologies has resulted in a shortage of talent in the engineering workforce. As educators, we are tasked with innovating the curriculum in a way that bridges the gap between theory and practice, thus adequately preparing engineers for the nation's expanding industrial workplace. This work-in-progress paper proposes a skills-based approach to designing experiential activities, based on the psychomotor domain of learning. Emphasis is on learning through a sequence of levels from observation to origination. Future work will include the implementation and assessment of these interventions in the undergraduate ECE curriculum.

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