Proceedings of the ASME 2025
International Design Engineering Technical Conferences and
Computers and Information in Engineering Conference
IDETC-CIE2025
August 17-20, 2025, Anaheim, CA, USA

IDETC-CIE2025-169661

DESIGN, DEVELOPMENT, AND TESTING OF SMART HAND TOOL SYSTEMS

Carlos D. Salazar[1], Rachel New[1], Chelsea McCullough[2], Tina Lassiter[2], Kenneth R. Fleischmann[2], Sherri R. Greenberg,[3] Zhenghui Sha,[1] Raul G. Longoria[1,*]

[1]Walker Department of Mechanical Engineering
[2]School of Information (UT iSchool)
[3]The Lyndon B. Johnson School of Public Affairs
The University of Texas at Austin, Austin, TX

ABSTRACT

This paper presents methods used to design and develop a smart hand tool system that takes advantage of low-cost sensing, machine learning, and real-time monitoring to optimize tool usage and improve human-tool interaction. A multidisciplinary team took a user-focused approach, balancing engineering design, prototyping, and testing with qualitative research and quantitative analysis to derive user needs and requirements. A prototype sensor unit (PSU) that can be adapted to various tools was developed to enable the real-time acquisition of data on motion, power consumption, orientation, and user activity. The prototype was experimentally validated on multiple tool types, and ML-enabled features including skill assessment, task recognition, battery life prediction, load estimation, and anomaly detection were developed and tested. Skill assessment ranking of user proficiency based on a Skill Index Score (SIS) correlated well with GD&T-based evaluations. Task recognition algorithms achieved over 77% accuracy, while battery life prediction closely matched real usage data. Load estimation was found to provide force predictions with an average error of ±1.18 N, and anomaly detection identified deviations such as excessive force and tool stoppages. These features were processed online using PSU and edge computing features. The results demonstrate the feasibility of further developing AI-enhanced power tools with real-time monitoring and performance evaluation, paving the way for advances in human-tool collaboration, skill development, training, and next-generation smart manufacturing applications.

Keywords: Human-tool interaction, smart hand tools, machine learning, edge computing, data-informed decision-making

*Corresponding author: r.longoria@mail.utexas.edu
Draft for review: Version 1.0, October 20, 2025.

1. INTRODUCTION

Conventional hand and power tools are essential for a wide range of tasks, but their varied use makes it difficult to monitor key variables or assess performance. The wide variability in working conditions presents additional challenges and limitations. Ongoing advances in sensing technologies, artificial intelligence (AI), and real-time data processing have inspired and enabled the development of smart hand tools capable of real-time monitoring, performance evaluation, and data-informed decision-making [1, 2]. Such innovations aim to reduce errors, enhance productivity and safety, and support training with data-driven insights. However, the adoption of smart tools faces technical and practical barriers. Some manufacturers have begun integrating onboard sensors and developing connected tools that enhance user control, track performance, and integrate with digital platforms. However, a broader application of sensors, data, and algorithms to fully support and anticipate user needs remains limited. The needs and values of tool users must be understood to improve the likelihood of adoption of smart hand tools. Proposed intelligent features will rely on reliable sensing, as well as the accuracy of classification algorithms and multisensor fusion, to improve activity recognition accuracy in dynamic work environments [2, 3]. Furthermore, implementing edge computing solutions for on-device processing can enable real-time decision-making while reducing latency and power consumption [1]. For example, predictive models for state-of-charge (SOC) monitoring and fault detection can help improve maintenance scheduling and extend tool life [1]. Existing systems also lack personalization, failing to take into account user-specific factors such as skill level, fatigue, and real-time task demands, critical elements to optimize user assistance and overall tool functionality.

The significant contributions of this paper are twofold. First, it describes a multidisciplinary and collaborative approach for developing and evaluating smart tool systems, ensuring that both technical performance and user needs are adequately addressed. Second, a prototypical smart tool framework is described that integrates low-cost sensors, machine learning algorithms, and edge computing to demonstrate how a family of powered hand tools can be enhanced to create a versatile smart tool platform. The results show how smarter and more adaptable hand tools can be developed that include features such as performance monitoring, battery life prediction, user performance evaluation, anomaly detection, and means of providing real-time feedback.

A brief review of existing smart tool technologies and sensing challenges is presented in Section 2. Section 3 describes user data collection and analysis, while Section 4 reviews the design and prototyping of a smart tool platform developed for this study, reviewing system architecture, hardware integration, sensor selection, and the implementation of embedded AI algorithms and smart features. Section 5 then presents the testing and evaluation methodology used to validate the tool's capabilities, followed by a presentation of the experimental results. An in-depth discussion of the findings, their implications, and potential limitations is given in Section 6, and Section 7 concludes by summarizing key contributions and proposing directions for future research and advancements in smart tool technology.

2. BACKGROUND

Traditional hand and power tools remain indispensable in many industries and work places; however, they lack the ability to capture and analyze key process variables, user interactions, and working conditions. Smart tools equipped with sensors and data processing capabilities have emerged as a promising solution to address these limitations. These tools enable real-time activity recognition and the monitoring of process variables, helping to tackle challenges such as work-related musculoskeletal disorders and inconsistent task execution [2]. Activity recognition through sensor-based monitoring is of particular interest for tasks that cannot be automated, and recent studies have demonstrated the feasibility of using sensor-based approaches to recognize specific tool activities. For example, Tettamanti et al. [1] explored the use of sensors placed directly on tools to classify different screwdriver operations, such as drilling, screwing, and unscrewing, with high accuracy using machine learning (ML) models. Similarly, New et al. [3] investigated data-driven ML classification algorithms, exploring other powered hand tools. Their study went beyond classification by demonstrating that these ML decision-making algorithms can be deployed 'on the edge' using a low-cost microcontroller running TinyML, enabling real-time predictions [3]. Similarly, Leudesdorff et al. [2] introduced a sensor system for real-time classification of manual construction tasks to improve exoskeleton control. Their work emphasized the importance of tool kinematics and activation signals in identifying different power tool operations, particularly in overhead and wall-based tasks. By integrating an inertial measurement unit (IMU) and pressure sensors into power tools, they were able to classify tasks such as drilling and tightening screws with high reliability.

Beyond motion tracking, smart tool systems have also incorporated additional sensors to monitor tool-workpiece interaction, power consumption, and user behavior in more depth. For example, Semeraro et al. [4] and Thomas et al. [5] demonstrated battery monitoring strategies to estimate state-of-charge and battery health, which are essential for effective tool management and uptime. This research underscores the role of sensor-based classification in developing adaptive support systems for workers, reducing musculoskeletal strain, and improving workflow efficiency.

These advances in sensor-equipped tools align with the larger visions of Industry 4.0, which incorporate technologies such as artificial intelligence (AI) and the Internet of Things (IoT) to facilitate advanced manufacturing processes [6], as well as Industry 5.0, which elevates the role and well-being of humans in manufacturing [7]. The integration of smart tools into different industrial domains offers multiple benefits, including improved safety, reduced operational errors, and enhanced workforce training. Using real-time sensing and intelligent feedback mechanisms, these tools can provide personalized guidance to users, optimize tool performance, and facilitate skill evaluation.

Companies such as Atlas Copco and Milwaukee Tool have developed commercial tools with smart features that enhance production efficiency by enabling faster and more accurate operations compared to conventional tools. These tools integrate advanced hardware, support lean manufacturing and improve ergonomics and safety for operators [8, 9]. Among these advancements, Milwaukee's ONE-KEY™ Smart Tools stand out for their integration of advanced connectivity, real-time data transfer, inventory management, and security features. However, despite these improvements, there remains substantial potential for further innovation to better assist users and optimize tool functionality.

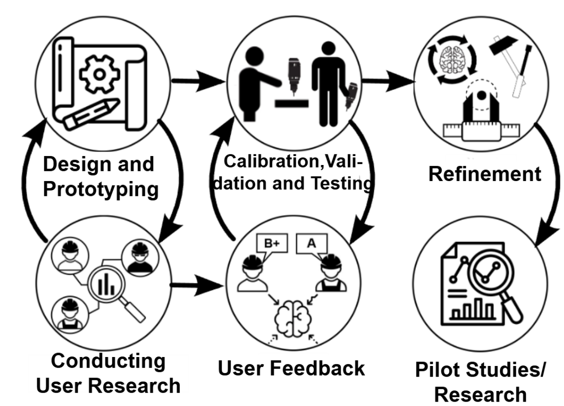


FIGURE 1: Multidisciplinary process for the development of a Smart Tool

A user-centered design approach ensures that tool and AI enhancements fit user needs. Figure 1 proposes a structured design and development process. The intent is follow such a process in order to develop smart tool systems that incorporate AI-driven features such as: 1) user skill evaluation for personalized functionality and targeted skill development, 2) fatigue detection to enhance safety and reduce errors, and 3) advanced battery monitoring with predictive analytics for uninterrupted operation. Additionally, smart tools may include several non-AI-powered features, such as anomaly detection, force estimation, and tracking of key operational metrics, including the number of passes, cuts, drilled holes, and screws driven. A smart tool could also monitor the average time between tasks, orientation of the tool, tool usage duration, and down-times. By combining these types of elements, a smart tool not only has the potential to improve operational efficiency but also prioritizes user well-being and continuous learning, setting a new benchmark in AI-augmented tool design. The next two sections describe how these process steps were followed, in an effort to assure that a smart tool platform meets both technical performance requirements and the functional needs of end users.

3. SMART TOOL USER NEEDS AND REQUIREMENTS

To identify the desired characteristics of smart tools, the researchers employed a qualitative research approach, integrating semi-structured interviews, focus groups, and participatory design workshops. These methods were used to gather insights from skilled trade workers, supervisors, and workforce trainers on the essential features and functionalities required for smart tools.

3.1 Data Collection

Qualitative research was conducted that included observation of work and training environments followed by semi-structured interviews with skilled trade workers and their supervisors in multiple municipal divisions, including Parks & Recreation, Water, Watershed Protection, Fleet Mobility and the Airport. The interviews explored tool usage patterns, challenges, and workers' perspectives on technology integration [10]. Workers provided direct feedback on specific tool functionalities, such as real-time guidance, force feedback, and safety alerts. Supervisors, on the other hand, highlighted broader concerns, including training needs and workplace safety [10].

In addition to individual interviews, focus groups with supervisors and workers were conducted to validate and refine the preliminary findings. Example questions and participant feedback are shown in Table 1. These sessions facilitated discussions on potential applications of smart tools, allowing participants to critique and expand on previously collected insights. In the interest of brevity, details on the design of the interview protocol and the qualitative analysis approach are not included here, but can be found in Collier et al. [10].

3.2 Participatory Design and Validation

A crucial component of the research was the participatory design workshops, where trade workers and supervisors collaborated with researchers to conceptualize smart tool prototypes. The workshops involved activities in which participants provided input on tool ergonomics, sensor placement, and real-time feedback mechanisms. This approach ensured that the design process was user-centered and reflective of actual workplace needs [10].

The iterative nature of the study, which combined interviews, focus groups, and workshops, allowed the researchers to refine the characteristics of smart tools based on real-world trade work scenarios. Key themes that emerged from the study included the need for real-time performance feedback, enhanced safety features, and personalized training capabilities [10].

3.3 Data Analysis

The qualitative data collected were analyzed using thematic analysis, in which researchers systematically coded interview and focus group transcripts to identify recurring themes and priorities for smart tool development [10]. This method facilitated a structured approach to distilling worker and supervisor insights into actionable design principles for the innovation of smart tools.

By integrating participatory research methods with qualitative analysis, the study ensured that proposed smart tool features directly addressed the needs and preferences of skilled trade workers. As one worker stated, "If a machine tool could say 'Hey, incorrect accessory, please try another or... give the operator a warning of those types of things, I think would be extremely helpful '" [10]. This insight, among others, contributed to smart tool development ideas.

4. DESIGN AND PROTOTYPING

The design objective to improve user feedback, ensure ease of integration with existing tools, and facilitate real-time monitoring of process parameters was supported by the results of user interviews, as discussed in Section 3. We incorporated a combination of low-cost sensors and embedded systems to manage data acquisition and feedback mechanisms, with the goal of testing a sensor-integrated smart tool capable of monitoring key process variables.

4.1 Tool Prototyping Platform

The Milwaukee 2904-20 M18 FUEL™ 1/2" Hammer Drill/Driver and M12™ Cordless Rotary Tool, shown in Figure 2, were selected as development platforms. Both tools are powered by Milwaukee's EDLITHIUM™ battery technology, and the 2904-20 is compatible with the M18™ battery system, while the Rotary Tool uses the M12™ battery platform. Although these tools are designed for different voltage systems, third-party adapters are available that allow M18™ batteries to power M12™ tools by stepping down the voltage appropriately. This selection aims enables design of a uniform sensing platform across different types of tools and applications.

4.2 On-Tool Sensing, Monitoring, and Feedback

To monitor key process parameters, we developed a Prototype Sensor Unit (PSU) equipped with multiple low-cost sensors, as illustrated in Figure 2. This unit was previously validated for monitoring critical process variables for welding applications [11]. The PSU consists of a BNO055 IMU (Bosch Sensotec) for tracking tool orientation and movement, an ACS712 (Allegro Microsystems) 30A current sensor, a 0-25V DC voltage sensor (HiLetgo) for monitoring battery state, a LMV324 sound detector (sparkfun.com), an Arduino Nano 33 BLE microcontroller, and an SD card reader module. All devices are mounted within a 3D-printed PLA enclosure (45mm x 28 mm x 38 mm), and the total weight is 45 grams. It is a compact and versatile unit that enables real-time data acquisition, facilitating comprehensive analysis of the tool's and user's performance. The PSU was integrated into the Milwaukee M18™ battery pack, as shown in Figure 2, enabling the use of a single battery in various tools, such as drills,

TABLE 1: Example Interview Questions and Participant Feedback on Smart Tools

Interview Question	Participant Feedback (F=functionality, S=safety)
What kinds of feedback might be useful to you and/or your team members about your use of hand tools on the job?	•"Or if you were using a drill bit and it did get to the point where it wasn't ... getting ready to break, if like you gave me a red flag or something like that, had some type of sensor on it that would kind of alert you." (F, Participant W1) •"Oh, safety guards when it comes to skill saws. If it was set up where the safe the skill saw might not work if it didn't have safeguarding place" (S, Participant W1) •"I guess if it had overheating features or something to let you know that the tool's getting hot." (F, Participant W8) •"So if it tells you maybe a red to green light that your angle or whatever particular way you're using it might be the most efficient" (F, Participant S5)
Are there any ways that the tools you use could be improved that could help you with your work? (rep question?)	•"If somebody had a wrench that said, you're going the wrong way, Dofus [sic]. Turn your wrench over... So, if you had ... a little green light red light. This is loosen, this is tighten." (F, Participant W4) •"If a machine tool could say, Hey, incorrect accessory, please try another or give us a specific kind of type warning ... I think would be extremely helpful." (F, Participant S7)

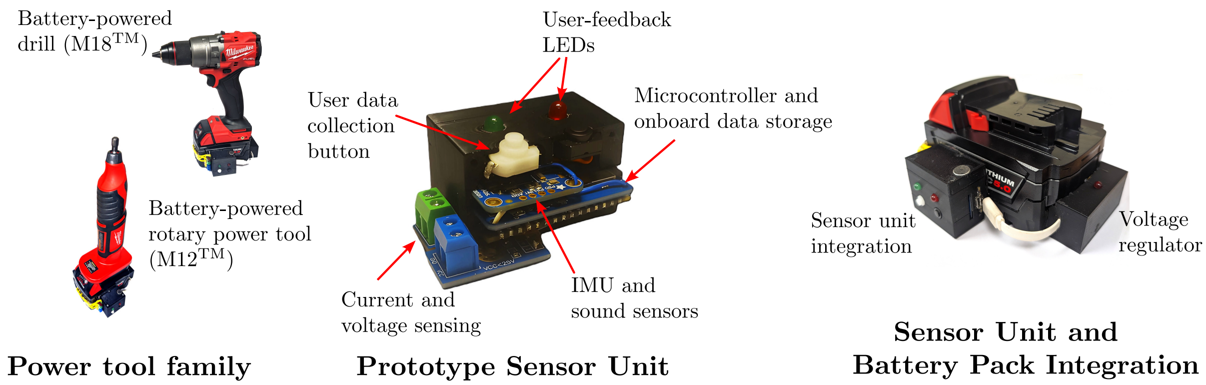


FIGURE 2: A prototype smart tool design used to demonstrate sensor integration onto an off-the-shelf power tool family with a uniform battery platform. Two off-the-shelf Milwaukee® brand power tools were used.

saws, and rotary tools. A voltage regulator was used to ensure stable power delivery to the Arduino Nano 33 BLE.

By continuously monitoring parameters such as tool orientation, applied force, torque, and sound variations, the system aims to provide user feedback through various channels. These include: a) visual indicators with LEDs and a display screen to inform users about deviations from optimal operating conditions and to provide more detailed information about tool parameters, operational status, etc., and b) auditory alerts about improper tool use or when potential defects are detected. Future iterations will integrate vibration-based alerts to notify users when excessive force or incorrect angles are applied.

Real-time sensing and feedback can improve precision and efficiency and support the training of less experienced workers, helping them develop better tool handling techniques over time. In addition, the system's data logging capabilities allow for post-process analysis, allowing users, supervisors, and engineers to review performance trends, detect inefficiencies, and refine operational guidelines.

4.3 Smart Tool Features

Based on interviews conducted with tool users, several key intelligent features emerged as critical to enhancing productivity, safety, and user satisfaction. The synthesis of user requirements and engineering insight result in a more robust and forward-thinking approach for the development of a smart tool prototype. This ensures that any proposed features addressed immediate user needs and also anticipated future challenges and opportunities in the evolving landscape of workplace technology. The following features were selected for study: skill and fatigue assessment, tool/task recognition, battery remaining useful life prediction, load estimation, and anomaly detection.

4.3.1 Skill Assessment. We adopted an approach to assess a user's skill level based on multiple performance metrics, not unlike the use of automated performance metrics used in surgical applications [12]. A weighted-sum-method was adopted [13] to define a Skill Index Score (SIS),

$$\mathrm{SIS} = w_1 E_c + w_2 T_s + w_3 A_d + w_4 P_v + w_5 E_r \tag{1}$$

where the w_i are weighting factors (relative importance of each factor), E_c is energy usage (integral of the current), T_s is task speed (time taken to complete the task), A_d is angle deviation (using gyro data), P_v is a measure of stability (using acceleration data), and E_r is the error rate = Number of errors/total operations, where errors are defined as parts not meeting the tolerance standard). Prior to calculating the SIS, each variable is normalized to a [0,1] range to ensure compatibility across different units and scales. This normalization allows the weighted sum to reflect relative performance rather than absolute magnitudes. Economy of motion, a key concept in performance evaluation, is captured through a combination of angle deviation (A_d) and stability (P_v), which together reflect how smoothly and consistently the tool is handled during a task. A scoring system was formed to rate beginner to advanced tool users. The ability to assign different weights to these factors is crucial, as different applications may prioritize different aspects of performance. For example, in one scenario, precision and quality may be paramount, even at the cost of longer execution time, whereas in another, efficiency and speed might be more critical despite minor imperfections.

4.3.2 Tool/Task Recognition. The ability for a smart tool to autonomously recognize both the type of tool and/or the specific task that is being performed is highly desirable. Once a given tool type is identified, the PSU should be able to identify specific activities. For a drill, for example, the system may need to differentiate between drilling holes and driving screws based on the information provided by the PSU. Similarly, a rotary tool might have to recognize if it is used for sanding, engraving, routing, or cutting by analyzing sensor data. Furthermore, tool/task recognition can contribute to improved safety measures, ensuring that the tool operates within appropriate parameters for each task type, reducing wear and tear, and preventing misuse. The methods and techniques adopted for this study are more fully described in New et al. [3].

4.3.3 Battery State and Remaining Useful Life Prediction. Battery remaining useful life (RUL) is a critical aspect of many systems and devices, from energy storage systems to mobile electronics. Accurately estimating the remaining battery capacity (state of charge, SOC) enables optimized power management, enhances user experience, and prevents unexpected failures. Machine learning (ML) techniques offer a robust approach to battery state prediction by analyzing complex relationships between different battery parameters. For a smart tool, the prediction of the remaining battery useful life on various operational and environmental parameters can be formulated with SOC (%) as a key variable.

4.3.4 Load Estimation. Accurately estimating the loads on the tool, such as the forces and torques induced during drilling operations, is essential to monitor performance and optimize tool efficiency. These quantities can be measured directly in a laboratory setting, as demonstrated by Bales et al. [14]. For field tool use, an *indirect* estimation approach can be accomplished using measured motor current. The current drawn by the tool can be correlated with the torques and forces induced during the tool-material interaction. This method will require some empirical calibration to establish a relationship between electrical power consumption and mechanical loads, as discussed in previous research [15].

4.3.5 Anomaly Detection. Anomaly detection enables identification of deviations from normal operating conditions. The PSU can be programmed to detect irregularities in tool operation, user handling, or material interaction that may indicate potential issues such as improper technique, equipment wear, or hazardous conditions. In this study, operational limits for current, sound, and motion were established. Any data point exceeding these limits is classified as an anomaly and is further analyzed using data from other sensors to determine potential causes and implications. By implementing anomaly detection, a smart tool can provide guidance to promote safety, prolong tool life, and improve user efficiency and performance.

5. PROTOTYPE TESTING AND EVALUATION

Calibration and validation tests were carried out to evaluate the integration of the tools with the PSU sensors and battery management. For brevity, these results are not included here, but all other tests and results are described in the following sections.

5.1 Testing Smart Tool Features

Skill Assessment. Skill assessment was conducted using a dataset from a companion study on skill evaluation in smart powered hand tools [16]. This dataset was generated through a series of controlled experiments in which participants of varying skill levels performed predefined tasks using rotary hand tools equipped with the same sensors as the PSU. The study in [16] explored multiple methods for skill assessment, including geometric dimensioning and tolerancing (GD&T) principles, statistical motion analysis, machine learning-based ranking, and anomaly detection techniques. In this paper, we applied the Skill Index Score (SIS) methodology, which weighs total task duration, motion efficiency, and energy consumption, to evaluate user performance across different tool operations.

In this study, we also examined the effectiveness of the SIS model for ranking user proficiency in realistic task settings. Results of the SIS calculation are presented in Table 2, compared to rankings from [16]. Normalization was performed to standardize all variables across different scales, then a weighted scoring approach was applied to reflect the importance of different factors, as might be done in workplace environments, emphasizing the error rate and task speed. As such, we assign a weight of 0.4 to the error rate and 0.3 to the task speed. For the remaining factors, which contribute to the assessment of process stability, angle deviation, and total energy used, we assumed equal importance and assigned a weight of 0.1 to each.

The computed SIS values enabled the ranking of individuals based on their performance. The comparison between SIS rankings and the rankings derived from GD&T principles [16] shows a general agreement, with minor variations in rank order. In particular, individuals with prior tool experience (indicated by *) consistently achieved higher SIS values, confirming the impact of experience on performance. Figure 3 provides a visual representation of the SIS distribution among subjects, emphasizing the distinctions between different levels of expertise.

Using the SIS scores, participants were categorized into three levels: Beginner, Intermediate, and Advanced. The threshold values for classification were set based on performance distribution, with Advanced users scoring above 71, Intermediate users between 41 and 70, and Beginner users below 40.

Tool/Task Recognition. The methodology for task recognition is based on the approach outlined in [3], which demonstrated the use of smart tool instrumentation and machine learning to identify different tool operations. In that study, task classification

TABLE 2: Comparison of Rankings Based on Geometric Dimensioning & Tolerancing (GD&T) Principles [16] and the Skill Index Score (SIS)

GD&T [16]		SIS			
Rank	Subject	Rank	Subject	Score	Level of Expertise
1	A*	1	C*	93.6	Advanced
2	C*	2	E*	87.5	Advanced
3	D*	3	D*	87.2	Advanced
4	B*	4	A*	83.7	Advanced
5	E*	5	B*	76.3	Advanced
6	F	6	G	63.9	Intermediate
7	G	7	F	58.9	Intermediate
8	I	8	J	42.7	Intermediate
9	H	9	I	36.9	Beginner
10	J	10	H	17.0	Beginner

Note: Users with prior tool experience are indicated by the symbol '*'[16].

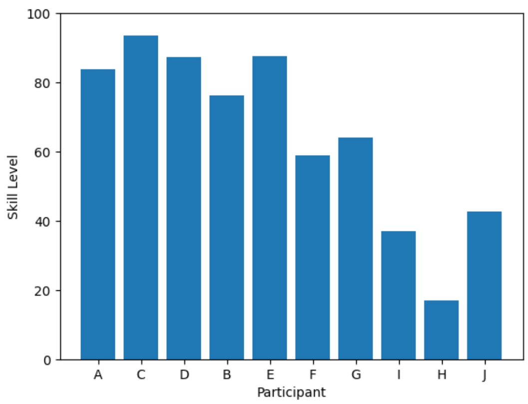


FIGURE 3: Comparison of SIS scores for different participants. Higher scores indicate better performance.

was achieved by analyzing motion data from an inertial measurement unit (IMU), electrical characteristics from current sensors, and audio signals from an onboard microphone. Task recognition was performed using a combination of data collected in [3] and additional data obtained from an individual participant, ensuring a broader validation of the recognition framework. The dataset includes sensor readings from smart hand tools performing various operations, focusing on both drilling and rotary tool applications. Specifically, two primary tasks were executed using a drill: drilling holes and driving screws. In addition, for rotary tools, the tasks included sanding, engraving, cutting, and routing. The sensor data collected enabled real-time identification of tool operation modes. For drilling tasks, the system was capable of distinguishing between drilling a hole or when a screw was being inserted. Similarly, in rotary tool applications, distinct motion patterns, force variations, and current draw fluctuations allowed for accurate differentiation between sanding, engraving, cutting, and routing. The integration of machine learning models further improved classification accuracy by learning characteristic signal patterns associated with each task. To classify tool tasks, a lightweight convolutional neural network (CNN) was employed. Raw sensor data was segmented using a sliding window of 40 samples with 50% overlap. Each window was transformed into a 7×15 statistical feature matrix by computing seven statistical descriptors (mean, std, kurtosis, etc.) across 15 sensor channels. This matrix was treated as a 2D input image for the CNN. The model architecture consisted of a Conv2D layer with 45 filters, a 2×2 max-pooling layer, followed by flattening, dropout (rate = 0.5), and two dense layers. The final output layer used softmax activation to predict one of six task classes (e.g., drilling, cutting). This CNN model was selected for its ability to extract spatial patterns from structured sensor statistics and for its compatibility with embedded deployment.

By incorporating an additional participant's data into the existing dataset using the PSU, we evaluated the adaptability of the task recognition system to different users and emphasized the versatility of both the PSU and the smart tool concept.

The task recognition model successfully identified tool operations based on sensor data, achieving high classification accuracy across different tool tasks. The confusion matrix, shown in Figure 4, provides an overview of the classification performance. The system was effective in distinguishing between drilling, screwing, cutting, routing, sanding, and engraving, with a classification accuracy exceeding 89% for most tasks. Drilling (class 0) was correctly identified 95.08% of the time, while screwing (class 1) showed slightly lower accuracy of 89.29% due to some misclassification with drilling. Cutting (class 2) achieved a perfect 100% recognition rate. Routing (class 3) was correctly classified 97.22% of the time, with minor confusion occurring with engraving. Sanding (class 4) demonstrated an accuracy of 91.82%, while engraving (class 5) had a classification accuracy of 95.95%, with some misclassification involving sanding.

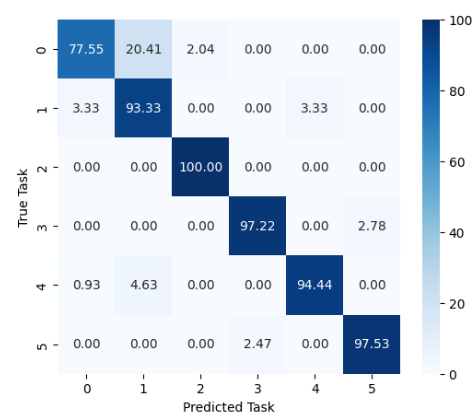
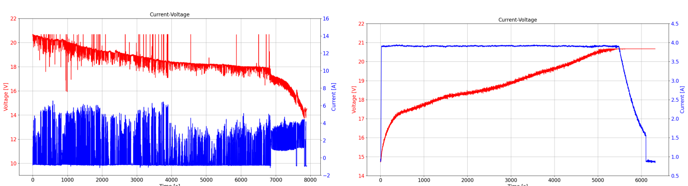


FIGURE 4: Task recognition confusion matrix

To evaluate online performance, the trained model was embedded on an Arduino board using TinyML. When running the model in the embedded system, the classification accuracy remained high, although a slight decrease was observed due to hardware constraints, such as lower computational power and reduced floating-point precision. Despite these limitations, the system maintained an accuracy above 85% in all tasks, demonstrating its feasibility for edge computing applications in smart tools.

Battery Remaining Useful Life Prediction. During the data collection process for drilling holes, screw driving, cutting, sanding, engraving, and routing, battery usage data was continuously recorded. Sample data is shown in Figure 5a. In addition to monitoring battery consumption during tool operation, data on battery charge cycles as shown in Figure 5b were also collected. These data provide insight into power usage trends and enable modeling for battery life prediction. First, the recorded data are used to prepare time series inputs to train a Long Short-Term Memory (LSTM) model [17] to estimate SOC. A sliding window is applied to create overlapping sequences to improve the model's learning capability. The SOC computation is based on the Coulomb counting method, which is adjusted for small time windows to ensure precise estimations of the remaining battery capacity. For the sake of brevity, the results of the ML-estimation are not shown here. However, the SOC estimation was used to develop a predictive model for open-circuit voltage. Figure 6 compares measured open-circuit voltage (OCV) to the LSTM model prediction results as a function of estimated SOC. The trends predicted by the model compare well with the measured OCV-SOC relationship. Minor deviations are observed at lower SOC levels, indicating potential inaccuracies in capturing voltage fluctuations when the battery is nearly at the cutoff voltage, which is a built-in cutoff voltage to protect the cells from deep discharge.

The integration of an LSTM-based time-series model, combined with a sliding window approach, significantly enhances the precision of SOC estimation by leveraging historical charge and discharge data. This approach improves the model's ability to generalize across different battery conditions, as evident from the alignment between measured and predicted values in mid-to-high SOC ranges. Further work is needed to improve these types of models and to investigate their use for remaining useful life prediction.



(a) Discharging (b) Charging

FIGURE 5: (a) Current and voltage measurements collected during the discharge process while using the tool for various tasks (b) Current and voltage curves during the battery charging process.

Load Estimation. Force estimation was achieved by leveraging the relationship between motor current draw and the load experienced by the tool, similar to that in [15]. As the tool encounters resistance from the workpiece, the motor compensates by drawing more current, which correlates with the applied force. Experiments were carried out with a rotary power tool (RPT) configured for routing and subjected to a known range of applied forces while cutting grooves in soft wood. A calibrated load cell measured the actual applied force (on the workpiece), while the

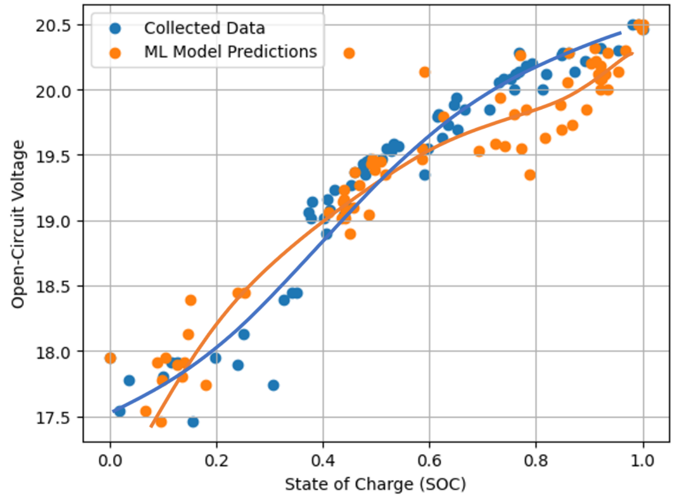


FIGURE 6: Comparison of measured battery open-circuit voltage versus LSTM model results as a function of estimated state of charge

current sensor monitored power consumption. The data were used to develop a linear regression model, $F = 42.3 \cdot i_m - 40.2$, where F represents the estimated force and i_m denotes the measured current in amperes. This model had an average error of ± 1.18 N compared to the load cell measurements. Although material inconsistencies and tool wear introduce variability, such a model can be sufficient for practical applications in real-world work environments.

Anomaly Detection. Data collection was carried out during the normal operation of both a drill and a rotary tool, ensuring a representative data set for various tasks. The raw data was then analyzed using statistical metrics to define the normal operational limits for each task. These metrics included measures such as mean, standard deviation, and interquartile ranges, which helped establish thresholds beyond which data points were considered anomalous. Once these thresholds were determined, any values falling outside the defined limits were classified as anomalies. To validate these detected anomalies, we examined video recordings of the corresponding tool operations. This step allowed us to assess whether the out-of-limits peaks in the data corresponded to observable anomalies in real-life scenarios, such as irregular tool behavior, operator-induced disturbances, or unexpected material interactions. This cross-verification ensured that the detected anomalies were not artifacts of noise or sensor errors, but instead reflected genuine deviations from normal operation.

The anomaly detection system successfully identified deviations in tool operation by analyzing sensor data collected from the PSU. Monitoring the current signature allowed for the detection of activity fluctuations and abnormal peaks, which, in real-world scenarios, often correspond to tool stoppages due to the cutting tip becoming lodged in the material. Figure 7 illustrates these current anomalies, highlighting sudden variations that indicate irregular operation. In addition to current monitoring, thresholds were established for sound levels, motion patterns, and tool orientation. Any recorded values exceeding these predefined limits were flagged as anomalies.

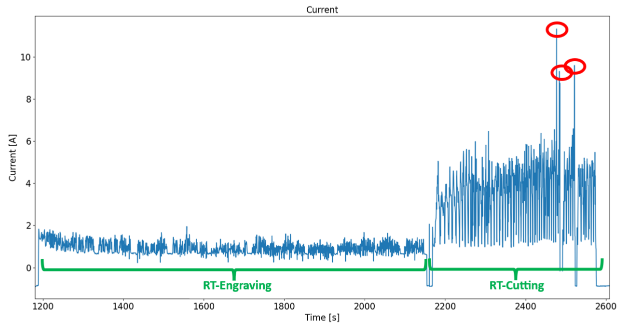


FIGURE 7: Anomaly During Cutting Task

Additional Features. Using the data collected from the previously mentioned experiments, we analyzed the system-generated reports and compared them with the corresponding video recordings. This verification process involved assessing the recorded task duration, the number of passes, holes drilled, cuts made, and screws driven. Additionally, physical validation was conducted by examining the drilled wood and completed cuts. The analysis also included verifying the average time per pass and evaluating the tool's orientation by examining roll, pitch, and yaw angles recorded during the tasks.

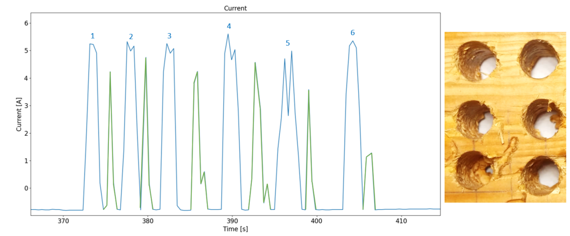
The PSU, integrated with embedded algorithms, successfully facilitates real-time monitoring of various tool operations. The system first identifies the task being performed and then detects and quantifies key operational parameters, including the number of holes drilled, screws inserted/removed, and the number of passes or cuts completed. These parameters can be continuously tracked throughout an operation, providing users with a comprehensive overview of their progress. In addition, the system records time-related metrics, such as the average time per pass, total time spent per operation, and cumulative working time over the entire work session. These measurements enable a detailed analysis of workflow efficiency and tool utilization. Furthermore, the system effectively captures roll, pitch, and yaw angles, providing valuable information on tool orientation and user handling. All data collected are compiled into a detailed performance report, providing a structured summary of tool usage and efficiency metrics. An example of such a report is presented in Figure 8.

```
----Report----
Tasck = Routing
Num Passes = 6
Avg.Time/Pass = 17.41 s
Avg.Force = 3.05 lbf
Avg.Work Ang = 91.03°
Avg.Travel Ang = 88.6°
```

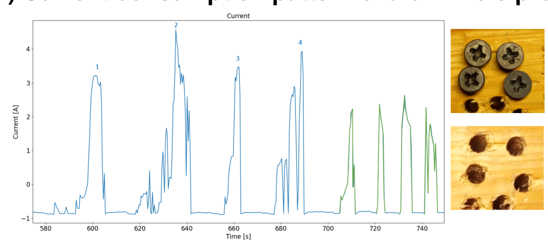
```
----Report----
Tasck = Drilling
Num Holes = 4
Avg.Time/Pass = 8 s
Avg.Force = 4.88 lbf
Avg.Work Ang = 89.21°
Avg.Travel Ang = 88.09°
```

FIGURE 8: Work report at the end of the task

As previously mentioned, the initial step involves identifying the specific task being performed to enable subsequent analysis of the current patterns. Figures 9 and 10 depict the current signatures associated with each task. By applying various algorithms, the system can accurately determine the number of holes drilled, as shown in Figure 9a, or identify the number of screws inserted, as illustrated in Figure 9b. Additionally, Figure 10a presents the number of passes completed during a routing process, while Figure 10b illustrates the number of cuts made.

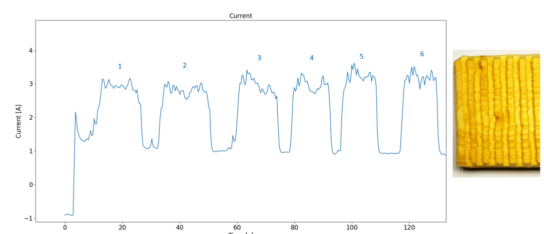


(a) Current consumption pattern of a drill hole process

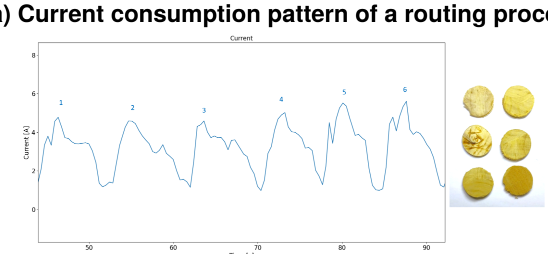


(b) Current consumption pattern of a screwdriving process

FIGURE 9: Current consumption patterns produced by the ST-Drill



(a) Current consumption pattern of a routing process



(b) Current consumption pattern of a cutting process

FIGURE 10: Current consumption patterns produced by the ST-Rotary Tool

The system-generated reports were validated through a comparative analysis with video recordings of the performed tasks. This verification process confirmed that the recorded task duration, number of passes, holes drilled, cuts made, and screws driven corresponded closely with visual observations. Additionally, physical validation was conducted by examining the drilled wood and completed cuts, ensuring consistency between system measurements and real-world outcomes.

6. DISCUSSION

Skill Assessment. SIS rankings closely aligned with a GD&T-based ranking from [16], particularly among five skilled participants. However, SIS can capture additional performance aspects such as execution speed and stability. Further, SIS may be effective in showing how experience plays a role in skill, as expected. The SIS is also able to detect variance among the experienced users, a useful feature worth exploring further in future testing. Further, significant gaps in skill levels are found in novice users, showing that the SIS framework shows promise in providing a structured approach to skill assessment adaptable to different tool use contexts. It should be kept in mind that the ranking of participants is inherently relative, meaning that skill levels are assessed in comparison to the specific group of individuals participating in a study rather than against an absolute standard.

Tool/Task Recognition. The results highlight the effectiveness of a sensor-based task recognition system in accurately distinguishing between different tool operations. The high classification accuracy in most tasks indicates that the integration of IMU motion data, electrical characteristics, and audio signals can provide a reliable basis for task identification. However, the presence of perfect (100%) or near-perfect classification values suggests a possible overfitting issue. This potentially limits the ability to generalize to unseen data (new users) and suggests that a different combination of input features or additional regularization techniques should be explored to improve the system's robustness. Despite the model's performance, certain misclassifications were observed. The confusion between screwing and drilling suggests that these tasks share overlapping sensor characteristics, such as similar force profiles and motion patterns. Additionally, a minor misclassification between engraving and routing suggests that further refinement in feature extraction may enhance performance.

Battery Remaining Useful Life Prediction. Trends in open-circuit voltage prediction compared well with measured data; however, some discrepancies highlight areas for further improvement. Specifically, early-stage SOC estimates show greater variability, which may be attributed to transient effects during tool startup or variations in power demand across different tasks. Training a model with more data could further refine the SOC predictions. This work represents an initial step toward implementing an ML-based model for battery remaining useful life prediction. To improve the accuracy and reliability of the model, more tests and data collection will be necessary under various operating conditions, tool types, and usage scenarios.

Load Estimation. The findings support the effectiveness of motor current-based force estimation as a cost-effective and adaptable method to monitor tool interaction forces. The linear relationship between current draw and applied force simplifies implementation across different power tools without requiring invasive modifications to tool handles or work environments. However, certain factors introduce variability in force estimation accuracy. Material inconsistencies, such as density variations in softwood, can affect the resistance encountered by the tool, influencing the current draw. Despite these limitations, the method remains practical for applications where an approximate force estimation is sufficient. Future work will explore more robust modeling techniques.

Anomaly Detection. For each task, predefined operational limits were established to distinguish normal tool behavior from anomalies. The anomaly detection process begins with identifying the current task and then applying these limits to detect deviations. Figure 7 illustrates the current patterns associated with engraving and cutting using the rotary tool. Within the cutting task, three anomalies were detected, marked by the red circled peaks in the figure. These peaks exceed the normal operating range and are thus classified as anomalies. To validate the system's accuracy, video recordings of the experiment were reviewed. The analysis revealed that these anomalies occurred when the operator applied excessive force, causing the tool to stall and become stuck in the workpiece. This confirms the system's ability to accurately detect irregular tool behavior. Integration of anomaly detection into smart hand tools improves safety, reliability, and performance monitoring. By identifying operational irregularities in real-time, the system facilitates immediate corrective actions, minimizing potential hazards, and preventing equipment damage. Furthermore, it has the potential to provide instant feedback to users, enabling them to refine their techniques, or, if necessary, automatically stop tool operation to prevent further issues.

Additional Features. The real-time monitoring capabilities of the PSU demonstrated high accuracy and reliability in capturing task-related parameters, making it a valuable tool for assessing user performance. The system's ability to automatically quantify operations such as drilling and cutting provides an objective method for tracking work progress, reducing reliance on manual documentation or subjective observations, and shows the potential for training and the delivery of assistance through a feedback system. Compared to conventional evaluation methods, such as direct observation or post-task inspection, this system provides continuous quantitative insights into both task efficiency and tool handling behavior. The automated reporting feature allows supervisors and engineers to analyze performance trends over time, facilitating data-driven decision-making for training and workflow optimization. Although the machine learning (ML) algorithm can already distinguish between drilling and screwing, it could be further refined to recognize when the drill bit is being inserted or extracted, as well as when a screw is being driven in or removed. By leveraging a more advanced algorithm, the drill's current pattern could be analyzed to detect these transitions with greater accuracy. As illustrated in Figure 9a, the six holes are marked in blue, representing the insertion phase of the drill bit, while the green segments indicate when the bit is being extracted. Although these patterns are visually discernible, an ML algorithm could automate this classification, ensuring precise and real-time identification of drilling phases. Similarly, Figure 9b depicts the process of screw insertion and extraction. The blue segments correspond to the insertion of four screws, whereas the green segments represent their removal.

Discussion on User Feedback, Refinement, and Pilot Studies. Before user testing can be conducted to gather insights from skilled trade workers, additional prototype refinements need to be made, including hardening of the PSU for field deployment. Only then can pilot studies "in the field" be planned and conducted to study human tool usage, monitoring worker fatigue, influence on training, etc. Such studies remain future work at this time.

7. CONCLUSIONS AND FUTURE WORK

This study reviewed the design and evaluation of methods for developing smart hand tool systems. A Prototype Sensor Unit (PSU) was developed and successfully integrated with commercial power tools, emphasizing the use of low-cost sensors and edge computing to enable monitoring of user performance, tool operation, and system health. These methods can be deployed 'on-tool' in a practical and cost-effective manner.

This work combined the efforts of a multidisciplinary team exploring how innovations in sensing technologies, machine learning, and AI can be used to create smart hand tool systems that benefit both users and their organizations. Future work will expand on the efforts reported here to improve smart tool engineering as well as to understand how smart tool systems can be effectively used in the workplace. The findings suggest uses in workforce training, human-tool collaboration, and adaptive tool design. Future work should focus on refining predictive models, enhancing online processing capabilities, and dealing with challenges to deployment. Of particular interest is the prediction of battery remaining useful life and the development of reliable skill and fatigue assessment methods to further optimize tool performance and user experience. Integrating onboard smart tool features, as demonstrated in this work, with a higher level of AI-enabled capabilities can further support both novice and skilled tool users in complex workplace environments.

Future research should focus on expanding the dataset to include diverse users, tools, and task conditions. This can improve the ability to generalize algorithms for battery status prediction, skill evaluation, task recognition, and anomaly detection. The broader data will also support development of more reliable models capable of handling variability in user behavior, tool configurations, and operating environments. These future studies should also assess safety and usability implications, such as those that might arise from errors in task recognition algorithms.

ACKNOWLEDGMENT

This work was funded by Good Systems: Ethical AI at UT Austin for the "Smart Hand Tools: Building the Future of Work with Ethical AI" project, Microsoft, and MITRE.

REFERENCES

[1] Tettamanti, C., Giordano, M., Altheimer, J., Linhart, L. and Magno, M. "Towards Model Development for Sensor-Based Activity Recognition at the Construction Site." *9th International Workshop on Advances in Sensors and Interfaces (IWASI)*. 2023. IEEE.

[2] Leudesdorff, B., Strümpler, L.R.S., Dobosz, T., Maufroy, C., Schneider, U. and Bauernhansl, T. "Sensor System for Real-Time Classification of Manual Construction Tasks with Power Tools for Exoskeleton Control." *IEEE Intl. Conf. on Systems, Man, and Cybernetics (SMC)*. 2024.

[3] New, R., Salazar, C.D., Bendaña, J., Sripada, S.V.S., Chinchali, S., Fleischmann, K.R. and Longoria, R.G. "Design, Development, and Testing of a Smart Hand Tool: Achieving Work Task Recognition Using Synthetic Data and Edge Intelligence." *ASME IDETC-CIE2024*. 2024. Washington, DC. DOI 10.1115/DETC2024-142360.

[4] Semeraro, C., Caggiano, M., Olabi, A.-G. and Dassisti, M. "Battery monitoring and prognostics optimization techniques: Challenges and opportunities." *Energy* Vol. 255 (2022): p. 124538.

[5] Thomas, J.K., Crasta, H.R., Kausthubha, K., Gowda, C. and Rao, A. "Battery monitoring system using machine learning." *J. of Energy Storage* Vol. 40 (2021): p. 102741.

[6] The Manufacturing Technology Series EAST Customer Care. "The Role of Smart Machine Tools in Industry 4.0." Website (2025). URL https://east.mtseries.com/news/smart-machine-tools/. Accessed February 2025.

[7] J.Leng, Sha, W., Wang, B., Zheng, P., Zhuang, C., Liu, Q., Wuest, T., Mourtzis, D. and Wang, L. "Industry 5.0: Prospect and retrospect." *J. of Manufacturing Systems* Vol. 65 (2022): pp. 279–295.

[8] Atlas Copco USA. "It's time to get Smart with your handheld tools." Website (n.d.). URL https://www.atlascopco.com/en-us/itba/plp/time-to-get-smart-with-your-tools. Accessed February 2025.

[9] Milwaukee. "Smart Tools for Trade-Specific Productivity." Website (2025). URL https://onekey.milwaukeetool.com/connected-tools. Accessed February 2025.

[10] Collier, C., Fleischmann, K.R., Greenberg, S.R., Lassiter, T., Kim, J.B., Salazar, C. and Longoria, R.G. "Works for Me: Personalizing Skilled Trade Worker Training via Smart Hand Tools." *Proc. Association for Information Science and Technology* Vol. 61 No. 1 (2024): pp. 92–102.

[11] Salazar, C.D. and Longoria, R.G. "Comparative Analysis of Real-Time and Simulated Monitoring Techniques for MIG Welding." *ASME IDETC-CIE2024*. 2024. Washington, DC.

[12] Hung, A.J., Chen, J., Jarc, A., Hatcher, D., Djaladat, H. and Gill, I.S. "Development and Validation of Objective Performance Metrics for Robot-Assisted Radical Prostatectomy: A Pilot Study." *J. of Urology* Vol. 199 No. 1 (2018): pp. 296–304.

[13] Marler, R.T. and Arora, J.S. "The weighted sum method for multi-objective optimization: new insights." *Structural and Multidisciplinary Optimization* Vol. 41 (2010): pp. 853–862.

[14] Bales, G.L., Das, J., Tsugawa, J., Linke, B. and Kong, Z. "Digitalization of Human Operations in the Age of Cyber Manufacturing: Sensorimotor Analysis of Manual Grinding Performance." *J. of Manufact. Sci. and Engin.* Vol. 139 No. 10 (2017): p. 101011.

[15] Bendaña, Jose. "Analyzing Power Driven Hand Tool Operation Using Low-Cost Sensors." Master's Thesis, The University of Texas at Austin. 2023.

[16] New, R. and Longoria, R.G. "Evaluating Skill Detection Methods for Smart Powered Hand Tools." *ASME IDETC-CIE2025*. 2025. ASME, Anaheim, CA, USA. Accepted.

[17] Murphy, Kevin P. *Probabilistic Machine Learning: An Introduction*. The MIT Press, Cambridge, MA (2022).

