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# *Embedded Sensing and Machine Learning-Based Interactive Experience Evaluation of Contemporary Jewelry from a Wearable Art Perspective*

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***Abstract.*** Wearable computers and embedded interaction systems have changed contemporary jewelry into interactive systems that can sense users' actions and provide them with a feedback. In this research, a computational analysis system is designed by combining embedded interaction system for touch sensing, wireless sensor network for data collection, and machine learning to study interactive experiences in contemporary jewelry from wearable art point of view. An interactive brooch based on ESP32 microcontroller board with embedded touch sensing by MPR121, feedback provided by RGB LED, and wireless communication by Bluetooth Low Energy (BLE) is proposed. In order to implement interactive actions in this prototype and collect behavior data related to task completion time, touch frequency, response latency, and error rate, a within-subject experiment with 48 participants is conducted to compare static brooch with interactive one in terms of usability, immersion, emotional expression, and wearing comfort. Random forest classification model with 300 decision trees is trained to classify high immersion and low immersion cases according to collected behavioral and experience features with five-fold cross validation. As a result of experiments, it was revealed that the proposed prototype increased the level of immersion from 3.29 to 4.10 and emotional expression from 3.21 to 4.25. The random forest model showed F1-score equal to 0.806 and area under ROC-curve equal to 0.872, while response latency was the most significant feature among predictors. Thus, the presented work shows how embedded interaction systems and machine learning can be utilized to conduct quantitative evaluation of wearable art experiences.

***Keywords:*** Wearable computing, embedded touch sensing, human-computer interaction, random forest classification, contemporary jewelry

## 1. Introduction

With the emergence of wearable computing, embedded sensing, and mobile communication technology, the functional boundary of modern jewelry design is being altered slowly, turning the jewelry from passive adornments on the body to active devices capable of sensing and reacting to the wearer's activity. The research on wearable technology has shifted to concentrate more on user

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behaviors, perceived values, and experiences, yet the quantitative relationship between the technical performance and artistic experience is still not well-established [1]. Moreover, the research on smart jewelry shows that digital functionalities should be kept in harmony with the aesthetic aspect, physical bonding, and emotional characteristics of jewelry [2]. In consideration of the above problem, the study uses a static brooch and a touch-sensitive brooch. ESP32, capacitive touch sensing, LED feedback, and Bluetooth communication constitute the interactive system, which collects the task time, touch rate, response time, and error rate. Then SUS, UEQ-S, immersion, and comfort scores will be compared to find out the difference of experience. After that, a random forest model will be adopted to predict the high and low immersion states as well as discover the influential behavioral and technical factors in interactive experience.

## 2. Literature review

### 2.1. Wearable art development

Wearable art takes the body as one of the key elements for generating artistic significance, where wearing positions, movements of the body, and the visibility in society affect the perception and expression of the work of art. In the context of the involvement of computer technologies in jewelry design, the jewelry itself gradually transforms into a hybrid of bodily decoration, interface, and digital medium. Systematic studies of jewelries-like wearable devices demonstrate that the technology and fashion expressions are starting to establish new kinds of relations [3]. Participation of the body is not only limited to the passive wearing but rather expanded to active operation, thus creating coordination issues among movement pattern, feedback, and emotion. The framework of UEP-ACT involves users, emotions, product, activities, context, and technology into one interactive system [4]. This kind of relationship means that the process of wearing should be analyzed based on task efficiency, interaction frequency, immersion, and emotion expression, thus making a link between the embodiment experience and interaction behavior.

### 2.2. Interactive jewelry technology

Typical interactive jewelry triggers such kinds of responses as lighting, sounds, vibrations by the use of touch, gestures, proximity, and physiological inputs, and diverse technology combinations have direct impacts on the size, power consumption, comfortability, and stability of the devices. Studies on dynamic mechanisms of interactive jewelry show that interaction design relies largely on the mapping between body movement and feedback mode, and the accuracy of the input is the key determinant of wearers' understanding and control over the interactive object [5]. Studies on user needs and experiences of wearable fashion objects indicate continuous connections among user requirements, application contexts, and wearer experiences; this implies that technical performances need to be evaluated through the process of wearing [6]. In this case, it is possible to create an interaction loop with the use of capacitive touch sensing, ESP32, LED feedback, and Bluetooth communication, continuously tracking touch duration, latency, mode switching, and errors.

### 2.3. Computational experience modeling

Evaluation of interactive experiences requires taking account of both perception and behavior so that experience differences generated by various designs may be measured and even predicted. The SUS scale is capable of assessing overall usability with relatively low costs of measurement and is

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appropriate for quick evaluation following completion of tasks using an interactive prototype [7]. UEQ-S measures efficiency, clarity, stimulation, and novelty using pragmatic and hedonic quality aspects and serves as additional metrics of the functional and aesthetic experience of interactive jewelry [8]. While questionnaire scales measure overall levels of experience, task time, number of touches, reaction time, errors made, and comfort may correlate nonlinearly as well. Random forest algorithm performs classification by combining several decision trees and allows for obtaining the importance of each input variable [9]. Once immersion is categorized as high and low, five-fold cross-validation may be used to evaluate the stability of the model and identify those technical and behavioral variables contributing more to high-immersion experience.

## 3. Experimental methods

### 3.1. Prototype implementation

The interactive prototype featured ESP32 WROOM 32 as the core controller. The touch detection was carried out with the help of an MPR121 capacitive touch sensor and the lighting feedback was provided by an RGB LED with three modes set in advance. The connection between the touch sensor and the ESP32 was made via I²C interface with 50 Hz sampling frequency. The touch and release thresholds were set to 12 and 6, respectively. The debouncing period of 80 ms was utilized for avoiding redundant switching of lighting modes due to continuous touch. After the valid touch had been detected, ESP32 recorded the timestamp and performed the switch of the lighting mode, followed by sending the data on touch time, feedback time, mode number, and error status to the Android phone via Bluetooth Low Energy protocol. Response latency was calculated as the period between touch event confirmation and LED update. The static and interactive brooches had the same look, size, and weight. The equivalent weight filler was installed in the static version to balance the wearing load. Prior to the formal experiment, eight subjects were invited to participate in the pilot test with 30 touches per each.

### 3.2. Wearing experiment

The formal experiment gathered 48 subjects between the ages of 18 and 35, which used a two-condition within subject design. Half of the subjects were assigned to experience the static brooch first, while the other half were assigned to experience the touch responsive brooch first. Both prototype conditions were conducted with 60s wearing adaptation period, task execution, and experience evaluation. For the interactive condition, the subjects had to perform three tasks, which include single feedback activation, toggling through three light modes, and expressing a particular emotion through the jewelry. All three tasks were performed three times each. The time taken to complete the tasks, touch count, mean response latency, and errors were recorded through the Android app simultaneously. Afterwards, the subjects completed the SUS, UEQ S, immersion, emotion expression, and wearing comfort questionnaires [10]. The illumination, wearing position, seating distance, and operational instruction for the experiment were constant. Each session took about 25 mins. Log data and questionnaire responses were matched based on the IDs of participant and task respectively. Those trials where BLE packet loss is over 5% or program interrupted were excluded from the analysis.

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### 3.3. Statistical and model analysis

Data processing first examined log completeness. Continuous variables were then standardized using Z score normalization, followed by internal consistency testing of the scales. SUS, UEQ S, immersion, emotional expression, and comfort scores from the static and interactive prototypes were compared using paired samples t tests [11]. The score difference between the two conditions for each participant served as the unit of analysis. The test statistic was calculated as shown in Equation 1.

$$t = \frac{\bar{d}}{s_d/\sqrt{n}} \tag{1}$$

Here, $\bar{d}$ represents the mean paired difference between the two conditions, $s_d$ denotes the standard deviation of the differences, and n=48 represents the number of valid participants.

Only data generated by the interactive prototype were then used to train the random forest classifier. Immersion scores were divided into high and low experience categories using the median. Task time, touch frequency, response latency, error rate, SUS score, and comfort score were used as input features. The model contained 300 decision trees, with a maximum depth of 4 and a minimum of 3 samples per leaf. Five fold stratified cross validation was applied. The final category was determined by majority voting across the decision trees, as shown in Equation 2.

$$\hat{y}(x) = \arg\max_{c\in\{0,1\}} \frac{1}{B}\sum_{b=1}^{B} \mathbf{1}[h_b(x) = c] \tag{2}$$

Here, B=300 represents the number of decision trees, $h_b(x)$ denotes the classification result of the bth tree, c represents the low or high immersion category, and $1[\cdot]$ is the indicator function. Accuracy, Precision, Recall, F1, and Permutation Importance were reported. High complexity parameter tuning was not performed to control overfitting under the small sample condition.

## 4. Results

### 4.1. Interaction difference

As shown in Table 1, the touch responsive prototype produced consistently stronger user experience scores than the static prototype. The SUS score increased from 68.4±7.6 to 78.9±6.7, while UEQ S increased from 1.06±0.41 to 1.69±0.38. Immersion rose from 3.29±0.51 to 4.10±0.47, and emotional expression increased from 3.21±0.56 to 4.25±0.45. All four differences reached $p<0.001$, with Cohen's dz ranging from 1.07 to 1.53. These results indicate that touch activated lighting strengthened perceived control and bodily participation, while also extending jewelry from visual ornamentation toward an interactive means of emotional expression. Wearing comfort decreased slightly from 4.33±0.40 to 4.16±0.45, with a smaller effect size of $dz=-0.37$. The electronic module therefore introduced a limited physical burden without offsetting the improvement in interactive experience. Interaction logs recorded a mean task time of 7.84±1.63 s, a response latency of 132.6±18.4 ms, and an error rate of 4.8±2.1%. Response latency was negatively associated with SUS $r=-0.47, p=0.001$, whereas touch frequency was positively associated with immersion $r=0.38, p=0.008$. The combined questionnaire and log results indicate that interactive quality depended on both technical responsiveness and the degree of active bodily engagement.

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Table 1. Questionnaire results and interaction log statistics for the two brooch prototypes

| Indicator | Static Prototype M±SD | Interactive Prototype M±SD | t(47) | p | Cohen's $d_z$ |
|---|---|---|---|---|---|
| SUS | 68.4±7.6 | 78.9±6.7 | 7.43 | <0.001 | 1.07 |
| UEQ S | 1.06±0.41 | 1.69±0.38 | 8.04 | <0.001 | 1.16 |
| Immersion | 3.29±0.51 | 4.10±0.47 | 9.35 | <0.001 | 1.35 |
| Emotional Expression | 3.21±0.56 | 4.25±0.45 | 10.61 | <0.001 | 1.53 |
| Wearing Comfort | 4.33±0.40 | 4.16±0.45 | −2.56 | 0.014 | −0.37 |
| Task Time (s) | N/A | 7.84±1.63 | N/A | N/A | N/A |
| Touch Frequency | N/A | 2.71±0.63 | N/A | N/A | N/A |
| Response Latency (ms) | N/A | 132.6±18.4 | N/A | N/A | N/A |
| Error Rate (%) | N/A | 4.8±2.1 | N/A | N/A | N/A |

## 4.2. Model prediction

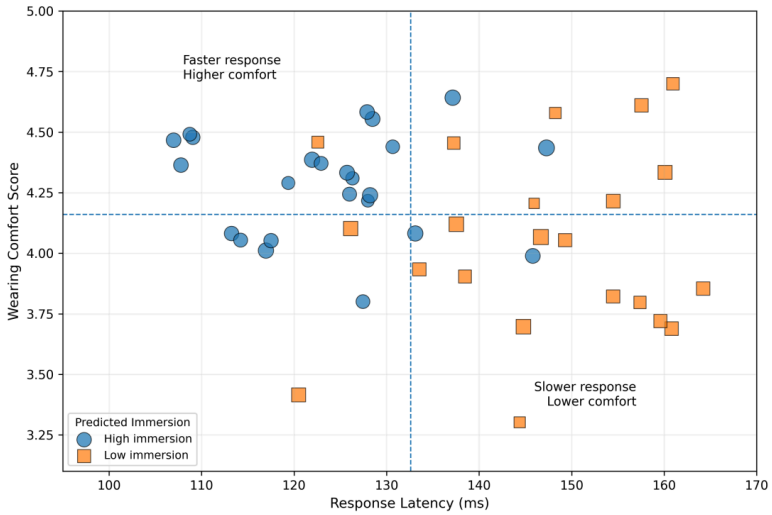



Figure 1. Wearable art experience distribution under random forest classification

The random forest classifier achieved an Accuracy of 0.813±0.055, Precision of 0.826±0.061, Recall of 0.792±0.073, F1 of 0.806±0.057, and ROC AUC of 0.872±0.046 under five fold cross validation. The results demonstrate that behavioral logs and wearing experience variables contained sufficient information to distinguish high and low immersion states. Permutation analysis identified response latency as the strongest predictor, with an importance of 0.246±0.031, followed by wearing

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comfort at 0.211±0.028 and SUS at 0.187±0.025. Touch frequency, task time, and error rate contributed 0.153±0.022, 0.112±0.019, and 0.091±0.017, respectively. As shown in Figure 1, high immersion observations were concentrated mainly in the region combining shorter response latency with higher wearing comfort. Larger points in this region also corresponded to stronger emotional expression. Low immersion observations were more frequently distributed toward longer latency and lower comfort. This distribution indicates that wearable art experience was shaped by a coupled relationship between system responsiveness, bodily suitability, and expressive engagement. Faster feedback alone was insufficient when wearing comfort remained low, while comfortable wearing conditions produced stronger immersion when accompanied by stable interactive response.

## 5. Discussion

The higher levels of immersion and expression reveal that there was a change in the bodily interaction of the user with the jewel because of the touch behavior. The LED feedback translated the physical interactions to instant visual feedback, which gave the jewel an expressive ability. Comfortability dropped from 4.33 to 4.16, meaning that the electronic element brought about some level of physical load. The response latency proved to be a better predictor than touch frequency in the random forest algorithm. Frequent use alone could not lead to high levels of immersion since instant feedback played a bigger part. Comfortability and SUS also emerged as important predictors, meaning that artistic interaction relies on the bodily interaction of the user and system ease of operation.

## 6. Conclusion

The study of interactive experience in contemporary jewelry has been conducted through the lens of wearable art based on an interactive brooch that utilizes ESP32 board and capacitive touch sensing along with LED feedback and Bluetooth low energy. In a within-subjects experiment with 48 participants, logs from the system as well as users' experiences were gathered. With paired samples testing, differences between the two prototypes in terms of usability, immersion, and emotional expression have been established. In addition, random forest classification has distinguished states of high and low immersion and established the latency in response, wearing comfort, and SUS as the features. It can be concluded that computing technology has turned interactive experience in embodied jewelry into a quantifiable and predictable data-driven process.

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