BraidFlow: A Flow-annotated Dataset of Kumihimo Braidmaking Activity

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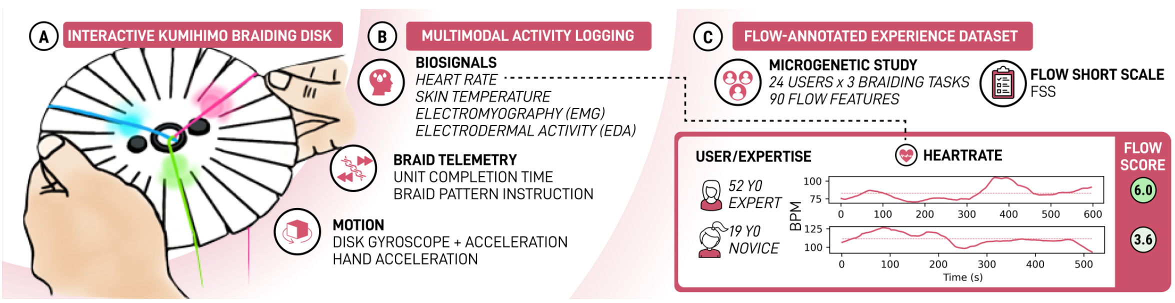

Figure 1: (A) BraidFlow uses an instrumented Kumihimo braiding disk to capture the experience of 24 users engaged in braidmaking task; (B) this flow-intensive activity is documented with quantitative data from off-the-shelf sensors, braiding telemetry, and qualitative data. (C) Each feature in the dataset is annotated with labels derived from the Flow Short Scale (FSS) to support the research community in understanding the conditions that trigger and sustain cognitive flow.

ABSTRACT

Entering a cognitive state of flow is a natural response of the mind that allows people to fully concentrate and cope with tedious, and often repetitive tasks. Understanding how to trigger or sustain flow remains limited by retrospective surveys, presenting a need to better document flow. Through a validation study, we first establish braidmaking as a flow-inducing task. We then study how braidmaking can be used to unpack the experience of flow on a moment-by-moment basis. Using an instrumented Kumihimo braidmaking tool and off-the-shelf biosignal wristbands, we record the experiences of 24 users engaged in 3 different braidmaking tasks. Feature vectors motivated from flow literature were extracted from activity data (IMU, EMG, EDA, heart rate, skin temperature, braiding telemetry) and annotated with Flow Short Scale (FSS) scores. Together, this dataset and data-capture system form the first open-access and holistic platform for mining flow data and synthesizing flow-aware design principles.

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CCS CONCEPTS

• **Human-centered computing Interaction design process and methods**; *Empirical studies in interaction design*.

KEYWORDS

sensor data; creativity; data collection; cognitive flow

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1 INTRODUCTION

Flow is a cognitive state where a user's expertise and the challenge of the task at hand match (*skill balance*), allowing the user to optimize physiological activity and fully concentrate and cope with difficult tasks. This *action-perception coupling*) [18] is regularly encountered in skilled textile crafts where users are often fully immersed and engaged [12]. As a positively valenced state [18], flow can also be linked to "the joy of making" associated with tedious and error-prone craft practices [12].

Despite extensive research on flow, studies continue to use flow primarily as a qualitative metric; understanding the conditions for flow to occur and the consequences of flow states over time has been less intensively studied [18]. Since current flow assessment approaches require long retrospective psychometric surveys, studying flow on the moment-by-moment scale remains challenging. Emerging research has identified physiological correlates that could be used to determine flow continuously and non-obstructively using sensor-based approaches [16–18, 38]; however, there remains a disconnect between the mechanisms that contribute to a user's flow in context and presents a need to better document flow. Consequently, public datasets that describe cognitive experience typically represent a single contextual factor [9, 44, 51, 52] and those that specifically describe flow [24] do not have the scale needed to isolate user variations and enable flow modeling.

We study how a flow-intensive task like braidmaking can be used to unpack the experience of flow and its counterpart, fall, on a moment-by-moment basis. We chose to study Kumihimo braidmaking, a traditional Japanese braidmaking technique that uses a braidmaking disk to help hold and track braiding yarns, making it easy to learn and observe [11, 31]. This work is not aimed towards developing methods to induce or sustain flow but to better document the flow experience for both design and scientific inquiry. Our work contributes:

- An open-source interactive Kumihimo braidmaking tool used as a research instrument for studying flow activity. The Kumihimo tool is instrumented with off-the-shelf physiological and activity sensors and provides live programmable visual and sonic feedback to users. The disk is capable of logging braiding telemetry, including braiding progress, motion, and interaction data. The disk can be used to repeatedly study minute changes in detail, such as individual skill progression (i.e., microgenetic design [1]). The disk similarly supports on-the-fly braiding pattern instructions, which can be used to dial in task difficulty and track and monitor performance (e.g., number of rows, speed, overall length). Through a validation study, we confirm that the Kumihimo tool does not inhibit flow and that braidmaking is a high-flow activity using the Flow Short Scale [39].
- An open-access flow experience dataset documenting the flow and braidmaking experience of 24 participants with 72 repeated tasks (3 unique tasks each). We extract over 90 flow-motivated features from multi-modal sources, including interaction logs, motion data from the braiding disk (IMU), muscle activity of the forearm (EMG), motion activity of the wrist (IMU), and physiological activity of the body (EDA/heartrate/skin temperature). Each feature vector is annotated with self-reported flow scores derived from flow models in literature [39, 49].
- A statistical data analysis describing initial insights of flow behaviors from the dataset. The data is analyzed at a *session-level* (i.e., features generated from the overall braiding session) and at a *window-level* (i.e., features extracted by sliding windows across time series data). We analyze how flow perception is linked to a user's expertise, motion, and physiological responses during the braidmaking process.

In this paper, we first position our work against existing cognition, flow, and braidmaking documentation methods. We then present the design of a research instrument for tracking braiding behavior using a Kumihimo disk. The disk is then used during an initial validation study with 10 participants, followed by a data collection study with 24 participants. An analysis of the resulting BraidFlow Dataset is then used to assess the validity of current flow theories and identify opportunities for design. Although our dataset documents the experience of flow in braidmaking, findings from the dataset can be used to communicate to other designers and researchers behaviors to observe or reflect upon when understanding the interplay between the body, mind, and material in creative practices. We discuss future research directions for leveraging flow and flow detection as design variables in creative interfaces across different domains in HCI.

2 RELATED WORK

Since flow cannot be seen as a discrete situation triggered by some phenomena, measuring and modeling flow remains a challenge [18]. Different research communities have developed customized methods of assessing flow; we describe efforts for capturing flow activity and analyzing flow data. Since the braiding tasks form the center of our data collection process, we situate our Kumihimo braiding task for data collection among prior research in braidmaking and hand textiles.

2.1 Experience Datasets and Cognitive Flow Models

Tangible and playful interfaces hold promise in naturalistically capturing data describing human cognition. Sharlin et al. demonstrated how tangible instrumented cubes could be used to understand user performance on a 3D construction and spatial assessment task[54]. In the context of flow activity, Klarkowski et al. [33] designed three different video game levels aligned to existing flow design principles but, when empirically tested, found inconsistencies in expected flow experiences. Balancing capturing the full experience, including unexpected contextual factors, with models that apply across users remains a difficult pursuit. Eteke et al. [19] captured 74 minutes of motion data of a match between two tennis players, leveraging an expert-labeling method [24] (their tennis coaches) to label their dataset into flow and fall states. Others have explored multimodal approaches for capturing user experience or cognition-based datasets [24, 29, 47]. Advances in machine learning have helped create cognitive models to classify flow using sensorimotor modalities such as physiological signals: heart rate variability [42, 51, 52], ECG [44], EEG [9] pupil dilation [42]. However, several contextual factors limit the applicability of a single modality to detect flow accurately.The BraidFlow Dataset represents the largest dataset documenting flow activity that combines multimodal sensor data and qualitative transcripts and videos. In addition, flow activity in the dataset is annotated with flow labels derived from existing models in flow literature [39, 49, 50].

2.2 Understanding Flow & Creative Activity

There is disagreement amongst flow scholars on how to create and sustain *flow* states. Csikszentmihalyi et al. [13] proposed that challenge-skill matching is necessary to induce flow, whereas Leach et al. noted that balancing challenge and skill is not always an antecedent of flow [21]. Alternative models and definitions of flow have gained traction. Barthelmas et al. [3] proposed a revised flow model which incorporates the value of the activity to the user as a factor. Jalife et al. found inconsistencies in Csikszentmihalyi flow theory when approached from a cognitive science perspective and proposed a more concise and singular *fuse* property – the fusion of activity-related sensory stimuli and awareness [25] – to identify and explain flow phenomena. Frameworks applying these flow theories have been used to analyze creative activity to help understand flow at a more granular level [15, 26]. We acknowledge the problematic framing of flow in our work and propose an open-access dataset that provides rich information to flow researchers for testing and evaluating both holistic and granular flow hypotheses juxtaposed with qualitative data. Our dataset uses a microgenetic study design to further examine how physiological flow experiences might differ from user to user. Microgenetic studies involve a high density of observations which can be useful for investigating the interactions through which learners acquire new competencies [55].

2.3 Sensing Neurological States via Physiological Signals

Physiological signals can be used to indicate a user's neurophysiological state. Direct physiological signals like electromyography (EMG) for muscle stimulation or capnography for respiratory (RESP) rates can be manipulated by a user's environment [2]. Physiological senses such as voluntary breathing or voluntary muscle movement can be exercised by the user's free will. By utilizing indirect physiological signals, these signals cannot be easily manipulated during the user's neurological state of flow [2, 38]. Andres et al. [2] used indirect neurophysiological sensing, including electroencephalogram (EEG), heart rate (HR), and galvanic skin response (GSR), to determine that instinctive reflexes from peripheral vision, which indicated a change in neurological activity by EEG [2]. Léger et al. [43] found an association between an increase in the EEG alpha band and a decrease of spectral power in the beta band, indicating a cognitive state of relaxation and a more automated neurophysiological state [38, 43]. Our work operationalizes how these sensing approaches could be used to support the design of interactive systems. Our Kumihimo research instrument is purposefully designed with off-the-shelf biosignal wristbands to improve access to studying flow and physiological signals.

2.4 Studying Braidmaking and Hand Textiles

Textile-handicrafts making has been practiced by diverse people as a cultural and historical art-making activity [11, 35, 60]. Chottikampon et al. [11] conducted an eye-movement measurement-based study to compare the expert and non-experts braid makers, finding that expert braiders' eyes remained focused on the center of the Marudai disk (a stationary version of the Kumihimo disk) and that non-experts showed the development of this skill [11]. To provide better braid-making instructions to non-experts, Kimura et al. [31] studied the differences between the Kumihimo and Marudai disks. Results revealed that the Kumihimo disk is more effective in braidmaking for non-expert users [31]. Furthermore, using a Kumihimo disk for beginners helps to learn strands movement around the disk during braiding. This experience provides better control of strands while braiding on Marudai. Subsequently, Kimura et al. extended their study, emphasizing different factors of Marudai braidmaking, such as the height of stands, strands, and stand angle, to avoid the complexity of moving strands and provide instructions for beginners [32]. To accommodate the range of skill levels in our flow study, we use a Kumihimo disk. We also introduce braiding telemetry to capture individual braiding instructions, movements, and interactions with our research instrument.

3 TRACKING BRAIDING BEHAVIOR

A braid is formed when several flexible yarns are intertwined with each other into either flat or round structures that exhibit high tensile strength [36]. In craft practices, the act of braidmaking is a skilled practice that aligns well with flow's *action-perception coupling* requirement: manipulating multiple yarns and maintaining tension requires physical dexterity while keeping track of braid instructions can require full cognitive attention. To better study and influence flow, braidmaking also affords a simple way to alter the difficulty of the task by increasing the number of yarns, allowing us to alter the task to match a user's skill level (*skill-balancing*).

To better study braidmaking activities, we designed an instrumented braiding disk, i.e., a circular slotted structure that helps hold and track different yarns [31], that draws from traditional Japanese Kumihimo techniques for producing both functional load-bearing cords and decorative cords [11]. The instrumented disk was designed to maintain the same lightweight and untethered features of the traditional Kumihimo disk while also logging braiding telemetry (braid steps and progression, disk motion) and providing multimodal feedback (visual LED, buzzer tones)[1]. Using WebSocket communication, the disk operates as a connected device that streams sensor data wirelessly and allows braiding instructions to be sent on the fly. Designing around the Kumihimo practice provides important advantages in accessing grassroots innovations from the braidmaking community (e.g., weighted spools, cooperative yarns, online tutorials).

Technical and Fabrication Details. The Kumihimo disk is composed of a custom PCB board housed within a laser-cut slotted disk (Figure 2).

- **PCB**: An FR-1 printed circuit board was milled on a BantamTools CNC machine in a toroid shape (outer: 160 mm ⌀, inner: 20 mm ⌀, height: 1.6 mm). On the user-facing side, the board exposes a 24-LED NeoPixel Ring (Adafruit 1586) and two surface-mount momentary push buttons; on the underside, the board contains a 9-axis absolute orientation inertial measurement unit (IMU) (Adafruit 2472), a piezoelectric buzzer, a microcontroller (Adafruit Feather WiFi M0 WIN5100), and a dedicated 500mAh lithium battery.
- **Acrylic Disk & Housing**: Using paper.js, we created a parametric model capable of expressing slotted disks with a variable number of slots and slot type (e.g., to support multiple yarn sizes). Disk designs are then exported as support vector graphics (SVG) and laser cut from 3 mm cast acrylic; a 3D

[1] Hardware and software design files, a bill of materials, and fabrication instructions have been made available as supplementary materials

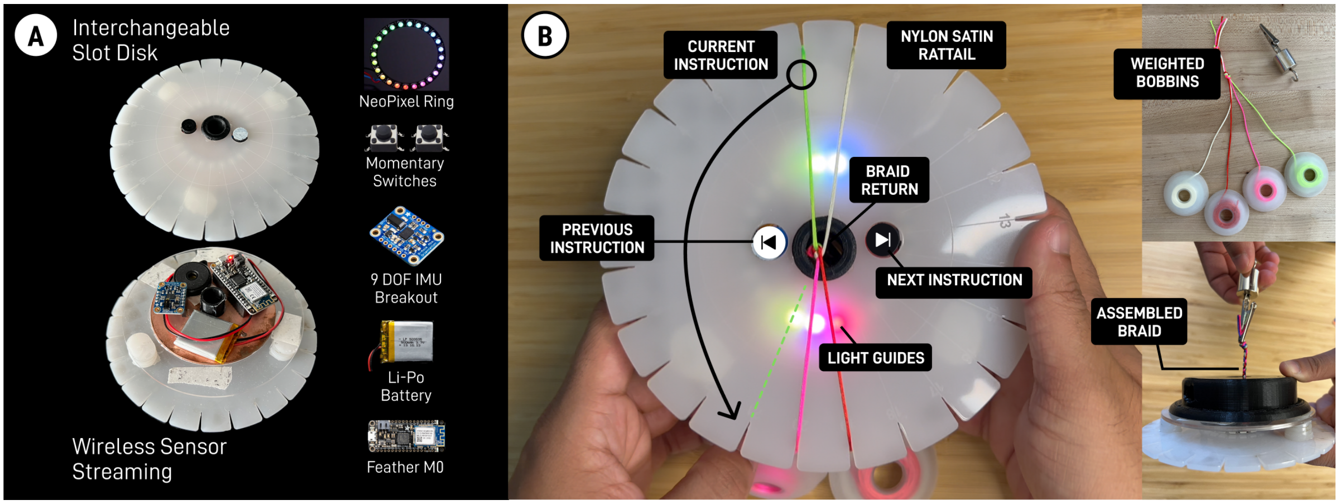

Figure 2: The BraidFlow Kumihimo Disk. (A) A plastic Kumihimo disk is cut from acrylic and instrumented with a custom PCB for enabling visual and haptic feedback and motion sensing; (B) the user can control braiding instruction using momentary buttons; weights are added to the strands and assembled braid to maintain tension in the braid form.

printed enclosure was attached to the underside of the disk to protect electronics and provide a handhold.

- **Communication**: To enable real-time communication, the disk was configured as a WebSocket client that connects to a cloud WebSocket server; the cloud server acts as a router directing JSON messages between (1) scripts used to control the expression of lights and buzzer sounds on the disk, and (2) scripts used to direct sensor stream data into a MongoDB database.
- **Telemetry** For each braid instruction, the disk sends a timestamp of the instruction and the instruction identifier. IMU orientation data is streamed and logged throughout the braiding session at a sample rate of 3.8 samples per second. Using this data, we can track braiding instructions and the user's overall braiding speed. Inspecting the IMU data provides qualitative information on a user's interactions with the disk (e.g., flipping it over to inspect the braid).

3.1 Interactive Braiding Instructions

To relay braiding instructions to users, we first reformulated popular braiding techniques to fit a 24-slot disk. For example, a simple flat braid uses four yarns and six distinct slots (A-F). We then encode instructions as the movement of a single yarn between two slots (A → C). A *braiding cycle* is defined as the number of instruction that needs to be carried out until the yarn positions match the initial yarn positions. Completing one braiding cycle produces one braid unit. To help with tracking yarn positions, each yarn is assigned a unique color. To indicate an instruction (e.g., A → C), the disk illuminates the LEDs corresponding with slots A and C with the yarn's unique color. To reduce error, the LEDs corresponding to filled slots are also illuminated. The user has control to move forward or backward in the instruction set using the two momentary buttons on the disk, accompanied by a buzzer feedback melody.

In our supplemental materials, we provide the instruction set for forming a 4-stranded flat braid (V; 6 instructions), a 6-stranded flat braid (X; 10 instructions), and a 4-stranded round braid (R; 6 instructions) (Figure 4).

4 VALIDATION STUDY

In designing the instrumented Kumihimo disk, many unforeseeable factors may have been introduced that alter the kumihimo braidmaking experience. For instance, while theoretical flow models indicate that braidmaking and other needlecrafts are flow-inducive tasks, this has yet to be verified in an experimental study. If braidmaking is indeed flow-inducing, is a short braidmaking session sufficient for a participant to experience a flow state? Can a participant who does not have experience braiding or used a Kumihimo disk enter into these flow states?

We conduct a validation study to (1) assess Kumihimo braidmaking as a viable activity for study, (2) understand whether the instrument is able to collect rich data while minimizing obstructing the activity and braidmaker, (3) assess if braidmaking can be studied in an experimental setting.

4.1 Recruitment and Participant Selection

We recruited participants from *anonymized* mailing lists within our institution. Due to COVID-19 pandemic precautions, only participants 18-65 years old were eligible for the study. The study comprised of 10 participants (5 female, 5 male), 24.9 ± 3.78 years old. All participants were right-handed and 6 participants had prior experience in needleworking crafts.

4.2 Study Task

Study parameters were chosen to best emulate a natural braiding session. We chose a simple braiding pattern to reduce cognitive load and allow participants to rely more on their working memory.

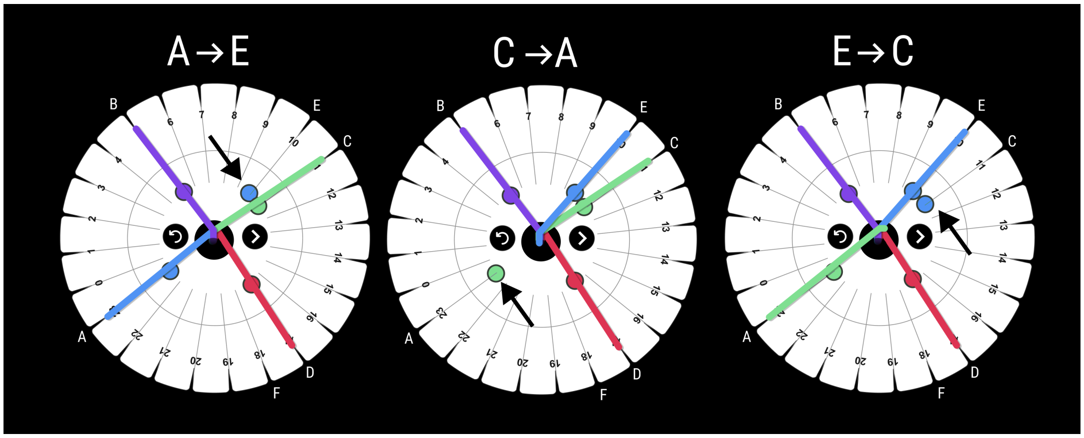

Figure 3: Braid Instructions. The first three instructions of a 4-strand round-braid are displayed. Strands are secured to slots, and the LED instruction informs the user what yarn movements to make. A user advances these instructions using a push button, repeating the pattern until a fully-formed braid emerges.

Identifier	Braid	Strands	Shape	Unit Instructions
X		6	Flat	10
V		4	Flat	6
R		4	Round	6

Figure 4: Braid Types. The instrumented disk relays instructions for three types of Kumihimo braid patterns of differing complexity.

The within-subjects study tasked participants with creating a flat braid (Type V) for 10 minutes using two different Kumihimo disks:

- **Passive Traditional Kumihimo Disk (P-TKD)** - We designed a minimally instrumented braiding disk as our baseline condition. Using an off-the-shelf lightweight foam Kumihimo disk, we carved a cavity to recess a PCB with an Adafruit Feather module and 9-axis IMU (Adafruit 2472) sensor. The foam slots of the disk allow yarns to be more securely held in place with tension, removing the need to have weighted spools.
- **Passive Instrumented Kumihimo Disk (P-IKD)** - The plastic disk described in Section 3 was configured into a passive data-collection form - no interactive instructions, lights, or sounds were used. Weighted spools were used to keep yarns in tension.

Protocol. After obtaining informed consent, participants filled out a demographics questionnaire assessing potential flow antecedents (e.g., braiding experience). Participants were then introduced to a tutorial video on interpreting and operating the Kumihimo disk and written braiding instructions. The two conditions of the study (baseline and instrumented) were alternated, and each task lasted 10 minutes; users were not aware of the cut-off time to mitigate confounds from time stress [57]. We conducted a post-task survey to measure participants' Flow Short Scale (FSS) score using the revised flow model [39, 49] (Appendix A.1) adapted to braiding tasks. This was followed by a short semi-structured interview, probing participant experience, emotion, time perception, and fatigue.

Study Setup. The user study area consisted of an ergonomic chair and a table. All the necessary materials, such as the braidmaking disk, thread for braiding, and instruction manual were placed on the table (Figure 7). An iPad was placed on a stand and positioned to record table activity. A desktop iMac was used by the users to fill out all the necessary questionnaires and run the braiding disk software.

4.3 Results

Both the baseline condition and instrumented condition yielded the same distribution ($FSS_{\text{P-TKD}}: 5.3 \pm 0.26$, $FSS_{\text{P-IKD}}: 5.4 \pm 0.27$). A Wilcoxon signed-rank test indicates that there is no evidence of difference between the levels of instrumentation of the disk ($W = 12.0$, p-value$= 0.2512$). For context, FSS Scores reported from empirical studies of flow have reported values of 4.34 in the middle of a college lecture [50] and 3.29 for a basketball shooting task [23]. Our results indicate that braidmaking is able to achieve much higher

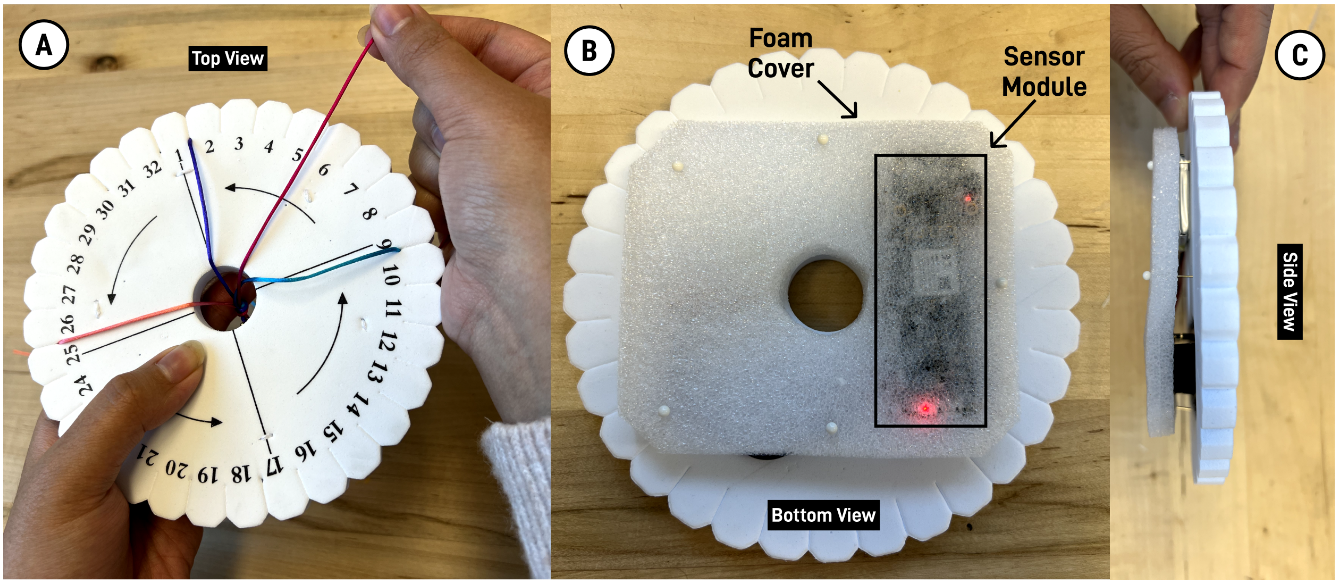

Figure 5: Data Validation (P-TKD). A traditional Kumihimo disk is instrumented with a custom PCB for enabling motion sensing; (A) top view, (B) bottom view and (C) side view. This disk forms the Passive Traditional Kumihimo Disk for our validation study.

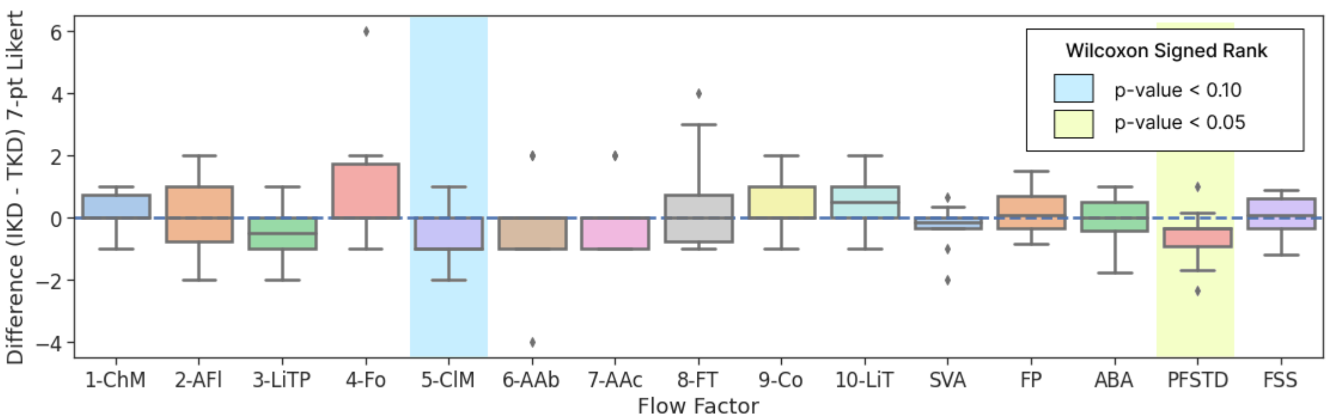

Figure 6: Boxplot Comparison between Traditional and Instrumented Disk Flow Experience

FSS scores in short experimental periods and that the ergonomics of the instrumented kumihimo disk do not affect the flow experience.

We performed a Wilcoxon signed-rank test to assess the null hypothesis that the instrumented disk P-IKD shows no difference in flow factors from the traditional disk P-TKD (control treatment). We applied a two-sided test on 21 flow factors (a subset is depicted in Figure 6); in instances where several ties were encountered or a normal distribution was encountered, we used a paired t-test to assess for differences in the two treatments. Only two factors had statistically significant differences ($\rho < 0.05$): Demand(FSS #16; $\Delta\mu$ =-1.1, t(9)= 0.032, ρ=0.010) and Perceived Fit of Skill and Task Demand (FSS-D #2; $\Delta\mu$ -0.6, W(10) = 8.5, ρ=0.048). These negative trends in these factors indicate that the instrumented disk was perceived as making the braiding task less demanding and easier. Performance using the disks corroborates this finding: users produced 26.46% more braid units on average using the P-IKD compared to P-TKD.

Notably, larger differences in Demand were reported by participants with prior needlecrafting experience. Initial trends indicate that these skilled participants reported marginally higher overall FSS scores when using the instrumented Kumihimo disk ($+0.3 \pm 0.2; n = 6$) while novices experienced a decrease in FSS ($-0.2 \pm 0.2; n = 4$). This aligns with the skill-balance hypothesis that an easier task and high skill allow users to enter flow more readily.

We inquired users on whether the users felt that they were being observed during the tasks. 9 out of 10 users reported not feeling observed. Participants indicate that the instrumented disk

(P-IKD) did not hinder their experience in the task and we observed overall positive feedback when users were asked to compare which version of the braiding disk they preferred. In our interviews, we inquired about the ergonomics of the disk and participants were not uncomfortable while working with the instrumented disk (P-IKD):

U9 [P-IKD] was more comfortable to hold.

One user pointed out that the weight of the disk was causing difficulty at times but still considered the instrumented disk more stable to work with:

U2 [the task] was comparatively easier because the apparatus [P-IKD] itself is better than the previous [P-TKD] one. At the same time, I was having difficulty because [P-IKD] was heavier.

Users also noted that the task faded into the background:

U9 [the task] almost felt like second nature. So [I can do this task] when I watch TV and listen to music.

Our validation study indicates that Kumihimo braidmaking is a flow-inducing activity and that the ergonomics of our instrumentation approach do not affect the flow experience but do reduce the task difficulty. This validation study studied the Kumihimo research instrument in isolation, and we anticipate other potential confounds will occur when integrated with other forms of instrumentation (e.g., physiological sensor wristbands or electrodes) or interaction (e.g., interactive instructions). We will use the results from the validation study to distinguish between confounds attributed to the passive Kumihimo disk versus other forms of instrumentation.

5 DATA COLLECTION STUDY

We conducted a formal data collection, expanding the scope of the Kumihimo disk to capture additional modalities of information. Our goal was to construct a dataset comprising both quantitative and qualitative data that could be used by a diverse set of researchers to understand the mechanisms behind the flow. We also prioritized using readily available sensors for designers to incorporate within their own interactive systems.

5.1 Recruitment and Participant Selection

We recruited participants from *anonymized* through the university mailing lists. Due to COVID-19 pandemic precautions, only participants 18-65 years old were eligible for the study. The final BraidFlow Dataset describes the braiding experience of 24 participants (14 female, 10 male), 25 ± 1.58 years old. The dataset was balanced on expertise using a self-report Likert questionnaire assessing experience with different needlecrafts and qualitative descriptions of prior projects participants had completed in the past; this resulted in 12 experienced participants and 12 newcomer participants. 19 participants were right-handed, 3 left-handed, and 2 were ambidextrous.

5.2 Study Design

Setup. The study was conducted in a lab setting and consisted of the instrumented braiding disk, an E4 wristband[2], and a Myoware EMG sensor as shown in Figure 7. Although we planned to place the E4 wristband on the non-dominant hand to minimize motion artifacts[46], we encountered that participants often held the Kumihimo disk still with their dominant hand and used their non-dominant hand to move yarns. To minimize these motion artifacts, we placed the wristband on the dominant hand with the E4 electrodes aligned to the ring finger to capture electrodermal activity (EDA), motion, and heart rate data.

Surface EMGs are widely used in non-medical and engineering applications [27]. We used two-channel MyoWare and placed one electrode on the forearm muscle (*Palmaris Longus*) and the ground electrode near the elbow [20]. The **MyoWare** electrodes measure the muscle activity during rest and forceful or light contraction of the dominant hand muscles. There is a trade-off in using off-the-shelf sensors – while affordable, these sensors are prone to signal noise. We address these issues by removing dirt and oil from the skin with an alcohol wipe prior to placement and manually calibrating and checking sensor values against a set of template exertions of the forearm.

The user study area consisted of an ergonomic chair and a table. All the necessary materials, such as the braidmaking disk, thread for braiding, MyoWare EMG sensors, E4 sensor, and alcohol wipes, were placed on the table (Figure 7). An iPad was placed on a stand and positioned to record table activity. A desktop iMac was used by the users to fill out all the necessary questionnaires and run the braiding disk software.

Protocol. Each user was then asked to perform 3 braidmaking tasks: a simple flat braid (V), a complex flat braid (X), and a simple round braid (R). The protocol mirrors the validation study protocol with the exception of a waiting period for sensors and wristbands to obtain baseline data. Ordering was counterbalanced on a Latin square, and each task lasted 10 minutes; users were not aware of the cut-off time to mitigate time stress confounds. The same questionnaire (Appendix A.1) and interview were conducted as in the validation study.

6 THE BRAIDFLOW DATASET

The Braidflow Dataset is stored within a NoSQL database (MongoDB) as JSON documents. Each data modality (e.g., braiding telemetry, IMU, EDA, EMG) was stored as a separate collection, each with two types of feature sets: *session-level features* - features generated from the overall braiding session, and *activity-window features* - features extracted by using a sliding window (10 seconds, 50% overlap) across the time series data. Flow is not an instantaneous [14] event. To capture the temporal qualities of flow, we use sliding windows of 10 seconds for telemetry and motion data and 90 seconds to capture physiological data. Motion and physiological data are stored as time-series with absolute time, relative time, and its corresponding sensor data. The collections describe 72 sessions across 24 users and include:

- **Demographics.** [# of features: 13] User demographics include age, gender, dexterity and self-reported skill, and expertise classification. We balance our dataset on skill and use that as one of the lenses to analyze trends in the extracted features.
- **Braiding Telemetry.** [# of features: 6] For braiding telemetry, the dataset encodes the braiding pattern, braidwork features, and duration of each braiding session. Braidwork features are extracted based on braiding speed, advancing or

[2]https://support.empatica.com/hc/en-us/categories/200023126-E4-wristband/

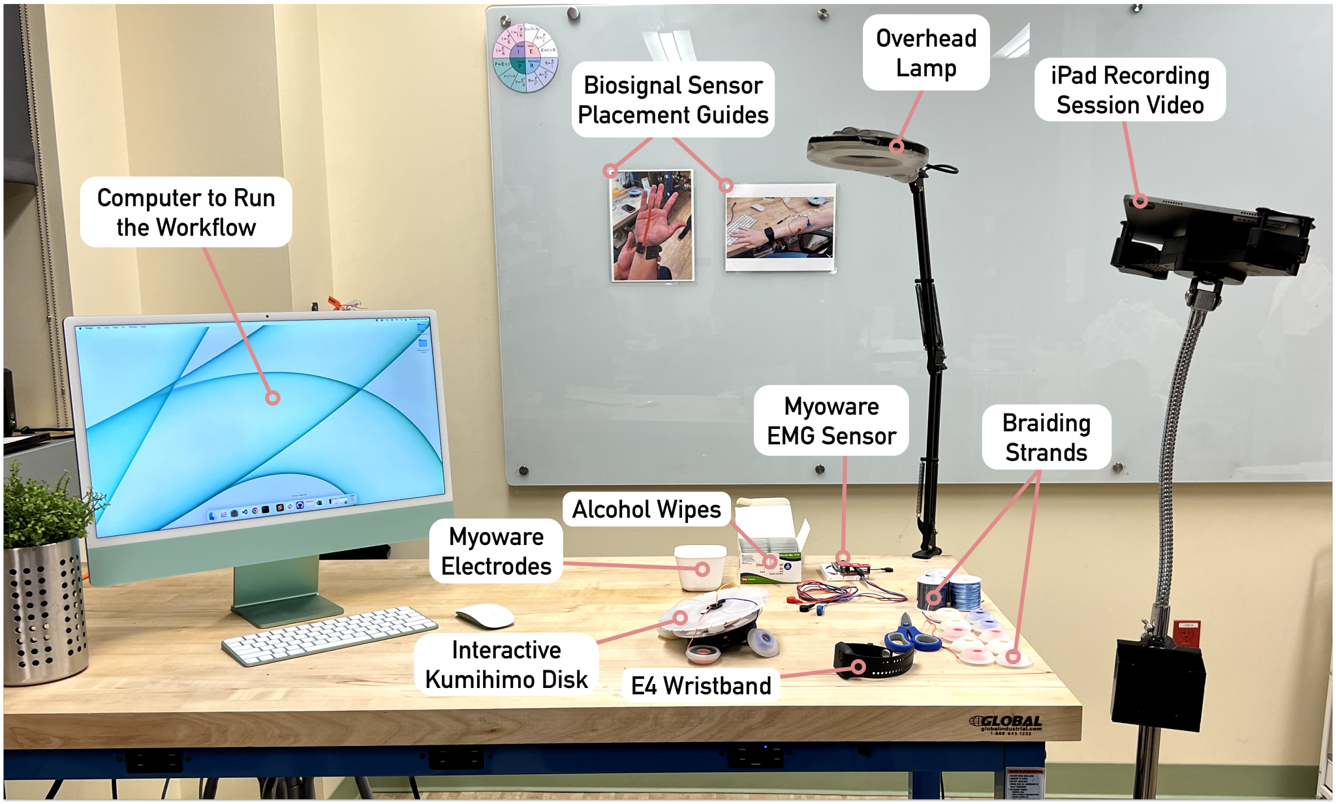

Figure 7: Braiding Study Setup. A mise-en-place view of the braiding task study setup. The participants used an interactive Kumihimo disk while wearing an Empatica E4 wristband and Myoware EMG sensors. The tasks were recorded on an overhead iPad, situated away from the working space of participants to avoid hindrance. [Note: The validation study setup did not have biosignal-related sensors.]

USERS

Gender	10 Male	14 Female	
Handedness	19 Right	3 Left	*
Experience	12 Newcomers	12 Experienced	

* 2 Ambidextrous

TASKS

Braid	Strands	Instructions	Total Duration
V-Braid	4	6	217 min
Round	4	6	233 min
X-Braid	6	10	224 min

FEATURES

Data Origin	Data Source	# of Features
Self-Report	Demographics	13
Braiding Disk	IMU Braid Telemetry	17 6
Wristbands	IMU EMG EDA Heart Rate Skin Temperature	12 14 14 7 7
		Total 90

Figure 8: The BraidFlow Dataset. The braid-flow dataset breakdown shows user demographics, task variation, and feature extraction from data collection from different modalities.

undoing braiding steps, and the overall braiding instructions completed. Session-level features are normalized by factoring in braiding session duration.

- **Motion Data.** [# of features: 29] Two sources of motion data are collected from braidmaking sessions: IMU of the user's dominant hand and the Kumihimo disk. The user's dominant hand IMU (32Hz) sensor consists of an accelerometer and is worn on their dominant hand (wrist) while they are performing the tasks. The Kumihimo disk's IMU (4Hz) consists of an accelerometer and a gyroscope. While generating the motion features, we consider the acceleration and speed of the braiding disk as well as the E4 wristband in all axes. We try to capture if there is an autotelic motivation during the braidmaking process by checking if a user flips the braiding disk to glance at their braid.

- **Biosignals.** [# of features: 42] The users' physiological data are sourced from two devices: an Empatica E4 wristband and a Myoware EMG sensor. We include the heart rate (1Hz), electrodermal activity (4Hz), skin temperature (4Hz), and muscle activity (EMG, 8Hz) of each user's dominant hand. Physiological data is stored as a time-series with absolute time, relative time, and its corresponding sensor data. We extract the baseline, mean, range, and standard deviation of the heart rate and skin temperature of a user during the sessions. We also calculate the frequencies of the peaks and valleys in the signals (heart rate, skin temperature). For featurizing the electrodermal activity (EDA) and electromyography (EMG) data, we measure the amplitude, recovery time, and rise time of the skin conductance response. Mean, range, and standard deviation of values are reported for phasic features. We quantify the nature of the signal in the EDA and EMG data by calculating the area under the curve of the signal using the composite trapezoidal rule for tonic features. EDA and EMG signal-cleaning and feature extraction is done using the NeuroKit toolbox [45] in Python 3.
- **Flow Short Scale.** [# of labels: 21] We annotate the dataset by using 16 questionnaire items from the Flow Short Scale and deriving 5 additional labels by averaging the score of specific items. The full list of questions and derived labels are detailed in the Appendix.
- **Qualitative Data.** The dataset includes post-task interview transcripts and videos of all braidmaking sessions. The transcripts were generated from audio recordings; both videos and transcripts had identifiable characteristics removed.

Numerical features were z-score normalized except in instances where a theoretical range was present (e.g., Likert Scale) and min-max feature scaling was more appropriate. Session-level features were further normalized by session duration. Qualitative data was anonymized and compressed. The full list and description of 90 extracted features are available as supplementary material.

7 RESULTS

This section details the insights we gained from the data collection study. We first present a numerical report of statistically significant features (*Scores and Ratings*) and present themes formed from engaging with both qualitative and quantitative data.

7.1 Methods

Quantitative Analysis. We performed a set of statistical significance tests to understand the differences between our independent sample populations (Newcomers and Experienced Users (N, E)) and dependent sample conditions (Braid Type (V, X, R)). For normal distributions, we performed a two-sided independent t-test and paired t-test, respectively. For skewed distributions, we performed a Mann-Whitney U Test and a Wilcoxon signed-rank test, respectively.

Flow Indicator Features. In our analysis, we first examine each feature in our dataset against the flow labels that annotate each braiding session. We use the Pearson correlation coefficient (r) to analyze the relations between these pairings of features. We report strong ($0.8 > r > 0.6$) and moderate ($0.6 > r > 0.5$) correlation results; for instances where neither are found we indicate weak flow indicators to signal potential trends ($0.5 > r > 0.4$).

Window Level Features. Since each braiding session of approximately 10 minutes might not exhibit the same characteristics throughout the entire session, we divided the braiding sessions into bins of 10 equal sub-sessions, S1 through S10, and conduct an equivalent analysis on these subsessions. We present our findings across the different modalities of data in the themes below. Flow labels are abbreviated below as FSS#X and correspond to items in the Flow Short Scale questionnaire (Appendix A.1); derived factors are annotated as FACTOR#X. Unless otherwise annotated, all Likert values reflect values from a 7-point scale.

7.2 Ergonomics and Flow Inhibition Effects

Compared to the validation study, our experimental setup included additional worn sensors and interactive instructions. All participants were able to successfully use the Kumihimo disk and reported minimal discomfort in wearing the Myoware and E4 wristband (Myoware comfort: 6.5 ± 0.1, E4 comfort: 6.4 ± 0.1). Average FSS scores between the dataset and validation populations showed no significant difference ($t(19) = 0.87$; $\rho = 0.3858$), indicating that there was no evidence of the study protocal having adverse effects on the flow experience of users.

7.3 Flow Indicator Features

Using the complete BraidFlow dataset, we first identify overall session-level flow indicators independent of braiding task or user expertise (Figure 10). A total of 8 weak flow indicators were encountered: 4 braiding features negatively correlated to LOST IN THOUGHT (FSS#10), 3 positively correlated biosignals tied to cognition (FSS#4 FOCUS, FSS#8 FORWARD THINKING), and 1 negatively correlated motion feature to ACTION FLUIDITY (FSS#2). We test all 77 non-demographic features with the 16 FSS items and 5 FSS Derived Factors and only report those with $\rho<0.001$.

Experience-based Flow Indicators. Our correlations analysis showed that experienced users form strong positive ties between SELF EVALUATION (FSS#15) and the number of revolutions in the braid that they completed (Figure 11). This directly ties in with the "Results Worth Effort" subscale found in the Creativity Support Index [10] and indicates the resulting braid acted as a reward. However, this relationship was not encountered with newcomer participants. We noted, from our interactions with these participants, that they rarely looked at their braid during or after the task, potentially leading to different criteria for how newcomers assessed success or satisfaction. Similar to Figure 10, we test all 77 non-demographic features with the 16 FSS items and 5 FSS Derived Factors and only report the ones with $p<0.001$.

Task-based Flow Indicators. Flow indicators features for the EASY (R) braiding task included 4 moderate braiding features positively tied to SELF EVALUATION (FSS#15). These features are based on

	BRAID TYPE (n=45)					EXPERTISE (n=68)				
FLOW LABEL	Mean (R)	Mean(X)	p	Statistic	Ha	Mean (E)	Mean (N)	p	Statistic	Ha
FSS #1: CHALLENGE MATCH	4.7	5.1	0.470	U=221.5		5.3	4.7	0.350	U=502.5	
FSS #2: ACTION FLUIDITY	5.5	5.5	0.806	U=242.0		5.5	5.3	0.980	U=575.0	
FSS #3: LOSS OF TIME PERCEPTION	4.8	4.8	0.982	U=251.5		4.7	4.6	0.921	U=569.0	
FSS #4: FOCUS	5.6	5.2	0.582	U=229.0		4.9	5.7	0.101	U=447.0	
FSS #5: CLEAR MINDEDNESS	5.1	5.0	0.668	U=234.0		4.6	5.2	0.078	U=436.0	E<N
FSS #6: ACTION ABSORPTION	5.6	5.7	0.915	U=248.0		5.5	5.8	0.214	U=479.5	
FSS #7: ACTION ACCORD	5.7	5.3	0.238	U=202.0		5.7	5.2	0.223	U=480.5	
FSS #8: FORWARD THINKING	6.1	5.7	0.297	U=209.0		5.8	5.7	0.735	U=550.5	
FSS #9: CONTROL	5.7	5.4	0.620	U=231.5		5.6	5.3	0.671	U=543.5	
FSS #10: LOST IN THOUGHT	4.0	3.8	0.661	t=0.4		3.8	4.1	0.471	t=-0.7	
FSS #11: RELEVANCE	3.1	3.3	0.766	t=-0.3		3.0	3.4	0.388	t=-0.9	
FSS #12: CARE	4.5	4.3	0.747	t=0.3		4.2	4.7	0.280	t=-1.1	
FSS #13: WORRY	2.5	3.0	0.345	t=-1.0		2.6	3.2	0.182	t=-1.3	
FSS #14: PERCEIVED DIFFICULTY	2.0	3.3	0.004	t=-3.1	R<X	2.6	2.9	0.584	t=-0.6	
FSS #15: SELF EVALUATION	7.4	6.5	0.075	t=1.8	R>X	6.9	6.9	0.849	t=0.2	
FSS #16: DEMAND	4.0	4.6	0.106	t=-1.7		4.7	4.1	0.039	t=2.1	E>N
FACTOR #1: FLUENCY OF PERFORMANCE	5.6	5.3	0.430	t=0.8		5.3	5.4	0.809	t=-0.2	
FACTOR #2: PERCEIVED FIT	4.4	4.8	0.035	t=-2.2	R<X	4.8	4.6	0.259	t=1.1	
FACTOR #3: ABSORPTION BY ACTIVITY	4.8	4.9	0.816	t=-0.2		4.8	4.8	0.959	t=0.1	
FACTOR #4: SUBJECTIVE VALUE OF ACTIVITY	3.4	3.6	0.726	t=-0.4		3.3	3.8	0.173	t=-1.4	
FACTOR #5: FSS SCORE	5.3	5.1	0.604	t=0.5		5.1	5.2	0.869	t=-0.2	

Figure 9: Flow Experience - Braid Type and Expertise Paired t-tests or Wilcoxon signed-rank tests were performed to assess for significant differences between means. Braid type V was removed from our analysis because it did not show significant difference when compared to R. (n) represents the degrees of freedom.

SAMPLE	FLOW LABEL	FEATURE SPACE	FEATURE	r	p-value	TREND	CORRELATION
ALL	FSS #2: ACTION FLUIDITY	Disk Motion	Heading Movement (Rotating Disk)	-0.41	< 0.001	-	WEAK
ALL	FSS #4: FOCUS	Biosignal	EMG Recovery Time Mean	-0.43	< 0.001	-	WEAK
ALL	FSS #8: FORWARD THINKING	Biosignal	Skin Temperature Mean	0.43	< 0.001	+	WEAK
ALL	FSS #10: LOST IN THOUGHT	Braiding	AdvanceWork	-0.42	< 0.001	-	WEAK
ALL	FSS #10: LOST IN THOUGHT	Braiding	Work	-0.41	< 0.001	-	WEAK
ALL	FSS #10: LOST IN THOUGHT	Braiding	Revolutions	-0.42	< 0.001	-	WEAK
ALL	FSS #10: LOST IN THOUGHT	Braiding	Trials	-0.40	< 0.001	-	WEAK
ALL	FACTOR #1: FLUENCY OF PERFORMANCE	Biosignal	Skin Temperature Mean	0.40	< 0.001	+	WEAK

Figure 10: Flow Indicators across All Users and Tasks

SAMPLE	FLOW LABEL	FEATURE SPACE	FEATURE	r	p-value	TREND	CORRELATION
NEWCOMER	FSS #4: FOCUS	Biosignal	Skin Temperature Mean	0.70	< 0.001	+	STRONG
NEWCOMER	FSS #8: FORWARD THINKING	Biosignal	Skin Temperature Mean	0.63	< 0.001	+	STRONG
EXPERIENCED	FSS #12: CARE	Disk Motion	Lateral Acceleration Mean	0.61	< 0.001	+	STRONG
EXPERIENCED	FSS #12: CARE	Disk Motion	Acceleration Mean	0.62	< 0.001	+	STRONG
EXPERIENCED	FSS #12: CARE	Disk Motion	Lateral Acceleration Std	0.61	< 0.001	+	STRONG
EXPERIENCED	FSS #12: CARE	Disk Motion	Acceleration Std	0.61	< 0.001	+	STRONG
EXPERIENCED	FSS #12: CARE	Disk Motion	Speed Mean	0.61	< 0.001	+	STRONG
EXPERIENCED	FSS #15: SELF EVALUATION	Braiding	Revolutions	0.61	< 0.001	+	STRONG
NEWCOMER	FACTOR #1: FLUENCY OF PERFORMANCE	Biosignal	Skin Temperature Mean	0.64	< 0.001	+	STRONG

Figure 11: Flow Indicators between Newcomers and Experienced Users

advancing in the braidwork, which aligns with users feeling competent while evaluating their task's outcome. The slower pace of the more complex braids likely contributed to lessened perceptions of competence. In contrast, the SKILL MATCHING braid (X) had 9 moderate disk motion features positively tied to CARE (FSS#12). Since the X braid required 10 braiding movements to complete a braid unit, this result indicates that users perceive physical motion as an expression of care and attention as opposed to more performance-oriented behaviors encountered with easier tasks. This shift in motivation from performance to care could serve to explain why skill matching allows users to achieve action-perception coupling.

All braiding tasks had 11 moderate biosignal features negatively correlated to FOCUS (FSS#4), FORWARD THINKING (FSS#8), and ACTION ACCORD (FSS#7), with mean skin temperature being the most prominently correlated across these FSS Components and contributing to a positive correlation with the overall FSS Score (FACTOR#5, r=0.57). This finding correlates with the theory that flow activates the body over longer and more sustained periods of time [18], and indicates a potential to explore skin temperature as a proxy to components of the Flow Short Scale.

7.4 Braiding Analysis

Scores and Ratings. The R braid was perceived as the easiest of the braiding tasks (FSS#14 (V>R: t(44)=-2.34, p=0.025); (X>R: t(44)=-3.1, p=0.004)). The X braid, on the other hand, achieved skill balance for more participants: FACTOR#2 (V>R: t(44)=-1.93, p=0.060), (X>R: t(44)=-2.17, p=0.035). According to flow models [50], this would result in X braid having a higher proclivity for flow; however, no significant difference in the overall FSS score was encountered (FACTOR#5: X(M=5.1), V(M=5.0), R(M=5.3)).

The Effort-Reward Balance in Braidmaking. The effects of effort and reward on task performance and decision making is well studied within behavioral psychology [59]. For braiding, effort stems from moving and maintaining tension on the yarns and keeping track of the braiding pattern. The degree of complexity and effort required is controlled by the number of strands in a braid and the number of instructions needed to complete one braid unit. Over time, as muscle memory develops, the braiding pattern can become second nature. Part of the reward associated with braidmaking is the relatively complex artifact that forms from a very simple material and technique. We leveraged two features from the dataset as indicators of effort - advancework, or the execution of a braiding unit positively added to the length of the braid and undowork, or the undoing of a braiding unit especially as a consequence of error. Braiding telemetry features indicates that the X braid required the most effort from users (MW: Braids; p<0.001). Furthermore, since the X pattern consisted of moving more strands in a more complex pattern, the braids were produced much slower, making the X braid task a high effort and low reward task that resulted in delayed gratification. By the end of a 10-minute braiding session, a typical X-braid session would produce between $50-54\%$ less braid than the V and R pattern (respectively), making the V and R tasks low effort and high reward tasks that resulted in more immediate gratification. Consequently, while the complexity of the pattern played a role in the amount of physical effort required, it had little to no effect on cognitive effort. Our dataset indicates that undowork showed no statistical difference across the three tasks. Users indicate the braidmaking goals were clearly defined and unambiguous (FSS#8 - 5.8 ± 0.2), indicating that the challenge perception was concentrated primarily on physical effort over cognitive effort. We attribute this result to the immediate and persistent braiding instructions on the Kumihimo disk.

Braid Pattern Effects on Practice Curves. When performing a creative task, repeating an action over time improves the efficiency of the user as they become more familiar with the action as captured by the Power Law of Practice [28]. Within braiding, we observed users becoming faster and more accurate as they became familiar with the braiding pattern. This can be seen in our session-level analysis, as shown in Fig 13. Familiarity also welcomed self-sufficiency, as the users became less reliant on the LED instructions on the Kumihimo disk, often using it simply as a means of verifying their steps.

> U33 (R) I found the pattern very quickly and was just pressing the button to make sure that I was right.

Users also expressed their gradual understanding of the braiding pattern and were able to produce more braid as the task progressed:

> U10 (R) It definitely went faster as I did more because I got like the pattern, so I didn't really need the lights.

Some novice users uncovered that the strands do not have to be at the exact slot in the disk because there are multiple places one could potentially put a thread that ends up correct in relation to the other threads as well as the one indicated by the LEDs.

> U7 (X) I recognized the pattern, I knew what I was doing so. There wasn't anything to think about. You just follow the dots and sometimes the dots have you autocorrect for stuff that made little sense.

From the dataset, we observed a clear increase in the advancework feature in the second half of the session (S5-S10) compared to the start of a session (S1, S2) with p-values ranging from 0.001 to 0.027. Interestingly, we noted that braiding output was greater across all sub-sessions for the V (p=0.001) and R (p=0.002) tasks. In contrast, the X pattern showed a steeper learning curve which could also coincide with it requiring high effort and low reward. Users found the X-braid to be more difficult, taking longer to identify the pattern and struggling to keep track of the strands:

> U35 (X) I think I could do the other two [V and R] by hand (without the LEDs).

> U36 (X) I was like this shouldn't be this hard, why am I sweating with this? [For R] ..it was easier for me to predict which color would light up so it was easier for me to maintain the momentum.

While there was consensus on the difficulty of X-braid, some users mentioned difference in pattern understanding between V-braid and R-braid:

> U39 (V) The pattern to make it takes a little bit longer to understand [than R].

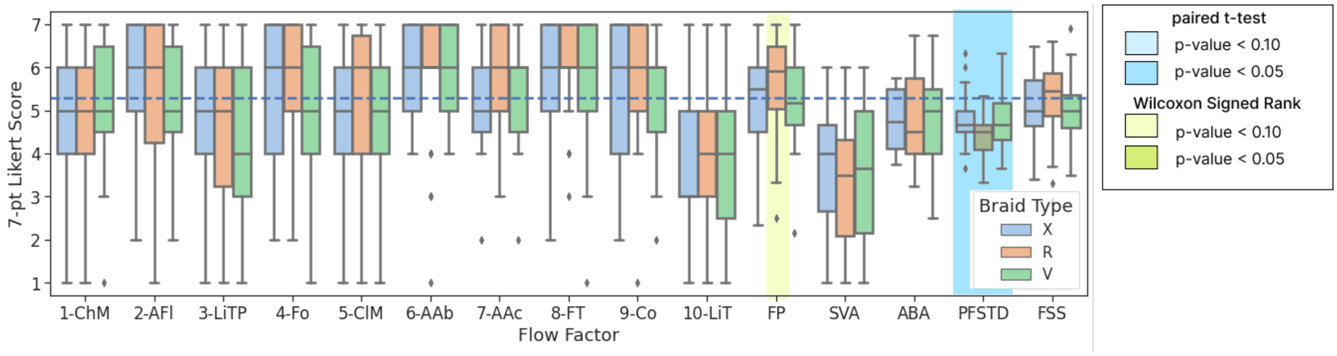

Figure 12: Braid Type and Flow Experience. Paired t-tests or Wilcoxon signed-rank tests were performed to assess for significant differences between means.

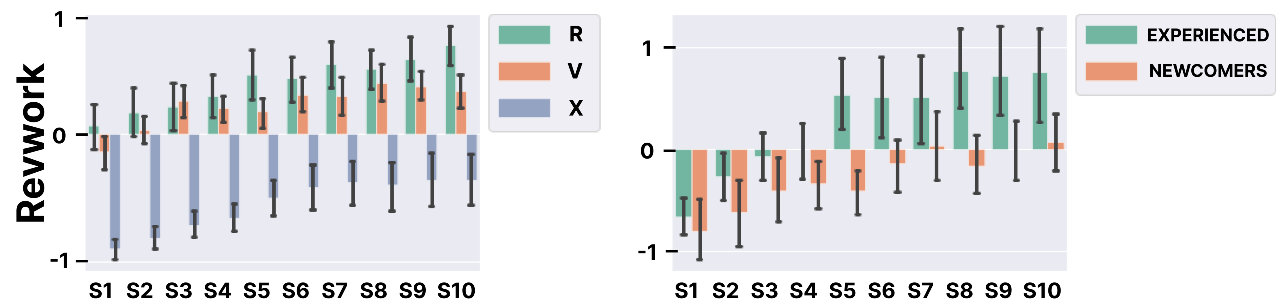

Figure 13: Session Level Analysis. Revwork is defined as the total work done in one revolution of a braid (z-normalized). Here we have the revwork plots for comparing between the three tasks (V, X, R) and expertise (Newcomer, Experienced).

7.5 Motion Analysis

The act of braiding consists of small, consistent, and repetitive movements whose accuracy dictates the efficiency of the task and the quality of the final braid artifact. The Kumihimo disk, while acting as a guide for the braiding movements, also introduces opportunities for new movements such as flipping the disk to check the braid being made, or moving the disk itself to aid in manipulating the strands. These movements can also serve as indicators of the users' mental states when combined with their FSS scores. We analyze the disk's motions through the disk IMU, the user's hand motions through the wristband's IMU as well as their FSS scores and present the following observations from the dataset.

Scores and Ratings. We observed higher activity in terms of acceleration of the wristband on users' hand in V braid compared to the X braid pattern: (*Acceleration Peaks in Lateral Direction.* V>X: U=199.0, p=0.068), (*Acceleration Peaks in Medial Direction.* V>X: U=191.0, p=0.047), (*Acceleration Peaks Overall.* V>X: U=202.0, p=0.078).

The braiding disk shows higher means in the overall acceleration and speed during R braid compared to X braid: (*Acceleration Mean Overall.* R>X: U=206.0, p=0.093), (*Speed Mean Overall.* R>X: U=205.0, p=0.089).

Time Flies with Early Movements. Familiarity with the braiding pattern reduces the cognitive effort required to make progress. As the braider's hands get attuned to the movements, determining the next steps require minimal conscious thought, creating opportunities to let the mind wander and multitask while the braiding activity recedes to the background. It is likely that the speed of the movements also increases as a result of the ease with which the movements are performed, leading to a greater braiding output.

The FSS questionnaire consists of two items that capture this state of the mind and body: loss of time perception (FSS#3) and clear mindedness (FSS#5). From the dataset's disk acceleration and speed features, we observed that users were more active in sessions where they were lost in thought throughout the majority of the sub-sessions (S1-S2, S5-S10; p<0.001, r>0.70). While this may seem counterintuitive, this could be explained by the repetitive motions of the repeated pattern requiring little conscious thought. Additionally, sessions that began with speedy hand movements were more likely to be perceived as sessions where time was lost (S1-S2; p<0.001, r>0.74). This appears to be a promising pattern as an early detection mechanism for determining whether a session will result in a loss of time perception. Users reported similar sentiments in the post-task interviews:

> U32 (X) It did get monotonous at one point because it got repetitive and I knew what was going to happen next, I was actually able to fast track because I knew where the LED would move.

> U33 (V) Once I got the pattern, my brain would think about other things.

Along similar lines, users attributed the low cognitive effort of their braiding session to the task being easy:

U7 (R) It's easy. (I was) just like singing little songs in my head cause it's thoughtless, I just matched the colors. So I didn't have to think about it at all.

Care and curiosity. In braiding, there are two approaches to moving a yarn from one slot to another. One approach is to adjust the positioning of the hands to the yarn positions. The other approach is to rotate the disk to minimize the lifting motions and therefore, the effort required to advance in braidwork. Bringing the yarn closer through disk rotation additionally made it easier to manipulate the thread, making the process more efficient and potentially leading to a higher braiding output. From the dataset, we observed how the rotation acceleration of the disk correlated with more braiding units being completed (lateral acceleration: $p = 0.005$, $r = 0.34$).

Another movement of interest is the flipping of the disk upside down which could capture the braider inspecting their braid or adjusting the tension on the yarn, both of which indicate a quality of care and craftsmanship by the braider. Contrary to the rotational movements, flipping the disk to check the braid or adjust the tension on the yarn slowed down the braiding process as it disrupted the natural rhythm caused by the repetitive motion (medial acceleration: $p = 0.017$, $r = -0.32$). The reduction in speed could also be a consequence of the yarns coming out of the slots when the disk is flipped abruptly and without caution, as one user reported:

U35 (R) I felt really bad when I flipped it and all the strings came out and disrupted my pattern. I had gone into a length where I could not keep tension without the braid skewing so I was trying to re-center it.

Additionally, we observed that users were more likely to flip the disks towards the beginning and end of a task compared to the sub-sessions in the middle, indicating a need to verify correct movements towards the beginning and a curiosity for the final product towards the end (medial acceleration: S1>S3 ($p = 0.001$), S1>S5 ($p = 0.034$), S2>S3 ($p = 0.001$), S2>S5 ($p = 0.039$), S2>S9 ($p = 0.009$)). This notion was further verified by post-task interviews:

U7 (V) I would flip it over occasionally to check and see, make sure my hand was able to hold it the way I was thinking I was holding it and that was it.

7.6 Expertise Analysis

Skill level, or expertise, plays a crucial role in determining the workflows of creative tasks and the quality of the final product. Experience builds a repertoire of tacit information, or nuances, about the task workflows that can only be acquired through time and practice, which a new practitioner (referred to as newcomer in our analysis) will lack. As our dataset is balanced on skill level, we wanted to observe how expertise affects the braiding process and, consequently, how the braiding process affects experienced users versus newcomers.

Scores and Ratings. FSS#16 *Demand* is a measure between 1 to 7 which relates to the perceived demand of a task. Newcomers to braiding perceived Demand to be higher than Experience users: (*Demand.* Newcomers>Experienced: $t = 2.1$, $p = 0.039$). *Clear Mindedness* (FSS#5) is measured by users' responses to how clear in thought they were during a task. Newcomers reported a higher average for Clear Mindedness compared to experienced users: (*Clear Mindedness.* Newcomers>Experienced: $U = 436.0$, $p = 0.078$).

Material Risk and Experience. We observed experienced braiders completing more braiding units than newcomers as per our expectations. Probing further into the observation, we noted that there was a clear distinction in the movements of the experienced users and newcomers. Experienced users seemed to make larger disk rotations when compared to newcomers (lateral acceleration: $p < 0.01$) which can allude to the confidence with which experienced users handled the task as well as the desire to minimize physical effort. We observed a certain stiffness and reluctance in the movements of the newcomers particularly in rotating the disks. Post task interviews suggested that perhaps the lack of disk rotations was a precaution against the yarns getting tangled.

An unexpected observation that stemmed from the braid telemetry of experienced users and newcomers was that there were no statistically significant differences between the number of corrective actions between experienced users and newcomers. While we expected newcomers to make more mistakes and rectify those mistakes by retracing their steps, the LED instructions may have played a role in keeping the newcomers on track. Consequently, the novelty of an instrumented braiding disk could have caused experienced users to make as many mistakes as newcomers.

Cool bodies, cool minds. Our physiological signals such as skin temperature and heart rate are rich indicators of our emotional states. Skin temperature has been related to relaxation as body temperature drops during sleep; a higher baseline heart rate can be a response to a pleasant stimuli [34, 40]. Within creative practices, skill level plays a role in the mindset with which a practitioner approaches a task and navigates frictions and opportunities. We observed statistically significant differences in the mean skin temperature between experienced braiders and newcomers, with experienced braiders having a lower skin temperature which suggests that they were more relaxed during the process [8]. Additionally, experienced braiders also had a higher heart-rate baseline which can potentially indicate their enjoyment of the task:

U11 (Experienced User) I was also more determined to get it done because I wanted to make it longer. I wouldn't say I was getting bored; I was quite entertained. Relaxing, I would say.

Post-task interviews reflected that experienced users approached the braiding tasks more holistically, whereas newcomers focused more on the technicalities of the braiding process. This analysis is supported by user responses in the post-task interviews:

U42 (Newcomer) I was trying not to make a mistake.

U10 (Experienced User) It's good to relax like it doesn't take a lot of thought.

8 DISCUSSION

In this work, we validated that our research instrument was capable of documenting the flow experience without interrupting users. Notably, no single modality of sensor data was able to provide a strong indication of flow; however, several of the flow indicators we identified can serve as a road-map for the design of flow-aware interactions.

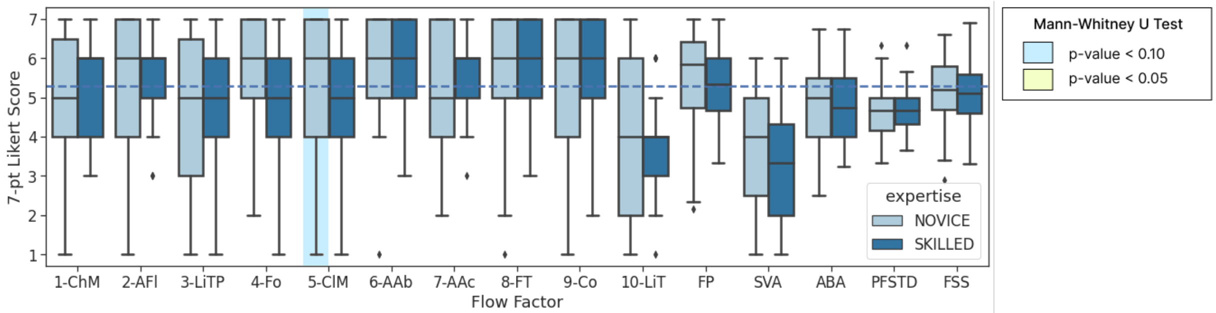

Figure 14: Expertise and Flow Experience. The dashed blue line indicates the mean FSS Score from the validation study. Independent t-tests or Mann-Whitney rank order tests were performed to assess for significant differences between means.

8.1 Using Flow as a Design Variable

Flow improves a person's general sense of well-being and is a vital part of the human experience, but it is highly elusive and takes significant effort to attain [48]. Entering and sustaining the flow state remains a complex phenomenon. In this work, we analyzed how a creative task can provide cognitive flow information based on a user's experience. The presented dataset with curated flow-based features can act as a guide to generating design principles that can lower the barrier to entering a flow state. Studies regarding sustaining the flow state have shown promise in using flow as a design variable for interactive applications or tools [4, 5]. These tools can create positive experiences by using concepts from flow literature surrounding challenge-matching and autotelic personality effects [30]. Prior research surrounding flow brings contrasting viewpoints on whether challenge-skill matching is necessary to attain flow states [13, 21]. Through our analysis, we found evidence that challenge-matching the skill level of users do not always correlate to their positive flow experience. Our dataset can serve as a starting point to generate more insights into what constitutes towards the flow experience of users in similar tasks. Together, lowering the effort to reach a flow state and being able to sustain flow once achieved could lead to design principles that can inform *flow-aware* applications.

8.2 Detecting Flow in other Creative Activities

The experience of flow corresponds precisely with the qualities that form a resilient creative practice: a distorted sense of time (to offset tedious actions), the disappearance of the self-conscious (to overcome psychological blocks), a lack of extrinsic motivation (reducing the need for external motivators), and most critically a lessened impact of failure (to build resiliency) [13]. Our data collection instrument was used to collect flow-annotated data for Kumihimo braidmaking tasks; however, the experience of flow has been studied in other domains including but not limited to programming [61], music and arts [22, 53], and gameplay [41]. While it is possible to expand the architecture to other creative practices, it may require the integration of new sensors and features and the removal of existing ones. The observations from our dataset are indicators of the usefulness of different features in understanding the flow experience and can be used as a baseline for making informed decisions about data collection systems for creative tasks. For example, setting up electromyography sensing on the body may be costly, time-consuming, and cumbersome for creative tasks where integrating on-body hardware is difficult. However, a much more cost-effective, less complex, and easier-to-integrate skin temperature sensor can provide useful information to subscales of the FSS score. When integrated into ubiquitous devices such as mice [56], the flow may have traction as a practical and effective cognitive state to track and create flow-aware interactions. Moderating the skill-challenge balance is an integral part of attaining flow while performing a task. Bennett et al. [6] have done multifractal analysis on signal data to understand skill levels in tasks. There is potential in this space to study user movements in depth to form a more holistic view of a user's skill level. Understanding skill differences between users beyond the *newcomer* and *experienced* classification could lead to new discoveries in developing positive flow experience based on a user's skill set.

8.3 Capturing the Complexity of Flow State

Our dataset is aimed to be a foundation for documenting flow experiences through quantitative and qualitative data at a large scale, creating opportunities for classification of flow and fall[3] experiences during sessions of creative activity. Within the makerspace, the ability to detect flow can facilitate the development of systems that aid in sustaining and triggering flow states during fall states. Prior work has created cognitive models to classify flow using sensorimotor modalities [9, 42, 44, 51, 52]. However, flow is a complex state, and it does not exist in isolation [58], calling for a multi-modal view of the human experience. Due to the limitations of assessing flow, conceptual models often portray flow as a binary. Our work reinforces that flow occurs more gradually expressed in biosignals such as skin temperature. While these types of flow-detection systems would be useful for post-hoc reflection, our findings also indicate that other features can serve as useful flow antecedents that can help assess the proclivity of a situation, user, task to trigger a flow experience. Mining session-level flow indicators hold promise in determining how the flow experience changes on a minute-by-minute base and points toward a future where entering deep flow states may be possible.

[3]We borrow the term *fall* from Havlucu et al. [24] to denote the absence of cognitive flow

Limitations. In our analysis, strong holistic correlations do not exist between flow labels and captured features in the BraidFlow Dataset, indicating that detecting flow is not a single modality task. We confirmed that expertise and task difficulty can be used to identify good candidates for flow modeling. Understanding human flow psychology is a complex process; through BriadFlow, we provide a triangulation approach, combining sensor data, survey-based quantitative data, and qualitative data from interviews to aid efforts in understanding cognitive flow. Our flow dataset focused on the flow-inducing task of braidmaking – braidmaking activities saturated the Flow Short Scale questionnaire leading to skewed distributions. Although many participants experienced fall states (both through observation and self-report), even these fall states registered with high FSS scores compared to other studied tasks. This could indicate that our findings may be applicable to high-flow activities such as braidmaking or other needlecrafts. The data collection study for this research was conducted in a lab environment where users wore sensors (E4 and Myoware) and were interviewed after each braidmaking task, which could have led to unmitigated stress. The biosignals of users in a lab environment could be different, and can relate to variations in the findings in a different setting. Although our physiological sensing was from multiple sources, we did not have EEG sensors. We chose to omit EEG, despite its use in related work, due to the susceptibility to motion artifacts from physical activities [7]. Our dataset focused on the singular flow experience; however, prior research in flow has found collaborative play has a higher flow than the single user (player) [41]. We scoped out data collection to include single-user data and envision data collection in a collaborative setting in our future work.

9 CONCLUSION

In BraidFlow, we presented a multi-modal dataset and data-capture system to understand cognitive flow at a microgenetic level. Through a validation study, we confirm that the Kumihimo tool does not inhibit flow and that braidmaking is a high-flow activity using the Flow Short Scale. We then conducted a data collection study, where we recorded the experiences of 24 users engaged in 3 different braidmaking tasks to form a flow-annotated dataset. We use statistical testing to find and analyze trends in the data from braid telemetry, sensor-based signals (IMU, EMG, EDA, heart rate, skin temperature), and familiarity with the task (expertise). We envision this dataset to be a foundation for understanding flow in creative activities.

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A APPENDIX

A.1 Flow Short Scale and Derived Flow Features

The first 16 items are gathered from the Flow Short Scale questionnaire [18, 49]:

FSS#1: CHALLENGE MATCH I feel just the right amount of challenge
FSS#2: ACTION FLUIDITY My thoughts/activities run fluidly and smoothly
FSS#3: LOSS OF TIME PERCEPTION I do not notice time passing
FSS#4: FOCUS I have no difficulty concentrating
FSS#5: CLEAR MINDEDNESS My mind is completely clear
FSS#6: ACTION ABSORPTION I am totally absorbed in what I am doing
FSS#7: ACTION ACCORD The right thoughts/movements occur of their own accord
FSS#8: FORWARD THINKING I know what I have to do each step of the way
FSS#9: CONTROL I feel that I have everything under control
FSS#10: LOST IN THOUGHT I am completely lost in thought
FSS#11: RELEVANCE Something important to me is at stake here
FSS#12: CARE I must not make any mistakes here
FSS#13: WORRY I am worried about failing
FSS#14: PERCEIVED DIFFICULTY To me, making this braid was (Semantic Differential - 7pt: Easy – Difficult)
FSS#15: SELF EVALUATION I think my competence in making this braid was (Semantic Differential - 7pt: Low – High)
FSS#16: DEMAND For me personally, demand of making this braid...(Semantic Differential - 7pt: Low – High)

Derived Items.

FACTOR#1: PERFORMANCE FLUENCY The average of items #2, #4, #5, #7, #8 and #9.
FACTOR#2: PERCEIVED FIT OF SKILL AND TASK DEMANDS The average of items #14, #15, and #16.
FACTOR#3: ABSORPTION BY ACTIVITY The average of items #1, #3, #6, and #10.
FACTOR#4: SUBJECTIVE VALUE OF ACTIVITY The average of items #11, #12, and #13.
FACTOR#5: FSS SCORE The average of items #1-#10.

For the core 16 items, 7-point Likert scale (anchored on Strongly Disagree to Strongly Agree) was used. The items used in this scale were sub-categorized based on two factors - related to performance fluency and related to activity absorption. Items 2, 4, 5, 7, 8, 9 were used to measure the performance fluency and items were used to determine the activity absorption [37, 39]. In addition to that, rest of the items were used to check the importance of each task that was perceived by the participants.

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