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A Wearable E-Textile Force-Sensing Garment for Characterising Caring Touch

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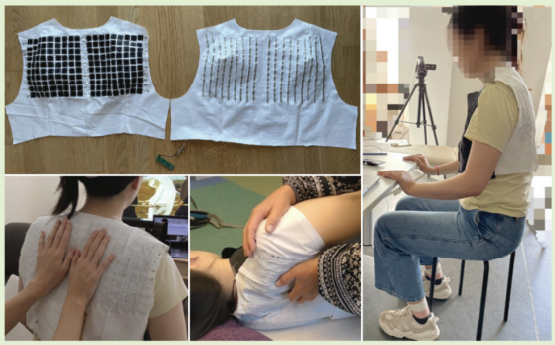
***Abstract*— To enable better human-machine and human-robot interaction in healthcare applications, there is a need to improve haptic devices, assistive and companion robots to touch humans in a way that can be perceived as comfortable, safe and trusting. Towards this vision, we developed a flexible, wearable matrix force-sensing garment capable of recording dynamic force behaviour of caring touch from four healthcare experts in their natural therapy environment, and enable the touch recipient to provide feedback on the perceived quality of the same touches. Instead of assuming particular touch gestures are caring, we explored the application of the sensing and analysing system to characterise a caring quality of touch across different gestures. We were able to characterise distinctive features for touch aimed for sensory aspects and for moving the body. Our findings demonstrate that caring touch is not limited to specific gestures or a single parameter but is rather characterised by how the touch is performed across multiple features, with deliberateness - the careful and smoothness in the increasing and decreasing of force, emerging as a shared characteristic of caring touch regardless of the specific gesture employed. The study also demonstrates the feasibility of using raw tactile sensor data to assess subjective touch quality.**



***Index Terms*— caring touch, affective haptics, machine learning, assistive robotics, care haptics, force sensing e-textile**

I. Introduction

Haptic interaction is one of the most significant aspects of Human-machine interaction (HMI), shaping the future of human-machine relationships. Inter-human touch, especially caring touch from healthcare professionals plays a critical role in promoting emotional and physical well-being. This has motivated high expectations for touch from haptic devices and robots to aid in care applications [1]. To realise such potential, haptic stimulation and robots need to be able to touch humans in a way that feels more comfortable, safe, and trustworthy. We define "caring quality" as what's in a touch that makes the touch recipient feel safe, secure, and trusting. This definition arose from the qualitative analysis of the data from our study [2], and is supported by literature in the healthcare sector [3]–[5]. However, current haptic stimulations are still very limited in the range of sensations they can deliver, and there is still a bottleneck in developing richer and more fine-grained sensations [6], [7]. Many cross-disciplinary challenges exist, one of which is to determine what are the physical attributes of haptic behaviour that help bring out a felt caring quality and how to translate qualitative descriptions of an experience into technical requirements for configuring haptic systems.

Currently, the main work on haptic sensing in the context of affective touch or care focuses on the recognition of touch gestures [8]–[10]. This approach does not address the above-raised research question and it is fundamentally problematic as there is much evidence against the arbitrary association of gestures with affective intentions (elaborated in the next section). Furthermore, in the current affective sensing literature, the felt quality of the touch being investigated is undocumented. We were motivated to develop a wearable sensing system to facilitate the generation of useful knowledge to address this gap. This paper makes the following contribution. It presents a low-cost, wearable and customisable force sensing matrix garment that enables collecting force data alongside the subjective perceived experience of the same touch in natural touch interaction, and an approach to characterise physical features of the caring quality of touch, instead of gesture recognition. The preliminary results identify the feature of deliberateness as a shared character of caring quality in touch and demonstrate the feasibility of using raw tactile sensor data to assess subjective touch quality.

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The rest of this article is structured as follows. We first provide a scope of relevant work and the knowledge gap that this study addresses. We then describe the sensor design and characterisation, study set-up, and methods for data analysis. Following this, results are presented, and the implications for designing caring haptic stimulations are discussed before a brief conclusion.

II. Relevant Work

A. The Limitations of Gesture Sensing

Currently, the main work on haptic sensing in the context of affective touch or care focuses predominantly on the accuracy of touch gesture recognition [8]–[11]. Gesture sensing is underlined with the assumption that if a certain gesture is performed, such as stroking, hugging, then a caring quality can be expected, and haptic designers often arbitrarily assign affective intent to certain gestures [11]. This approach can be problematic, as elaborated in the following. The first is that it risks being exclusive, inferring that other gestures cannot communicate care intent. Second, it carries the risk of misinterpretation. This is because the same gesture can be used to convey different emotional content. For example, holding can be used to convey many intentions, including the intention to calm and the emotion of sadness [12] and stroking can be used for communicating love, sadness or envy [13]. In addition, the nuances within one gesture can act as another source for misinterpretation, for example, stroking with a low force may feel comforting, while stroking with a much greater force can feel threatening. Thirdly, in natural interaction, to convey one intent, often a combination of gestures is used in seamless transitions. For example, in [12], holding, rubbing and stroking were all used in combination within one touch episode that was intended to calm.

Often, in these studies [10], [11], non-expert participants were asked to perform predefined gestures according to instructions only on the sensor, meaning the perspective of any touch recipient on the felt quality of such touches is not taken into consideration. To care is to elicit an emotional response from the touch recipient [12], thus for a caring quality to be successful, it is not enough only for it to be intended, it must also be felt [2]. [12] collected both the physical characteristics of different affective gestures as well as the subjective feedback on the felt experience of the same touches. In our study, we build on this approach.

B. Towards Characterising Quality Instead of Gestures

Experiential qualities can be considered as the properties or traits of a design that can lead to or characterise a user's experience of interacting with said product or service [14], [15] . Due to the ambiguity of touch gestures in implying the meaning of care, as discussed above, perhaps a more useful question to investigate is *what physical attributes of haptic behaviour can help bring out a felt caring quality*. Physical properties constitute the characteristics of touch, convey caring intentions, and can be manipulable by haptic designers [2]. Yet, this important link remains under-explored in the current affective haptic sensing literature. Research in neuroscience has informed the link between a slow stroking velocity (1-10cm/s) and a positive psychological response [16]. A few scientific studies have investigated the characteristics of tactile behaviour used in communicating various emotions, such as duration, intensity [13], velocity, and size of the contacting area [12]. Further, design-oriented studies employing qualitative methods have successfully engaged with the richness and nuances of felt experiential qualities of touch from technologies [17], [18]. Yet translating qualitative descriptions about the touch characteristics in these studies into technical design parameters remains a challenge. There is a need for sensing tools to facilitate the understanding of the rich nuances of touch with care intentions that can directly inform the technical development of haptic stimulations. We chose to learn from caring touch experts, because healthcare practitioners are in possession of a wealth of skills and know-how on how to touch to care. Tapping into this body of knowledge can shed light on what constitutes a caring quality and how to design a touch that means to care.

C. Force-based Wearable Touch Sensing Systems

The temporal dynamic of force, for which the normal force is more commonly investigated, is one of the most important physical attributes in embodying the intention and nuance of a touch [19], [20]. The most common techniques for sensing location and force levels in human touch range from FSR, capacitive sensing and deformation sensors. Force sensing for caring touch requires sensitivity towards lower force levels. As informed by the literature, stroking as an affective touch exerts a force within the range of 0.2 - 0.5N [16], [20]–[22] and [23] reported a force of 2.5N for deep massage pressure therapy. Although force-sensitive resistor (FSR) sensors are more readily available, light contact is often barely detectable or detected with poor resolution. Quantum Tunneling Composites (QTC) can achieve a high sensitivity however the material is not easily accessible and light touch such as brushing stroke often could not be detected [11], [24].

To enable the collection of both force profile and felt quality about the same touch the sensor needs to be placed on the body of the touch recipient. This requires the sensor to be lightweight, flexible, and compliant to the body in order to minimise any disruption to the natural interaction between the practitioner and the touch recipient. This also requires the sensor to cover a large area of the body in order to accommodate a range of gestures. Deformable sensors would not be compliant to the body curve due to their required thickness and they are usually developed for much smaller surfaces [25], [26]. We turn to an e-textile resistive matrix structure with a garment-tailoring technique. Piezoresistive e-textile tactile sensors have the advantage of being lightweight, low cost, easy to manufacture, mechanically flexible, and customisable for whole-body sensing [27], [28]. It also has the advantage of being able to collect pressure data regarding location and force behaviour while facilitating natural interaction, as used in [29]–[31]. We build our work on sensing systems presented by Donneaud et al. [31] and Skach [29]. Shear force is an important characteristic of inter-human caring touch, however currently profiling shear force

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requires much more sophisticated manufacturing processes and computational modelling with less wearability [8]. If proven useful, modelling normal force can be a much cheaper and accessible tool for more research teams.

III. Materials and Methods

A. Sensor Design and Characterisation

Our design follows the same principles as the sensors presented by Donneaud et al. [31] and Skach [29]. The pressure sensing system consists of a 10 × 18 grid fabricated using a three-layer sandwich structure. The outer and inner layers contain perpendicular strips of conductive fabric arranged in a grid formation, with vertical traces connected to digital pins and horizontal traces connected to analogue pins of a Teensy 4.1 microcontroller. Between these conductive layers, we placed small squares of Velostat at each intersection point. When pressure is applied to a specific cell, the Velostat's electrical resistance decreases proportionally to the applied pressure, creating a connection between the corresponding vertical and horizontal conductive lines. Figure 1 demonstrates how activation of the red-marked cell results in signal detection through the analog pin A1. By sequentially activating each digital output line while reading all analog inputs, the system can map the pressure distribution across the entire grid with varying intensity levels corresponding to the pressure magnitude at each point. The output voltage V_{out} for each cell during the analog reading equals to (1):

$$V_{\text{out}} = V_{\text{digitalPin}} \cdot \frac{R_{\text{known}}}{R_{\text{sensor}} + R_{\text{known}}} \tag{1}$$

In this equation, the value of R_{known} is 8200 ohms which was selected among 0-10k ohms being the range best amplifying the lower force range of 0-500g; R_{sensor} is the resistance of the sensor; and $V_{\text{digitalPin}}$ is the voltage supplied by the digital pins when activated. This approach allows for high-resolution pressure mapping while minimising the number of required microcontroller connections. The touch behaviour was recorded at around 200 Hz with 180 sensors of data cells per frame.

To maximise contact between the body's curvatures and the sensor surface, a tailoring technique was employed to make the sensor in the form of a vest match the body contour of one of the touch recipients and, in particular, her upper back. This sensor fabrication method allows customisation to other parts of the body, enabling extending the study of touch to other body locations in the future. We experimented with the upper back because the upper back is a large part of the body that accommodates a variety of touch gestures, with less chance of noise due to breathing or intuitive body movements. This is also the position that is often addressed by all four healthcare experts who participated in our study. The entire sensor vest, including the microcontroller board, weighs around 106 g. The sensitivity to applied force ranges between 0 - 10 N (0 - 1000 g). This range was informed by the literature on caring touch [16], [21], [22], [32], as well as our measuring of force range when applying a range of touch gestures. MATLAB (R2024a) software was employed to generate a visualisation of the force mapping over time for each gesture.

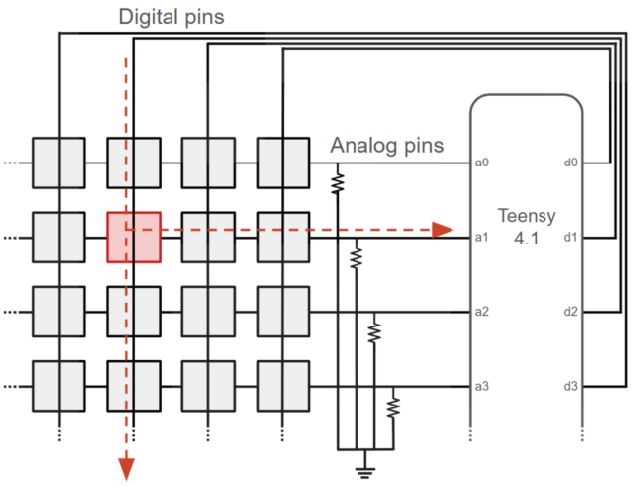

Fig. 1. Schematic diagram of the pressure grid sensor with Teensy 4.1 microcontroller. The diagram illustrates the connection between the 10×18 conductive fabric grid and the microcontroller's analog and digital pins. The red highlighted cell demonstrating signal path from an activated pressure point to analog pin A1.

While flexible textile sensors typically exhibit higher variance than printed counterparts [27], their force estimation accuracy remains within the range of human perceptual tolerance (reported correlation coefficient of force magnitude perception ranges from 0.70 to 0.97) [28], [33]. As Lee et al. [28] note, this variability is acceptable in e-textile sensing given the practical advantages of conformity over large areas of the body. To evaluate consistency across different array sizes, random subsets of 10 and 20 cells were selected out of the 180 cells. Both subsets exhibited strong linearity (R^2 = 0.92 for 10 cells and R^2 = 0.91 for 20 cells). Variability analysis revealed an average relative SD of 13.5% for 10 cells and 19.4% for 20 cells. In both cases, variability was highest at low loads (26.1% at 50 g for 10 cells; 32.1% at 50 g for 20 cells) and decreased substantially at higher loads (down to 6.9 and 10.5%), confirming consistency and reliability of the sensor's force response. These results demonstrate that while inter-cell heterogeneity increases with larger subsets, the overall response remains consistent within an acceptable range. Despite the inter-cell variability, regression analysis of individual cells revealed a high degree of linearity ($R^2 = 0.946 \pm 0.0295$). This indicates that the variability arises not from random instability or noise within each cell, but from systematic differences in gain and baseline offset between cells, which can be attributed to manufacturing variation and local mechanical effects such as differences in material compression, velostat patch uniformity, and local contact conditions within the textile structure, which are common to e-textile sensors [27]. This variance can be efficiently mitigated through per-cell calibration for applications that rely more on absolute force measurements. In our work, absolute force accuracy is secondary to the extraction of dynamic touch features via machine learning. The reported force range is included primarily as a contextual descriptor, linking our results to prior literature on touch and force perception. Taken together, the grid maintains strong linearity and acceptable consistency for our application in

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characterising a combination of features regarding the dynamic behaviour of touch through machine learning.

B. Data Collection

In an effort to gather a wide range of gestures and perspectives, we worked with experienced healthcare practitioners from four different practices: a physiotherapy practitioner, a psychotherapist practicing NeuroAffective touch, a Feldenkrais practitioner and a Tactile Stimulation Practitioner. Physiotherapy is widely considered as a touch-based practice, which is also a focused discipline in healthcare literature studying touch practice [34], [35]. NeuroAffective Touch refers to the therapeutic use of touch as a bridge to body-mind integration, especially in addressing trauma-based, unconscious emotional responses that cannot be reached through talk therapy or bodywork alone [36], [37]. Feldenkrais is a somatic practice in which a practitioner uses touch to enact movement of the body to help increase body awareness and address pain [38]. The Tactile Stimulation Touch method has been practised in Sweden for over 30 years in care, rehabilitation and education [39]

We worked with each participant over two sessions. First, we conducted a semi-structured interview to better understand their touch practice and their typical touch patterns to carry out the care intention. Then two members of the research team (hereafter referred to as the "researcher touch recipient/RTR1 or RTR2") experienced for themselves the caring touch patterns from the practitioners. The two touch recipients were the same researchers for all the sessions. Each practitioner first conducted the touch session on RTR1 and then repeated it on RTR2. Through the interview and the felt experience from the touch recipients, together with the experts, we were able to establish the most significant caring touch patterns on the back. This approach of identifying more contributing patterns and features of touch behaviours to further characterise has also been used in [12]. Each practitioner then repeated the selected touch pattern(s) on RTR1 who wore the sensor vest. Each touch pattern was recorded three times over the sensor vest. Before recording each touch pattern, the respiration pattern of RTR1 was recorded with the sensor. Informed consent was obtained from each participant.

C. Data Analysis for Feature Extraction and Prediction

As part of our effort to characterise the physical properties that bring out the caring quality, we investigated a collection of features through a machine learning process. The features were informed through reflections from both touch experts and touch recipients and through literature. When selecting the features, we also took into consideration the practicality of translating these features into technical terms for configuring the hardware of haptic or robotic systems.

- Velocity

Gentleness in touch is widely recognised to be associated with care intent, which was also repeatedly reflected by our touch recipients as what contributes to the perceived caring quality. The gentleness in movements can be impacted by two parameters: the first one can refer to slow velocity across the skin. Literature in neuroscience has informed that stroking at a slow speed (1-10cm/s) can feel more soothing as it excites a particular group of nerve fibre C-afferents that stimulates the part of the brain associated with emotion and rewards [16], [32]. Velocity was measured using centre-of-pressure tracking across the sensor array using cluster analysis, identifying clusters and calculating the distance of movement over time in cm/s. The raw velocity values were converted to caring scores using a piecewise non-linear function optimised for caring touch informed by literature [16], [21] and expert touch data.

The function assigns highest scores (0.90-1.0) to static touch and very slow movements (0-3 cm/s), good scores (0.75-0.90) to stroking velocities in the optimal range (3-10 cm/s), and progressively lower scores to faster movements, reflecting that slower, more controlled touch is generally perceived as more caring. The mapping was designed such that velocities typical of gentle stroking and massage (3-15 cm/s) remain within an acceptable caring range (0.50-0.90), while very rapid movements ($>$25 cm/s) receive low scores ($<$0.25).

- Deliberateness

The second parameter that impacts the gentleness in movements is what we call deliberateness. As pointed out in [20]: faster speed in reaching the maximum force on the skin is associated with a more forceful quality, while a slower speed in reaching the maximum force on the skin reflects a gentler quality of touch. We use deliberateness to describe this feature. Deliberateness was assessed using the smoothness and intentionality of movement by combining spectral arc length, jerk-based smoothness, movement intermittency, and traditional change rate analysis. Higher scores indicate slower, smoother, more controlled movements between pressure levels with fewer abrupt changes. Deliberateness is computed as a weighted combination of four smoothness metrics (S_t: traditional, S_s: SPARC, S_j: jerk, S_i: intermittency) where the weights reflect the relative importance of each smoothness measure in characterising caring touch.:

$$S_d = 0.5S_t + 0.2S_s + 0.15S_j + 0.15S_i \tag{2}$$

- Rhythm:

Rhythmic pressure can promote a calming effect [20], [40], and variation in pressure can feel more engaging: "*The variation of the pressure levels make it very pleasant and fun.*" [RTR2], also in [20], [41]. Rhythm was calculated by analysing pressure oscillation patterns using zero-crossing detection on mean-centred signals to identify consistent cycles, combined with frequency domain analysis to detect dominant rhythmic frequencies, with a higher score reflecting a more regular, predictable rhythmic pattern.

- Spatial:

[12] measured the size of the body contacting area as one parameter to describe affective touch. More than one practitioner in our study had also pointed out that if their touch is intended for relaxation or sensory integration, they would engage a larger surface of the body. Spatial Score measures

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how the pressure is distributed across different cells measuring the percentage of cells activated. Higher values indicate a more optimal distribution of pressure, not too focused on a single point nor too diffuse across the entire sensor array.

- Symmetry

Evaluates the balance by comparing activation levels between left and right sides of the sensor array. Higher values show more even, balanced pressure application across both sides.

- Consistency

Evaluates pressure stability over time by measuring the coefficient of variation in pressure application over time, with lower variation indicating a more consistent, caring pressure. Therefore, the score is highest when pressure remains at a steady level. The consistency score is computed as:

$$S_{\text{consistency}} = \max\left(0, \min\left(1, \frac{1}{1+\text{CV}}\right)\right) \tag{3}$$

where $\text{CV} = \sigma/\mu$ is the coefficient of variation of the average pressure over time, with σ and μ being the standard deviation and mean pressure respectively. Lower CV values (more stable pressure) yield higher caring scores.

We employ a two-stage approach for feature analysis. For feature extraction the overall caring touch score is calculated as the unweighted average of six equally-weighted features (rhythm, consistency, spatial distribution, symmetry, deliberateness, and velocity).

To explore the potential for automated caring touch assessment, we developed a 1D convolutional neural network (CNN) model to explore the feasibility of predicting caring touch features directly from raw sensor data. The model takes windowed sequences of pressure sensor readings as input and outputs continuous touch feature scores on a 0-1 scale, representing a regression approach rather than traditional gesture classification. Our CNN architecture consists of multiple convolutional layers with progressively increasing filter sizes (8, 16 filters), followed by global average pooling and dense layers with dropout regularisation to prevent overfitting. We selected a 1D convolutional neural network architecture to effectively capture the temporal dynamics in caring touch patterns, as the sequential pressure variations across time contain critical information about rhythm, smoothness, and deliberateness. We explored alternative architectures such as LSTM although found 1D CNNs provided a good balance of temporal pattern recognition and computational efficiency.

IV. Results

A. Significant Caring Touch Patterns

The analysis of the qualitative data has been reported in a separate paper [2]. In this paper we focus on the analysis of data from the force profile from the matrix sensor. The analysis is partly informed by and triangulated with the qualitative data.

1) Holding: Holding was mostly used by the psychotherapist practising NeuroAffective Touch. It was also used by the Tactile Stimulation Practitioner at the beginning of a session and as a connection when changing positions of the stroking, and by the Physiotherapist at the end of a touch pattern. When

Fig. 2. Force sensing prototype material, how its worn on the touch recipient and touch gestures performed to the touch recipient over the sensor prototype

the psychotherapist holds (No. 3.2s in Fig 2), she uses two open palms next to each other, in the middle of the back between two shoulder blades. She maintained pressure for a duration of time, then shifted the force from one palm to another, then back to holding with two palms applying equal pressure. The Tactile Stimulation Practitioner and the Physiotherapist exert symmetrical force on both palms at the same time without shifting the forces, although the Tactile Stimulation Practitioner applies lighter force than the Physiotherapist. The feedback from the touch recipient includes: "*I like this. It makes me feel that I am being held. I want to open myself up. I can talk about stuff. I can talk about emotions in this way*." [RTR2]

2) Light Stroking: Light stroking is the main touch pattern used by the Tactile Stimulation Practitioner. She shared one of her stroking patterns, which she called "skiing". In this pattern, she first used two hands to hold the shoulders of the touch recipients with very gentle force for a few seconds, then stroked across the back to switch sides of the two hands, gently held for a few seconds, then her hands would slide down the back in a criss-cross fashion like skiing down the slope. The feedback from touch recipients includes: "*It's more joyful and more relaxing, on the surface level of my body*", and "*the movement of her hands are really gentle. So I can feel her kindness*.[RTR1]"

3) Cat Paw Walking : The Cat Paw walking pattern is used by the physiotherapist to facilitate sensory integration and it was selected for its novelty and pleasant quality. As shown in No. 4.3s in Fig 2, to exercise this touch, the physiotherapist puts two hands into fists, rolled from the scaphoid joint to the knuckles to create a rolling movement from the bottom of the

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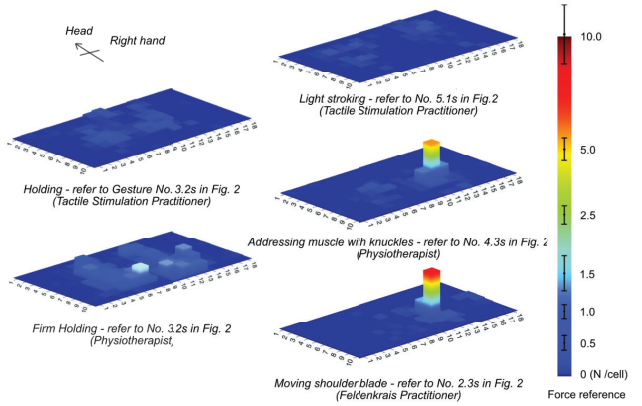

Fig. 3. Comparing force levels and sizes of body-contacting surface of touch for stroking the skin, holding, addressing muscle and shoulder blade. The error bars in the colour gradient are derived from five repeated measurements across ten randomly selected cells, performed at the following reference weights: 50 g, 100 g, 150 g, 250 g, 500 g, and 1000 g.

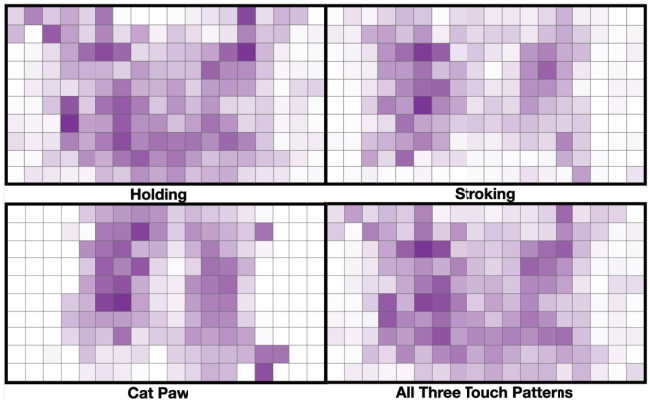

Fig. 4. Heat map on the duration of touch at each cell from all gestures.

upper back until the top of the shoulder. After three repeats, the physiotherapist ends the set with a holding gesture in the middle of the upper back. Feedback from the touch recipients includes: "*The pace is very elegant and considerate. I felt like a considerate cat walking on my back. A cat is trying to relax my muscles*" [RTR 1], and: "*The variation of the pressure levels makes it very pleasant and fun. Because when she rolls her fist from the end of her palm to the finger, the middle finger, where the bone tip is the knuckle, the previous pressure change is very predictable. And this is like from gentle and careful, and then there's the end point where she pressed with the knuckle really firm, and it's like a sharp edge pressing, which I also like*." [RTR 2]

4) Moving the Body: The Feldenkrais practitioner touches to move the body. She demonstrated a touch pattern of moving the right shoulder blade (No. 2.3 in Fig. 2). The touch recipient lied on the left side of the body. The practitioner used her right hand to support the shoulder and upper right arm of the recipient, and used her left hand to move the right upper body of the recipient by pushing the joints and shoulder blade. She used the thumb to hold the shoulder blade and the other four fingers to grab the shoulder blade from underneath while applying force to move the shoulder blade, with the middle finger applying the greatest force. Feedback from the touch recipients includes: "*I felt the quality of the touch is like she really knows what she's doing. She uses one hand to hold my shoulder blade, and then she uses the other hand to make a quite big movement on my body. But I don't have any doubts at all. I feel very trusting of her, very safe*." [RTR2]

Gestures shown in Fig. 3 range from light holding and stroking (0.25 - 0.5 N), firm holding (0.5 - 1.5 N), addressing the muscle (1 - 5 N), and the bone (up to around 7 N). Among these, the observed force indication of stroking touch is within a range of around 0.25 - 0.5 N, which is in agreement with the current literature on CT-optimal stroking touch [21], [32], [42]. The indicative force level of touch when addressing muscles also echoes existing literature, where [43] reports a measurement of deep pressure massage at 2.5 N. By sampling 2000 pressed frames from each touch pattern, removing sensor readings below 10 ADC counts, and averaging across the selected frames, Table I summarises the median, mean, maximum, and standard deviation of the ADC counts within the contacted cells region of each gesture. Due to limited calibration, the ADC counts reported in the table do not directly correspond to absolute pressure values but are used as relative indicators for comparison across touch patterns.

TABLE I
AVERAGE ADC COUNTS FOR EACH TOUCH PATTERN.

Gesture	Mean	Median	Max	SD
Holding	20.581	14.324	57.537	19.110
Stroking	22.687	16.983	64.668	8.144
Cat-Paw	36.724	28.557	95.358	25.974
Moving Body	36.865	20.349	122.648	36.054

B. Most Touched Locations

Fig. 4 shows the heat map of the accumulated time that each sensing cell had been exposed to pressure. Among these, the locations within and below the shoulder blades are pressured most frequently. For example, holding pressurises symmetrically on the non-bony part of the back between the two shoulder blades (both the physiotherapist and the Tactile Stimulation practitioner), over both shoulders (Tactile Stimulation practitioner), and embracing the shoulder blades (psychotherapist). The outer edges of the back connecting the side of the body and the area right beneath the neck are the areas least touched.

C. Varied Force Profiles when Touching Different Anatomical Parts of the Body

The nuances in a touch to care are connected to what level of the anatomy the touch practitioner is seeking to touch, and our dataset captured touches that aimed at the skin, at the muscle, and at the bone. For the Tactile Stimulation practitioner, she uses spread palms to deliver the light stroking touch which is addressed to the skin to promote relaxation. The physiotherapist prefers to use fingers or knuckles when addressing

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muscles to treat pain and to use palms to engage a wider body surface for sensory integration. Whereas, the Feldenkrais practitioner emphasises addressing the bones, often addressed by a single finger, to move the body for the purpose of raising body awareness. As shown in Fig. 3, the force profile of touching these three body textures differs substantially in terms of the surface area covered and the amount of force applied: the stroking treatment aimed at the skin is with the biggest surface area and lowest force; the muscle treatment shows a higher force level and smaller surface area, and addressing the bone is with a very small contacting surface, usually with only one figure applying very high force.

D. Different Force Nuances within One Touch Gesture

In addition to different distinctive touch gestures and patterns employed by each practitioner, we found that within one gesture, such as holding, there are different nuances expressed in both the force profile as well as the recipient feedback, and yet, what is particularly interesting is how the experience of care remains even when the pressure of the hold varies across gestures or practitioners. For example, RTR2 compared the holding gesture from the Tactile Stimulation practitioner at the start of the session as *"very like gentle, but not that firm"* which: *"makes me feel safe, like my mind doesn't have to wonder what it's about ..."*(No. 5.1 in Fig. 2 and "Holding"(Tactile Stimulation Practitioner) in Fig. 3), while when referring to the physiotherapist holding her at the end of her session as *"firm, like a finishing, very grounding... I found that has a greater connection... and I really want more (of this)"*(No.4.2 in Fig. 2 and "Firm Holding" in Fig. 3). The holding from the Feldenkrais practitioner, although applying a much greater force and can still feel secure and trusting (see quotes from RTR2 in section IV-A-4) . The differences in force levels can also be observed from the force visualisation in Fig. 3.

E. Feature Extraction and Prediction Accuracy

Our analysis of 20 touch interaction files across the four touch patterns revealed distinctive differences and similarities in different features. Fig. 5 reports the radar chart showing the resulting score of each feature for the four patterns of touch.

- Holding is characterised by high rhythm (0.961), and deliberateness (0.939) scores, reflecting the controlled, intentional nature of sustained contact. The high spatial distribution (0.91) and symmetry (0.822) scores indicate that holding is typically performed with both hands, spreading out and covering a wider surface of the back with even force distribution. The velocity analysis revealed the lowest (0.89), with an average velocity of 2.37 cm/s across all holding interactions, indicating minimal movement while maintaining caring quality.
- Cat Paw touch is characterised by high spatial symmetry (0.88) and rhythm scores (0.96), but lower consistency scores (0.35), reflecting the varied pressure patterns typical of this playful, engaging interaction. The rhythmic variation of pressure or "pace" referred to by the touch recipient is one feature for the Cat Paw touch to feel pleasant. The average velocity of 11.49 cm/s resulted in moderate velocity scores (0.71).
- Stroking is characterised with high scores in spatial distribution (0.93) and high deliberateness (0.93), but lower velocity scores (0.51). The velocity of stroking is 14.24 cm/s. The consistency scores (0.49) reflected the dynamic nature of stroking movements while maintaining deliberate control.
- Moving the body touch exhibited high consistency (0.738), high deliberateness (0.905) but low spatial symmetry (0.475) which reflects that the practitioner applies constant force in order to move the body, with a quality of smoothness. As the practitioner only performed on one side of the shoulder blade, this touch has the lowest symmetry score (0.475). Creating an asymmetric sensation is a method in Feldenkrais practice to enable awareness of the body. The moderate velocity score (0.73) suggests that the controlled movement speed contributed to the overall caring quality.

Fig. 5. Features extracted that describe touch with normalised caring quality. Higher scores reflect a more caring touch, with the central scores reflecting the overall caring score.

The result reveals two distinctive feature patterns. The holding, stroking and cat paw walk which aimed at sensory aspects addressing an immobile body shared high scores of deliberateness, rhythm, spacial coverage and symmetry, whereas the touch aimed at moving the body shows highest scores in deliberateness and consistency. While our feature extraction uses equal weighting across all six features, the AI model training employs gesture-specific feature combinations to improve prediction accuracy.

To explore automated caring touch assessment, we trained a 1D CNN to predict feature scores from raw sensor data. The AI model aimed to predict an average of the relevant features for each of these two types of touch, deliberateness, rhythm, spatial coverage and symmetry for the holding, stroking and cat paw walk, which emerged as consistently high-scoring characteristics across these gestures, whereas for moving of the

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body it predicts the average of the deliberateness and consistency features, reflecting the importance of smooth, sustained force in enabling safe and trusting body manipulation. This grouping was informed by expert interviews, touch recipient feedback, and the observed divergence in feature profiles across gesture types. We chose this approach to better align the scoring with the intentionality behind the touch, rather than treating all features as universally applicable across all gestures.

Using hold-out validation (30%) across three gesture types the 1D CNN achieved MAE = 0.073, with individual errors ranging from 0.023-0.105 with overall average performance shown in Table II. The model generalised across holding, stroking, and paw gestures, demonstrating feasibility for real-time caring touch quality assessment. In comparison a 3-layer LSTM network achieved an MAE of 0.089 demonstrating slightly worse performance than the CNN. This performance demonstrates the feasibility of using raw tactile sensor data to assess subjective touch quality, validating our feature extraction approach while suggesting potential for future work to improve these models for real-time caring touch assessment systems. In the future this AI model could be used be used as the foundation to enable on-body haptic actuating systems to deliver varying caring touches.

TABLE II

AVERAGE 1D CNN TEST EVALUATION PERFORMANCE PER GESTURE.

Gesture	True	Predicted	Error
Holding	0.906	0.978	0.0727
Stroking	0.905	0.984	0.079
Paw	0.906	0.966	0.060
Mean Absolute Error			0.073

V. DISCUSSION

A. Insights on Characteristics that Code Caring Quality of Touch

Our results further evidence the limitation of relying on certain gestures to infer caring meaning in touch. The gestures and touch patterns used by the therapists, although all perceived as trusting and caring, range from holding, stroking, cat paw walking, moving the body, with force level ranging from 0.25 -7 N. Our result also underlines the risk of relying on a single parameter, e.g. force level or velocity, and the need to profile combined features, which is in agreement with [12]. The velocity of the stroking touch in our study is greater than the range of affective touch stroking velocity suggested by literature [16], suggesting that velocity may not be the only parameter characterising a caring quality. High spatial distribution and smooth changing of force can make a stroking at slightly faster speed feels caring. Our data generated understanding of the nuances within one touch gesture that can be caring, and that it is not the case that a gentle force is inferred as caring, and a firmer force not, but rather that changing the force associated with a touch can provide different dimensions and interpretations to a caring touch. Our finding also reveals the nuance of characteristics in touching different anatomical constitutions of the body.

It is more about *how* the touch is enacted that encodes caring intent and enables perceived caring quality. When touching for sensory purposes rather than moving the body, high deliberateness, spatial and symmetry and low velocity in combination characterise the caring quality. Whereas for the purpose of moving the body where consistent force needs to be maintained, high deliberateness and consistency score are associated with communicating caring intention and felt more trusting. This can be particularly informative for assistive robots that help with human mobility, that the research agenda of which can be extended from safety to perceived caring quality. High deliberateness - the careful and smooth initiating, and increasing and decreasing of force emerged to be a critical design parameter for a touch to feel caring, a finding we have not come across in existing literature. Future work can test with more dataset to explore whether it can be viewed as a universal feature for embodying touch with caring quality.

B. Limitations and Future Work

Our study demonstrated the feasibility of a force-resistive e-textile sensor in profiling caring touch, future work could improve the manufacture process to enhance reproducibility and explore other machine learning methods in modelling accuracy. We envision the sensing system to be employed in guiding or training on-body haptic actuating systems or assistive and companion robotics in a care context for them to touch better. The small dataset in this study may not capture the full variability of touch practices. In addition, different body types, gender, and cultural factors can influence the results. Future work that includes a larger and more diverse dataset can help attest the generalisability of the findings in this study in wider contexts.

VI. CONCLUSION

In this study, we evidenced the feasibility of a low-cost and customisable force sensing matrix garment that enables collecting force profile and subjective perceived experience of the same touch in natural environment. Machine learning analysis revealed features contributing to perceived caring quality in touch aimed at sensory aspect on the immobile body and aimed at moving the body. Our results foregrounded deliberateness as a potential shared attribute adding to the literature of designing haptic stimulations for care applications. It also demonstrates the feasibility of using raw tactile sensor data to assess subjective touch quality.

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