Effect of Prior Relationship on Attention-seeking Touch

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ABSTRACT

This research explores the area of affective computing by investigating the effect of relationships on social touch in an attention-seeking context. Social touch is a fundamental aspect of human interaction, being of importance in areas such as human-computer interaction, educational or workplace dynamics, and healthcare. A user study was conducted on 31 participants to gather touch gestures. Each participant needed to respond with a touch after reading a scenario in an attention-seeking context. Half of the scenarios were about familial interactions, and the other half were about stranger interactions. Leveraging machine learning techniques, models were built to classify between familial and stranger touches. Random Forest models with data segmentation based on a sliding window approach achieved the highest accuracies. Features were extracted on a global, channel, and sequence level, based on these segments. Nested cross-validation was used to evaluate the models. The best-performing RF model used a window size of 9 seconds and a step size of 4 seconds. It achieved an accuracy of 0.70. Results indicate a statistically significant difference in social touch between family members and strangers, although this difference is not exceptionally high.

KEYWORDS

Social Touch, Affective Computing, Dataset, Attention-seeking, Machine Learning, Interpersonal Relationship

1 INTRODUCTION

Social touch plays a critical role in human development, affecting the emotional state, attachment, and social reward [7]. It is a crucial component in our set of senses to survive. Touch is the first sense to develop in a human fetus [12]. Our sense of touch provides us with the capabilities to receive information about our environment. Touch is necessary for humans to gain an understanding of complex spatial arrangements and develop a sense of reality [19]. By touching objects, we as humans learn what is safe to touch and not. In short, touching gives us the possibility to develop, making it essential for our survival.

Next to the fact that touch is imperative to our survival, touch goes beyond that. It also incorporates emotions. It is universal social behavior to touch people [20]. Humans are sensitive creatures. It was even found that touch has healing power. Touch aids us in developing into strong and sensitive individuals, can calm us, enhance personal trust, give comfort, and help us bond with others [8]. We need our loved ones, friends, and families to touch us. Although human social touch is a complex matter, it has been shown that a stroke on the skin can convey multiple emotions, including comfort, love, and sadness [14]. Humans can become touch-deprived if they do not obtain enough affection through touch. Meijer et. al [25] have researched touch deprivation and affective touch perception during the COVID-19 pandemic. They found that there was a significant increase in touch deprivation when the duration and severity of COVID-19 regulations increased.

Social touch is a nuanced and multifaceted topic. One context to which research in this field can be applied is an attention-seeking context. This includes eliciting attention, by acting in a certain way. Every single person encounters this every day. Whether it is to obtain attention from a colleague, a family member to hug, or a classmate because they make too much noise during a lecture, attention-seeking is part of all-day activities. It fits within our human desire to be loved and accepted, and to prevent feeling lonely [6]. Attention-seeking is commonly compared to other types of touch, and it occurs in all relationships.

Comprehending human social touch is useful for many applications. By unraveling social touch, deeper insights into emotional responses and human interactions can be provided. These insights can for instance be used in the field of human-computer interaction, educational settings, workplace dynamics, and in the healthcare sector.

This research utilizes artificial intelligence (AI) to enhance our understanding of social touch. The world currently is on the cusp of a technological revolution, where artificial intelligence (AI) is about to enhance or reinstate various aspects of our lives [34]. AI systems propose a unique opportunity to find patterns in data that we as humans cannot immediately see. This approach can help to shed new light on how social touches are given and perceived by humans.

This paper utilizes artificial intelligence to research the influence of relationships on social touch in an attention-seeking context.

2 PROBLEM STATEMENT

Among the things that challenge us in this world, is the comprehending of social touch. Although touch comes naturally to most individuals, we are not aware of how complex it is. Next to this, research can aid in lots of applicative areas. An example is the human-computer interaction field. Within this research field, we want to develop robots capable of sensing and responding to our touches. As socially intelligent robots are likely to become more common in the near future, robots should be able to engage in tactile interaction with humans. This requires the ability to sense,

41th Twente Student Conference on IT, July 05, 2024, University of Twente, the Netherlands

classify, and interpret human touches [22]. Another application where understanding social touch is important is in an educational setting. Research has highlighted the importance of social touch in an educational setting, helping to create meaningful relations and contributing to a better physical, social, and cognitive state for students [10]. Also, a better understanding of attention-seeking social touch can help teachers manage their classrooms more effectively. This same principle applies to workplaces, where employers can improve the general well-being and the effectiveness of their teams with a greater understanding of social touch. Last, understanding social touch can aid in the healthcare sector as well. Research has shown that tactile touch leads to significantly lower levels of anxiety [13], making it important in different types of therapies. An example of this is moderate pressure massage therapy, which helps to reduce stress [11]. Social touch gives an enhanced feeling of comfort and trust, fostering better caretaker-patient interactions.

Attention-seeking touches are not only among the touches we give the most, but they are also feasible to generate in a lab environment. Giving an attention-seeking touch for a scenario requires less emotional empathy than needed for pure emotional touches, because of the prevalence of attention-seeking touches. This makes it easier for participants to provide touches, improving the user study's feasibility and quality.

Several studies have been conducted on social touch, the influence of relationships on touch, and classifying social touch with machine learning. However, the study of social touch in attention-seeking contexts using machine learning specifically, by considering interpersonal relationships, is lacking.

2.1 Research Questions

The problem statement described leads to the following research question:

- **RQ**: Does social touch differ in interactions with a family member or a stranger in an attention-seeking context?

To fully answer this question, this question is broken apart into the following sub-questions:

- **SQ1**: What do current studies present regarding social touch behaviors in familial and stranger interactions?
- **SQ2**: How can we measure social touches in attention-seeking contexts?
- **SQ3**: Can a machine learning model be trained effectively to distinguish social touch involving family members and strangers within an attention-seeking environment?

3 LITERATURE REVIEW

This research focuses on the difference in social touch interactions between family members and strangers in an attention-seeking context. In this section, an analysis of several fields within affective computing and social touch is provided. Much research exists within the broad topics of affective computing and social touch. Three fields are identified to narrow done the scope of this literature review. By doing so, the most relevant research for this specific study is included. The three fields are the role of prior relationships on touch, attention-seeking social touch, and machine learning related to social touch.

3.1 Role of Prior Relationship on Social Touch

First of all, an enhanced understanding of current studies regarding the link between prior relationships and social touch is valuable for this research.

Numerous research has been conducted on how the strength of a relationship determines the allowance of social touch. Suvilehto et al [30] researched in 2015 what parts of our body we allow others to touch. They did this for relatives, friends, and strangers. These allowed-to-touch body regions formed a map of which the area could directly be linked to the strength of the emotional relationship with that person. It seemed that the emotional bond with the toucher is linearly dependent on the amount of touch that was given, but independent of when that person was last encountered. They also found that cultural differences are minor. Jakubiak et al. [20] investigated in 2021 how the relationship between touchers affects the desirability to give and receive touch. This study looked at dating, engaged, and married individuals, as well as married couples. They found out that the strongest predictors of desire for touch are being female and having a high relationship quality.

Also, research has been conducted on how social touch is experienced for different types of prior relationships. Saarinnen et al. [28] conducted a review in 2021 of 99 research studies. They found that social touch can convey different emotions in different contexts and that it might not always result in pleasant feelings or neutral responses. The responses to touches are affected by a wide range of factors, including the appearance of the toucher, stigmatization of social touch in culture, minority status, and familiarity with the toucher. The familiarity with the toucher was similarly researched by Coan et al. in 2006 [9]. In this research, 16 married women were subjected to the threat of electric shocks while holding hands of either a stranger, their husband, or no hand at all. A pervasive attenuation was observed in the activation of behavioral threat response neural systems when women held their husband's hands. On the opposite, this attenuation was more limited when holding the hand of a stranger. It was noticed that the observed effect in spousal hand-holding varied as a function of marital quality. The better the participants ranked their marriage, the less their behavioral threat neural systems activated while holding hands.

Next to this, research has been done on the interpretation or decoding of social touches as well. Hertenstein et al. investigated in both 2006 [15] and 2009 [14] how social touches are interpreted between strangers. They placed a barrier between participants, and the toucher needed to touch the forearm of the recipient. They found that anger, gratitude, happiness, fear, love, disgust, and sympathy could be decoded purely based on the touch. This was feasible without any visible tactile simulation. Thompson et al. [32] extended on this in 2011, to see if this was the case in both stranger and familial interactions. They investigated that both strangers and romantic couples could identify universal and prosocial emotions, but only romantic couples were also able to decode self-focused emotions, like envy and pride. They are seen as more abstract emotions, thus requiring a closer bond.

One compelling observation in these presented studies is that they frequently focus on how the quality or closeness of a relationship affects touch, rather than investigating stranger interactions. Also, most of them seek to inquire about general social touches. Not often is this applied to attention-seeking contexts, nor in comforting or warning scenarios.

3.2 Attention-seeking Social Touch

Although much research exists on the topic of social touch, and the appliance of machine learning within this scope, applying touch to an attention-seeking context is not often done. Numerous studies incorporate attention as one of the reasons for which touch can be applied, but they do not focus on differentiation within this scope.

Among the researchers that conducted an exploration of attention seeking, is Baumann et al. [5]. The goal of their research was to emulate human attention-getting practices with wearable haptics. Although these devices frequently need our attention, they lack the capabilities humans possess to intrusively get someone's attention. Their observations describe that simple mechanisms situated on your body, like a bracelet, can already convey a wide range of socially attention-getting expressions.

Another research with a focus on attention seeking was done by McIntyre et al. [24]. They conducted an experiment where touch messages were communicated between a sender and receiver. Attention was one of their six types of touch. Attention achieved the highest accuracy. It was the easiest for the receiver to predict this class, compared to more difficult classes to predict like love or calming.

These papers reveal the easiness of both predicting and giving an attention-seeking social touch. However, both did not differentiate in any way within the attention-seeking class itself.

3.3 Machine Learning and Social Touch

In 2014, Jung et al. [23] introduced the Corpus of Social Touch (CoST), later made publically available to the research community [21]. CoST is a collection of 7805 instances of 14 different social touch gestures. A sensor grid was wrapped around a mannequin arm and participants were asked for three variations of touches, namely gentle, normal, and rough. Recognition of 14 touch classes was done utilizing Bayesian classifiers and Support Vector Machines. This resulted in an overall accuracy of 64% and 53% respectively. It laid down the foundation for more research.

In accordance with this dataset, a challenge was hosted in conjunction with the 2015 ACM International Conference on Multimodal Interaction (ICMI). This Social Touch Challenge was a collaboration between Merel Jung and Mannes Poel from the University of Twente and Laura Cang and Karon MacLean from the University of British Columbia. The goal was to spark interest in touch modality and promote research on the subject of data processing techniques for social touch. Two datasets were publicized for this challenge, to be specific the earlier mentioned CoST and the HAART dataset. The Human-Animal Affective Robot Touch (HAART) dataset consists of 7 gesture types over different surfaces, where human-pet interaction was simulated. The most used classifier was Random Forest (RF). Researchers who trained these RF models include Balli Altuglu et al. [4], Gaus et al. [2], and Ta et al. [31]. Other methods used were logistic regression by Hughes et al. [16], multiboost by Gaus et al. [2], and Support Vector Machines by Ta et al. [31]. The best-performing models were created by Ta et al. [31], with an accuracy of 60.8% and 70.9% on the CoST and HAART datasets respectively. At the point of organizing this challenge, the state-of-the-art solution for the CoST task was created by van Wingerden et al. [33]. They created a Neural Network (NN) of one hidden layer with 46 neurons, which achieved an accuracy of 64% on the test set. The state-of-the-art solution for the HAART task at the point of this challenge was given by Flagg et al. [1]. They employed RF, NN, logistic regression, and Bayes networks. The RF model achieved the highest accuracy of 86%.

Adjacent to the Social Touch Challenge, more research has been conducted on social touch utilizing the CoST and HAART datasets. For instance, Hughes et al. [17] discussed how previous investigations have focused primarily on the extraction of features from entire gestures, limiting the potential for real-time classification. They used deep learning techniques, such as recurrent neural networks (RNN) and convolutional neural networks (CNN), to extract features and provide predictions at a certain point in a sequence. These approaches provided a similar level of accuracy as the presented models in the Social Touch Challenge and allowed to make real-time predictions at a rate of 6 to 9 Hertz. Albawi et al. [3] similarly created a CNN model, that performed better compared with previous work, at an accuracy of 63.7%.

Analogously, more touch experiments for machine learning have been conducted. An example is the experiment conducted by Silvera Tawil et al. [29]. Their goal was to contribute to the future success of intuitive human-robot interaction. They built a classifier based on the 'LogitBoost' algorithm, which correctly predicted the type of touch from eight classes in approximately 71% of the trials. Nunez [26] investigated social interactions to improve haptic devices that capture the complexity of human touch. In one of their user studies, they formed a naturalistic social touch dataset by gathering human-human touch data from couples and close friends. This data was used to produce haptic signals through actuators. It was validated that these signals could successfully communicate the desired emotion. Last, Ramasamy et al. [27] used an existing database of vibratory signals to train an RF classifier. This database consisted of index finger touches, either touching themselves or another person. The accuracy of the model reached over 90%.

Other research in machine learning and social touch include Huisman's research [18]. They conducted a survey that provides an extensive overview of the intersection between haptic technology and social touch. They describe how the use of machine learning techniques to classify social touch can contribute to the development of more sophisticated haptic interfaces. This means that interpreting and reproducing the nuances of human touch can be achieved more accurately, enhancing social interactions mediated by technology in the future. Likewise, Jung's paper [22] from 2017 describes that robots must sense, classify, and interpret human touch and respond properly, to mimic human perception and giving of touch more accurately. They also describe how interactions with social robots will become more common in the future.

An important view shared by many of the presented papers within this subsection is that machine learning is a feasible solution to classify human touch. Many classifiers have been built on the publicly available CoST and HAART datasets. They have shown that RF and SVM models achieved the highest accuracies. To attain similar results and overcome the selection and extraction of features, CNNS could be used as well. This paper diverges by specifically zooming into prior relationships in an attention-seeking context. Research has been done on both as separate topics, but no research has specifically tried to train machine learning models to seek a difference in social touch for different prior relationships in attention-seeking contexts.

4 METHODOLOGY

This study adhered to a detailed study design. This adopted methodology includes a user study and computational analysis, done by training machine learning models on the data from the user study. It proposes a way to resolve the main research question. The type of the collected data is quantitative data. The dataset consists of only primary data. The data collection methods as well as the machine learning methods are described in this section.

4.1 Data Collection Methods

The collection of the data was done jointly with two other students, Adrian Josan and Yixuan Zhuang. In this way, a larger dataset could be created. The other two students focused on the reason for attention seeking and cultural background. This part of the study required ethics approval, provided by the Computer & Information Sciences (CIS) committee of the University of Twente, under application number 240348. All components of the user study are described in this subsection.

4.1.1 Survey And Consent Form. Before every experiment, the participant needed to read and sign a consent form. This form contains a description of our research and informs participants of their rights. A random participant ID was assigned by the researcher. Next to this, the participant was also asked to fill in a small survey. Both were conducted at the same place as where the experiment took place, and always in person. This was always at the University of Twente. The survey consisted of 3 multiple-choice questions, 2 open questions, and 2 questions measured on a 5-point Likert scale. The two questions of important to this research are shown below.

(1) Are you left or right-handed?
(2) What family member do you feel the most approachable to touch?

Determining the participant's most approachable family member was used in the scenarios where the prior relationship is a family member. In this way, the preference to (not) touch certain family members was eliminated. Besides, it made the scenario more specific. This helped the participant to be able to give a better touch. The participant's handedness was used to determine whether we used a left or right mannequin arm.

The testing population was mainly students from the University of Twente, as well as family members, friends, roommates, and any other person willing to take part. Non-probability sampling was used, as a convenience for the data collection was of importance for this relatively short research. The experiment took at most about 10-15 minutes per person.

4.1.2 Experiment. Since it is difficult for humans to act in a certain way by just providing them with some keywords, this user study instead focused on scenarios. By providing a participant with a certain scenario, without explicitly mentioning the linked contextual factors, participants could act more naturally. We used two distinct reasons for attention seeking and had two scenarios for each reason. This means there are four scenarios in this research. The first reason is to warn someone, and the second reason is to comfort someone. Next to this, the scenarios will include either a family member or a stranger. This is of importance to this research. A comforting scenario describes a setting where the toucher would like to alleviate someone's feelings, often in the case of distress or grief. The toucher comforts someone to improve their general mood and well-being. A warning scenario describes a setting where the toucher would like to inform people of some danger and prevent an unpleasant event.

The scenarios were written with the help of ChatGPT. A prompt with a description of this research and the question to come up with warning and comforting scenarios in an attention-seeking context was given. Four scenarios were selected from the list. More information about the use of AI can be found in Appendix A. The decided-upon scenarios are:

(1) **Comforting**:
   (a) Imagine you are in a university building hall where [your family member/a stranger] is seated on a bench, holding their phone. They have just finished a distressing phone call and are now crying, with tears streaming down their face. Their posture is slumped, and they are wiping away tears with one hand. Your goal is to give a comforting touch to help them feel supported and secure during this moment of distress.
   (b) Imagine you are outdoors where [your family member/a stranger] has just fallen off their bike. They are seated on the ground, nursing a minor injury, such as a scraped knee or elbow, and wincing in pain. Their face shows discomfort, and they look shaken from the fall. Your goal is to give a comforting touch to help them feel supported and reassured during this moment of discomfort.
(2) **Warning**:
   (a) Imagine you are walking along a busy city street. The traffic is heavy, and there are many pedestrians around. You see [your family member/a stranger] walking ahead of you. They seem preoccupied, perhaps looking at their phone or talking to someone. Just as they are about to step off the curb to cross the road, you see a car speeding towards the intersection. The driver hasn't noticed the pedestrian, and it's clear they won't be able to stop in time. Your goal is to touch [your family member/the stranger] on the arm to warn them of the imminent danger and prevent them from stepping into the path of the oncoming vehicle.
   (b) Imagine yourself in a bustling bar, filled with chatter and laughter. You notice [your family member/a stranger] deeply engrossed in conversation, blocking the narrow passageway. Your goal is, concerned for the flow of movement, to touch their arm to remind them to move so that others can pass.

The tool used to record the touches is the Touch Sensitive Patch. This is a device that is created and provided by researchers at the University of Twente. It is a silicon patch capable of sensing the amount of pressure put on a sensor, on a 29 by 17 grid. The maximum rate at which it can record is about seven frames per second. This means we can measure three variables, namely location, duration, and intensity of touch. Every pixel on the grid records an intensity between 0 and 255.

Next to the Touch Sensitive Patch, some other materials were needed. We used a mannequin arm to attach the patch. We did this to the lower arm. Some fabric was put around the patch to make it feel more natural, instead of feeling silicon. The full setup of the experiment is displayed in picture Figure 1.

Figure 1: Full Setup of User Study

Every participant read through all four scenarios one by one. After reading a scenario, they needed to touch the mannequin arm in the way they felt was the most appropriate. When this was done, they could continue to the next scenario. Not giving a touch for a scenario was also valid. A participant always got one familial warning scenario and one stranger warning scenario, as well as one familial comforting scenario and one stranger comforting scenario. There are two ways of arranging the warning scenarios and two ways of arranging the comforting scenarios. This means the total amount of options equals four. They are displayed in Table 1. Every option can be shown to the participant in any order, meaning there are 4! = 24 permutations per option. The total amount of sequences for the scenarios therefore is 96.

Option Nr.	Scenario Nr.			
	1	2	3	4
1	FC1	SC2	FW1	SW2
2	SC1	FC2	SW1	FW2
3	FC1	SC2	SW1	FW2
4	SC1	FC2	FW1	SW2

Table 1: User Study Types of Scenarios Options (F=Family, S=Stranger, C=Comforting (with version nr.), W=Warning (with version nr.)

4.1.3 Software. Accumulating data from participants required a systematic approach. Therefore, both a user study web application as well as a recording program were created. After building the foundation for these systems, the other researchers helped to further develop these programs. After discussing with the other researchers, these programs were extended with a database, the survey was moved to the user study web application, and it was made sure that the two seconds before the first touch was also recorded.

First of all, a user study web application was created using the Flask framework in Python. This web application uses the basic Bootstrap framework, to not distract the participant with any fancy user interface while undergoing the experiment. The first page asks for the participant ID. When entering this and pressing the next button, a sequence of the experiment is automatically generated and saved together with the participant ID in the database. The chosen option from Table 1 was picked using the formula given below.

$$Option = (participantID - 1)\%4 + 1$$

For this option, the program takes a random permutation. This means the order of the scenarios was random.

The next page of the web application is the survey. The answers to this survey were saved together with the participant ID in the database as well. After this page, there is a final check of the provided answers. The next four pages show the scenarios, in the order of the computed sequence.

Second, a recording app was created using Python. The researcher statically filled in the participant ID while the participant was answering the survey. The scenario sequence for this participant is retrieved from the database, and the recording program starts four times in a row. It constantly records and drops frames so two seconds are kept, up until the touching has started. The beginning of a touch is recognized if any pixel on the grid has a value higher than 50. The researcher could see the touch live. One frame of a recording is visible in Figure 2. To stop recording, the researcher needed to press the space bar on their laptop. This recording was then saved as a JSON file, with a header that contains the participant ID, reason, relation, and the version of the scenario.

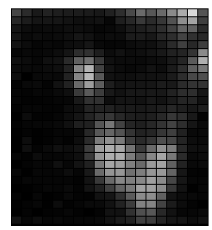


Figure 2: One Frame in a Touch Recording

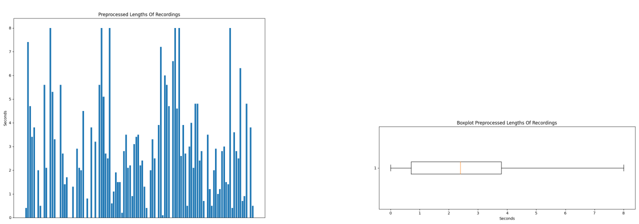
4.2 Machine Learning Methods

After the data collection process was concluded, an extensive analysis was done employing machine learning models. All stages, as well as justifications for choices, are given in this subsection.

4.2.1 Data Preprocessing. First of all, recordings needed to be trimmed. After creating a bar plot and a boxplot for the original recording lengths in seconds, it was found that 22 recordings were longer than 10 seconds. There are several reasons for these long recordings. The first reason is padding. The software to record touches already added 2 seconds of padding before the touch and only stopped when the researcher pressed the spacebar. This means that there was empty space in every recording. The second reason was random noise. For a few recordings, the sensor received some high-pressure noise on a few pixels, which triggered the program to start recording while the participant was still reading the scenario. This resulted in some recordings being over 30 seconds. Last, some participants already touched the arm quickly to feel how the mannequin arm felt, while the researcher just started the recording program. The padding was removed by removing frames at the beginning and end of a recording if none of the pixels in that frame reached the threshold of 40. The recordings with random noise or a small touch at the beginning still existed at this point. In order to resolve that, a list of touch sequence indices was generated per recording. Two indices of frames were put in the same sequence if they were less than 3 seconds apart. Since the researcher stopped every recording after the actual touch, only the last sequence was kept. This means that the last sequence was always the actual touch given by the participant.

Now that padding and random noise were removed from the recordings, the next phase in data preprocessing involved selecting and excluding outliers. The interquartile (IQR) method of outlier detection was employed, resulting in an upper bound of 10.6 seconds. All recordings longer than 14 seconds were given by three participants, so it was decided to exclude these participants from the dataset. Their participant IDs were 20, 23, and 28.

After excluding 3 participants, the IQR outlier detection method gave an upper bound of 8.45 seconds. Six recordings were a bit longer but were touches of a consistent pattern. For this reason, they were trimmed to a maximum of eight seconds. At this point, there were no outliers in the dataset anymore. The recording lengths in seconds of the preprocessed data were plotted in a bar plot and boxplot (Figure 3a and Figure 3b respectively). The unpreprocessed dataset consists of 31 participants and 124 entries. These 124 entries were distributed between 62 family entries, of which 3 were empty recordings, and 62 stranger entries, of which 14 were empty recordings. The final dataset consists of 28 participants and 112 entries. These 112 entries were distributed between 56 family entries, of which 3 were empty recordings, and 56 stranger entries, of which 14 were empty recordings.



(a) **Preprocessed recordings**

(b) **Boxplot preprocessed recordings**

Figure 3: Recording lengths in seconds for preprocessed recordings

4.2.2 Splitting And Segmenting Data. To effectively train and evaluate machine learning models, all recordings in the dataset needed to be designated to a train and test set.

Prior attempts included segmenting all recordings first, before splitting them to train and test sets. This led to overwhelmingly high accuracies but introduced an enormous data leakage bias. When the step size of the sliding window was low, fragments one shift away from each other could be divided among both the train and test set. This exacerbated the data leakage. Even when setting the step size to be equal to the window size, a recording could be split up in two, and the two parts could be divided among the train and test set respectively. Another attempt included splitting to train and test sets randomly based on recordings, before segmenting the data. There was one factor left here that introduced a bias, scilicet, that one participant's recordings could be shattered to the train and test sets. The model could learn participant-specific features rather than generalizable patterns, causing inflated accuracies.

The correct approach involved partitioning participants into a train and test set. This method ensured that no data from the same recording or participant appeared in both sets, thus preventing any bias. For both the train and test set, recordings were either used completely or segmented using a sliding window approach. The sliding window approach started with putting all recordings for a certain relationship in either the train or test set directly after one another. For this large amount of frames, segments were taken based on different window and step sizes.

4.2.3 Feature Extraction. By analyzing the data and researching previous works from Jung et al. [23] and Ta et al. [31], a list of features was extracted from the data. This was done on the global level, the channel level, and the sequence level.

First, features were extracted on the global level. This means that features are calculated based on all frames and pixels. There are 51 features in this category. They are the following:

- **Length**: Length of the segment (only useful when training on recordings);
- **Mean**: Average pressure on all channels over all frames;
- **Std**: Average std of pressures on all channels over all frames;
- **Max Pressure**: The maximum value present in all frames;
- **Active**: The percentage of active frames. A frame is active when one of the values in its frame achieves the threshold of T = 40;
- **Mean Columns**: The mean value for every column over all frames. This means it contains 19 averages since the patch has 19 columns;
- **Mean Rows**: The mean value for every row over all frames. This means it contains 27 averages since the patch has 27 rows.

Second, features were extracted on the channel level. The patch has 513 pixels (19 columns by 27 rows), so 513 values are calculated for every feature. There are 6 features in this category, meaning 3078 values are added to the feature list per segment. They are the following:

- **Mean**: Average pressure of every channel over all frames;
- **Std**: Average std of pressures of every channel over all frames;
- **Max Pressure**: The maximum value present in every channel;
- **Pressure Variation**: The mean variation of pressure in every channel;
- **Active**: The percentage of active pixels in the channel. A pixel is active when it reaches the threshold of T = 40;
- **High-Pressure Percentage**: The percentage of high-pressure pixels within the channel. The pressure on a pixel is high when it reaches 90 percent of the maximum value of all pixels of the segment.

Last, features were extracted on the sequence level. The amount of values here would depend on the length of the segments. They are the following:

- **Average Pressure**: Average pressure on the 513 pixels per frame;
- **FFTs**: Fast Fourier Transform features, which are calculated using the fft function in Scipy. The input is the list of average pressures.

The sequence level features were excluded when extracting features based on entire recordings because recordings differ in length.

4.2.4 Models. Initially, deep learning models like Convolutional Neural Networks (CNNs) and Long Short-Term Memory networks (LSTMs) were investigated. These models were not adequately able to make a statistically significant difference from random guessing. Consequently, Random Forest (RF) and Support Vector Machine (SVM) models were investigated. They achieved higher accuracies immediately. The initial RF models achieved the best performance by leveraging the extracted global, channel, and sequence-level features. These models were therefore further explored and developed.

4.2.5 Training And Nested Cross Validation. Nested cross-validation was performed to optimize and evaluate the machine learning models rigorously. This method involves an outer cross-validation loop as well as an inner cross-validation loop with hyperparameter tuning.

The outer cross-validation loop divides the participants into 4 folds. In every iteration, one fold represents the test set, and the remaining folds form the set to be used by the inner loop. The correct recordings are retrieved, features are extracted and the correct label vectors are formed.

Within each iteration of the outer loop, the inner cross-validation loop divides the remaining training data into 3 folds. One fold represents the validation data, and two folds form the train set on which the model will be trained. GridSearchCV is used in the inner loop to search for optimal hyperparameters, specifically the number of trees, by looking at the accuracy metric while differentiating this hyperparameter.

In this way, an optimal and carefully validated model per iteration of the outer loop is obtained. For every model, performance metrics such as accuracy, AUC, precision, recall, F1-score, and confusion matrices are stored. Their mean values, as well as standard deviations, can therefore be computed to evaluate robustly.

5 RESULTS

The performance of both the models trained on segments and the one on recordings was analyzed. Evaluations were done as described in the methodology. The results are described in this section.

5.1 Models on Segments

Several models for a range of window and step sizes were trained and evaluated. The average accuracy and its standard deviation were computed for each model. The accuracies and their 95% confidence intervals are displayed in Figure 4. The names of the models here depict the window and step size in frames. The frame rate of all recordings is 10 frames per second.

The best-performing models from this list were selected based on the lowest value from the 95% confidence intervals. The best-performing model among the segment-based models is the model with a window size of 90 frames (9 seconds) and a step size of 40 frames (4 seconds). This model achieved an accuracy of 0.696, with a 95% CI of [0.506, 0.886]. It attained an ROC-AUC score of 0.791, with a 95% CI of [0.637, 0.944]. The confusion matrix, computed as a sum of all validations on the different test sets, is presented in Figure 5. The classification report for this model, including the precision, recall, and F1-score per class as well as on average, is displayed in Table 2.

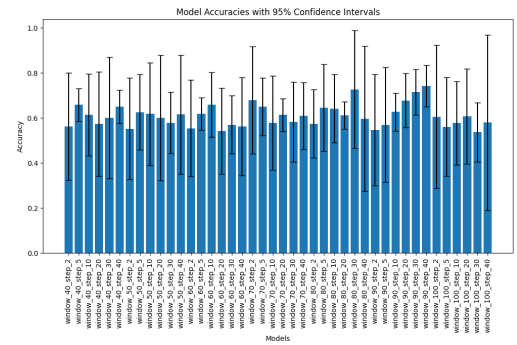


Figure 4: Model on Segments Accuracies with 95% CIs

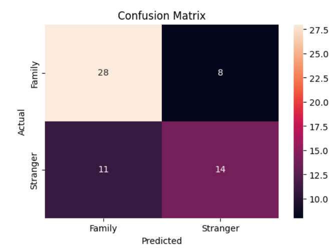


Figure 5: Confusion Matrix of Model window_90_step_40

	Precision	Recall	F1 score
F	0.72 [0.45, 0.98]	0.82 [0.51, 1.00]	0.75 [0.57, 0.93]
S	0.73 [0.33, 1.00]	0.58 [0.31, 0.85]	0.61 [0.45, 0.78]
MA	0.72 [0.55, 0.90]	0.70 [0.55, 0.85]	0.68 [0.51, 0.85]

Table 2: Classification Report of Model window_90_step_40 with 95% CIs (F=Family, S=Stranger, MA=Macro Average)

5.2 Model on Recordings

One model was trained on the recordings in their entirety. This model achieved an accuracy of 0.643, with a 95% CI of [0.447, 0.838]. It attained an ROC-AUC score of 0.671, with a 95% CI of [0.422, 0.887]. The confusion matrix is given in Figure 6, and the classification report is shown in Table 3.

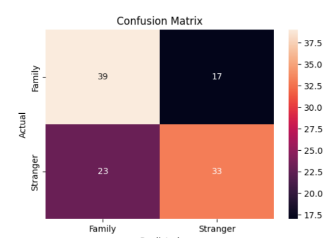


Figure 6: Confusion Matrix of Model on Recordings

	Precision	Recall	F1 score
F	0.64 [0.43, 0.84]	0.70 [0.54, 0.85]	0.66 [0.50, 0.83]
S	0.66 [0.46, 0.85]	0.59 [0.32, 0.86]	0.62 [0.39, 0.85]
MA	0.65 [0.45, 0.84]	0.64 [0.45, 0.84]	0.64 [0.44, 0.84]

Table 3: Classification Report of Model on Recordings with 95% CIs (F=Family, S=Stranger, MA=Macro Average)

Further analysis was performed to research the performance of the model for the comforting and warning recordings. This was feasible for the model on recordings since the label vector with reasons can be created by extracting the reason per instance. The accuracies are shown in Table 4.

	Comforting	Warning
Family	0.82 [0.56, 1.00]	0.57 [0.29, 0.86]
Stranger	0.57 [0.22, 0.92]	0.61 [0.30, 0.92]

Table 4: Accuracies of Model on Recordings for Comforting and Warning Scenarios with 95% CIs

6 CONCLUSION AND DISCUSSION

This study aimed to explore the influence of prior relationships on attention-seeking social touch, utilizing machine learning techniques. The main interpretations, implications, limitations, and recommendations are described in this section.

6.1 Interpretations

The findings from this study indicate that there is a difference in social touch depending on the interpersonal relationship between individuals in attention-seeking scenarios. The models trained on segmented touch data, especially the ones where data was segmented with a sliding window size of 90 frames (9 seconds) and a step size of 40 frames (4 seconds), derived the most promising results. With an accuracy of 0.696, it is statistically significant to assert that it performs better than random guessing. However, given that the model is conducting a binary classification, this accuracy level is not exceptionally high. The precision in both classes is quite good, but the recall is low for the stranger class. This means that the model's ability to predict instances of the stranger class from actual stranger instances was not as effective as its performance with the family class. At a ROC-AUC score of 0.791, the model is relatively good at discriminating between the two classes. Within the reason of attention-seeking, the model trained on recordings provided more insights. It shows that the model is better at predicting touches within the comforting class (accuracies of 0.82 and 0.57 for family and stranger respectively) than for the warning class (accuracies of 0.57 and 0.61 for family and stranger respectively). It was especially accurate in predicting the comforting family scenarios.

From these metrics, we can deduce with statistical significance that a difference exists in how family members and strangers give touches in attention-seeking contexts. This difference is slightly bigger for the comforting reason than for the warning reason.

6.2 Implications

These results build on existing evidence of a difference in social touch depending on prior relationships, as described in the literature review. This study provides new insight into the association between prior relationships and social touch in attention-seeking contexts specifically. The results demonstrate that a difference exists in attention-seeking contexts as well.

This can be extended to multiple domains, including human-computer interaction, educational or workplace dynamics, and healthcare. The awareness of how interpersonal relationships shape social touch in attention-seeking is relevant for improving emotional bonds between humans. This can help teachers and employers manage their classrooms and workplaces, as well as give therapists the ability to gain more comfort and trust from their patients. Furthermore, the enrichment of knowledge about social touch also aids the new generation of socially intelligent robots. They can be enhanced to interpret and respond to human touch cues more accurately.

6.3 Limitations

The study was not done without limitations. The generalizability of the results is limited by for instance the sample size, sample population demographics, and a small issue while gathering data. First of all, the sample size was N=31, of which N=28 participants were used to train the models. Every participant touched the patch for four scenarios. Because of time constraints, it was decided to conduct the user study on at least 10 persons per researcher. Next to the sample size, the results of the survey have demonstrated that 24 out of 31 were male and 28 out of 31 were in the age group of 18-24. This is a low diversity in gender and age demographics. The last limitation of this research was a small error during the data gathering. We set up both a left and right mannequin arm, so that a right-handed person could touch the mannequin's left arm, and a left-handed person could touch the mannequin's right arm. However, during the data gathering, the right mannequin arm did not fully work due to a corrupted connection. Because of this, we just placed the left mannequin arm in front of the dominant hand of the participant. This affected 4 left-handed people. Nonetheless, the results are valid concerning answering the main research question.

6.4 Recommendations

Further research is required to establish a clearer correlation between relationships and attention-seeking social touch. For instance, expanding the dataset to include a larger and more diverse sample could enhance the model performance. This would also enable the possibility to utilize deep learning techniques. Furthermore, integrating other data input methods such as cameras and microphones, could exhibit other implicit reactions from participants. Patterns in these behaviors, possibly also analyzed using machine learning techniques, can also unleash new implications. Last, the user study can also be conducted between actual family members and strangers. Participants might give a more natural touch when touching an actual person instead of a mannequin arm. These recommendations can lead to a better understanding of the role of interpersonal relationship on social touch in an attention-seeking context.

A USE OF AI

During the preparation of this work the author used OpenAI's ChatGPT 3.5[1] in order to generate the four scenarios from the user study of this research. This helped to formulate nuanced and clear scenarios. After using this tool/service, the author reviewed and edited the content as needed and takes full responsibility for the content of the work. The author edited the last lines of the retrieved scenarios to clearly state the goal of the touch.

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