

# Observational Study of a Digital Application to Detect Attachment in Dyads Using Markov Chains

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**Keywords:** Interpersonal Attachment, Digital Application, Observation, Mental Processes, Mental Health Care, Time Series Analysis.

**Abstract:** Attachment is a widely used term and basically refers to a strong emotional relationship that one person develops with another. It is often measured, for example, with the Adult Attachment Interview (AAI), one of the most popular tools, or the Child Attachment Interview (CAI), an adaption of the former. Even though these are two excellent tools for measuring attachment, they are labor-intensive and therefore not suitable for quick use without an adequate training period. Moreover, the mindset towards attachment has changed over time since the development of these tools, meaning that they can still be applied, but only in specific contexts. The digital application "IU" is intended to address these two issues by being easy to learn on the one hand and leaving plenty of freedom for measurement on the other. In this observational study, the interpersonal attachment of dyads captured by the app is interpreted as three-dimensional time series and analyzed based on a Markov chains. This approach shows how interpersonal attachment might be determined according to the homogeneity of the Markov chains, which could probably be improved by capturing other factors such as the interactions of dyads.

## 1 INTRODUCTION

In the field of psychology, attachment is a widely used term that first entered the healthcare system in the 1950s (Evans, 2004). In its origins, attachment refers to the strong emotional relationship that an infant or child develops with a caregiver (Bretherton, 1992). Back then, caregivers were mainly associated with mothers, so that research also focused on attachment between mothers and their children. One of the most popular methods developed through this mindset is the Adult Attachment Interview (AAI), a tool for classifying attachment patterns of adults based on childhood experiences with parents and the influence of these experiences on personality development (Main et al., 2008). Another tool is the Child Attachment Interview (CAI), an adaptation of the AAI for children (Target et al., 2003). Both AAI and CAI provide reliable results, as evidenced in multiple studies (Hesse, 1999; Privizzini, 2017; van Ijzendoorn et al., 2008). This is why these tools are very attractive and hard to replace. However, due to their structural similarity, they have one major drawback in common: they produce a high workload.

Nowadays, the mindset towards attachment has considerably changed. One of the main claims is that attachment is not only related to the child's behavior but also to the socio-emotional contexts of adulthood (Fearon et al., 2017). This can be seen in the various literature in which attachment is addressed, including studies on social relationships formation (Insel, 1997), on love couples (Brumbaugh et al., 2006), or even on patient care (Agrawal et al., 2004; Blanco et al., 2018). Because of this and because of the major drawback of the AAI and CAI, new and innovative measurement methods were developed or at least investigated. The Adult Attachment Projective (AAP), which uses attachment-related drawings (George et al., 2004), is one of the few art-based approaches. Other approaches that focus on movement patterns are hardly seen in research. A few examples on this topic are those that combine conventional attachment methods with the movements of the eyes, the facial expressions, or the people themselves (Altmann et al., 2021; Kammermeier et al., 2020; Uccula et al., 2022).

The approach in this article represents both an art-based and a movement-based measurement method. The measurement is performed on a tablet and has

already shown its potential using two-dimensional time series (Unger et al., 2020). In contrast to the approach from the previous proof of concept study, a further meaningful dimension supplements here the measurement of interpersonal attachment.

The assumption is that the addition of this third dimension may increase the accuracy of the method, leading to the research question: “Can interpersonal attachment of a dyad be captured as three-dimensional time series with a digital application?”. To test the question exploratively, the time series are checked for practical applicability using a Markov chain approach. It has not yet been examined in this context, but Markov models are increasingly being used in clinical psychological research. In addition to the individual case study by Elbing et al. (2022), corresponding approaches, e.g., the analysis of emotions of outpatients with schizophrenia (Strauss et al. 2019; Strauss et al. 2023), the development of a clinical decision support system for bipolar disorders (Valenza et al., 2013), the modelling of emotional brain states (such as “surprise”, “fear” or “anger”) among university students (Kragel et al., 2022), or the investigation of computer-based social interactions with virtual objects (Dolev et al., 2020; Prasetyo et al., 2020), indicate promising results.

## 2 METHODS

### 2.1 Participants

Participants were recruited via the internal bulletin board, social media, and verbal communication. Eligible participants were between 18-65 years old, were able to operate a tablet independently, had no acute disorders that could interfere with the use of a tablet, and were not pregnant due to unknown effects on stress levels. In addition, an informed consent form had to be signed by all participants before the examination could start.

With this inclusion criteria, a total of 60 people (43 females and 17 males) were motivated to voluntarily participate, a lot of whom registered directly with a familiar partner. The age of the participants ranged between 19 and 37 years ( $\bar{x}_{age} = 23.78$  years).

### 2.2 Examination Set-up

In a first step, the participants were organized into dyads, as the examination could only be conducted in a dyadic constellation. Participants registered with a partner were automatically assigned to each other.

Otherwise, they were randomly assigned to a partner. After 30 dyads were formed, the dyads were asked to arrive in a specially prepared laboratory room. The equipment included a table on which two tablets as well as two styli were positioned and two chairs for the participants to sit on. On site, there was also a person in charge who informed the participants about the procedure, checked their suitability, and had them sign the informed consent form.

Next, the participants had to place themselves opposite their partner. Once they were seated, the person in charge handed each of them one of the two tablets, which were already running an app called “IU”. Participants were now asked to enter an assigned identification number (ID) as well as their age and gender in the text fields provided by the app.

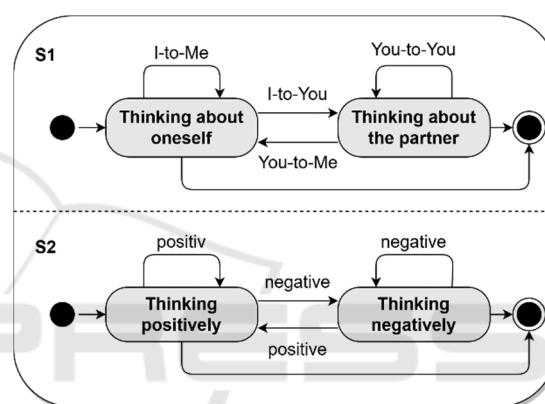


Figure 1: State diagram of the participants' measurable thoughts, showing the two first level states and the two second level states.

In the last step, the person in charge handed the participants a pen for digital drawing (stylus). The task for the participants was to seek eye contact for three minutes, while transferring their thoughts to the tablet with the stylus. The thoughts that are attempted to be captured are mapped on the basis of four mental states, consisting of two first level states and two second level states, as show in Figure 1. The two first level states express if the participants are thinking about themselves or about their partner, who is sitting opposite to them. Therefore, the former state is called “I”-state, named after the personal pronoun “I”, whereas the latter state is called “U”-state, named after the sound of the personal pronoun “You”. Both states can each reach one of the two second level states to express if the thought has a positive or negative orientation. On the tablet, the combinations of the four states are displayed by dividing the bottom (“I”-state) from the top (“U”-state) half of the screen and by dividing the left (negative orientation) from the right (positive orientation) side of the screen.

From this it follows that participants who are thinking about themselves move the stylus to the bottom half and participants who are thinking about the partner move the stylus to the top half. At the same time, participants have to consider the positive or negative orientation of their thought by moving the stylus either to the left (negative) or right (positive) side. The stylus is then meant to remain in the corresponding location of the screen as long as the thoughts do not change. If there is a change, the stylus is moved accordingly, which is likely to be expected during this examination.

### 2.3 Output Measures

While the participants look at each other and transfer their thoughts to the tablet by moving the stylus back and forth for 3 minutes, a tracking process runs in the background of the app. With this tracking, the pixel coordinates touched by the stylus ( $x_i, y_i$ ) and the time of this touch ( $t_i$ ) are saved for each participant  $j_k$  ( $k = A, B$ ) of the dyad  $j$  continuously, creating a time series  $(x_i, y_i, t_i)_{jk}$ . Such three-dimensional time series describes the course of the thoughts of a participant, whereby the x-coordinate, the y-coordinate, and the time each correspond to one dimension. To enable the individual time points of a time series to be assigned to the four mental states in retrospect, the vertical and horizontal screen divisions are additionally saved.

### 2.4 Statistical Analysis

The analysis of the thoughts is based on Markov chains, which aim to provide transition probabilities from a long and uninterrupted observation (Billingsley, 1961), as this method has repeatedly demonstrated its usefulness in medical contexts. However, since the raw values of the corresponding three-dimensional time series are not of interest, a reconversion into mental states must be conducted in advance. This can be done using the pixel coordinates ( $x_i, y_i$ ) contained in the time series  $(x_i, y_i, t_i)_{jk}$ . The chronologically correct order of these states is determined using the time dimension ( $t_i$ ).

According to the four mental states, the resulting Markov chain also has four states. To assign this, the horizontal screen division is considered first. If a y-coordinate is above this screen division, it is interpreted as “U”-state, and if the y-coordinate is on or below the screen division, it is interpreted as “I”-state. Afterwards, the vertical screen division is considered. If the corresponding x-coordinate is to the left of this screen division, the state is given a

negative orientation, and if the x-coordinate is on or to the right of this screen division, the state is given a positive orientation. This leads to the mental state constellations: thinking positive about the other (+U), thinking negative about the other (-U), thinking positive about oneself (+I), and thinking negative about oneself (-I).

After determining the Markov chains, the Markov property is subsequently tested. For this, the R package “markovchain” (Spedicato et al., 2016; version 0.9.1) is used. The method is based on a Chi-Square Test: if the corresponding p-value of the Chi-Square Test is above the level of significance of  $\alpha = 0.05$ , the Markov property is satisfied. The purpose of testing this property is to ensure that a future state depends only on the current state and not on any other past states (Asmussen, 2003), which is the necessary condition for a Markov chain. The Markov chains of a dyad  $j$  are furthermore tested against homogeneity. If, on the one hand, the Markov property is present and there is homogeneity between them, it is assumed that the time series of a dyad are similar. If, on the other hand, there is heterogeneity despite the Markov property, it is assumed that the time series are different. Since the optimal interval length between the mental states is unknown, the procedure is repeated for different intervals, a technique based on a study in which heatmaps through different grid sizes were created to examine the movement entropy of people (Unger et al., 2021). Starting with a 100 ms interval predefined by the app, the interval is repeatedly increased by 100 ms until the maximum of 10,000 ms is reached.

## 3 RESULTS

To begin with, the data was checked for completeness and applicability to the planned statistical procedures. It was noticed that the time series of two participants had too large gaps to apply the different interval lengths to the three-minute measurement time. The data of these participants had to be removed. In addition, the data of their associated partners were removed, because the time series of this dyad cannot be tested for homogeneity. For the analysis, 28 dyads with the corresponding 56 time series remained.

Table 1 shows the dyadic constellations that have been formed. In most Dyads, the participants were friends or colleagues. Only a few couples and a few dyads of strangers were formed. From Table 1, it can also be taken that the mean time since the dyads have known each other is neither particularly low, i.e., a few days or weeks (except for the strangers), nor

particularly high, i.e., more than 5 years, which provides a good and stable basis for the data.

Table 1: Amount of dyadic constellations with an indication of their self-reported form of interpersonal attachment and the mean time of knowing each other.

Interpersonal Attachment Form	Amount of Dyads	Known since (in Years)
Colleagues	9	1 ¾ [¼, 3]
Love Couples	2	3 ¼ [1 ½, 5]
Friends	14	1 ¼ [¼, 3 ½]
Strangers	3	-

Looking at the results of the Markov property test, it appears that most of the time series follow a Markov chain. In Figure 2, the amount of time series that satisfy the property is compared with the amount of time series that do not satisfy the property. It is easy to see that the Markov property increases with increasing interval length. Nevertheless, even at the smallest interval length of 100 ms, the proportion of satisfied Markov properties (40 ≐ about 71 %) is more than twice as high as the proportion of unsatisfied Markov properties (16 ≐ about 29 %).

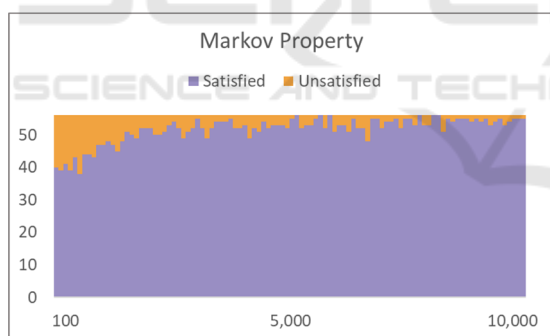


Figure 2: Overview of testing the time series with regard to the Markov property. The amount is shown on the y-axis and the interval (in ms) used for testing is shown on the x-axis.

After the Markov property has been tested, the homogeneity of the time series per dyad can be tested next. However, the only dyads suitable for the test are those in which both time series satisfy the Markov property, as these time series can be interpreted as Markov chains. Dyads can therefore have homogeneous, heterogeneous, or not comparable time series.

Figure 3 shows the results by comparing the amount of the three cases. As expected from the

previous test, there are only a few dyads with homogeneous time series when using the small intervals. It must be noted that, unfortunately, the time series that did not satisfy the Markov property often belonged to different dyads, so that there are many not comparable dyads, which could not be tested in the first place. But as soon as the intervals become larger and more time series satisfy the Markov property, the time series of the dyads become increasingly homogeneous. This can particularly be seen around the maximum interval length.

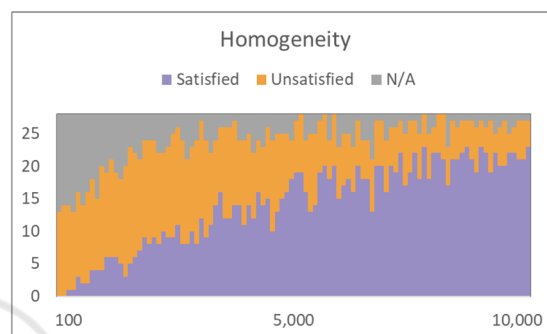


Figure 3: Overview of testing the time series of dyads against homogeneity. The amount is shown on the y-axis and the interval (in ms) used for testing is shown on the x-axis.

Figure 4 illustrates how both time series of a randomly picked dyad change with increasing interval lengths. The similarities that are consistently revealed despite the change can be found in the movements of both styli to mainly positive mental states. In particular, the state of thinking positively about the partner (+U) is predominant the greater the interval becomes.

Starting with the preset default interval of 100 ms, partner B shows noticeably more activity than partner A. The states of the two corresponding time series have a high probability of circling around themselves and therefore a minimal probability of changing to another state. The Markov property was not achieved for either time series with this interval length, so that homogeneity was not tested either, i.e., this dyad is not comparable.

With 1,000 ms, partner B is still the more active one, but the similarity that both think positively about their partner (+U) becomes more visible. Now, the probability of one state changing into another increases slightly as the points in the time series decrease. This time, the Markov property is satisfied for both time series. However, homogeneity can still not be achieved for this dyad, which is consistent with the different drawings.

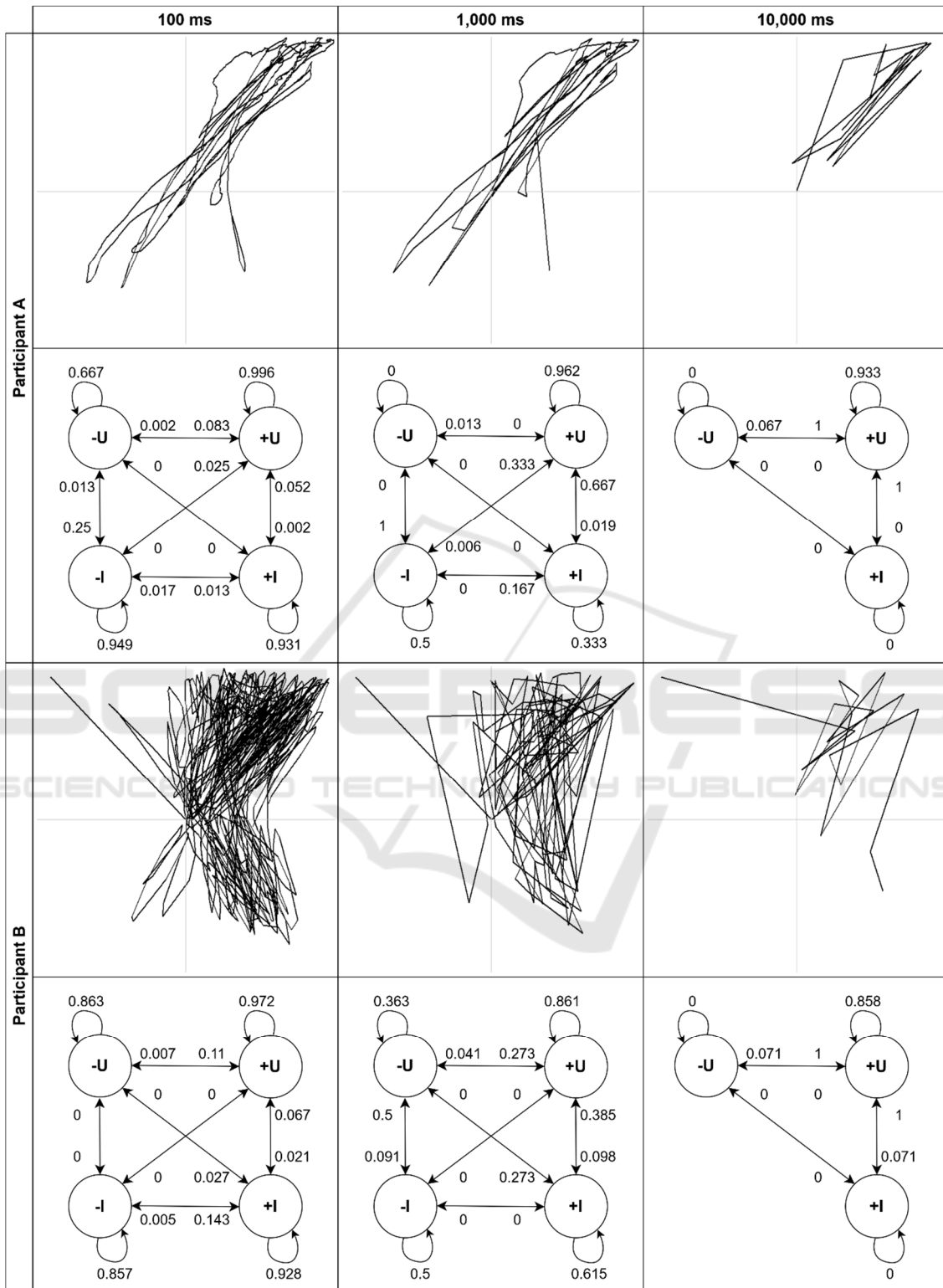


Figure 4: Time series of a dyad as Markov chains for the intervals 100 ms, 1,000 ms, and 10,000 ms. Above the Markov chains, the corresponding drawings of the participants are shown. The mental states are emphasized by the vertical and horizontal division lines within the drawings and match the positions of states in the Markov chains.

With last interval length of 10,000 ms, there are much clearer effects due to the change in the time series. The dyad has now much more harmonious drawings and the state of thinking negatively about oneself (-I) can no longer be detected, as it rarely occurred in the beginning. The consequence is that the Markov chains are simplified, so that both the Markov property and homogeneity are now satisfied for this dyad. The homogeneity is furthermore consistent with the similar drawings.

## 4 DISCUSSION

### 4.1 Key Results

The first analysis shows that the participants' thoughts generally can be modelled using a Markov chain approach. This becomes particularly clear when the lengths of the intervals between individual thoughts are increased. One reason for this could be that fewer states are included, as it can be seen in Figure 4 at an interval of 10,000 ms. Thus, it seems that this interval is no longer suitable for the analysis, even if all four states were still present in some cases. In contrast, when small interval lengths are applied, many of the participants' thoughts lose the Markov property and the probabilities that the states remain predominantly in their state are very high. It could indicate that either maintaining a mental state over a long period of time cannot be determined as Markov chain or that the screen area was too large to capture the states accurately over time by this measurement method. Whether thoughts can be accurately determined as Markov chains remains unclear. Although Markov chains have already been used as models, e.g., for the development of caries in periodontology (Lu, 1966) or for predicting the success of therapy, as in outpatient departments for epileptics (Kriedel, 1979) or in chronic cardiovascular diseases dependent on therapy variants (Grimm et al., 1988), these approaches never succeeded in gaining a global acceptance in the field of medical research methodology, which could be the reason for the lack of relevant literature.

Based on the analysis of the homogeneity within dyads, similarities can be drawn to the analysis on the Markov property. For example, the strong trend towards more homogeneous thinking dyads with increasing interval lengths could be due to the reduced states in thoughts, which most likely distorts reality. Therefore, high intervals also seem rather unsuitable here. In the smaller interval lengths, the homogeneous and heterogeneous thinking dyads are

relatively evenly distributed, i.e., there are dyads that are attached and dyads that are not attached. With respect to the former study (Unger et al., 2020), from which it appears that interpersonal attachment is higher among couples and friends than among colleagues and strangers, the approximately equally distribution of constellations seem to explain the equally distribution of interpersonal attachment in this study. It is in accordance with studies that investigated the interactions of dyads (Benjamin, 1979; Bollenrucher et al., 2023). It might indicate that this novel approach is able to measure interpersonal attachment with specific intervals, which at the same would support the former results on this app. By combining the two approaches, i.e., measuring thoughts and interactions of dyads simultaneously, an even more meaningful result could be provided. At least, it is worth investigating.

In terms of Markov chain models, they seem very useful for this type of stochastic research. As highlighted in a recent opinion paper on research methodologies for studying affect dynamics, Markov chain models are powerful tools for analyzing the underlying dynamics in the change of emotional states and may provide substantial insights into the dynamics of emotional responses and changes over time (Cipresso et al. 2023). In combination with machine learning approaches, Markov chains open further opportunities, as they can be used not only to analyze but also to predict emotional states (Sükei et al. 2021) or students' performance in a laboratory environment (Paxinou et al. 2021).

### 4.2 Limitations

The innovative measurement method presented here depends on continuous data collection and large gaps in the data could lead to incorrect predictions, which is one of the main limitations of this approach. Even small gaps in the data may occur, as it was not intended to entirely monitor the input. However, by increasing the time intervals for the analysis, these gaps can be covered.

Furthermore, the choice of interval lengths may represent a limitation. At the time of the examination, there was no literature on the optimal interval lengths for analyzing thoughts. Only studies from other areas that provide a solution to this issue could be found (Sugimoto et al., 2021; Unger et al., 2021). Nevertheless, the intervals could already be too wide at 100 ms and it may possible that the optimum interval was not covered by this incremental increase. Nevertheless, the total of 100 different intervals should provide a good basis for future research.

Another limitation is the division of the screen into four areas to represent the mental state. On the one hand, the pixels of the vertical and horizontal screen divisions relate to a specific state. The corresponding counter-state is thereby reduced by a few pixels. On the other hand, movements within a state are always assigned to this state, even if the thoughts were about the partner. While the former can be neglected, the latter shows that states could be missed. As this is the same for every participant, this error compensates for itself. An alternative measurement method would be to consider the direction of the movement. Here, the predefined path length of the movement should be calculated and tested against a minimum distance to compensate for the human tremor.

In terms of participants, the total amount is too small to draw a final conclusion of this study. In addition, only participants in a certain age range have registered. Other age groups could possibly change the result, as there could be cohort effects (Lindström et al., 2002). And lastly, it is unclear whether the participants understood their task immediately. As the study was conducted on the basis of the movements to be analyzed identically, the localization of the states to which the stylus had to be moved was predetermined. To achieve better results, it might be advisable to consider personal movement preferences or to include a familiarization phase in the future so that the participants develop a feeling for the way to move the stylus accordingly.

## 5 CONCLUSION

In this observational study, interpersonal attachment in dyads was measured with a digital application. During the measurement, the participants had to transfer their thoughts to the app. The thoughts are tracked as three-dimensional time series and analyzed as Markov chains. Overall, the results showed that the thoughts were mainly present as Markov chain. When analyzing these thoughts of the dyads for homogeneity, there were both heterogeneous as well as homogeneous thinking dyads. Despite the limitations, this study demonstrates from a methodological point of view how time series data captured by a tablet app as interpersonal attachment can be analyzed using stochastic process models outside the conventional methods of clinical studies. In contrast, the limitations also lead to the need to validate the results in further studies. Such studies should incorporate other factors in the measurement. In particular, the simultaneous examination of

thoughts and interactions of the dyads appears to be a promising research project. Even an examination with the addition of conventional tools, e.g., AAI or CAI, would be an interesting project for the future.

## ETHICAL VOTE

This study, which was conducted at Witten/Herdecke University between 2021 and 2023, was approved by the Ethics Committee of the Witten/Herdecke University (Reference S-185/2021).

## ACKNOWLEDGEMENTS

We would like to thank Theresa Frische and Fidan Brand for their support in recruiting participants and conducting the examination.

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