# Are people with chronic pain more diverse than we think? An investigation of ergodicity

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Abstract

This study investigates whether data from people with chronic pain conditions, including endometriosis (n = 58) and fibromyalgia (n = 58), exhibit ergodicity, a necessary condition for the generalizability of group-based research findings to individual cases. The study focused on frequently assessed variables in chronic pain, including pain intensity, pain interference, depressive symptoms, psychological flexibility, and pain catastrophizing. These data were collected twice daily for 42 days from each participant and then analyzed in two ways: first, as separate cross-sectional studies using the time points as the separate datasets, and second, as individual within-person studies using each individual person's time series. Results from the two approaches were then compared, including summary means and correlational analyses. For both the endometriosis and fibromyalgia samples, the between-person data showed substantially less variability, and other differences, compared to within-person data. This was evident in both the summary means and correlational analyses. Between-person correlations, for example, were relatively restricted in range, while within-person correlations varied widely, and were not well represented by the between-person estimates. After removing temporal dependency, the strength of within-person correlations decreased, further highlighting the differences in results from the two analytical approaches. The significant findings of this study have potentially profound implications for the field of chronic pain research. They not only underscore the limitations of relying solely on nomothetic methods for understanding individual pain experiences but also strongly advocate for a shift toward inclusion of more idiographic approaches. This shift could lead to more personalized and effective treatment strategies by better capturing the dynamic, highly individual, and heterogeneous nature of chronic pain. To put it bluntly, these results question the assumption that aggregated data collected from groups can accurately represent individual experiences in chronic pain. Keywords: chronic pain, endometriosis, fibromyalgia, group-to-individual generalizability, individual variability

## INTRODUCTION

Psychological treatment for chronic pain can increase well-being and reduce disability, with small to moderate effect sizes [3; 10; 12; 19; 43]. Yet, some individuals benefit greatly from treatments, and others do not. Perhaps this happens because we currently do not deliver treatment that are individually tailored or personalized [6]. While it is recommended that we personalize treatments [26], at the moment we know little about how to do this [18]. It appears that the knowledge and methods needed to deliver personalized treatment, will require improved understanding of processes or mechanisms of change, and that this will require a greater focus on the individual in general [17; 22; 29] and in chronic pain [25; 26].

Most researchers will see the value in focusing on the individual, and limitations of group-based methods, for understanding individual people, while for others this will seem counterintuitive. The logic of group designs is familiar, with the emphasis on large samples and a limited number of observations, focusing on the variance between people. It is less familiar to consider individually-focused designs, using a large number of observations and a small number of people, focusing on variance within people. It is important to examine limitations in conventional research designs, and to recognize what this alternate approach might add.

A typically unstated assumption underling group-based research is that findings derived from aggregated group data can only be generalized to the individual if the examined processes are *ergodic* [8; 31; 32]. For this to be the case, first, an assumption of homogeneity must be met. This means that variation in the data stemming from each individual should be compatible with the same statistical model [32]. Second, an assumption of stationarity must also be met, meaning that statistical characteristics of data, such as means and variances, remain stable over time [32]. Essentially, for ergodicity to be demonstrated it must be shown

that any statistical values derived in group data need to also hold true in any subsets within the group and all individuals within the group.

Numerous studies demonstrate a lack of ergodicity in psychological data [1; 2; 4; 7; 9; 24; 31; 35]. For instance, Fisher et al. [7] examined the assumption of ergodicity in depressed mood, worry, fear, positive and negative affect in a series of studies. In the included studies, variation within participants was compared to the variation across participants, using as many within-person data points as the number of participants included. Results indicated a clear lack of group-to-individual consistency and, hence, generalizability [7]. This was taken to mean that study results from data like these, derived from group-based research, are not automatically valid for the person to whom they might be applied [7; 11]. If data from people with chronic pain fail to support the assumptions of ergodicity, meaning that knowledge from group designs cannot be applied with the precision we have assumed, we may need to remedy this. First, however, we need to determine whether this is the case.

The purpose of the current study is to test the assumption of ergodicity, and whether one can assume group-to-individual generalizability, in data from people with chronic pain. This will be done by examining commonly studied pain variables, including pain intensity, pain interference, depression, psychological flexibility, and pain catastrophizing in people with endometriosis and fibromyalgia. We compare results obtained from two separate perspectives: the conventional aggregated group data approach versus an approach that examines data intensively over time for individual people. If the assumption of ergodicity is supported, results from these two perspectives should match.

## METHODS

### Participants and procedure

Participants eligible for the study were adults aged 18 or older suffering from endometriosis or fibromyalgia with persistent or recurrent pain for three months or more.

Fluency in written Swedish and access to an internet-enabled phone were required. Participants were also asked to agree to be contacted during the study to improve their response rate and to follow up on their responses if needed.

After providing informed consent, self-report measures were administered through REDCap, a secure online survey platform [13; 14]. Participants were then contacted with information about how to download and use m-path [30], a phone application for daily measures to be administered. After downloading the application, participants received a notification on their phone when it was time to complete the daily measures. Participants were notified at the start of a 180-minute response window for each of the two daily assessment occasions. A reminder was sent within 30 minutes if the participant did not fill out the measure. The daily measures were administered twice daily for 42 consecutive days with default times set to 10 AM and 9 PM, although these could be adjusted upon individual request.

In addition to the daily measure, participants received a short weekly measure through m-path. At the end of the 42 days, participants were invited through e-mail to once again respond to the full-length standardized measures through REDCap. The responses from these weekly measures and the full-length standardized measures are not the focus of this study and will be presented elsewhere. Ethical approval from the Swedish Ethical Review Authority was received before data collection (DNR: 2022-02032-01).

Participants provided informed consent via REDCap after being recruited through Facebook posts in groups focused on chronic pain, Instagram accounts focused on endometriosis, Facebook and Instagram ads, patient organizations, and through information given to people at health care clinics working with endometriosis and fibromyalgia. In total, 198 participants with endometriosis and 228 participants with fibromyalgia began providing

data. The number of participants who continued the study through m-path, regardless of pain condition, was 238.

According to a predetermined analysis and data collection plan (ClinicalTrials registration: NCT05518630), an equal number of participants and answered surveys were needed to investigate whether the data fulfilled the criteria for ergodicity. Thus, for each of the two samples, 58 participants who filled out at least the 58 daily surveys (70 % response rate) were randomly selected per participant for the analyses described below.

**Measures**

*Demographics and Pain Characteristics*

Participants were asked to provide data on age, gender, relationship status, family origin, work status, whether they self-identify as member of a minority group, education level, and financial situation. They were also asked to indicate their primary pain condition, whether a medical doctor had provided this diagnosis, their pain sites, pain duration, number of health care visits during the last six months, additional pain or health conditions, psychological and medical treatments, and which recruitment route led them to enter the study.

*Daily measures*

At each twice daily assessment, 18 items were administered. These items were selected from or based on standardized and validated questionnaire items, including from the Brief Pain Inventory (BPI) [5], Patient Health Questionnaire-9 (PHQ-9) [23], Multidimensional Psychological Flexibility Inventory (MPFI) [34; 38], and Pain Catastrophizing Scale (PCS) [36]. All items, except for current pain intensity, were focused on a specific time frame, the time elapsed since the previous measurement prompt (about a half day). The pain item focused on the current moment. All items were rated on an 11-point scale, with 0 corresponding to not being in pain, not experiencing pain interference, or not

agreeing with the statement in an item, while 10 corresponded to being in the worst possible pain, pain interfering completely, or agreeing very much with the statement in an item.

The first item in the daily measure was taken from the BPI, the item assessing current pain intensity. The next several items, also selected from the BPI, included pain interference with general activities, mood, relationships with other people, and ability to enjoy life, again since the time of the last measurement prompt. The BPI also includes an item on how pain interfered with sleep. In the evening, this item was instead rephrased as how the pain interfered with feeling well-rested. An additional item, created by the research team, was about how the pain interfered with one's ability to enjoy sex. The rest of the daily assessments consisted of two items from the PHQ-9 [23] assessing a lack of interest in doing things, and feeling down, depressed and hopeless, six items assessing psychological inflexibility from the MPFI [34; 38], and three items from the PCS [36] on pain catastrophizing. The full set of items can be found in the supplementary materials.

**Statistical analyses**

The univariate statistics and plots were calculated using the R packages 'dplyr' [42] and 'ggplot2' [41], and frequency distributions were constructed. Univariate within-person plots were produced by calculating the mean and standard deviation of each participant's time series. Univariate between-person plots were calculated by calculating the mean and standard deviation using each timepoint (T = 1 to T = 58) as a complete between-person group data set of 58 participants each. This resulted in distributions of means and standard deviations of 58 different group datasets, with 58 participants each for each of the two pain samples. The same was done for the 58 individual within-person data sets. Summary statistics of the within-person and between-person means and standard deviations were then calculated. For the within-person summary statistics, the mean of the individual means across days was calculated as well as the standard deviation. For the between-person statistics, the

mean was calculated by deriving the mean of the across-people data sets' means. The standard deviation was derived by calculating the standard deviation of the means.

Correlations were calculated using both raw data and data where temporal dependency had been removed. Firstly, Pearson correlations were calculated using the raw data. For between-person correlations, the correlations were calculated using each time point as an individual dataset across 58 participants, resulting in 58 sets of correlation coefficients. For within-individual correlations, the correlations were calculated using the data for each person across 58 occasions in time for each of the variables in each individual. This also resulted in 58 sets of correlation coefficients per pain sample. The correlation coefficients were then plotted using 'ggplot2'. In addition, the mean, standard deviation, and range were calculated for both the within- and between-person results.

Secondly, Autoregressive Integrated Moving Average (ARIMA) models were applied using the R-package 'forecast' [20] to remove the temporal dependency in the time series. ARIMA combines three components: (a) autoregression, which models the relation between an observation and a number of lagged observations. For example, an AR(1) model includes lag 1 and thus predicts the next value in the time series; (b) integrated, which means that the time series becomes stationary through differencing, meaning the removal of trends in the data, so that mean, variance, and autocorrelation remain the same in time; and (c) moving average models, which is similar to the autoregressive component but instead of using past values, it uses past forecasting errors to make predictions of the next value. The best model using all components is then chosen for the specific time series using Akaike Information Criterion (AIC), which ensures a good fit of the model while preserving the data structure. The residuals resulting from the individual ARIMA models were then retained for further analyses of both within- and between-person data using Pearson correlations.

To give examples of individual trajectories and trends in the data set, three sets of pairs were selected for individual plotting of the individual time series. The mean for each variable was calculated using the 'dplyr' [42] package in R. Then, a threshold for similarity between the two means was set before an iteration was created to find similar means respecting the threshold. The six participants were then selected for plotting using 'ggplot2' [41].

## RESULTS: ENDOMETRIOSIS SAMPLE

### Participant characteristics

The mean age for the 58 participants with endometriosis was 33.24 years (SD = 8.31). A majority identified as female (98.28 %), 35 participants (60.34 %) held full-time employment, the mean number of healthcare visits due to the condition the last six months was 5.02 visits (SD = 10.82), and 20 participants (34.82 %) described suffering from generalized pain. See Table 1 for further details.

*** TABLE 1 ***

### Univariate plots and statistics

Examining the univariate plots that depict both between-person and within-person distributions of mean values (Figures 1-5), a consistent pattern is observed across all variables. Compared to the aggregated data where variability is generally quite small, there is substantially greater variability in the time series of individuals. This is evidenced in both the point-by-point frequency counts of means and the density lines. Overall, in the within-person data all variables have means extending across the scale, ranging from around zero to approximately ten but not in between-person data.

Looking at the between-person data regarding depressive symptoms, as shown in Figure 4, the between-person data clusters around a mean of five to six. A remarkably similar pattern is shown in the between-person data for all variables featured in Figures 1

through 5. However, in each case, the comparison between the between-person and within-person for each variable is quite different. For the within-person data, there are rarely more than seven people who achieve the same value regardless of variable analyzed, and the distributions are generally quite flat. However, the data for catastrophizing are somewhat of a deviation from the pattern due to the within-person data featuring relatively large proportions of people who obtain low values, which is itself interesting.

Regarding pain intensity, compared with the between-person data, the within-person data exhibits greater uniformity (Figure 1). For example, when comparing pain intensity data with psychological inflexibility (as seen in Figure 3), lower scores are observed for pain intensity, although a subgroup with higher values is also present. In these data, none of the individuals have a mean score of nine to ten in their time series. For other variables, the general pattern reflects lower scores among individuals, highlighting the variability present in the datasets.

*** FIGURE 1-5 ***

In analyzing the range of means and standard deviations (SDs) presented in Table 2, it is evident that even if the means are identical across all variables due to the same data points being used for all calculations, both the SDs and the range of SDs are substantially smaller in the between-person data.

In the within-person data, most variables have a relatively low average mean, but there is also a notable variability observed in both the within-person means and the SDs as compared to the between-person data. This indicates differing degrees of variability over time among individuals. Specifically, the data shows that while some individuals exhibit significant variability in their time series, others demonstrate more stability.

*** TABLE 2 ***

**Distributions of correlations**

The histogram depicting the magnitude of correlations between psychological inflexibility and depressive symptoms shows only a small range in the between-person data, but a wide range in the within-person correlations; ranging from r = -0.05 for one participant in their time series to r = 1.00 for another. In addition, there is a pattern of very dissimilar mean correlations when comparing between-person data and within-person data (see Figure 6-8).

Correlations including pain catastrophizing as a variable (Figure 9 and supplementary materials), show another pattern, with similar means for between and within-person correlations. Nevertheless, the range of correlations in both the between-and within-person data is similar to the other bivariate combinations. Further, although the mean correlation appears similar for the between-person and within-person distributions, the SDs are highly dissimilar (see Table 3).

Overall, all pairs or variables examined resulted in larger mean correlations for the between-person calculations, while within-person calculations resulted in a larger range of correlations. For example, the between-person correlations between pain intensity and pain interference only ranged from r = 0.27 to r = 0.72. In contrast, the within-person correlations ranged from a negative correlation (r = -0.07) in one individual to a large positive correlation (r = 0.84) in another.

*** FIGURE 6-9 ***

*** TABLE 3 ***

After removing temporal dependency in the series data, and analyzing the residuals for the within-person correlations, there is a noticeable reduction of the mean correlation strength across all variable pairs (see Table 3). In terms of the difference between within-person and between-person correlations, the analysis reveals that all variable pairs

exhibit a 21.82 % to 52.94 % higher values when analyzed as between-person datasets. Further, a visual inspection of the plots (Figure 10-13) indicates a slight change in the spread of within-person correlations after removing temporal dependency. This pattern is also reflected in the spread and SDs presented in Table 2, showing smaller SDs after temporal dependency has been removed for all variable pairs but PCS and BPI.

*** FIGURE 10-13 ***

**Individual time series**

Of course, any calculation of an individual's mean is a form of aggregation, even when accompanied by SDs, and this will not fully capture the varying nature of some participants' data. After performing a min-max normalization to make the variables comparable, we can further examine two participants' data over time (Figure 14-15). In the figures depicting these examples one sees the same problems but with different patterns. Participant 1 has a seemingly noisy pattern in several of the variables featured. Participant 2 has some trends in his/her data including more extreme values at the beginning of data collection. However, the issues are similar: the lack of stability in all variables and, perhaps even more concerning, patterns in the data are inconsistent, meaning that the relationship between variables seems to change over time. We note that is occurs in the absence of intervention on our part.

*** FIGURE 14-15 ***

**RESULTS: FIBROMYALGIA SAMPLE**

**Participant characteristics**

The mean age for the 58 participants with fibromyalgia was 51.14 years (SD = 8.44). A majority identified as female (96.55 %), 13 participants (22.41 %) held full-time employment, the mean number of healthcare visits due to the condition in the last six months

was 1.83 visits (SD = 2.44), and 55 participants (94.83 %) described suffering from generalized pain. See Table 1 for further details.

**Univariate plots and statistics**

Similar to the patterns in Study 1, Figures 16 to 20 show substantially less variability in the summarized between-person data compared to the summarized within-person data. This is shown in both the point-by-point frequency counts of means and the density lines.

The between-person means cluster around higher scores in all variables, a different pattern compared to the results from people with endometriosis. For example, for depressive symptoms (Figure 19), the data is clustered around a mean of seven to nine. This is similar to scores on pain catastrophizing (Figure 20). The within-person distributions for fibromyalgia are similar to the endometriosis data. If anything, they are flatter with less clustering. Here, there appear to be more differences between the individual people compared to the participants with endometriosis

*** FIGURE 16-20 ***

Comparing the between- versus within-person analysis methods, it is evident that relatively narrow variability seen in the between-person statistics is not mirrored in the within-person statistics. Quite the contrary, there is substantial inconsistency between the two forms of analysis despite inclusion the same data. Even if the means of the two analysis methods are the same across all variables, which again is to be expected due to the same data being used for both methods, the pooled standard deviations differ in both range and mean for both methods.

Table 4 presents the range of means and standard deviations for both analyses. Similar to the endometriosis-sample, the within-person means have a large range in terms of average score over time, but also that there is varying variability within each time-series. As

shown in Table 4 some participants have a low standard deviation meaning the scores varied little over time for that specific participant, while others have a relatively large SD showing a less stable day to day pattern within the individual over time.

*** TABLE 4 ***

**Distributions of correlations**

Calculating the correlations and depicting them in histograms for the fibromyalgia participants (Figure 21-24) reveals a similar pattern to that of endometriosis. In all variable pairs, the between-person calculations resulted in a larger mean correlation but also a smaller range of actual correlations compared with the within-person calculations. For example, correlations between pain catastrophizing and pain interference (Table 5) ranged from a small negative correlation (r = -.11) in one participant to a large positive correlation (r = .90) in another. As another example, the between-person correlations between pain intensity and depression, ranged only from r = .64 to r = .86. But for the within-person analyses, these correlations ranged from r = -.27 for one participant over time to r = .82 for another (Table 5).

Comparing the distributions of correlations, we can also see a different pattern as compared to the results from the endometriosis sample. Namely, all distributions have a similar degree of difference between the mean magnitude of the correlations in the within-person and between-person analyses.

*** FIGURE 21-24 ***

*** TABLE 5 ***

When removing the temporal dependency from the within-person data and analyzing the residuals, an overall reduction in correlational strength is found across all variable pairs (see Table 5). This also increases the difference between the results of the two perspectives (Figure 25-28). Looking at the mean correlations of the two approaches,

correlations between all variable pairs show values that are greater by between 44 % and 87.9 % when analyzed as between-person data sets.

*** FIGURE 25-28 ***

**Individual time series**

By applying min-max normalization to render the variables directly comparable, we can gain a deeper insight into the temporal dynamics of the variables for two individuals with fibromyalgia (Figures 29-30). Compared with the endometriosis sample, the same two problems are again evident here. First, there is not much stability for any of the variables in either of the cases. Secondly, based on visual inspection, it appears that relationships between the variables featured change over time despite the data being purely observational.

*** FIGURE 29-30 ***

**DISCUSSION**

This study compares results obtained from the conventional group data approach focusing on variability between people versus an approach that focuses on individual people and how they vary within themselves over time. In both cases, the same commonly studied chronic pain variables were considered. What we observe is that these two perspectives do not provide symmetrical results. When examining individual data points over time (within-person), we see remarkable individual, person-to-person variability to a degree that is not captured in the group data (between people). This appears to challenge a fundamental assumption inherent in nomothetic studies. These results, including summary statistical indicators of central tendency, variability, and bivariate association, all show essential inconsistency, and indicate a lack of ergodicity. These results were observed in people reporting one chronic pain condition, endometriosis, and replicated in people reporting another, fibromyalgia.

Although the means of within-person and between-person distributions are mathematically identical—stemming from the same dataset but analyzed from different perspectives [32]—the variations in ranges and standard deviations (SDs) reveal substantial differences. When analyzing single variable frequency distributions, the perspective of within-person reveals results that are far more variable than expected compared to the between-person perspective, both between individuals *and,* for some individuals, over time as well. For instance, when examining the standard deviations (SDs) within individual time series, we notice significant variability in the variability of peoples' experience over time. This is an important concept to understand: when people report pain interference, as an example, their data vary in different levels between people, they can vary within themselves in relatively stability, in set time frames, and they can vary in how variable this variability is, looking across multiple time frames. Variability is multidimensional, within people, between people, and in time. It is noteworthy that this variability is lost in aggregated data, as is typical in nomothetic research designs, even when between-person distributions comprise the same data points found in the time series.

Looking at relations between pairs of variables the correlation analyses reveal occasional consistencies between the within-person and between-person perspectives. Very few correlations exhibit similar means when comparing within-person and between-person statistics. Nonetheless, the key observation here involves the ranges observed in these correlations across various variable pairs. Most notably, correlations between variables varied extensively, ranging from negligible or non-existent to strong when analyzed as within-person data, a result not captured by the between-person correlations.

When comparing the two samples, participants with endometriosis and fibromyalgia, different patterns emerged here as well: participants with fibromyalgia generally reported higher scores across measures and showed a narrower range of pain

intensity compared to those with endometriosis. This suggests that those with fibromyalgia have a more consistent experience of pain intensity

The implications of the results are manifold. First and foremost, the findings from this study challenge a fundamental assumption of group-based research methods used in chronic pain, namely that we can rely on aggregated data as a way to understand the individuals contained within the aggregation. The results from this study show this may not be fully justified or may need to be done with caution. A typical response to resolve this issue, whether regarded as a reliability or generalizability problem, could be to increase the sample size to accurately capture the many different experiences of the studied conditions. Unfortunately, this commonly conceived remedy almost certainly will fail to address the underlying problem and may even further obscure the complexities at play.

Neither larger sample sizes nor intentionally more diverse samples appear likely to solve the problem demonstrated here if traditional nomothetic methods are used. It seems that the inconsistency observed between group and individual data are inherent in the data. This is because none of the requirements for ergodicity are met, as we have neither consistency in the data between the group and the individuals, nor between the individuals, nor do we have consistency in the data over time. These same kinds of results have been demonstrated in other populations and other variables [1; 2; 4; 7; 9; 24; 32; 35].

Results from this study also show that aggregating data can create problems *even* if one begins by capturing change within an individual over time. An example of this is when examining distributions of within-person means in a histogram partially obscures the variation inherent in individual data. Despite being on an individual level, this form of aggregation can be misleading if it does not adequately represent the variability in the data *over time*, what we described as “variability in variability,” or the range of SDs. The contrast between individuals with high versus low variability over time reveals different patterns.

While these are observational data with no particular interventions administered to any of the individuals, the absence of an intervention does not mean that circumstances do not intervene or that day-to-day life does not include influences on the data, which it likely will. It is expected, or certainly not surprising to see significant variability in factors like pain intensity, pain interference, and depression over time. In a similar fashion, potential drivers of change in outcome processes such as pain catastrophizing and psychological inflexibility exhibit significant temporal instability, likely in a context dependent fashion, for many individuals. This clearly violates current assumptions required in the statistics we often use to analyze them (e.g., linear regression), but also clinical and theoretical assumptions [28; 37; 39; 40]. High variability in some participants' data is an important challenge. It not only calls for a careful choice between nomothetic versus idiographic research methods but also poses challenges when using research designs commonly seen as idiographic, such as Single-Case Experimental Designs (SCEDs), where a stable base is needed for predicting a null effect and detecting a potentially positive one [21].

In the within-person correlations, an unexpected pattern emerged within both samples, namely that for some people, there were no relationships between some variables where they might have been expected, such as between psychological inflexibility or pain catastrophizing and pain interference [27; 33; 38; 39]. The absence of these relations between variables was not detected in any of the between-person correlations and is an important matter worth further investigation. Once again, this highlights a need for caution in applying the “group average” to particular people.

Implications of the lack of generalizability demonstrated here may be numerous, particularly for clinicians and researchers conducting nomothetic treatment studies, which typically do not include intensive measurement methods. Just as our estimate of the magnitude of relations between psychosocial variables and measures of health and wellbeing

may be less precise than we assume, so too may be our estimates obtained for the effectiveness of treatments, undermining our ability to communicate likely outcomes of treatments to individual patients. Also, if data exhibit no functional relationship between what is seen as typical processes targeted for change within CBT or ACT and an outcome of interest, do we have the sensitivity to detect this and to orient treatment methods accordingly?

The gold standard for treatment research is, and long has been, the RCT, often using only two to three data points per individual. The current results indicate that there is a real risk in this. These data points may not reflect the potential variation that occurs in both process and outcome variables, even without changes associated with the delivery of treatment. If the results shown here are replicated in other research settings, this may mean we need to rethink how we determine treatment response in individual cases and how we determine mediators. We may have misclassified cases as successes or failures and wrongly deemed a treatment highly effective or ineffective, with a higher error rate than we might have assumed. Based on our analyses here, relying on a limited number of observations poses a substantial risk since it may lead to either an underestimation or overestimation of expected results for particular people. It appears that the assumed confidence interval around our estimates needs to be much wider, making this much more of a guessing game than we typically assume.

Highlighting the value of individual data need not imply disinterest in group data. It does not make sense to entirely abandon group data. It is rather the case that an expansion in the methods used appears needed. A more discerning approach in selecting between between-group and within-individual methods, and a greater inclusion of intensive longitudinal, individually focused methods may enhance the discoveries we make and the knowledge we need to produce better applications. While nomothetic methods may be suitable when the primary objective is to discuss groups or populations, idiographic methods

may be more informative when the aim is to understand process of change in treatment or inform specific individual treatment decisions. These specific decisions include determining the particular treatment methods or components needed to move a particular ultimate outcome, by moving a particular process of change, in a particular time and context, during an ongoing series of treatment encounters [16].

Idiographic methods may represent a significant opportunity and this could be a turning point in how we think about, understand, and address the needs of people with chronic pain. These methods do not merely represent better snapshots made from aggregating more data for each person. Instead these methods allow one to examine functional relations between potentially modifiable contextual elements with measures that reflect the outcomes being sought that are in both cases highly individual and in a way that is more dynamic and highly details, with high resolution in time. Instead of using group designs to understand individuals, we could understand individuals one at a time, then look for patterns or similarities between individuals, build relatively homogenous subgroups and derive general principles that better apply to individual people. This particular approach has been called idionomic [15]. The trick is to start with the highly detailed analysis of each single person before one begins to combine across people.

Although results here examine whether pain-related variables can be deemed ergodic, this cannot be regarded as the final answer, and the study is not without its limitations. Firstly, the study only includes two types of pain conditions: endometriosis and fibromyalgia. This also led to a skewed sample in terms of gender. Secondly, the measures used represent an important choice for this research question, and it is thus fair to ask whether proof for this theorem would be found if different measures were used. Lastly, this study focused solely on ergodicity in observational data. Future studies could also examine ergodicity in treatment studies including people with chronic pain.

To summarize, it appears that self-report data widely used in chronic pain research are not ergodic. As such, one cannot assume precise applicability of results from studies of people with conventional group designs to individual people with chronic pain. Results here challenge our reliance, or sole reliance, on conventional nomothetic methods as a way to understand individual people. Not only do results reveal significant variability in individual pain experiences between people and over time, but they also highlight something else. Studies employing intensive longitudinal data collection appear to be needed.

Future research in chronic pain may wish to address the question/absence of ergodicity in pain-related data. We may need to critically evaluate the prevailing reliance on nomothetic methods involving aggregated group data, particularly where the primary aim is to translate research findings into individualized care. It may be that failure to fully appreciate the individuality and attendant heterogeneity of people with chronic pain has held us back. If this is the case, a shift towards methodologies that capture the dynamic and individualized nature of pain may pave the way for more effective treatments. As we say, this may be an opportunity or turning point. We may need to change the way we think about behavior, processes of behavior change, and data, to ensure that our research methods are as personalized and adaptive as the treatments we want to design.



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All authors declare that they have no conflicts of interest.

## DATA AVAILABILITY

The data used in this study is not publicly available. Requests should be directed to the corresponding author and will be considered on a case-by-case basis in accordance with the relevant Swedish and European Union data protection and privacy legislation.

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# Tables

**Table 1.** Participant characteristics.

| | Mean (SD) or *n* (%) | |
|---|---|---|
| | Endometriosis | Fibromyalgia |
| Age | 33.24 (8.31) | 51.14 (8.44) |
| Gender (women) | 57 (98.28) | 56 (96.55) |
| Identify as part of a minority group | 7 (12.07) | 4 (6.90) |
| Education (highest completed) | | |
| Elementary | 2 (3.45) | 3 (5.17) |
| Secondary | 17 (29.31) | 21 (36.21) |
| College/university | 39 (67.24) | 33 (43.10) |
| Work status | | |
| Employed (full-time) | 35 (60.34) | 13 (22.41) |
| Employed (part-time) | 5 (8.62) | 12 (20.69) |
| Self-employed | 3 (5.17) | 1 (1.72) |
| Sick leave | 7 (12.07) | 17 (29.31) |
| Other (retired, student, etc.) | 8 (13.80) | 15 (25.86) |
| Financial situation | | |
| Very good | 10 (17.24) | 5 (8.62) |
| Good | 20 (34.48) | 18 (31.03) |
| Sufficient | 26 (44.83) | 21 (36.21) |
| Bad | 2 (3.45) | 10 (17.24) |
| Very bad | 0 (0.00) | 4 (6.90) |
| Relationship status (married/in a relationship) | 37 (63.79) | 40 (68.97) |
| Diagnosed pain condition | 55 (94.83) | 58 (100) |
| Pain duration (> 2 years) | 53 (91.38) | 58 (100) |
| Generalized pain | 20 (34.82) | 55 (94.83) |
| Pain sites (most frequent) | | |
| Abdomen | 50 (86.21) | 14 (24.14) |
| Pelvic region | 42 (72.41) | 29 (50.00) |
| Back region | 29 (50.00) | 54 (93.10) |
| Neck | 1 (1.72) | 49 (84.48) |
| Arms or shoulders | 2 (3.45) | 49 (84.48) |
| Prescribed opioids | 24 (41.38) | 8 (13.79) |
| Healthcare visits due to pain (last 6 months) | 5.02 (10.82) | 1.83 (2.44) |
| Recruitment site | | |
| Social media | 52 (89.66) | 44 (75.86) |
| Hospital or healthcare clinic | 3 (5.17) | 0 (0.00) |
| Other | 2 (3.45) | 12 (20.69) |
| Patient organizations | 1 (1.72) | 2 (3.45) |

*Note.* Pain sites were not mutually exclusive.

**Table 2.** Univariate within-person and between-person statistics - endometriosis

| | Within-person | | | | Between-person | | | |
|---|---|---|---|---|---|---|---|---|
| **Variable** | **Mean** | **SD** | **Range (mean)** | **Range (SD)** | **Mean** | **SD*** | **Range (mean)** | **Range (SD)** |
| **Pain** | 3.44 | 1.98 | 0.40 – 8.98 | 0.72 – 3.33 | 3.44 | 0.27 | 2.84 – 3.97 | 2.29 – 2.85 |
| **BPI** | 3.30 | 2.19 | 0.29 – 8.70 | 0.48 – 2.79 | 3.30 | 0.26 | 2.57 – 3.89 | 2.47 – 3.13 |
| **MPFI** | 2.31 | 2.07 | 0.04 – 7.56 | 0.18 – 3.59 | 2.31 | 0.23 | 1.74 – 2.83 | 1.83 – 2.84 |
| **PHQ** | 5.98 | 4.42 | 0.07 – 16.71 | 0.53 – 7.56 | 5.98 | 0.59 | 4.57 – 7.12 | 4.44 – 6.49 |
| **PCS** | 5.42 | 5.41 | 0.02 – 21.33 | 0.13 – 9.85 | 5.42 | 0.56 | 4.24 – 6.53 | 5.39 – 8.27 |

Note. *The SD of the group-based mean.

## Tables - Endometriosis



**Table 3.** Bivariate correlations between common process- and outcome variables - endometriosis

| | Within-person *(raw)* | | | Within-person *(residuals)* | | | Between-person | | |
|---|---|---|---|---|---|---|---|---|---|
| **Bivariate pair** | **Mean** | **SD** | **Range (mean)** | **Mean** | **SD** | **Range (mean)** | **Mean** | **SD** | **Range (mean)** |
| Pain - BPI | 0.65 | 0.18 | 0.17 – 0.91 | 0.53 | 0.20 | 0.10 – 0.87 | 0.75 | 0.06 | 0.62 – 0.87 |
| Pain - PHQ | 0.43 | 0.22 | -0.07 – 0.84 | 0.34 | 0.22 | -0.11 – 0.83 | 0.52 | 0.09 | 0.27 – 0.72 |
| MPFI - PHQ | 0.69 | 0.21 | -0.05 – 1.00 | 0.58 | 0.23 | -0.02 – 1.00 | 0.87 | 0.05 | 0.67 – 0.93 |
| PCS - BPI | 0.64 | 0.22 | -0.02 – 0.96 | 0.55 | 0.21 | -0.04 – 0.93 | 0.67 | 0.07 | 0.51 – 0.81 |

# Tables - Fibromyalgia

**Table 4.** Univariate within-person and between-person statistics - fibromyalgia

| | Within-person | | | | Between-person | | | |
|---|---|---|---|---|---|---|---|---|
| **Variable** | **Mean** | **SD** | **Range (mean)** | **Range (SD)** | **Mean** | **SD*** | **Range (mean)** | **Range (SD)** |
| **Pain** | 5.62 | 1.83 | 0.98 - 9.29 | 0.26 - 2.4 | 5.62 | 0.16 | 5.33 – 5.91 | 1.67 – 2.52 |
| **BPI** | 4.75 | 2.23 | 0.25 – 8.97 | 0.38 – 3.18 | 4.75 | 0.19 | 4.37 – 5.51 | 2.34 – 2.80 |
| **MPFI** | 3.39 | 2.31 | 0.03 – 8.77 | 0.13 – 2.98 | 3.39 | 0.15 | 3.06 – 3.74 | 2.31 – 2.89 |
| **PHQ** | 8.34 | 4.92 | 0.00 – 18.24 | 0.00 – 7.12 | 8.34 | 0.36 | 7.52 – 9.45 | 5.18 – 6.33 |
| **PCS** | 8.06 | 6.13 | 0.00 – 26.72 | 0.00 – 7.11 | 8.06 | 0.40 | 6.95 – 8.98 | 6.19 – 7.67 |

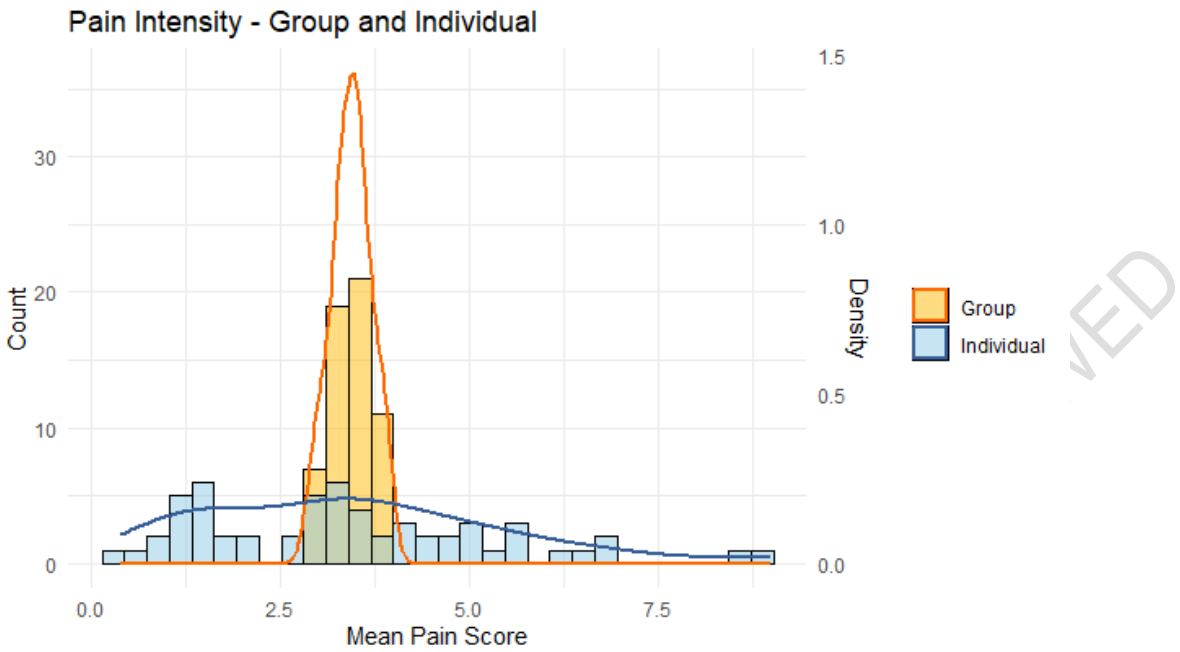
Note. *The SD of the group-based mean.

**Table 5.** Bivariate correlations between common process- and outcome variables - fibromyalgia

| | **Within-person *(raw)*** | | | **Within-person *(residuals)*** | | | **Between-person** | | |
|---|---|---|---|---|---|---|---|---|---|
| **Bivariate pair** | **Mean** | **SD** | **Range (mean)** | **Mean** | **SD** | **Range (mean)** | **Mean** | **SD** | **Range (mean)** |
| Pain - BPI | 0.55 | 0.23 | 0.02 – 0.91 | 0.50 | 0.19 | 0.09 – 0.80 | 0.72 | 0.07 | 0.40 – 0.86 |
| Pain - PHQ | 0.39 | 0.25 | -0.27 – 0.82 | 0.33 | 0.21 | -0.14 - 0.71 | 0.62 | 0.08 | 0.31 – 0.81 |
| MPFI - PHQ | 0.63 | 0.24 | 0.04 – 0.92 | 0.53 | 0.23 | -0.00 – 0.88 | 0.84 | 0.04 | 0.66 – 0.90 |
| PCS - BPI | 0.54 | 0.25 | -0.11 – 0.90 | 0.47 | 0.21 | 0.04 – 0.80 | 0.77 | 0.04 | 0.64 – 0.86 |

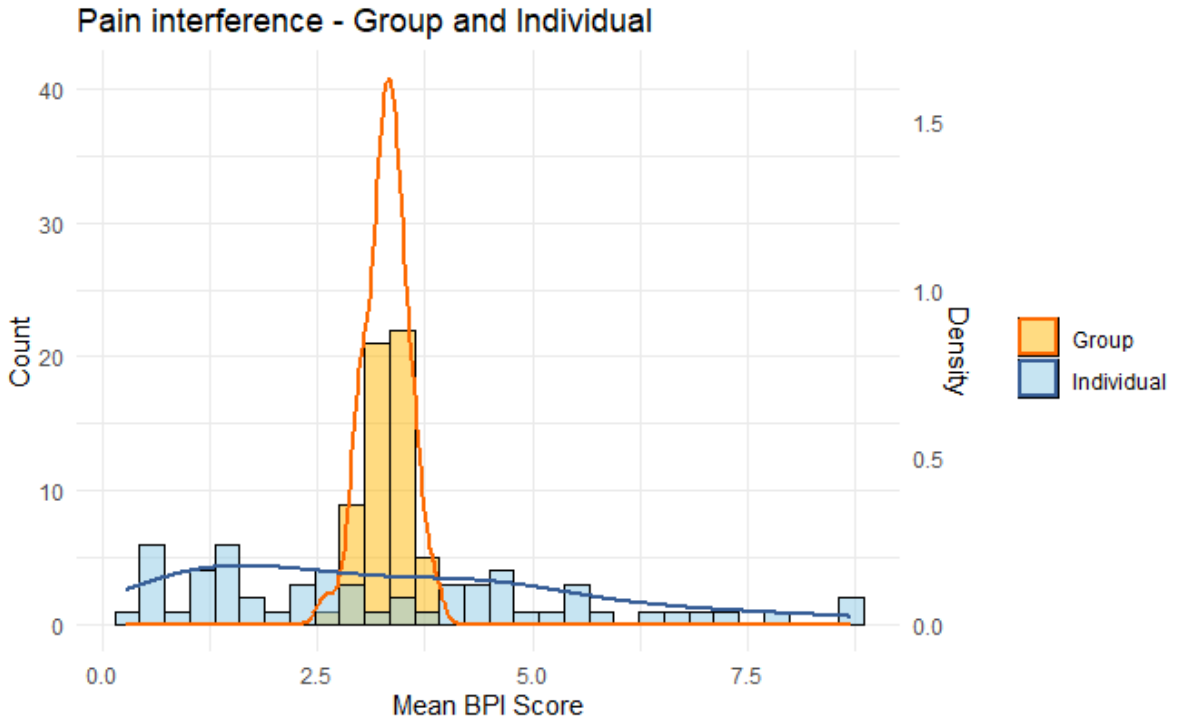
# Figures

**Figure 1.** Endometriosis: Pain intensity



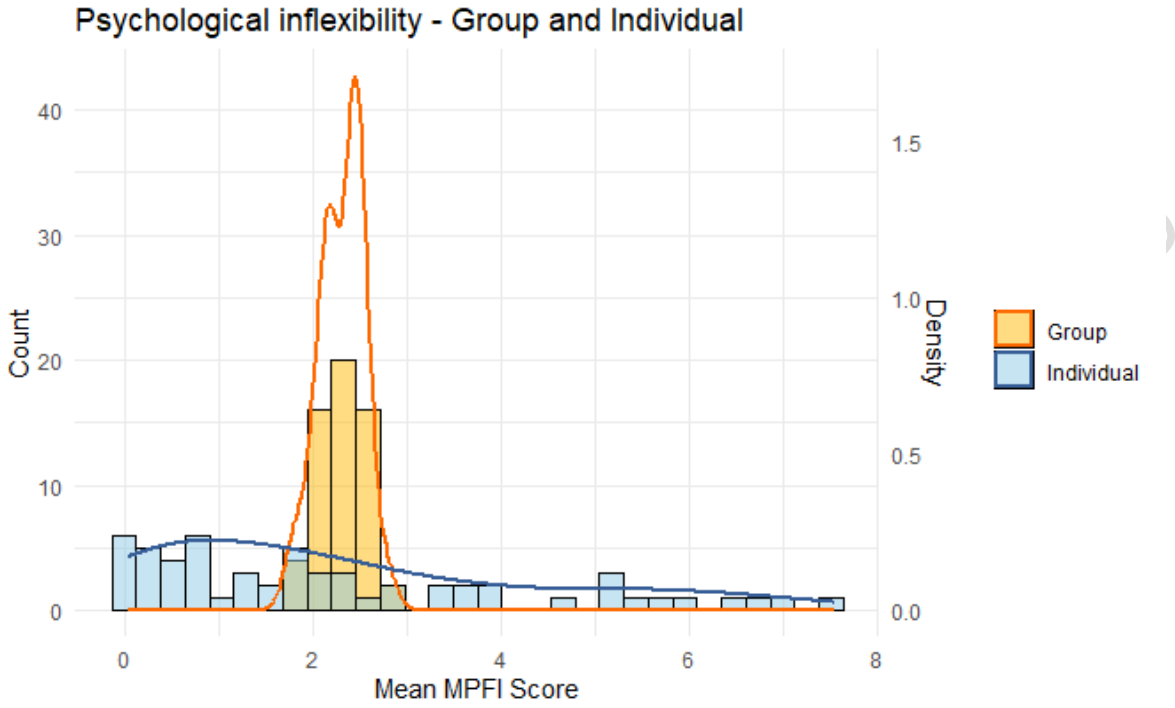

*Legend.* Figure 1 depicts both a histogram as well as a density plot of the raw mean pain intensity scores, for individuals (means of 58 time series without temporal dependency removed) and for groups (means of 58 cross-sectional data sets).

**Figure 2**. Endometriosis: Pain Interference



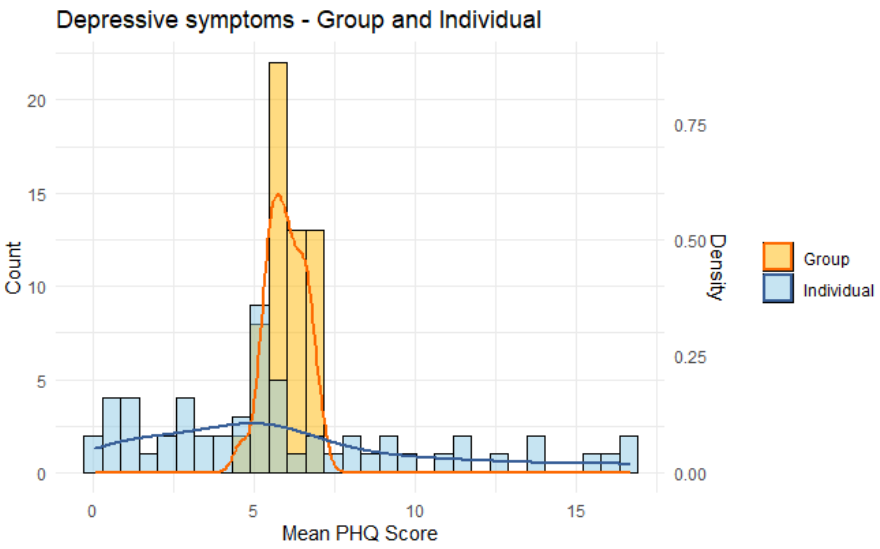

*Legend.* Figure 2 depicts the raw BPI pain interference score calculated for both groups and individuals.

**Figure 3** Endometriosis: MPFI



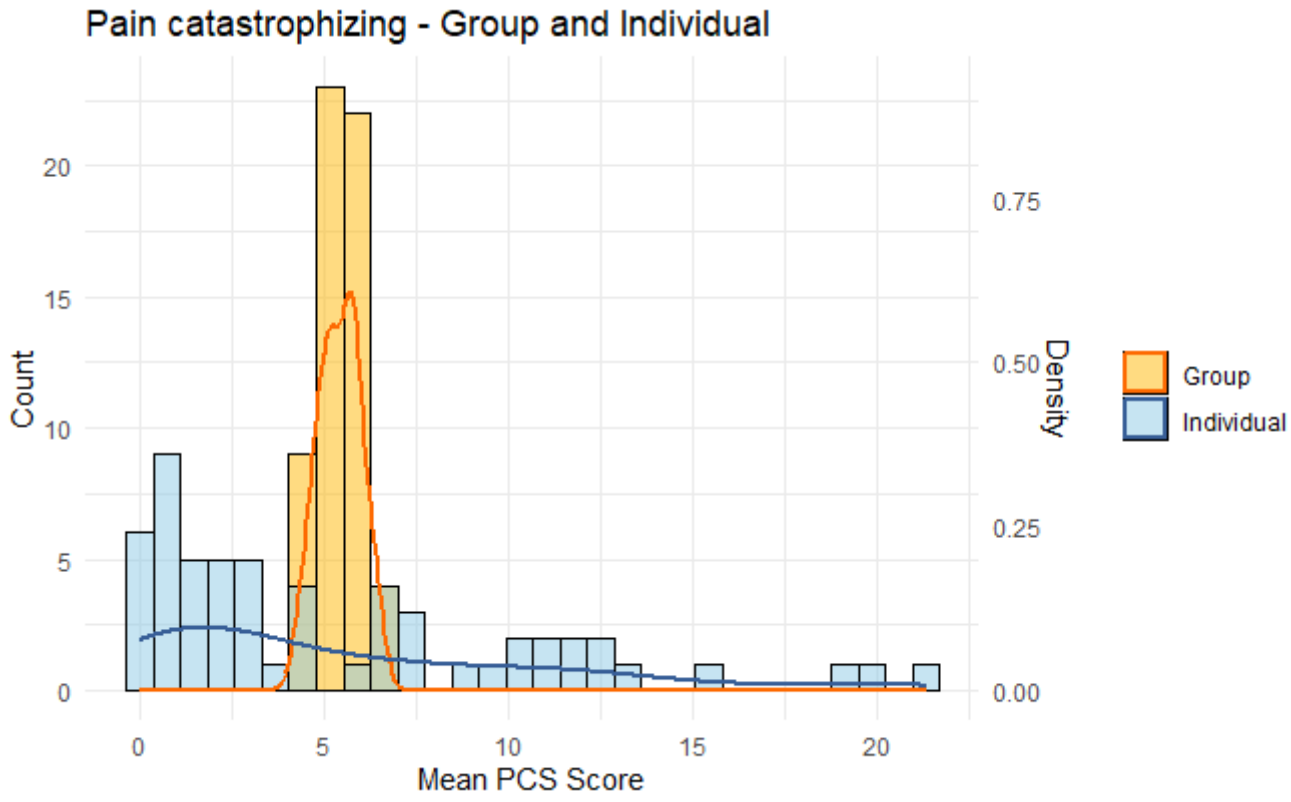

*Legend.* Figure 3 depicts the raw mean value of psychological inflexibility as measured by MPFI for group and individuals.

**Figure 4.** Endometriosis: PHQ



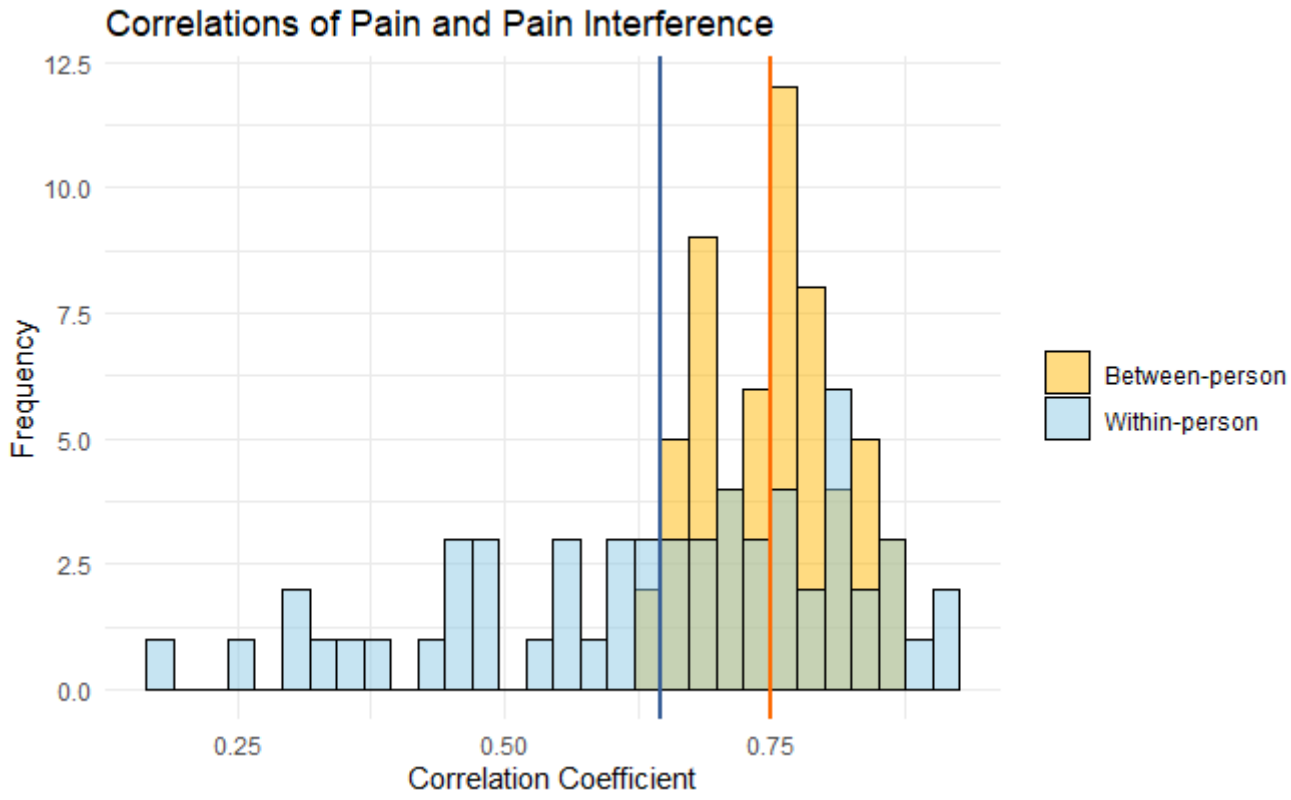

*Legend.* Figure 4 depicts the raw mean value of depressive symptoms as measured by PHQ-2 for group and individuals.

**Figure 5**. Endometriosis: PCS




*Legend.* In figure 5 depicting pain catastrophizing as measured by PCS for group and individuals

**Figure 6**. Endometriosis: Correlations between pain intensity and pain interference




*Legend.* The solid lines mark the mean correlation for between- and within-person correlations respectively.

**Figure 7**. Endometriosis: Correlations between pain intensity and depressive symptoms

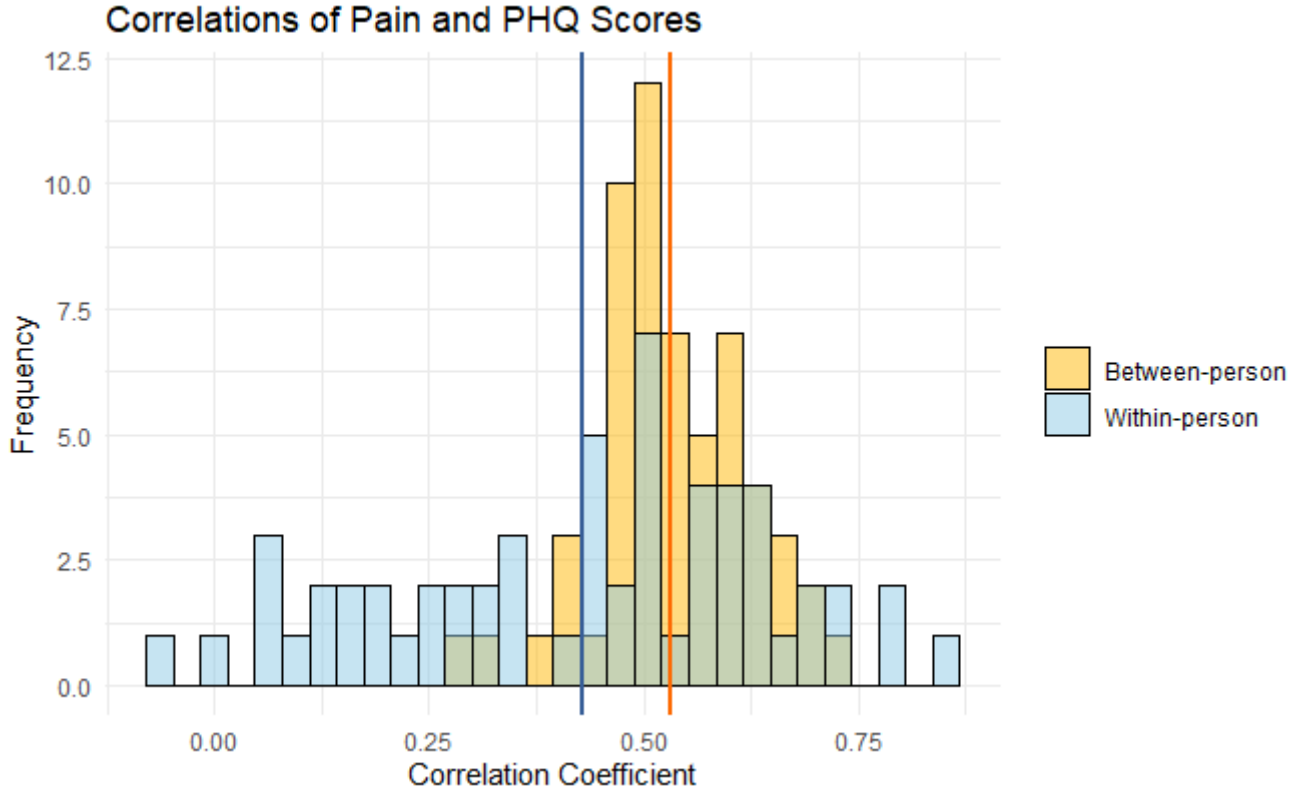



**Figure 8.** Endometriosis: Correlations between psychological inflexibility and depressive symptoms.

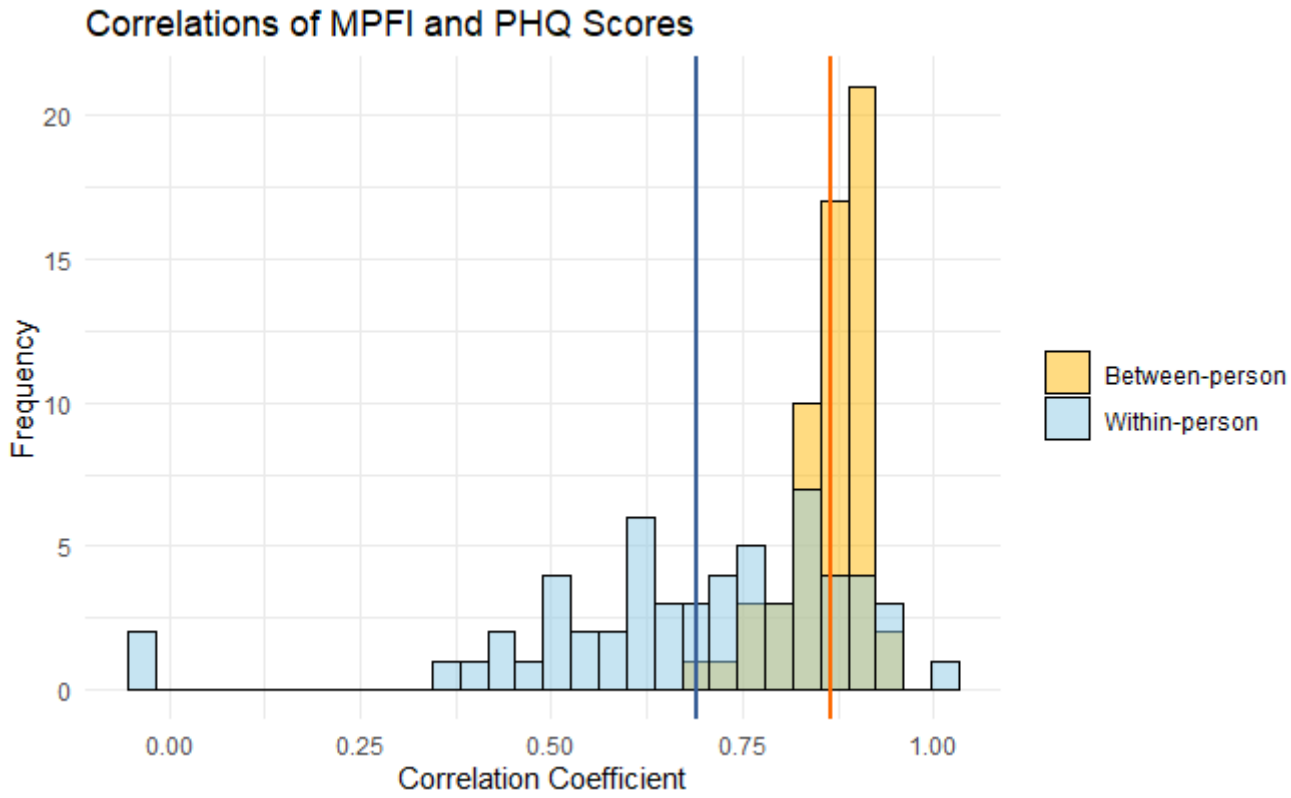





**Figure 9**. Endometriosis: Correlations between pain catastrophizing and pain interference

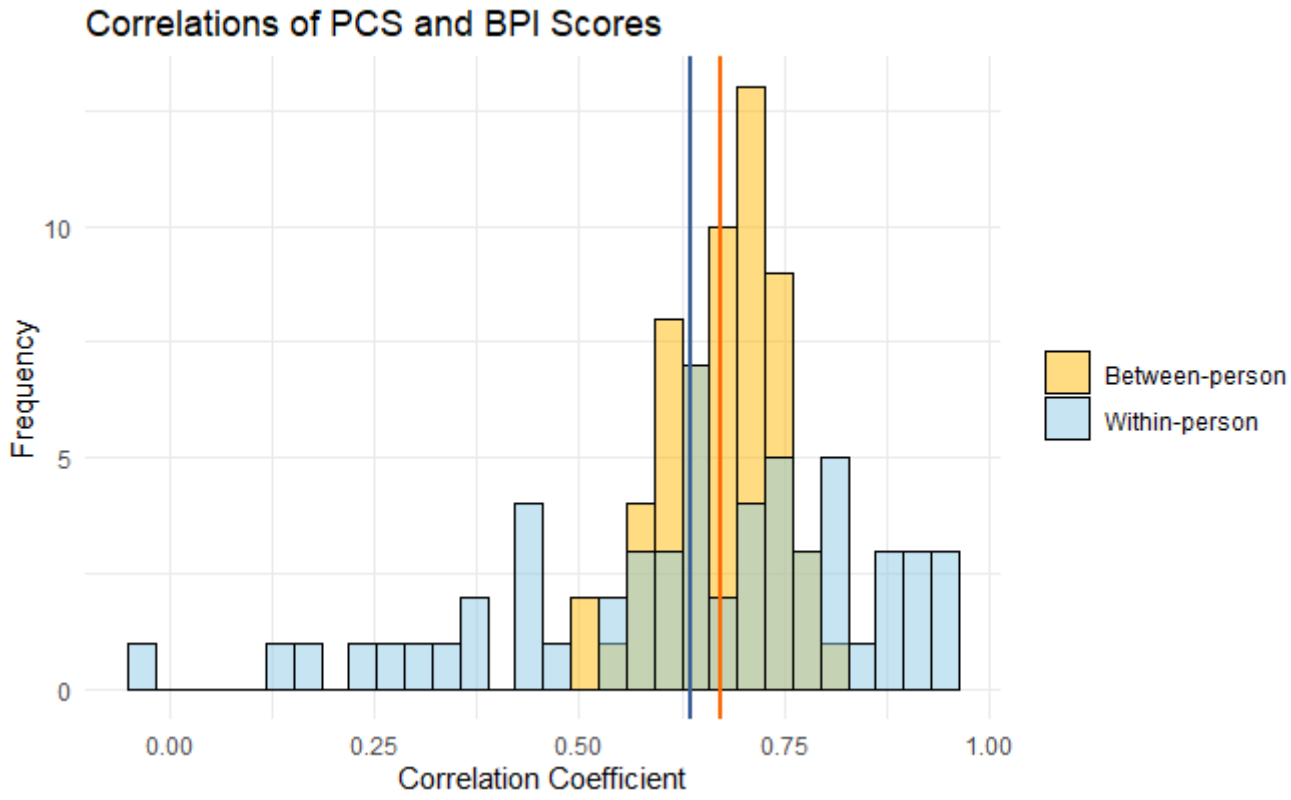



**Figure 10.** Endometriosis: Correlations between pain intensity and pain interference with temporal dependency removed

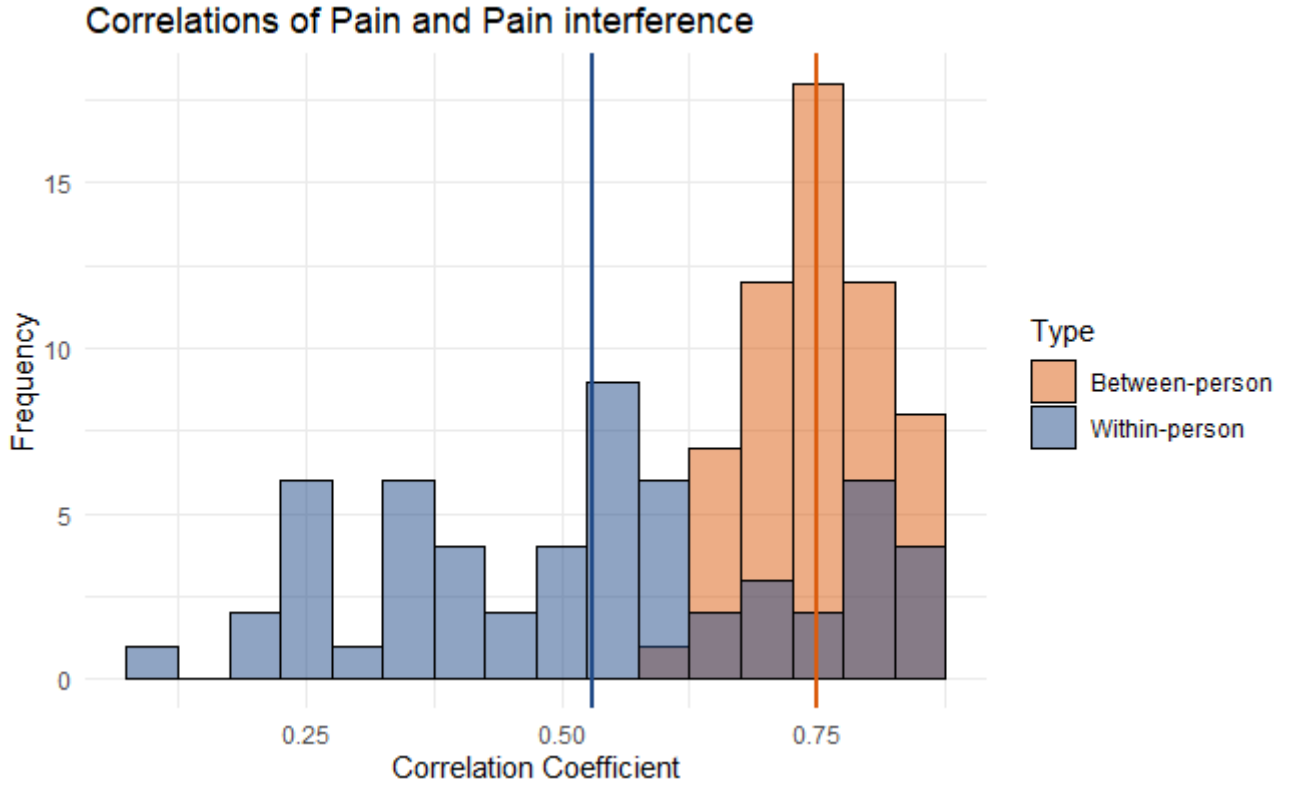


**Figure 11.** Endometriosis: Correlations between pain intensity and depressive symptoms with temporal dependency removed

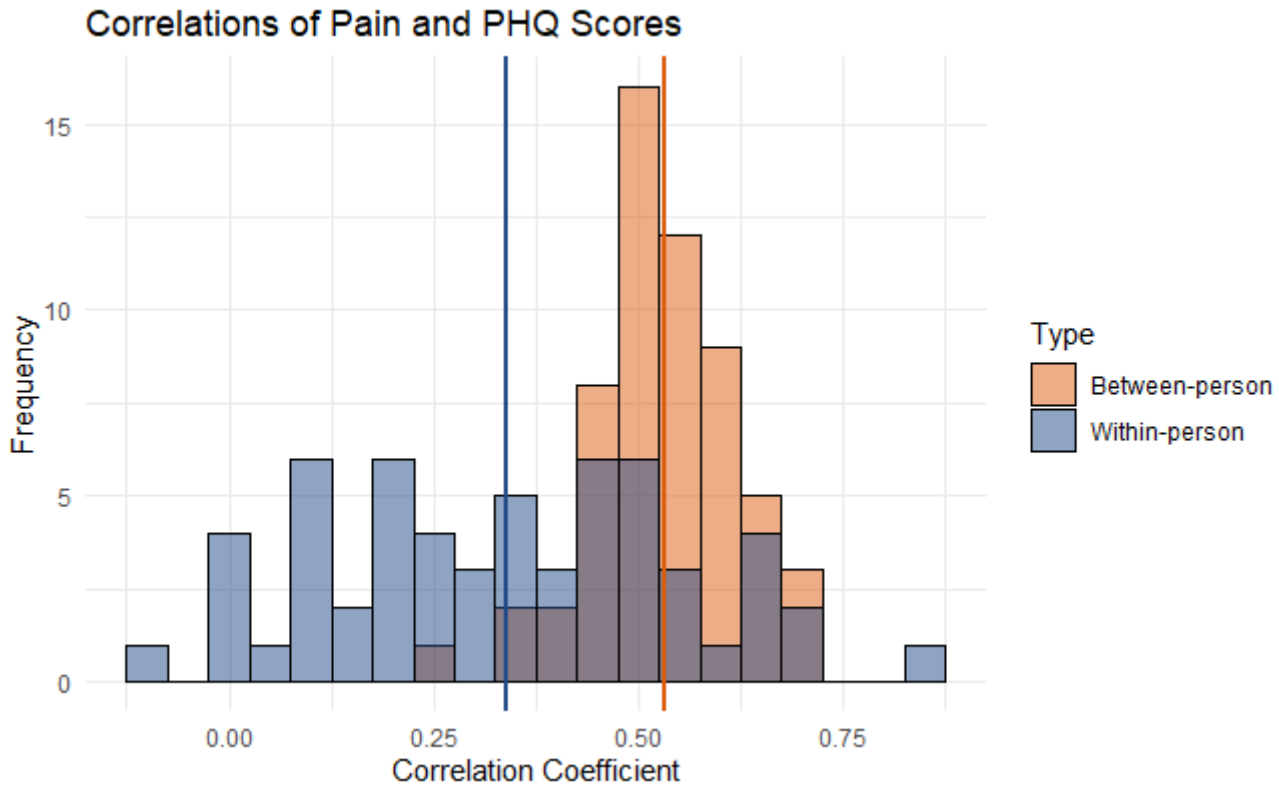



**Figure 12.** Endometriosis: Correlations between psychological inflexibility and depressive symptoms with temporal dependency removed

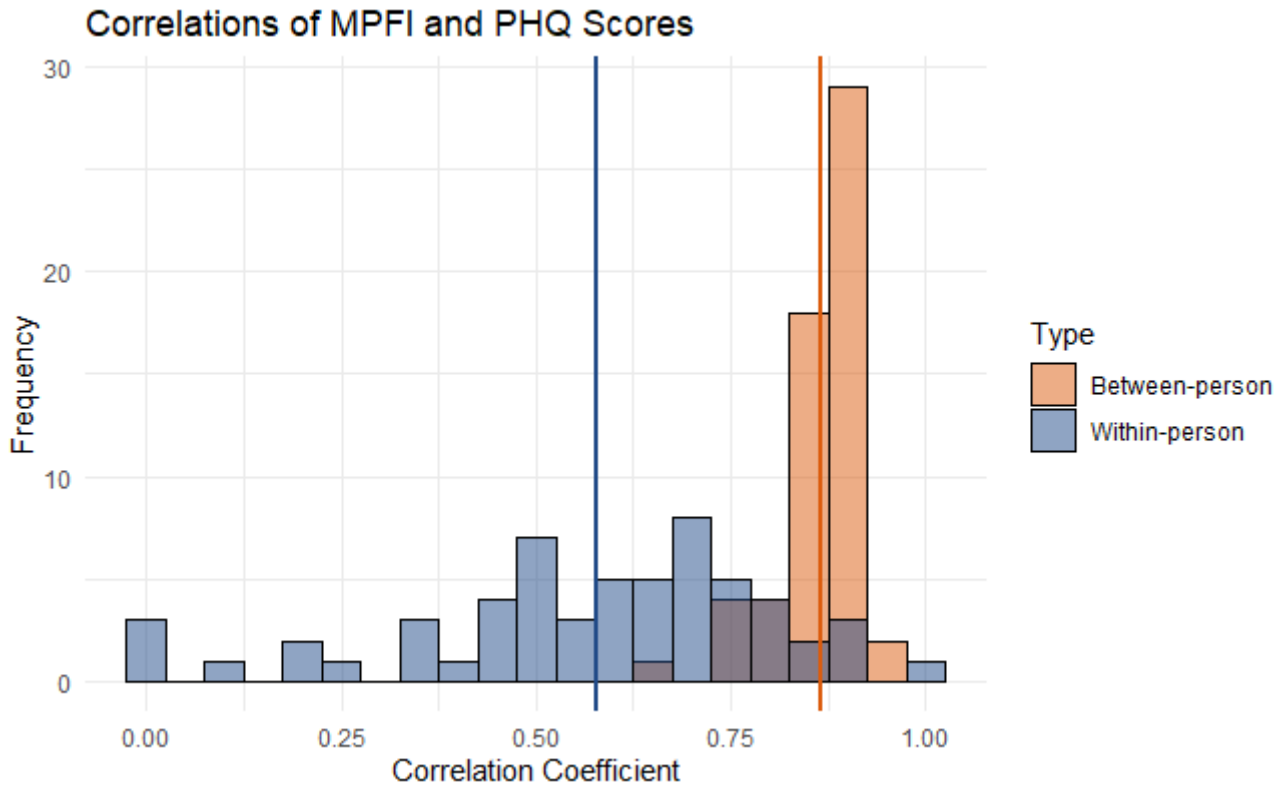


**Figure 13.** Endometriosis: Correlations between pain catastrophizing and pain interference with temporal dependency removed

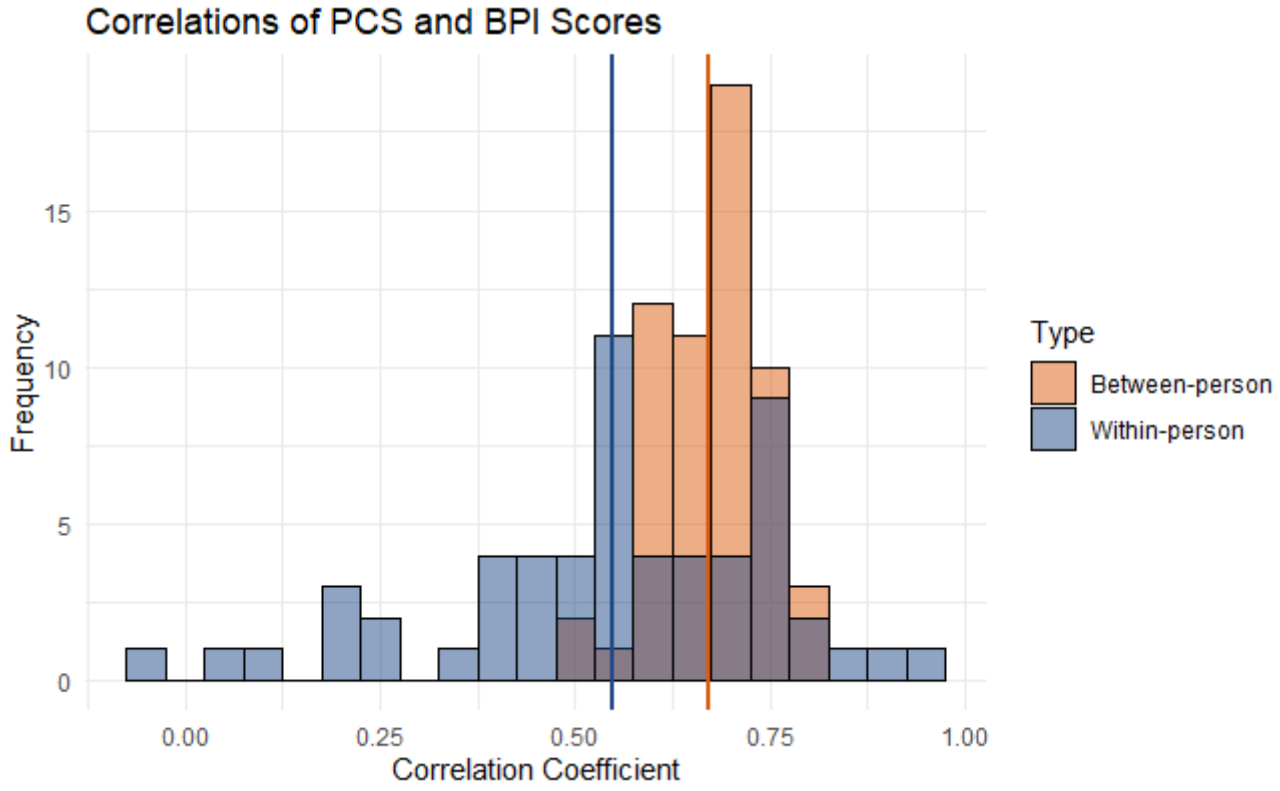



**Figure 14.** Endometriosis: A randomly picked time series – participant I

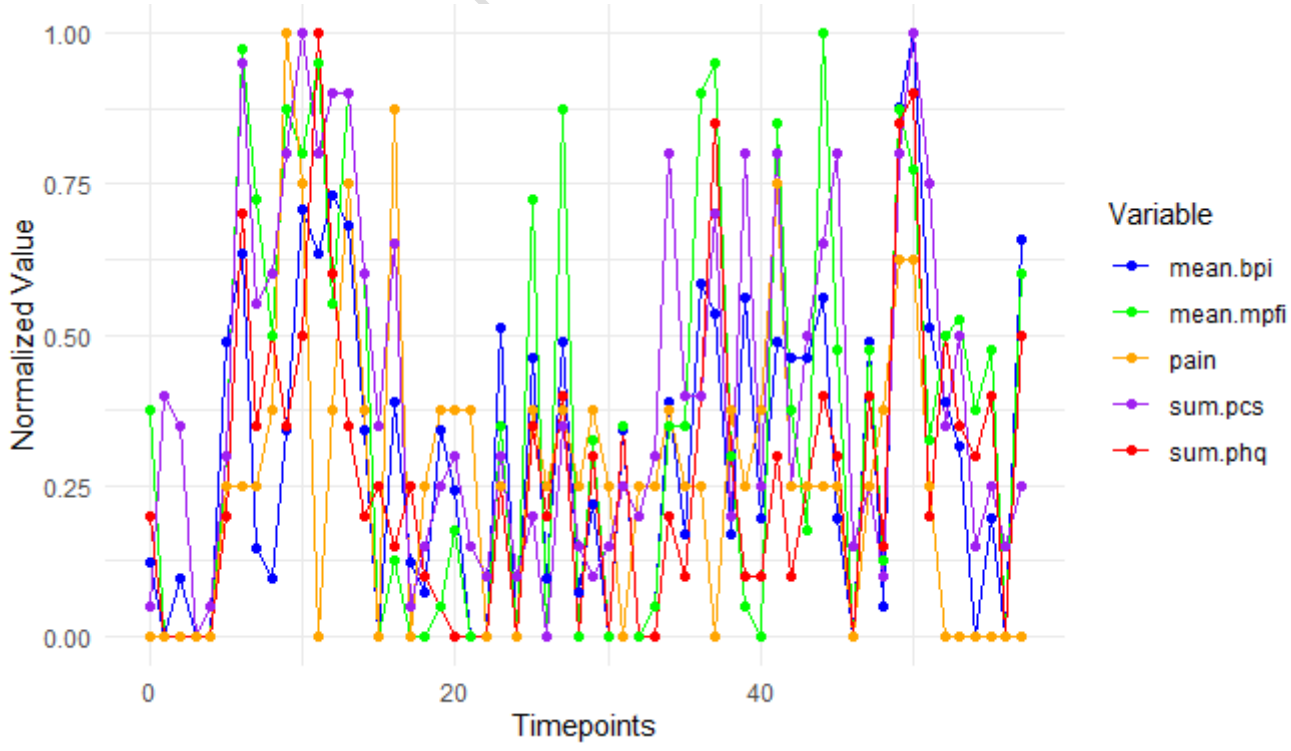
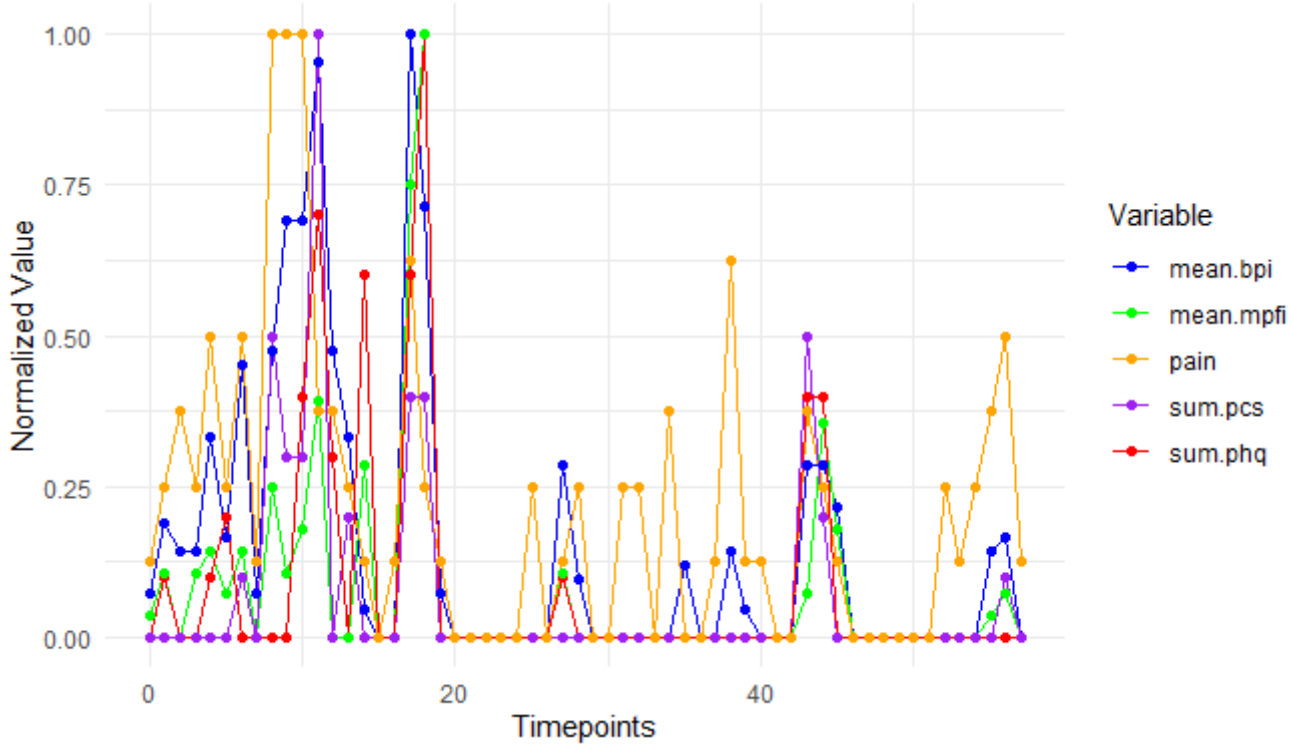
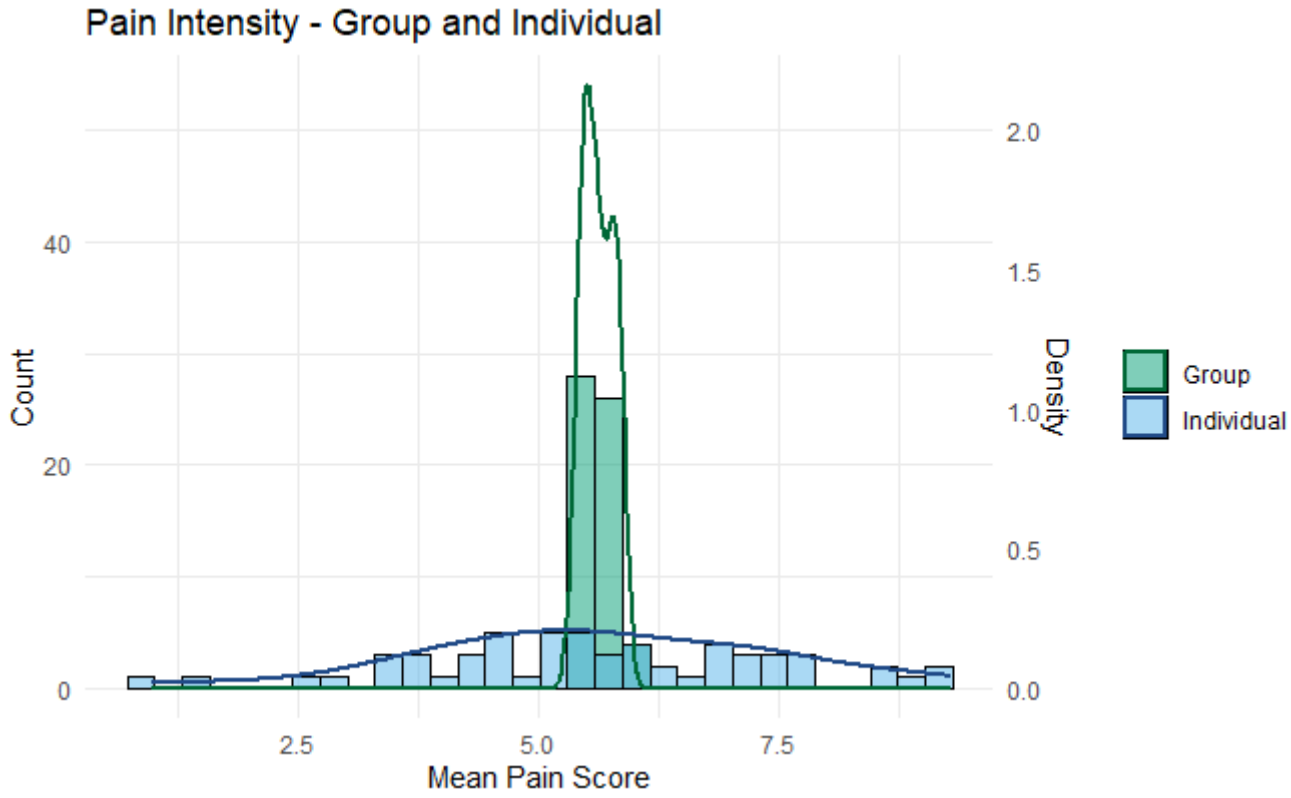


**Figure 15.** Endometriosis: A randomly picked time series – participant II



# Figures – fibromyalgia

**Figure 16.** Fibromyalgia: Pain intensity




*Legend.* Figure 17 depicts both a histogram as well as a density plot of the raw mean pain intensity scores, for individuals (means of 58 time series without temporal dependency removed) and for groups (means of 58 cross-sectional data sets).

**Figure 17.** Fibromyalgia: Pain interference

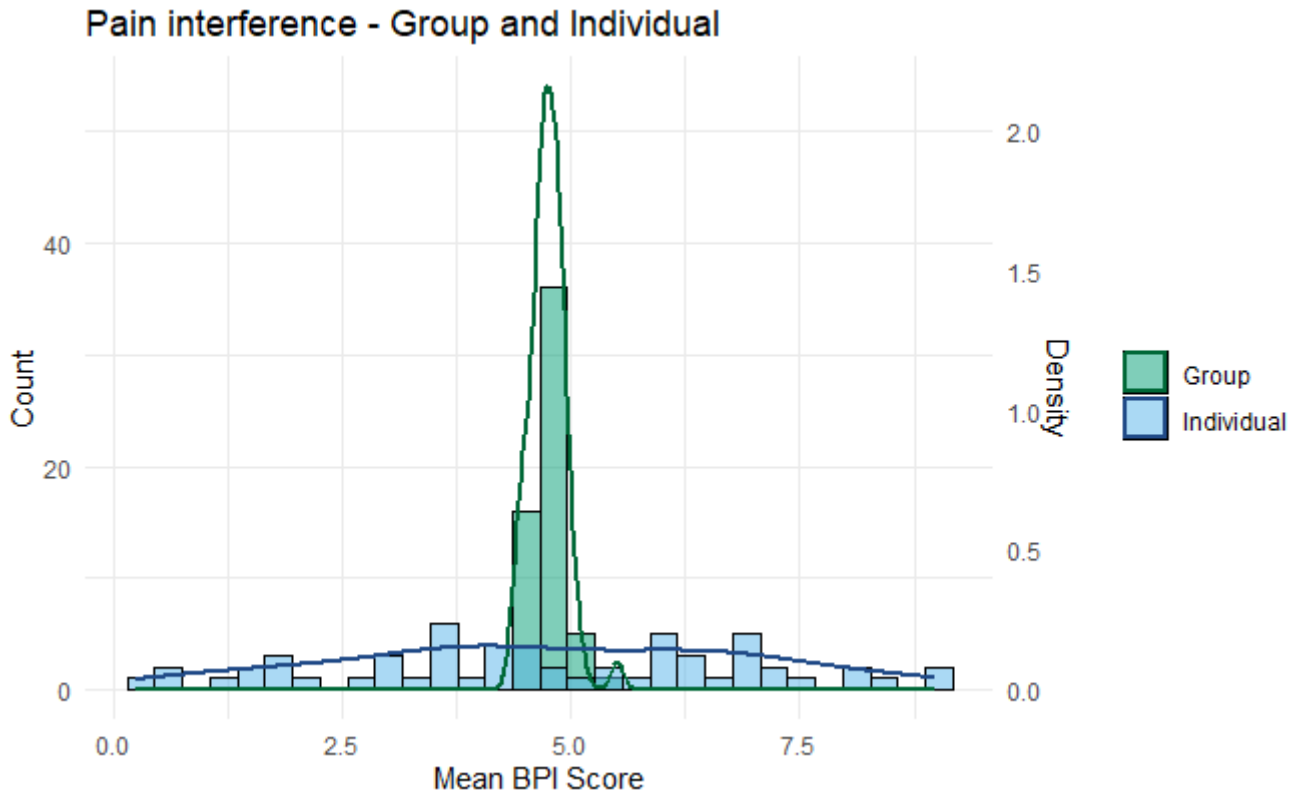



**Figure 18.** Fibromyalgia: Psychological inflexibility

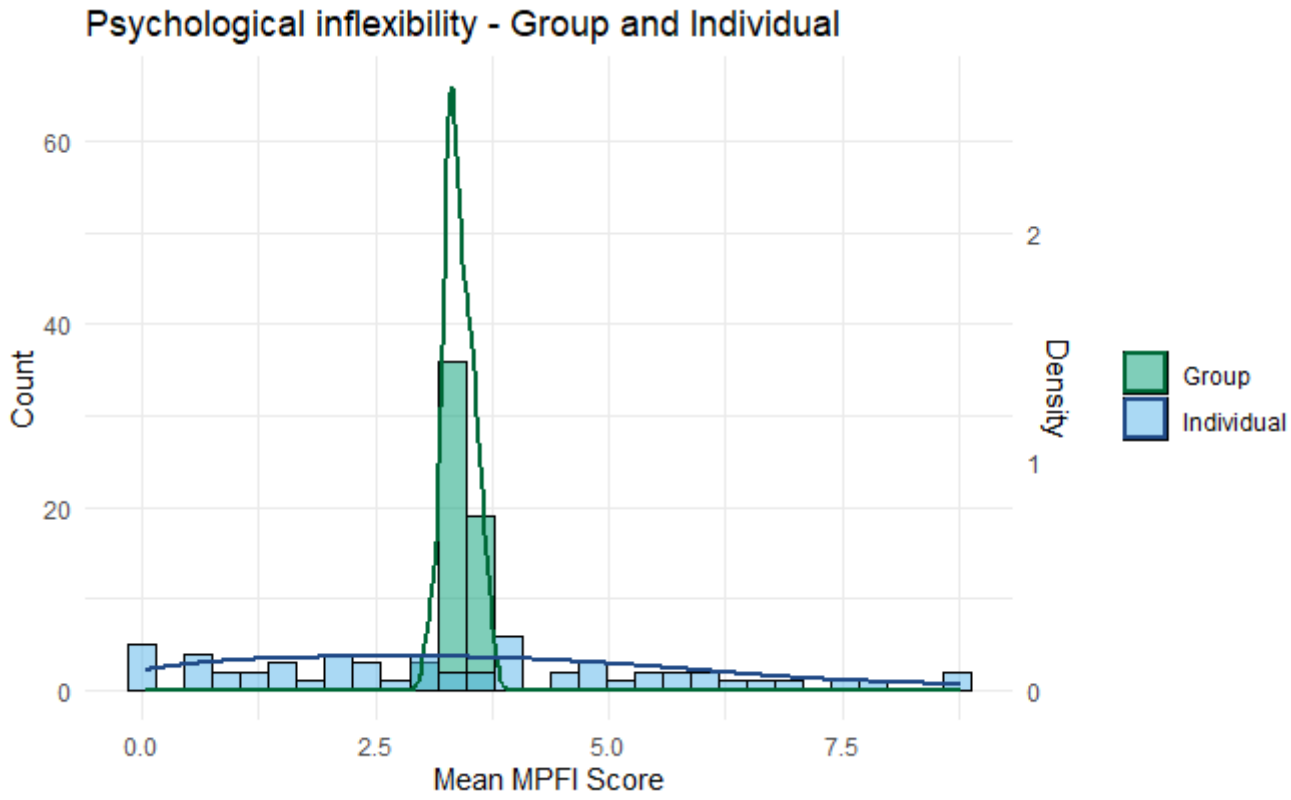



**Figure 19.** Fibromyalgia: Depressive symptoms

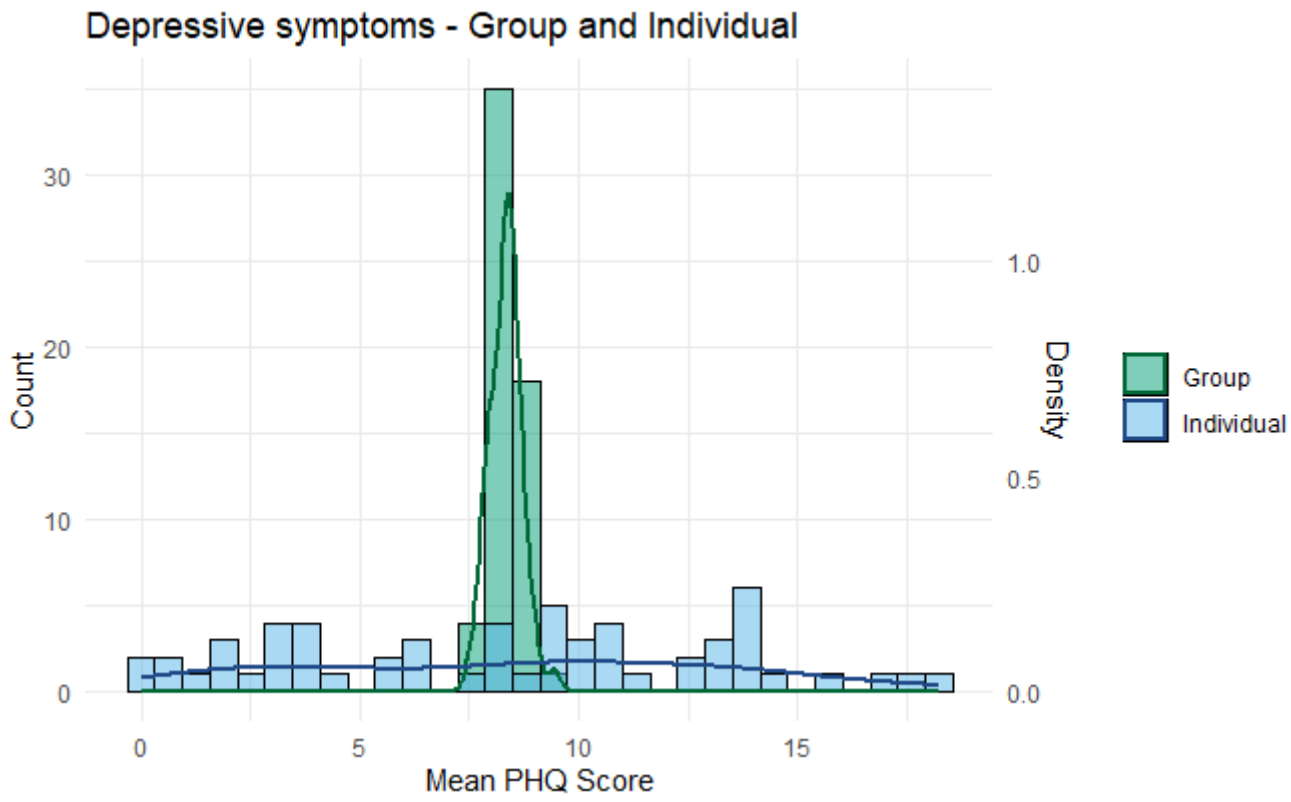



**Figure 20.** Fibromyalgia: Pain catastrophizing

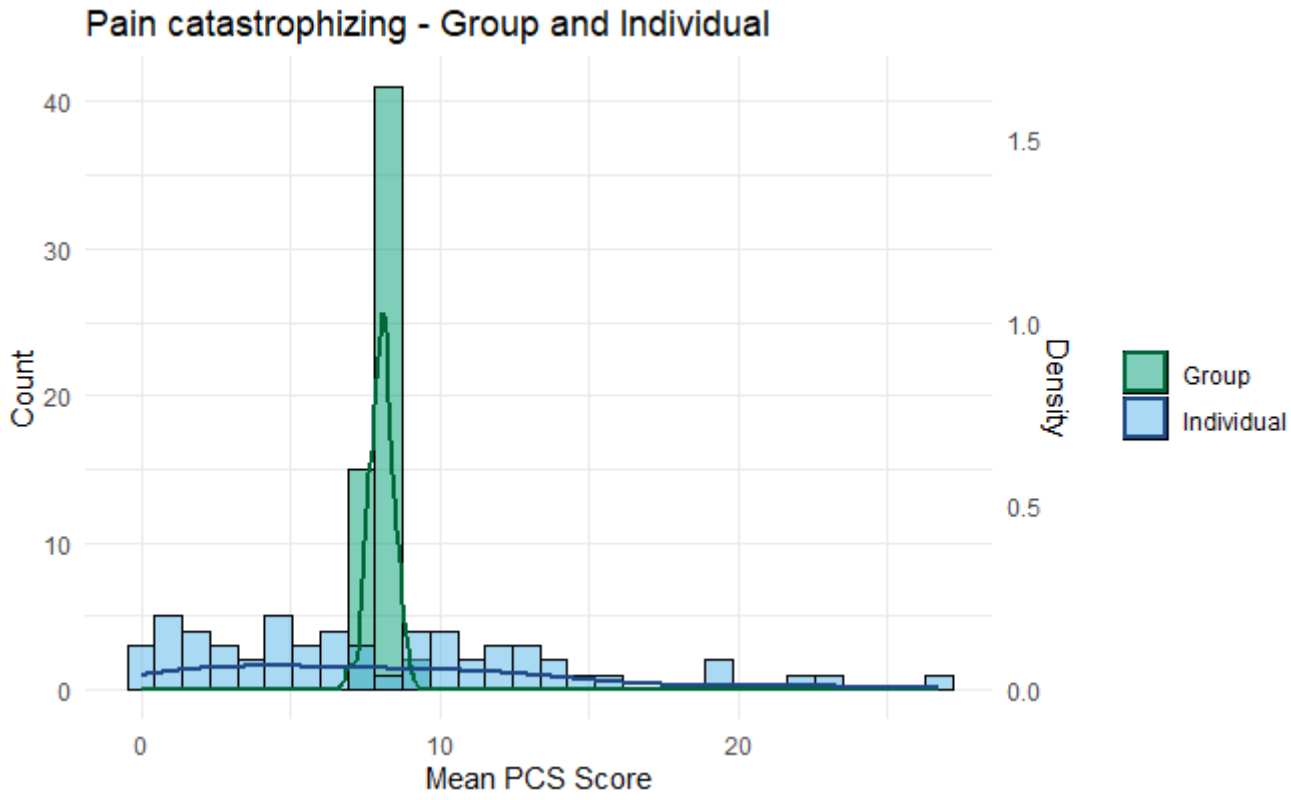


**Figure 21.** Fibromyalgia: Correlations between pain intensity and pain interference

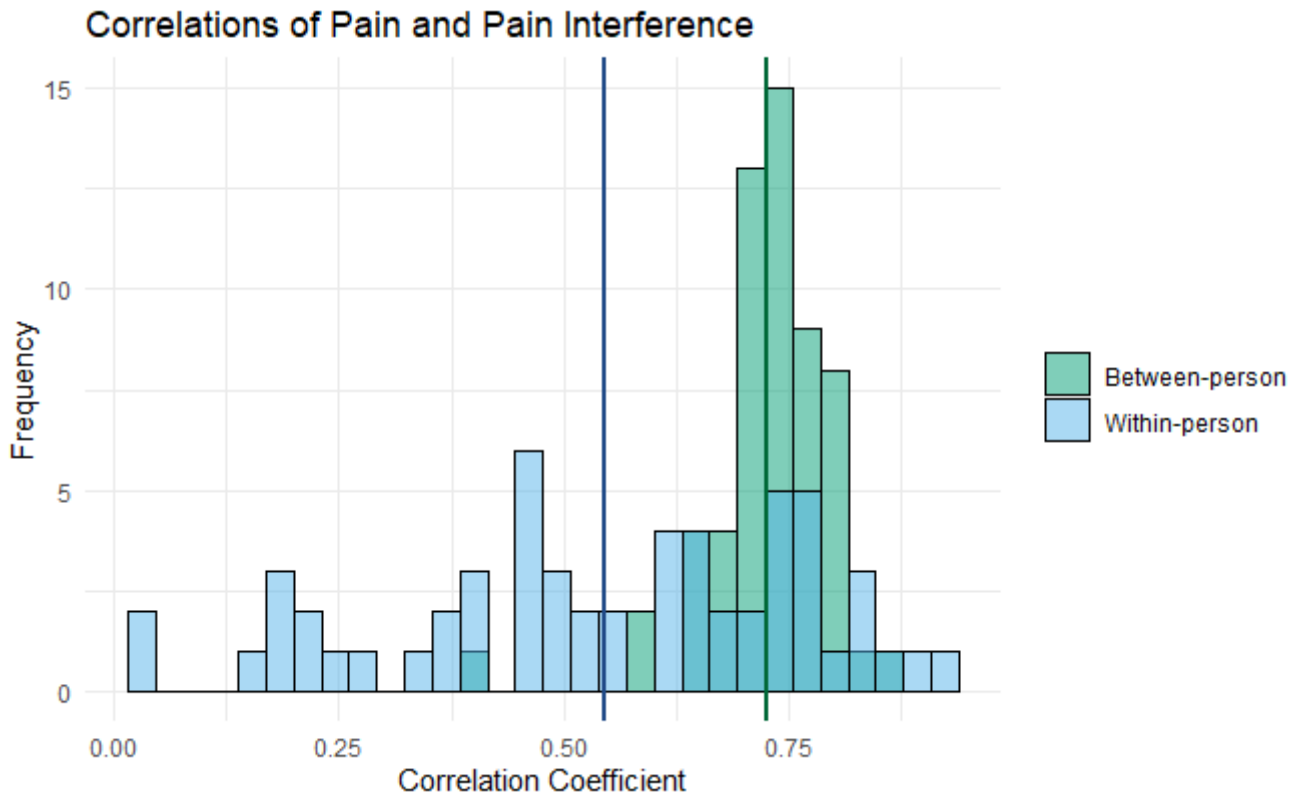



**Figure 22.** Fibromyalgia: Correlations between pain intensity and depressive symptoms

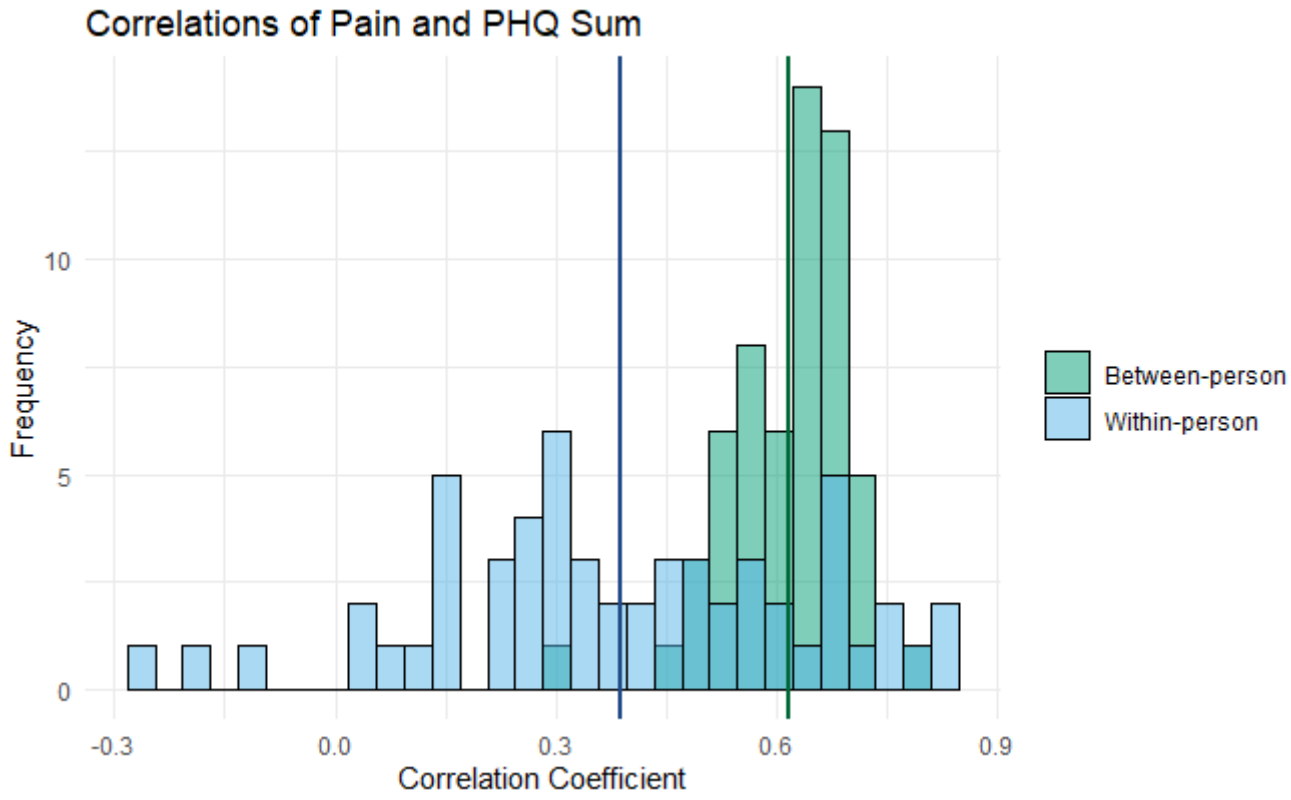



**Figure 23.** Fibromyalgia: Correlations between psychological inflexibility and depressive symptoms

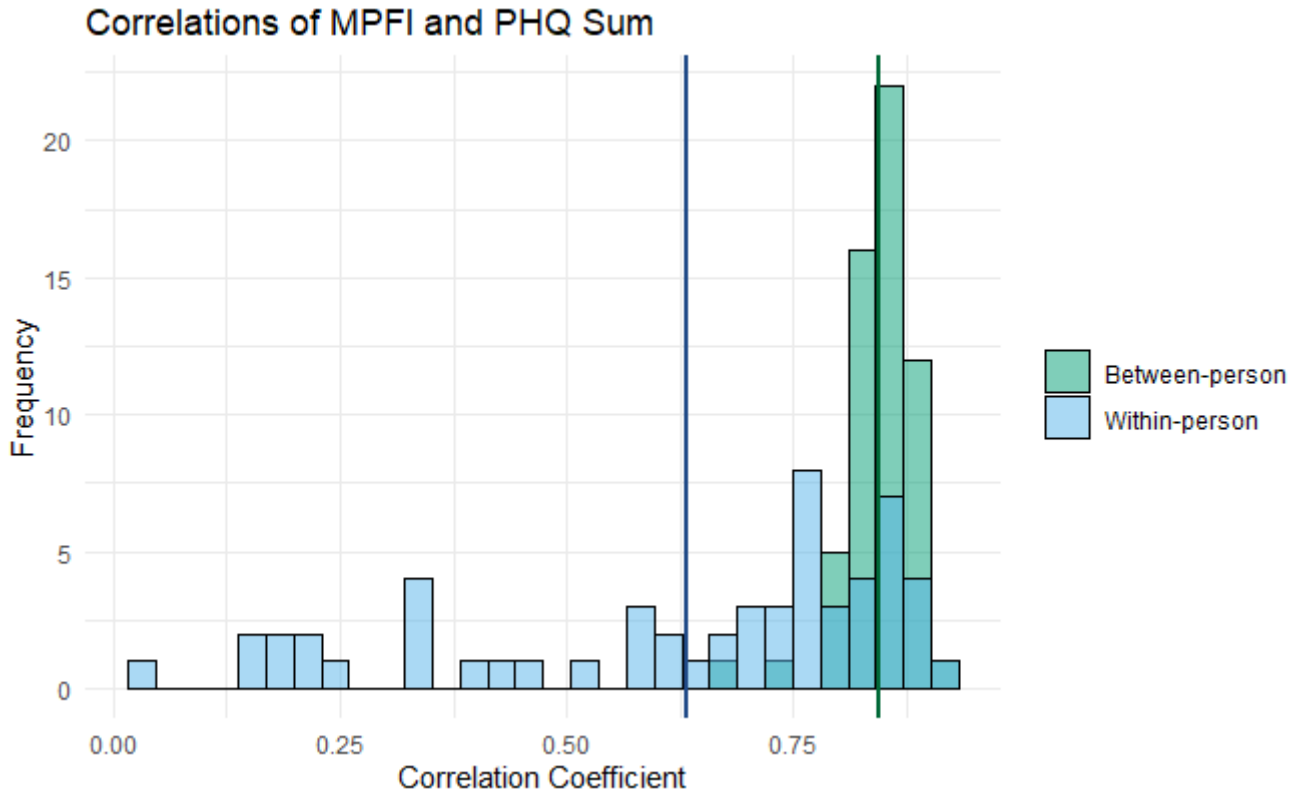


**Figure 24.** Fibromyalgia: Correlations between catastrophizing and pain interference

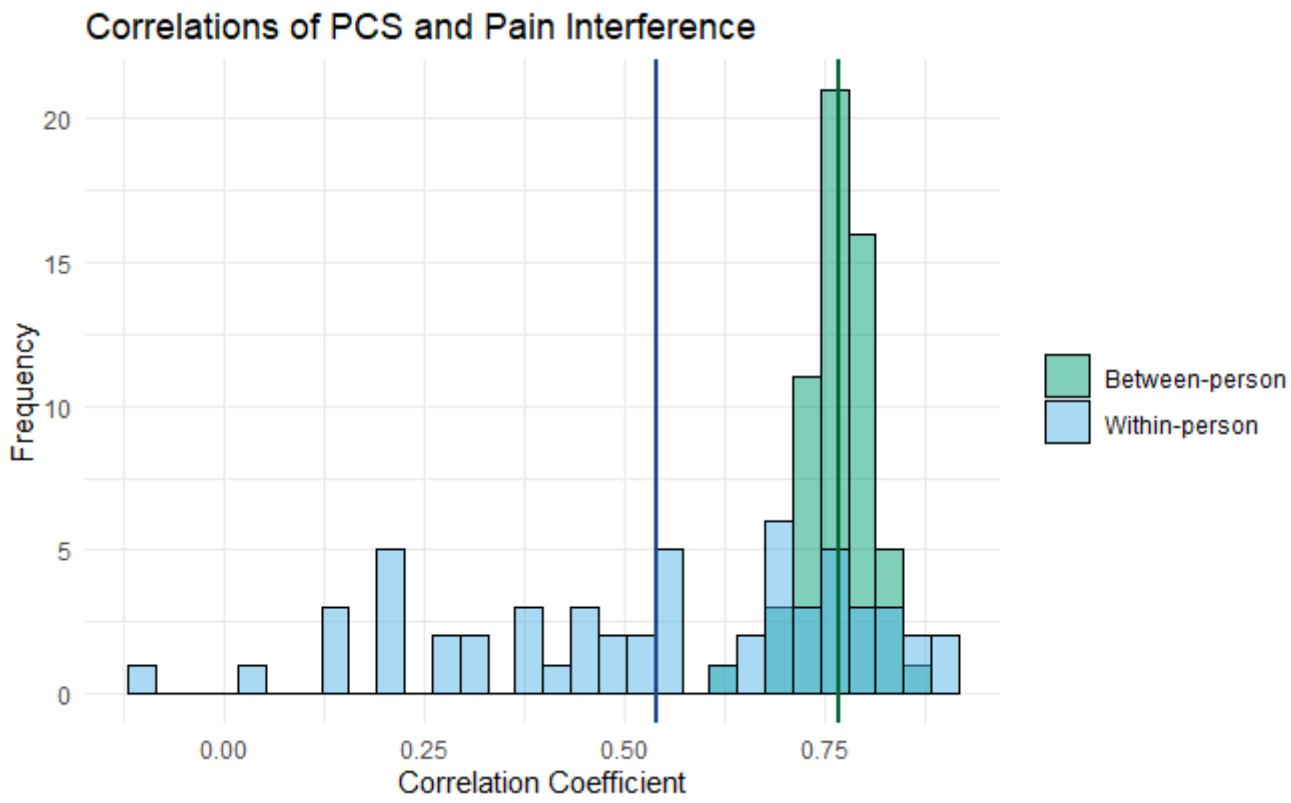



**Figure 25.** Fibromyalgia: Correlations between pain intensity and pain interference with temporal dependency removed

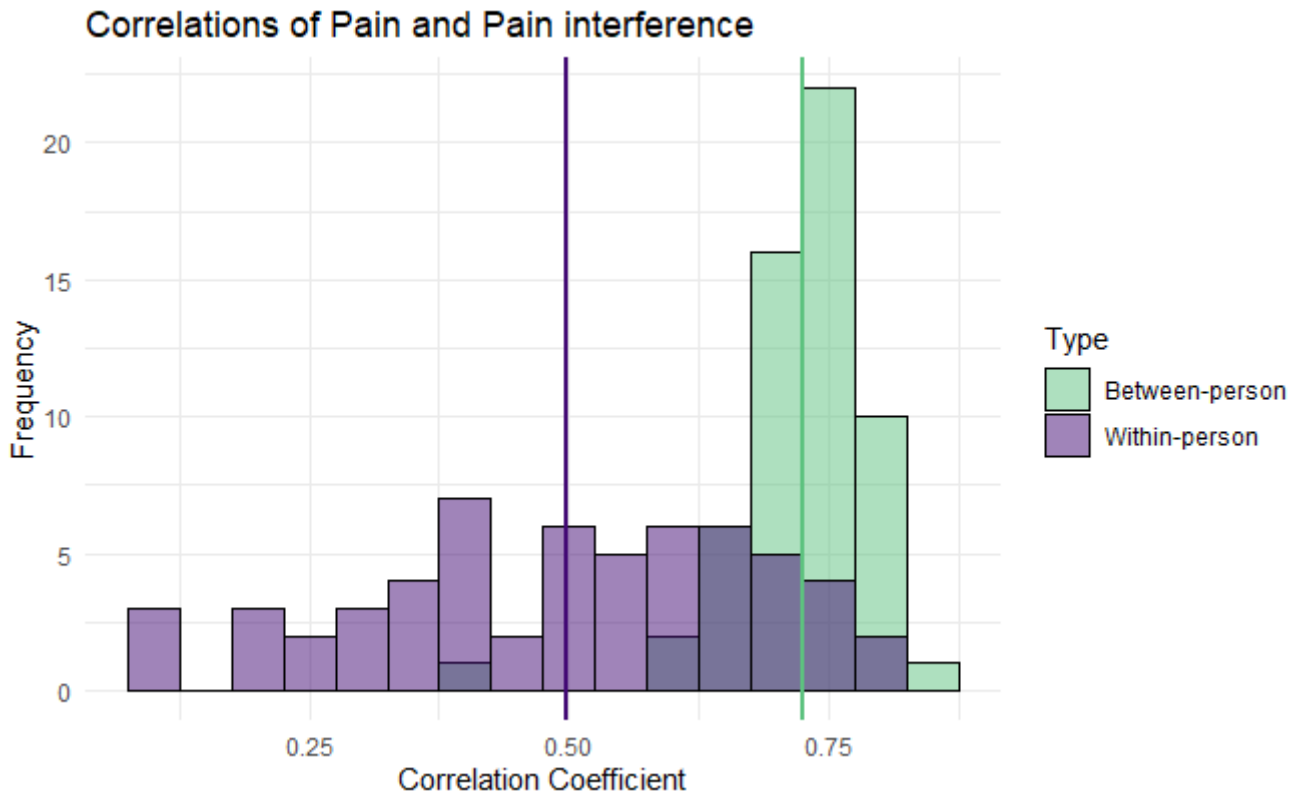


**Figure 26.** Fibromyalgia: Correlations between pain intensity and depressive symptoms with temporal dependency removed

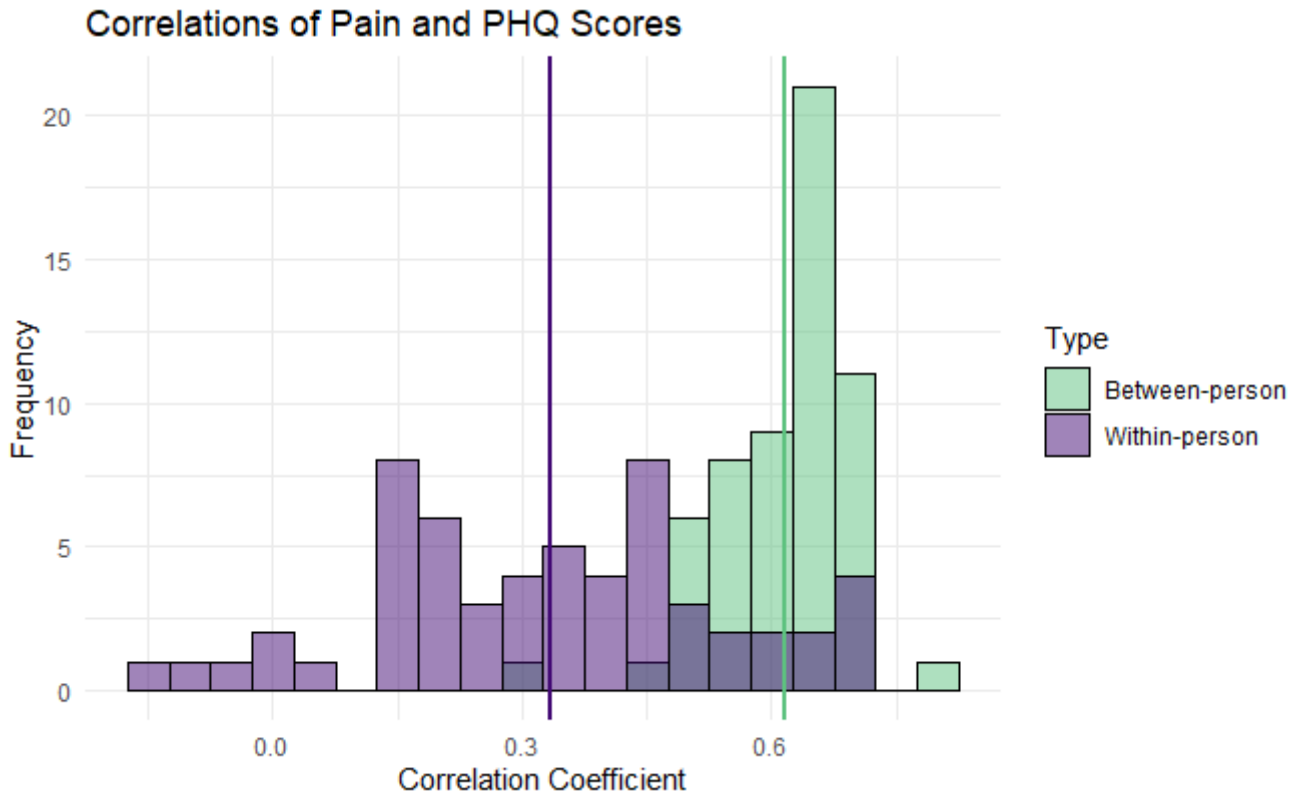



**Figure 27.** Fibromyalgia: Correlations between psychological inflexibility and depressive symptoms with temporal dependency removed

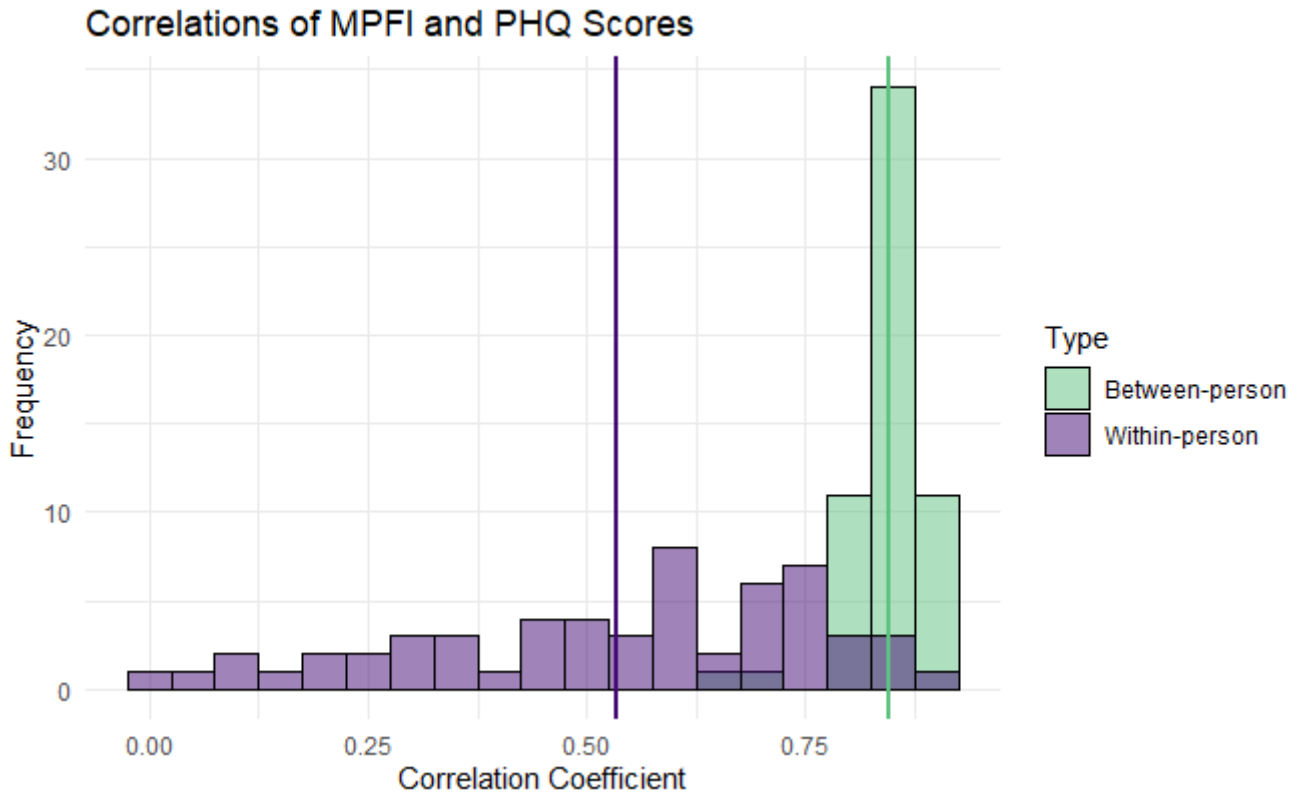



**Figure 28.** Fibromyalgia: Correlations between pain catastrophizing and pain interference with temporal dependency removed

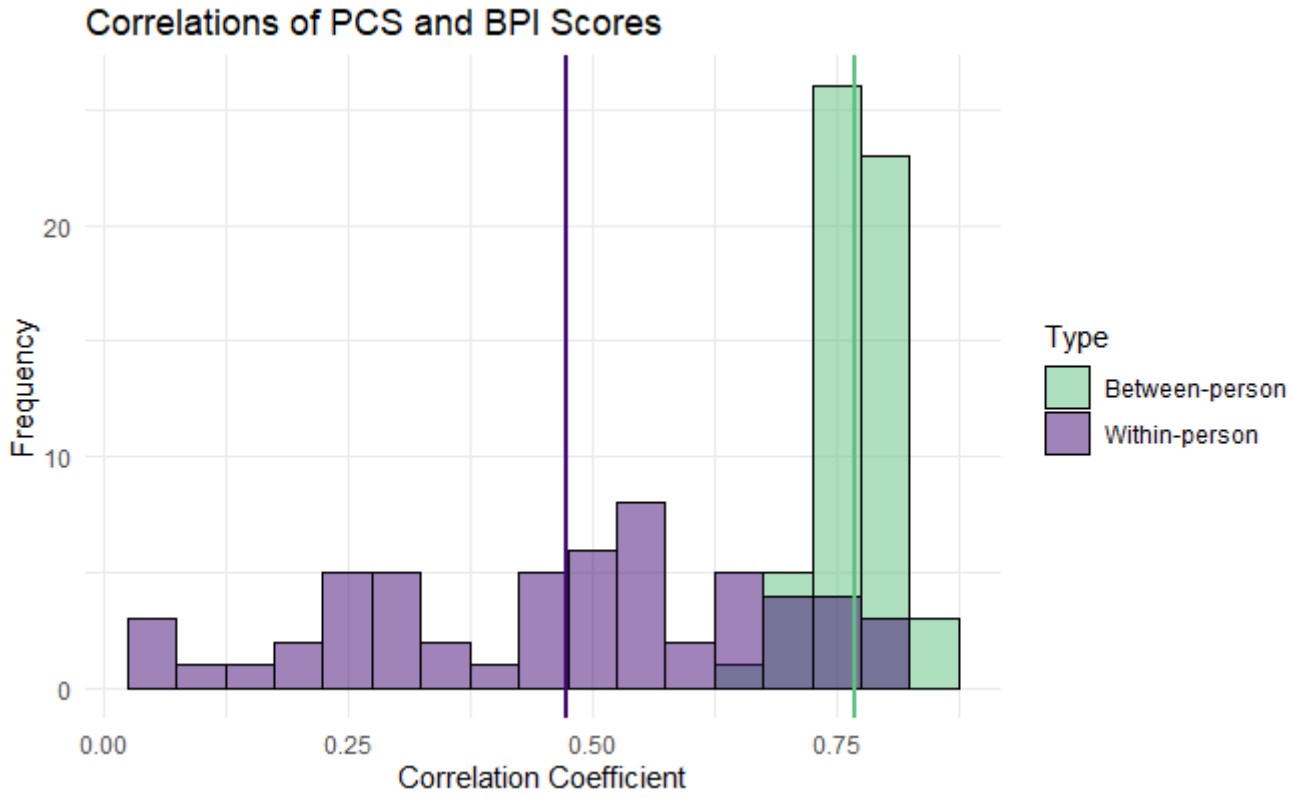


**Figure 29.** Fibromyalgia: A randomly picked time series – participant I

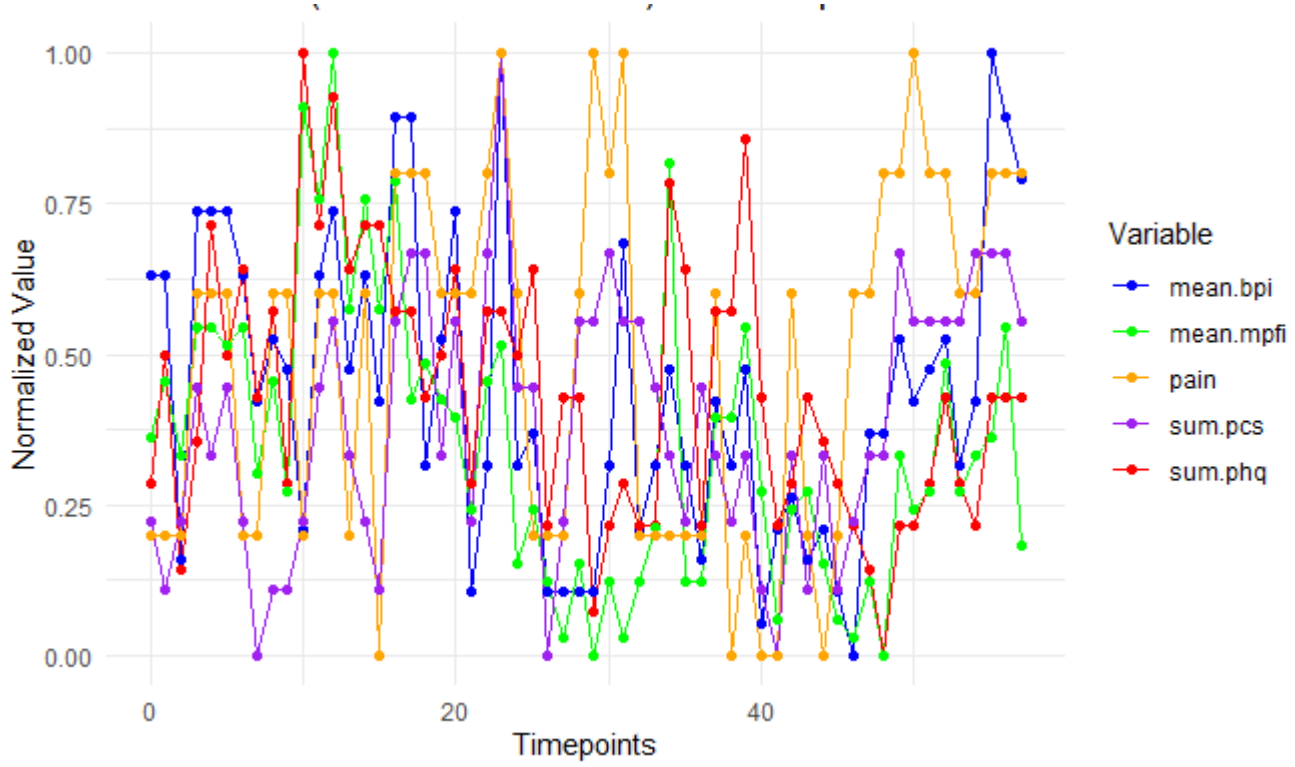



**Figure 30.** Fibromyalgia: A randomly picked time series – participant II