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Temporal dynamics of mental defeat in chronic pain: a longitudinal network analysis of ecological momentary assessment data

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Abstract

Mental defeat—negative self-appraisals in relation to pain—has been linked to greater pain interference, disability, and suicide risk in chronic pain populations. However, little is understood about how fluctuations in mental defeat shape daily pain experiences and responses. This study applied network analysis on time series data from an experience sampling study to examine these dynamic within-person relationships in 137 adults (M_{age} = 41.9, 84.7% female) with chronic noncancer pain, who completed online surveys 3 times daily over two 7-day periods spaced 6 months apart. Surveys captured in-the-moment ratings of mental defeat, pain (intensity, impacts, medication use), mood, stress, compassion (to self and others), attention (to pain, inward/outward, body/mind), and activity engagement (physical, social). Multilevel vector autoregression models generated temporal and contemporaneous networks, with stability verified through comparison with 1000 simulated models. The temporal network revealed 71 significant edges (top 25% edge weights: 0.07-0.15), showing that increases in mental defeat predicted subsequent increases in attention to pain and perceived pain impacts on self, relationships, and future. In turn, perceived pain impacts on routine and future predicted lower physical activity engagement. The contemporaneous network identified 62 significant edges (0.12-0.37), indicating that mental defeat was connected with increases in attention to pain and perceived pain impact on future, independent from the effects of pain, stress, and mood. Simulation studies confirmed high network stability. These findings offer insights into the interplay between mental defeat and cognitive, emotional and behavioural pain responses. They support the development of just-in-time interventions targeting mental defeat for pain management.

Keywords: Network analysis, Experience sampling method, Ecological momentary assessment, Chronic pain, mental defeat, Mood, Attention, Stress, Physical activity, Social activity, Self-compassion, Medication

1. Introduction

Chronic pain is increasingly recognised as a complex biopsychosocial condition,[38] frequently associated with mood disorders, cognitive dysfunction, sleep disturbances, and activity limitations. All these impact on quality of life, and importantly, shape the subjective experience of pain-related suffering, which adds a critical layer to understanding the lived experience of chronic pain.[44,53]

Pain-related suffering is distinct from nociception.[35] It is considered a cognitive–affective state triggered by perceived threats to one's self or identity.[3,36] The concept of "mental defeat" has been applied to describe and explain this mental state.[48] Originating from trauma and depression research,[11,12,23] mental defeat refers to negative self-appraisals in relation to pain, stemming from perceived losses of autonomy, agency, social status, and integrity. This concept offers a means to assess pain-related suffering engendered by pain's impact on identity.[36]

Earlier research shows that people with chronic pain seeking treatment in hospital pain clinics report higher levels of mental defeat than those not seeking treatment.[48] Mental defeat is associated with greater pain interference, lower self-efficacy, and increased disability[22,29,47] and has been linked to suicidal behaviour in chronic pain, even after accounting for sociodemographic, pain, and psychological factors.[4,46,50,51] These findings underscore its role in pain-related distress and disability. However, little is known about how mental defeat fluctuates in daily life or how it relates to momentary responses to pain. Addressing these gaps is essential for developing just-in-time interventions that can identify and respond to moments of heightened mental defeat.

Focusing on the intraindividual fluctuations in experiences, this study investigated the within-person temporal dynamics of

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mental defeat, psychological states, and behavioural responses to pain. A within-person approach reduces confounding from stable traits and improves detection of subtle changes that can be masked in between-person analyses. Insights generated will be more aligned with individual experiences and more valid in determining temporal sequences of relationships. Using data from a longitudinal ecological experience sampling study of adults with chronic noncancer pain, we examined momentary predictors of pain intensity and disability. Appling network analysis to the time-series data,[14,15,17,18] we modelled symptom changes over time and identified pathways through which mental defeat may influence pain perception, pain-related thoughts and feelings, and behaviour. This longitudinal network approach captures dynamic associations across a number of variables that are not detectable in cross-sectional designs and provides a temporal perspective essential for identifying mechanisms relevant to treatment development. Based on previous between-person findings,[6,22,29,32,47–49] we hypothesised that heightened mental defeat would be associated with narrowing of attention, worse mood, higher pain intensity and impact, and potentially, reduced activity and increased medication use. Within-person investigations of these temporal and contemporaneous networks were, however, novel and exploratory.[24]

2. Methods

2.1. Data set

This study analysed data collected for the Warwick Study of Mental Defeat in Chronic Pain (WITHIN). A detailed protocol was published and made available open access.[24] The WITHIN project had several objectives. This study reports the first findings from the project component that used longitudinal experience sampling methods (ESM) to investigate the dynamic interaction of mental defeat with pain and other relevant daytime psychological and behavioural variables using a network approach.

The study had 2 data-collection points (two 7-day monitoring periods, spaced 6 months apart), producing a total of 14 days' worth of observations for each participant. Three online surveys were administered each day to capture daily self-report fluctuations in all variables of interest spanning active/waking hours of the day. This means 3 observations a day for 14 days, generating 42 observations per variable per participant (**Fig. 1**).

A total of 330 people met eligibility criteria and registered interest in participating in the ESM study. Of these, 212 remained contactable by the research team and were consequently enrolled to start the first wave of experience sampling. At wave 1, 5 participants withdrew during the data collection (citing time and other personal constraints) and 1 participant's data were not included due to data corruption, producing a total of 206 participants who completed baseline questionnaires and the first wave of ESM data collection. Six months later, 148 participants re-enrolled to start wave 2 of experience sampling. A further 11 participants' data were lost to follow-up ($n = 4$ withdrew from the study citing time and other personal constraints; $n = 7$ due to data corruption). This resulted in a total of 137 participants who completed the study and contributed data to the current analysis, which used the time-series data from the daily survey (see section 2.4.2) for the network analysis and data from baseline questionnaire (see section 2.4.1) to characterise the sample (see supplemental digital content, Materials 1 for a participant flow diagram, http://links.lww.com/PAIN/C485). Welch t-tests and Pearson chi-squared tests found no significant differences between these participants and those who started but did not contribute data to the current analysis in any of the key demographic and baseline characteristics reported below in section 3.1.

2.2. Participants

Our participants were adults (aged 18-65) based in the United Kingdom who reported chronic noncancer pain that has been present or recurring for at least 3 months[41,54,61] and completed both data collection waves. Participants were recruited through multiple recruitment streams, including through General Practitioners (GPs) and hospital pain clinics, the National Institute for Health and Care Research (NIHR) Clinical Research Network, online recruitment platforms as well as UK-based community patient support groups, and self-referrals in response to study adverts shared on social media.

To determine eligibility, individuals who were interested in taking part in the WITHIN project and provided informed consent were asked to complete a short online screening questionnaire. A full list of the inclusion and exclusion criteria has been previously described in the study protocol.[24] In brief, inclusion criteria specified that potential participants must be: (1) English-speaking, (2) able to provide informed consent, and (3) on a stable pain treatment regime for the study duration (to minimise treatment interference). Exclusion criteria included: (1) reports of a significant comorbid psychiatric or medical condition that would impact on participants' pain experience or ability to give informed consent or perform the data collection procedure (eg, acute psychosis or dementia), (2) significant acute pain, (3) receipt of elective surgery or procedure requiring general anaesthetic during the study, and (4) participation in another research study using an investigational product in the past 3 months. Participants with comorbid anxiety and depression of mild to moderate severity were, however, included in the study. Although not the focus of this report, one of the objectives of the wider project was to examine the association between sleep and pain outcomes. A further criterion was therefore applied to exclude those who reported a comorbid sleep disorder (such as sleep apnoea, restless leg syndrome, periodic limb movement disorder, narcolepsy, or circadian rhythm disorders) to minimise potential confounds.

2.3. Patient and public involvement and engagement

Two members of the public with lived experience of chronic noncancer pain were consulted at the planning and implementation stages of the study. Patient and public involvement and engagement involvement included reviewing and commenting on readability/understanding of participant-facing materials (study information sheet; study information booklet which included information on how to use study equipment, how long to participate for, and postage instructions for returning equipment to the University; user instructional video; questionnaires; study debrief form). Three approved members of the Warwick Sleep and Pain Lab (one with lived experience of chronic pain) also piloted the study processes (signing up to a dummy schedule of SMS prompts, setting up, and completion of online survey using different devices) for one-week before the study launched, to ensure no technical errors occurred with daily survey.

2.4. Measures

2.4.1. Baseline questionnaire

All eligible participants starting the study completed a series of demographic and pain demographic questions as part of the

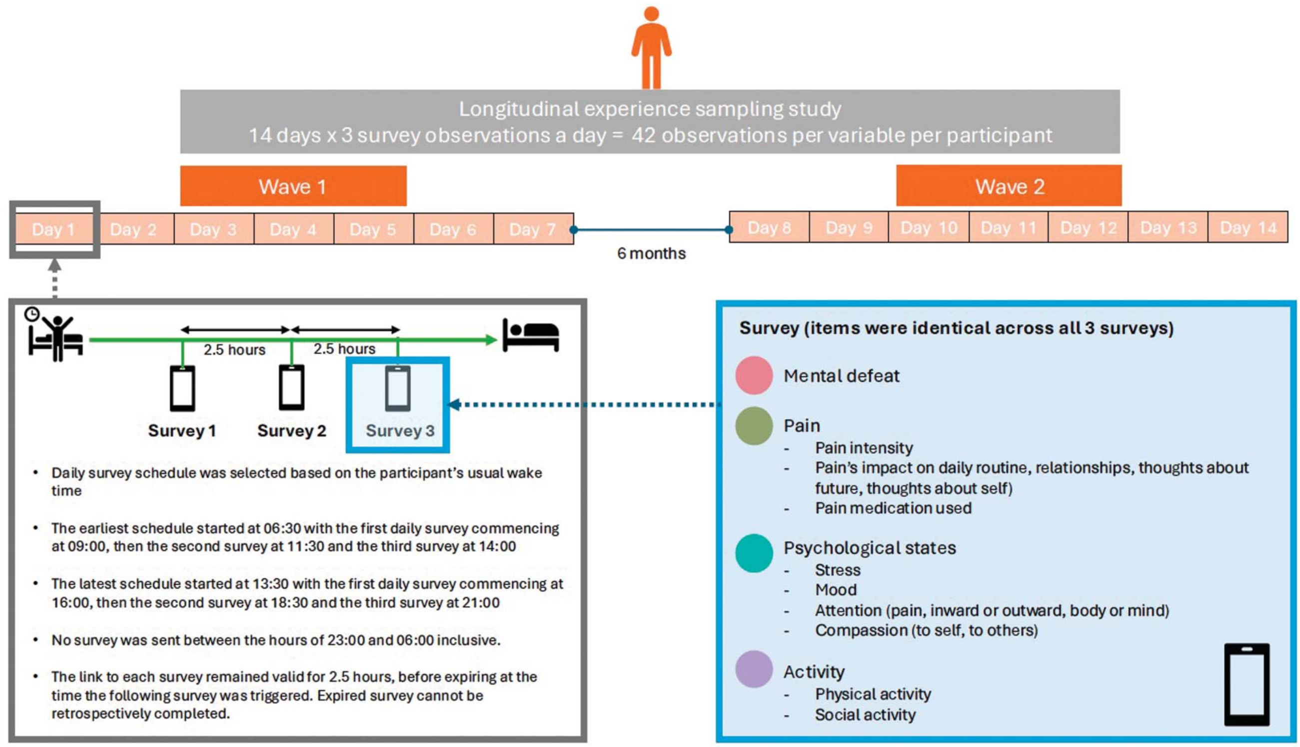

Figure 1. Study design and data collection schedule. Using a longitudinal experience sampling design, the study had 2 waves of data-collection (two 7-day monitoring periods, spaced 6 months apart), producing a total of 14 days' worth of observations for each participant. Three online surveys were administered each day to capture daily self-report fluctuations in all variables of interest, generating 42 observations per variable per participant. Grey outline box captures (and is expanded to illustrate) 1 day of experience sampling schedule. Content of each of the 3 daily surveys was identical. Variables of interest covered in these surveys are outlined in the blue box.

baseline questionnaire before commencing the experience sampling.[24] Basic demographics (eg, age, sex, ethnicity, employment status, education level), health indicators (eg, body mass index, average alcohol intake, smoking status), and pain characteristics (eg, pain diagnosis, pain duration, medication use, pain location, pain intensity, and interference) were assessed. Pain duration was measured up to a maximum of 30+ years. Pain medication use was quantified into a single score by using an adapted version of the Medication Quantification Scale-III.[26] This validated scoring system was adapted to include and reflect current prescription procedures in the United Kingdom. Pain location was assessed using a Body Pain Map[5] while pain intensity (as the average of pain rated at its worst, least, average, and current levels in the past 24 hours) and interference (with general activity, mood, walking, work, relationship, sleep, and enjoyment of life) were measured using the Brief Pain Inventory-Short Form.[5,30]

Baseline level of mental defeat was measured using the Pain Self Perception Scale (PSPS),[45,48] a 24-item scale describing negative thoughts and feelings about oneself due to pain. All items begin with the referent "Because of the pain," followed by statements such as "…I felt defeated," "…I felt destroyed as a person," "…I felt that there was no fight left in me," "…I felt humiliated and that I was losing my sense of inner dignity." Participants were asked to recall a recent episode of intense pain before rating the extent to which each of the items applied to their experience on a 5-point scale (0-4), where 0 means "not at all/never" and 4 means "very strongly." Summing all ratings gives a total score that ranges from 0 to 96, with higher scores indicating higher levels of mental defeat.

The PSPS has been validated in multiple clinical pain samples across different countries, demonstrating excellent internal consistency (eg, 1-factor solution through principle component analysis[22,48]; item-total correlations: 0.72-0.88,[48] 0.68-0.86[22]), construct validity (correlations with pain intensity: 0.41-0.51,[29,48] anxiety: 0.57-0.62,[22,47,48] depression: 0.63-0.66,[22,47,48] pain catastrophising: 0.4,[22] pain self-efficacy: −0.69[29]) and test–retest reliability (2 days: 0.92[48]; 1-2 weeks: 0.78[22]). There is also preliminary evidence to suggest that the level of mental defeat changes over longer periods of time in the absence of targeted intervention (over 6 months: 2.5-point increase from 35.3 + 25 to 37.8 + 28.5, Bayse Factor BF_{10} = 10.8[52]). More information about the PSPS's score distribution, face validity, cross-cultural validity, and diagnostic performance is provided in the scale's open-access user guide.[44]

2.4.2. Daily online survey

In each wave of data collection, the participants were asked to provide in-the-moment ratings through a short online survey that was administered 3 times a day through SMS to participants' own mobile phone devices.[24] The daily survey schedules were automatically programmed using Survey Signal (https://www.surveysignal.com/Default) to send links to daily surveys at the chosen schedule to participants' smartphones. Based on participants' previously self-reported usual wake times, survey schedules had identical patterns of time interval between each survey being triggered (2.5 hours between each). The earliest schedule started at 06:30 with the first daily survey commencing at 09:00, whereas the latest schedule started at 13:30 with the first daily survey commencing at 16:00. The timing of these schedules matched with participants' circadian preferences and avoided hours when participants might be sleeping, that is, no prompts were sent between the hours of 23:00 and 06:00 inclusive.

Prioritising speed and simplicity to capture the participants' experience in the moment, we used single-item proxy measures as well as shortened versions of multi-item validated scales. The brevity of the survey helped reduce burden and reactivity. Selection of item was based on the balance of item factor loadings, face validity, and accessibility, with input from the literature. Items in this daily survey included proxy measures in the format of visual analogue scales (VAS) to measure the following variables: mental defeat, pain (intensity, impacts, and pain medication use), psychological states (stress, mood, attention, and compassion to self/others) and physical and social activity engagement. These variables were chosen for the investigation of any possible links between mental defeat and pain and activity outcomes, as well as several psychological processes such as mood, stress, attentional focus, and self-compassion that are relevant to the development and persistence of chronic pain.[1,2,8,25,39,40,62] The daily survey therefore comprised 16 individual VAS. **Table 1** summarises VAS wording and respective anchors for each item.

2.5. Procedure

After providing initial informed consent, potential participants completed a short, online screening questionnaire for the purposes of determining eligibility. Those who did not meet the inclusion criteria were notified by a member of the study team, thanked for their time, and debriefed. Those who were eligible were sent a further invitation alongside another consent form for participation in the main ESM study and a baseline questionnaire to complete.

Participants then had a telephone call with a member of the research team to instruct them on the at-home participation procedures, select their chosen schedule for text-prompts for the daily surveys (in alignment with their usual self-reported wake time), and have any questions answered. Participants were then sent through post a package containing the study materials, including an information booklet and a link to instructional video (link) specifically produced for this study.

After the predetermined schedules of the daily survey, prompts containing the links to each survey were sent out to participants' personal smartphones through SMS. The participants were instructed to complete each daily survey as soon as practical. Experience sampling as a procedure can be demanding and involves directing attention toward the study when prompted while the participants go about their daily activities. For health and safety reasons, participants were explicitly instructed not to respond to survey text messages if it was unsafe to do so, for example, when driving, operating machinery, and crossing the road. As such, missing data for this type of intensive data collection procedure were expected.[37] Survey entries were defined as missing if they were dismissed by the participant (i.e., not completed before the expiry time and the triggering of the subsequent Survey 2 and 3 for each day). Data completion and handling of missing data is reported below in section 2.7.2. Each of the surveys were time stamped at the time of commencement and completion. The link to each survey remained open for 2.5 hours, before expiring at the time the following survey was triggered.

Experience sampling method is an intensive assessment exercise. The length and frequency of sampling reflects our attempt to balance data needs while minimising participation burden, nonadherence, and possible attrition. Time between the 2 waves of experience sampling points was 6 months, in line with pre-existing study protocols and to fit alongside wider project participation. Although this study focused on examining the within-person changes in mental defeat and its dynamic within-day impact on pain and psycho-behavioural responses, the space of 6 months between the 2 waves of data collection would allow future studies to examine changes in these variables and their dynamics over time, at both the within- and between-person levels.

Within 1 week of completing each wave, participants were emailed a debrief form which included signposting to various support resources. To thank the participants for their time and participation, they were also emailed a £10 e-gift voucher for each wave of experience sampling.

2.6. Ethics approval

The protocol of this study was approved by the Health Research Authority and West Midlands—Solihull Research Ethics Committee (Reference Number: 17/WM0053). The study was sponsored by the University of Warwick and conducted in adherence with the Declaration of Helsinki and applicable UK legislations.

2.7. Data analysis and statistical considerations

Statistical analyses were conducted in RStudio. Descriptive statistics (means, standard deviations, frequencies, and percentages) were calculated from baseline data to determine sample characteristics. Network analyses were conducted using the mlVAR package[15] with the default orthogonal estimation as in Veenman et al.[59] Network graphs that depict the dynamic temporal and contemporaneous networks were originally produced in RStudio using the qgraph library.[13,14] All daily survey variables (summarised in **Table 1**) were treated as individual nodes in the network model. Further details on the network approach to temporally structured data as applied to this study are provided below.

2.7.1. The network approach

Networks for individual participants (idiographic networks) are first estimated. These are then combined to produce the networks that describe the whole group of participants (nomothetic networks).

Three different nomothetic networks are produced per analysis: (1) temporal, (2) contemporaneous, and (3) between-subject.

(1) A temporal network predicts how a change in a variable would predict changes in variables (including itself) at the next time point. In our data, the first time point can either be survey 1 (predicting survey 2) or survey 2 (predicting survey 3). Our networks are within-day; we do not use survey 3 to predict variables for survey 1 the following day as modelling between-day changes violates the equidistance of responses times assumption of the model.[15]

(2) A contemporaneous network estimates the relationships between variables at the same time point, using the residuals of the temporal network. As such, the contemporaneous network represents the relationship between variables at the same time (e.g., survey 2 or survey 3) that are not explained by variables at the previous time point (survey 1 → survey 2 or survey 2 → survey 3).

(3) A between-subject network focuses on the relationships between variables across all participants in the sample. It does not estimate how the variables relate within-person over time.

In the study protocol, we originally stated we would report all 3 networks (temporal, contemporaneous, between-subjects) produced by the analysis.[24] However, a statistical demonstration of the instability of the between-subjects network has since been published.[28] In that, when analysing longitudinal data from multiple people at multiple time points, the existing method for estimating between-person effects can be biased by within-person effects and that the bias can vary depending on the length of time series and the proportion of between-person variance. We therefore followed the approach of Veenman et al.[59] to only report the temporal and contemporaneous networks.

To assess the stability of the networks produced, we simulated our results as per recommendations.[21] Using the mlVARsample function, our model was used to generate new synthetic data sets which were then used to estimate the "true" model. By comparing our model with the average performance of 1000 simulated models, we generated 5 metrics to assess the stability of our network:

Table 1

Visual analogue scales included in the daily survey.

Category of variable	Variable measured	Daily survey item full text	Text anchors (numeric scale)
Mental defeat	MD Mental defeat	In the last 2.5 h, how much has the pain brought back to life memories of times when you felt the pain had taken over?	Not at all (0)—Very much so (10)
Pain	Pain Pain intensity	What is your current pain level?	No pain (0)—Worst pain imaginable (10)
	Imp-Rout Pain's impact on daily routine	In the last 2.5 h, how much has the pain impacted on your daily routine (including work)?	Not much impact/interference (0)—A great deal of impact/interference (10)
	Imp-Rela Pain's impact on relationships	In the last 2.5 h, how much has the pain impacted on your relationship(s)?	Not much impact/interference (0)—A great deal of impact/interference (10)
	Imp-Futu Pain's impact on thoughts about future	In the last 2.5 h, how much has the pain impacted on how you think or feel about the future?	Not much impact/interference (0)—A great deal of impact/interference (10)
	Imp-Self Pain's impact on thoughts about self	In the last 2.5 h, how much has the pain impacted on how you think or feel about yourself?	Not much impact/interference (0)—A great deal of impact/interference (10)
	MedU Pain medication use	In the last 2.5 h, would you say that you have taken more or less medication than usual?	A lot less than usual (−5)—No difference (0)—A lot more than usual (5)
Psychological states	Stress Stress	What is your current stress level?	No stress at all (0)—Highest level of stress possible (10)
	Mood Mood	What is your current mood?	Very bad (0)—Very good (10)
	Atn-Pain Attention to pain	In the last 2.5 h, how much of the time have you been thinking about your pain?	None of the time (0)—A great deal of the time (10)
	Atn-IO Attention focus 1	In the last 2.5 h, has the focus of your attention been inward or outward?	Inward (0)—Outward (10)
	Atn-BM Attention focus 2	In the last 2.5 h, has the focus of your attention been on the body or mind?	Body (0)—Mind (10)
	Com-Self Compassion to self	In the last 2.5 h, how kind to yourself have you been?	Not at all (0)—Very much so (10)
	Com-Other Compassion to others	In the last 2.5 h, how kind to others have you been?	Not at all (0)—Very much so (10)
Activity	PA Physical activity	In the last 2.5 h, how physically active have you been?	Not physically active at all (0)—Very physically active (10)
	SA Social activity	In the last 2.5 h, how socially engaged have you been?	Not socially engaged at all (0)—Very socially engaged (10)

Table 2

Participant characteristics.

	Mean (SD)
Basic demographics	
Age	41.90 (11.74)
Gender (n, %)	
Male	20 (14.6)
Female	116 (84.7)
Other (includes: transgender, intersex, nonbinary)	1 (0.7)
Ethnicity (n, %)	
White/Caucasian	126 (92)
Black/African/Caribbean/Black British	1 (0.7)
Asian/Asian British	5 (3.6)
Mixed/multiple ethnicity	5 (3.6)
Education* (n, %)	
Tertiary	121 (88.3)
Secondary or below	15 (10.9)
Employment status (n, %)	
Working full-time	40 (29.2)
Working part-time	33 (24)
Unemployed	32 (23.4)
Student	10 (7.3)
Retired (incl. medically retired)	10 (7.3)
Other	12 (8.8)
Health indicators	
Body mass index† (BMI)	28.72 (7.53)
Body mass index† WHO category (n, %)	
Underweight (BMI <18.5)	5 (3.6)
Normal weight (BMI 18.5-24.9)	45 (32.8)
Preobesity (BMI 25-29.9)	36 (26.3)
Obesity class 1 (BMI 30-34.9)	26 (19)
Obesity class 2 (BMI 35-39.9)	13 (9.5)
Obesity class 3 (BMI >40)	10 (7.3)
Weekly alcohol intake (n, %)	
Never	41 (29.9)
Monthly or less	56 (40.9)
1-2 times a week	26 (19.0)
More than 3 times a week	14 (10.2)
Smoking habits (n, %)	
Never smoked/vaped	78 (56.9)
Former smoker/vaper	34 (24.8)
Current smoker/vaper	25 (18.2)
Pain characteristics	
Pain duration in years	10.50 (8.45)
Pain location‡—head (n, %)	46 (33.6)
Pain location‡—back (n, %)	84 (61.3)
Pain location‡—shoulders/arms (n, %)	80 (58.4)
Pain location‡—trunk (n, %)	69 (50.4)
Pain location‡—hips/buttocks/legs (n, %)	91 (66.4)
Pain in more than 1 location‡ (n, %)	99 (72.3)
Widespread pain§ (n, %)	58 (42.3)
BPI Pain Intensity¶	4.68 (1.73)
BPI Pain Interference¶	5.09 (1.70)
MQS pain medication use score‖¶	5.37 (7.54)
Mental defeat	
PSPS Total score¶	33.84 (24.34)

Pain duration was measured up to a maximum of 30+ years.
* Missing data occurred in n = 1 (0.73%) cases.
† Missing data occurred in n = 2 (1.46%) cases.
‡ Missing data occurred in n = 8 (5.84%) cases.
§ Widespread pain calculated based on pain reported present in the axial skeleton, left and right sides of the body, above and below the waist in accordance to IASP definition. Missing data occurred in n = 9 (6.57%) cases.
‖ MQS scores ranged from 0 to 31.40 in the sample. A higher score indicates higher medication usage.
¶ Missing data occurred in n = 8 (5.84%).

WHO, World Health Organisation; BPI, Brief Pain Inventory; MQS, Medication Quantification Scale; PSPS, Pain Self-Perception Scale.

(1) Sensitivity: A measure of the true positive rate; how often our models did identify relationships that also appeared in the simulated models (true positive/[true positive + false negative]). The sensitivity level ranges from 0 to 1; higher the better, with ≥0.8 generally considered a high level of sensitivity. A moderate level of sensitivity can be acceptable, because that at the very least means that the strongest relationships are discovered.[16]
(2) Specificity: A measure of the true negative rate; how often our models did not identify relationships that also did not seem in the simulated models (true negative/[true negative + false positive]). The specificity level ranges from 0 to 1, with ≥0.8 generally considered as indicating a high level of specificity. Achieving a high level of specificity is important, because when specificity is low, the estimation procedure identifies relationships that are not present in the "true" network.[16]
(3) Correlation: The correlation between the relationships (i.e., edge weights) in our models and the simulated models indicates how well the models mimic each other. The correlation coefficients range from 0 to 1, with a higher value indicating a stronger correlation. A correlation of ±0.5 or above is typically considered a robust, strong relationship.
(4) Bias: The absolute mean difference between the edge weights in our models and the simulated models; smaller the difference, lower the bias.
(5) Precision: A measure of how often our models had relationships that the simulated models had, given the total number of edges in the simulated network (true positive/[false positive + true positive]), higher the value, higher the level of precision.

2.7.2. Data considerations

There are 3 main assumptions to consider when using the mlVAR model: (1) multivariate normality, (2) stationarity in the data, and (3) equidistance response times. We assessed multivariate normality with Kolmogorov–Smirnov tests which showed normality was met. Regarding stationarity, we performed both Kwiatkowski–Phillips–Schmidt–Shin tests and Augmented Dickey-Fuller tests to confirm stationarity. Regarding the final assumption, equidistance between responses were maintained by limiting our analysis to modelling changes within day only (i.e., surveys 1 → 2; surveys 2 → 3, but not surveys 3 → 1), as per the standard approach.[15,16,59]

The mlVAR models require 20 or more consecutive pairs of observations, to avoid Berkson's bias,[9] whereby autoregressive parameters are produced with negative bias. Modelling within day changes with 3 daily surveys produces 2 pairs of observations a day (surveys 1→2, surveys 2→3). As such, to have a sufficient data to be included in this analysis, we combined data from both waves of example sampling for analysis. A participant completing all surveys (n = 3) all days (n = 7) for both waves (n = 2) would produce 42 observations (21 pairs). While this introduced a six-month gap between day 7 and day 8 onward because our models were concerned within day changes only, this avoided violation of assumption 3 (equidistance response times). In addition, further testing indicated stationarity (meaning stable distributions and autocorrelations of variables over time) for all variables for all participants across wave 1 and wave 2, indicating that it is statistically acceptable to combine data across the 2 waves.

2.7.3. Extra and missing data management

Very occasionally (due to scheduling of participation and postage delays), participants were able to provide more than 42 observations beyond the 14 days of data collection. These extra observations were not used for analysis.

Data received from wave 1 had 15.8% missing data, the equivalent of the average participant submitting 17.7 (of 21 possible) observations. Data received from wave 2 had 16.8% missing data, the equivalent of the average participant submitting 17.5 (of 21 possible) observations. By default, the mlVAR analysis would remove surveys with missing data row wise from the analysis. We therefore used the Kalman filter[27] to impute both missing questions and surveys. Only participants with less than 45% overall missing data had their values imputed to maintain data authenticity. This meant that participants who only completed wave 1 did not have their missing surveys from wave 2 imputed (i.e., excluded from analysis), to preserve data authenticity. The 45% cut-off was chosen based on additional analysis that compared simulation results with increasing levels of data imputation, which showed this is the cut-off that maximised inclusion of participants without inflating variable correlations. Where it was not possible to use the Kalman filter due to a variance of zero (e.g., a participant exclusively answered "1" to a question), previous values were used.

2.7.4. Data visualisation and interpretation

In the networks presented, variables of interest are represented by nodes. These nodes are connected by lines, called edges. An edge represents a relationship between the 2 nodes based on partial correlations. Partial correlations measured the strength and direction of the relationship between 2 nodes while controlling for the influence of all other nodes within the network. The coefficients (pcc) range from −1 to 1, with a value close to 0 indicating little to no linear relationship (i.e., conditional independence) and a value of −1 or 1 indicating a perfect unique (negative or positive) relationship.[16] There are no universally fixed thresholds for what constitutes a strong partial correlation in network analysis, but pcc tends to be modest in network studies fitting psychological data and a value of ≥0.8 was considered as an "implausibly high" partial correlation.[16] The networks have been visualised to place connected nodes close to each other and minimise the amount of overlap between edges. Only 15 variables (nodes) were visualised in both networks; one variable "Attention focus 2 (Atn-BM)" was excluded to enhance readability given it had no significant associations with other variables (see supplemental digital content, http://links.lww.com/PAIN/C485, materials 2 for the 16-variable version of the networks). In VAR models, statistical significance was assessed using nonparametric bootstrapping. If the 95% confidence interval for an edge weight did not include zero, the edge was considered statistically significant.[15]

The temporal network is a so-called "directed" network featuring a relationship from node A at time t to node B at time $t + 1$. A directed network can have both the edge A → B, and the edge B → A. These 2 edges are not equivalent. There are additionally self-loops in the temporal networks. A self-loop represents the partial correlation coefficient of a variable at time t with itself at time $t + 1$. By contrast, the contemporaneous network is an "undirected" network; the partial correlation coefficient at time t A → B is the same as the partial correlation coefficient at time t B → A.

The temporal and contemporaneous networks have 71 and 62 significant edges identified, respectively. For clarity and certainty, we have chosen to label the edge weights of the strongest 25% (based on pcc magnitude) of these significant edges in the temporal network, once the self-loops (i.e., autocorrelations) have been excluded. Similarly, in the contemporaneous network, we focussed our reporting on the top 25% of the significant intervariable edges with the greatest absolute values. The full

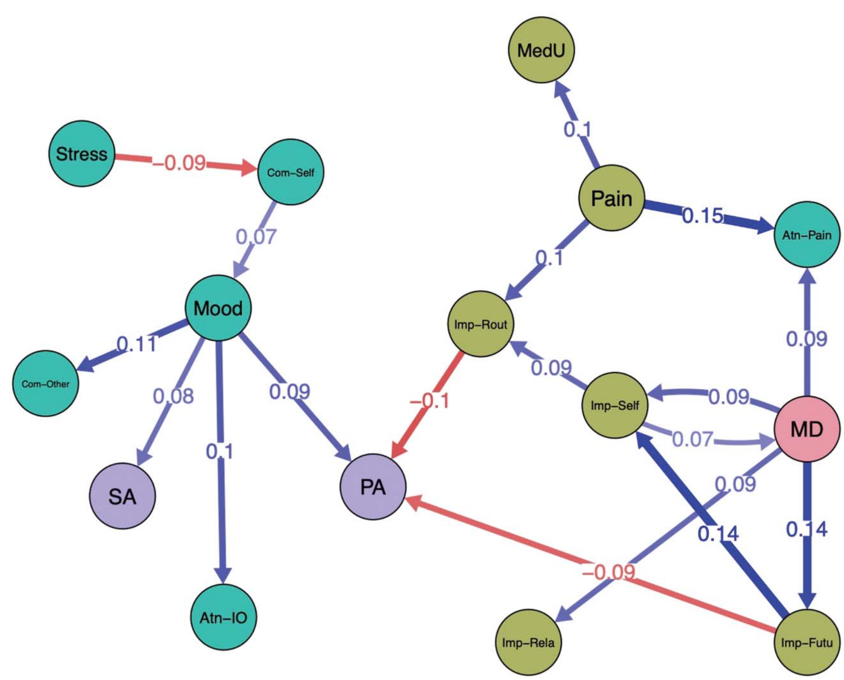

Figure 2. Temporal network. Node abbreviations are as follows: MD, mental defeat; Pain, pain intensity; Imp-Rout, pain's impact on daily routine; Imp-Rela, pain's impact on relationships; Imp-Futu, pain's impact on thoughts about future; MedU, pain medication use; Atn-Pain, attention to pain; Atn-IO, attention inward/outward; Com-Self, self-compassion; Com-Other, compassion to others; PA, physical activity; SA, social activity; Stress, Mood (self-explanatory). See Table 1 for the text and anchors of each daily survey item. Atn-BM, attention body/mind was not included in the network. Blue arrows indicate positive relationships, while red arrows indicate negative relationships. Arrows essentially are edges indicating directed associations between nodes. Thicker arrows denote stronger edge weight coefficients, that is, stronger relationships.

tables of values are provided in supplementary digital content (see materials 3 and 4, http://links.lww.com/PAIN/C485). Reporting of this study below follows the CREMA guidelines.[34] An adapted STROBE checklist for reporting EMA (ecological momentary assessment) studies[34] is provided in supplemental digital content (see Materials 5, http://links.lww.com/PAIN/C485).

3. Results

3.1. Participant characteristics

Characteristics of the participants are summarised in **Table 2**. The final sample analysed included participants who completed both waves of experience sampling (n = 137), wherein participants had a mean age of 41.9 years (SD = 11.74), were predominantly female (84.7%), White (92%), and had experienced chronic pain for an average of 10.5 years (SD = 8.45). Most participants (72%) reported pain in more than one location, with hips/buttocks/legs being the most common locations (66.4%), followed then by back (61.3%) and then shoulders/arms (58.4%). More than a-third of the participants (42.3%) presented with widespread pain, defined as pain present above and below the waist, in the right- and left-hand sides of the body and in the axial skeleton as per the International Association for the Study of Pain definition.[54] Their reported pain intensity at baseline was on average 4.68 of a possible 10 (SD = 1.73); pain interference level was on average 5.09 of a possible 10 (SD = 1.70). Average mental defeat scores at baseline were 33.84 (SD = 24.34) of a possible 96.

3.2. The temporal network

In this temporal network, a total of 71 significant edges were identified between the 16 variables of interest (see supplemental digital content, materials 2 and 3, http://links.lww.com/PAIN/C485) and the top 25% (n = 18) of these edges—representing node 1 predicting node 2 at the next time step—were graphically presented in **Figure 2**.

Autocorrelations were not presented in the figure for readability, but as expected, these were the highest with edge weights (pcc) ranges from 0.17 to 0.46, with the autocorrelation of mental defeat over time being 0.32. The rest of the edge weights presented in the network ranged from 0.07 to 0.15. Of these, we saw pain had 3 notable predictions with higher current pain level predicting greater attention to pain (0.15), increases in pain medication use (0.10), and impact of pain on daily routine (0.10) at the next time step. Pain's impact on daily routine, in turn, negatively predicted subsequent engagement in physical activity (−0.10).

Mental defeat contributed 4 notable predictions to this network. Similar to the pattern observed for pain, mental defeat was linked to increases in subsequent attention to pain (0.09). Increases in mental defeat also predicted greater perceived pain impact at the next time step; by the extent the pain had affected how one thought and felt about the future (0.14), themselves (0.09), and their relationships (0.09). Interestingly, pain's impact on one's thought about themselves was predictive of higher subsequent levels of mental defeat (0.07), forming a self-reinforcing loop. Furthermore, pain's impact on subsequent thought about the future was negatively linked to subsequent engagement in physical activity (−0.09).

Psychological variables such as stress and mood did not predict pain intensity at the next time step, but mood was directly and positively linked to both physical (0.09) and social (0.08) activity engagement. Better mood was also predictive of one's ability to pay outward, as opposed to inward, attention (0.10) and the extent of kindness one shows to others (0.11). Stress did not

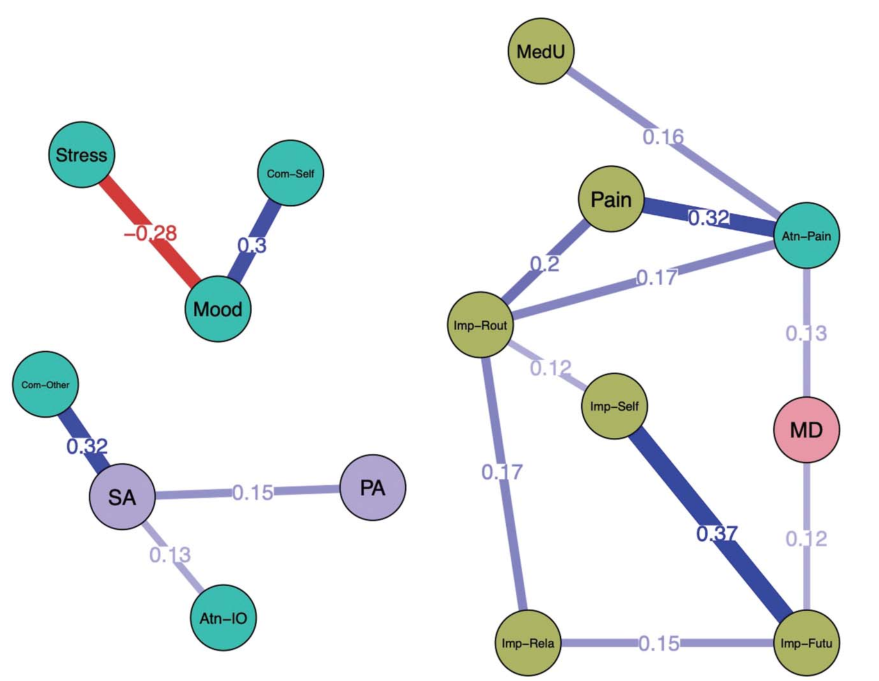

Figure 3. Contemporaneous network. Node abbreviations are as follows: MD, mental defeat; Pain, pain intensity; Imp-Rout, pain's impact on daily routine; Imp-Rela, pain's impact on relationships; Imp-Futu, pain's impact on thoughts about future; MedU, pain medication use; Atn-Pain, attention to pain; Atn-IO, attention inward/outward; Com-Self, self-compassion; Com-Other, compassion to others; PA, physical activity; SA, social activity; Stress, Mood (self-explanatory). See Table 1 for the text and anchors of each daily survey item. Atn-BM, attention body/mind was not included in the network. Blue edges indicate positive relationships, while red edges indicate negative relationships. Edges (e.g., connecting lines) indicate undirected association between nodes. Thicker lines denote stronger edge weight coefficients, that is, stronger relationships.

predict mood at the next time step, but was linked to lower self-compassion (−0.09), which in turn predicted subsequent mood (0.07).

3.3. The contemporaneous network

In this contemporaneous network, a total of 62 significant edges were identified between the 16 variables of interest (see supplemental digital content, materials 2 and 4, http://links.lww.com/PAIN/C485) and the top 25% (n = 14) of these edges—representing nodes predicting each other at the same time step over and above the temporal effects—were graphically presented in **Figure 3**.

Different from the connected temporal network (see section 3.2), there were 3 separate clusters of variables.

The first cluster included all pain variables, mental defeat, and attention to pain. The strongest associations were detected between pain and attention to pain (0.32) and between pain's impact on thoughts about self and on thoughts about future (0.37). Pain was also associated with greater perceived impact on daily routine (0.2) which in turn was associated with more attention to pain (0.17), and attention to pain was associated with increased pain medication use (0.16). The different types of pain impact were connected with each other, with impact on daily routine positively associated with impact on relationships (0.17) and thoughts about self (0.12), and impact on relationships positively associated with thoughts about future (0.15). At the same time step, mental defeat was not directly associated with pain but connected with both greater pain attention (0.13) and greater impact on thoughts about future (0.12).

The second cluster included engagement in physical and social activity, compassion to others, and an outward focus of attention. Engagement in physical activity was positively associated with engagement in social activity (0.15). Engagement in social activity was linked to an outward focus of attention (0.13) and greater compassion to others (0.32) at the same time step.

The third and final cluster included mood, stress, self-compassion, with worse mood contemporaneously associated with higher levels of stress (−0.28) and lower levels of self-compassion (0.30).

3.4. Network stability

As evident in **Table 3**, simulation results indicate that our temporal and contemporaneous networks were stable by mlVAR standards. Both of our networks achieved high levels of sensitivity (temporal = 0.81; contemporaneous = 0.97) and specificity (0.87; 0.70). The correlations between edges in our networks and the simulated networks were strong (0.76; 0.98) with a very low level of bias (0.01; 0.01). Overall, given the total number of edges in the simulated "true" network, the level of precision was 0.77 in the contemporaneous and 0.53 in the temporal network.

Table 3

Network stability as indicated by simulation results for the temporal and contemporaneous networks.

Sensitivity	Specificity	Correlation	Bias	Precision
Temporal network				
0.81 (0.07)	0.87 (0.04)	0.76 (0.07)	0.01 (0)	0.53 (0.05)
Contemporaneous network				
0.97 (0.02)	0.70 (0.05)	0.98 (0)	0.01 (0)	0.77 (0.03)

Standard deviation presented in bracket.

4. Discussion

Using a network approach to analyse 14-day experience sampling data, this study is the first to reveal the dynamic in-the-moment relationships between mental defeat and other pain, psychological and activity variables. Fifteen variables (nodes) were included in both temporal and contemporaneous networks, each demonstrating good stability with high levels of sensitivity and specificity and low bias. Notably, the networks revealed that within-person intervariate associations observed at the same time step (contemporaneous) can differ markedly from predictive relationships over time (temporal).

Structurally, our temporal network was more interconnected than our contemporaneous network. In the contemporaneous network, stress, mood and compassion to self-formed one cluster, while activity (social, physical), attention inward/outward, compassion to others formed another cluster. Mental defeat and attention to pain, on the other hand, were located in the third cluster with all pain-related nodes. In the temporal network, these separate clusters were joined up to form 1 connected network, through the effects of (1) perceived impacts of pain (on daily routine and one's future) on subsequent physical activity engagement, (2) mood on subsequent physical activity engagement, and (3) mood on one's ability to pay attention outward, be compassionate to others and engage in social activity. These observations illustrate the temporal linkages between cognitions, mood, and behaviour and provide empirical support to cognitive-behavioural models that highlight the possibility of promoting functioning outcomes through changing thoughts and feelings about pain.[7,10,20,33,55–58,60]

Another interesting between-network difference is that the link from pain intensity to medication use was only significant in the temporal but not the contemporaneous network. These findings illustrate a temporal influence of pain intensity increases on subsequent pain medication use. We also note that, while pain intensity predicted subsequent increases in pain medication use, the relationship was not reciprocal because an increase in pain medication use did not then predict a reduction in pain. This observation points to the persistence of pain sensation in our study sample irrespective of medication use. The range of edge weights (i.e., magnitude of association) was generally lower in the temporal than the contemporaneous network. This is expected because the temporal network detected relationships between variables that were spaced 2.5 hours apart, whereas the contemporaneous network assessed relationships of variables measured at the same time step. The time gap introduced additional noise that made it harder to isolate the effect of the predictor. The fact that the passage of time strengthens—rather than weakens—the predictive relationship from pain to increases in pain medication use underlines pain medication use as an active/intentional coping response. Increased pain medication use did not seem to be motivated by prior changes in mood, stress, or attentional focus.

Regarding mental defeat, it consistently emerged as a key driver of greater attention to pain and of perceived impact of pain on future across both networks. The temporal network, in particular, showed that increases in mental defeat predicted subsequent increases in these pain-related cognitions—rather than the reverse. Mental defeat also predicted later increases in the perceived impact of pain on the self and relationships at the next time step. These temporal effects are distinct from those associated with mood and stress. As expected, mood directly influenced later social and physical activity engagement, whereas higher perceived stress mainly reduced one's capacity for self-compassion. These discrepancies echo calls in the literature to better differentiate pain-related distress from depression.[42,43]

In the temporal network, we also observed a reciprocal loop between mental defeat and the perceived impact of pain on the self: higher mental defeat predicted greater subsequent perceived impact of pain on the self, which in turn predicted later increases in mental defeat. This finding is of theoretical relevance, aligning with the original conceptualisation that negative self-appraisal in relation to pain is central to mental defeat[48] and highlighting the self-focussed nature of this mental state. Clinically, because mental defeat fundamentally concerns how individuals appraise themselves in relation to pain, a range of cognitive (e.g., reappraisal, cognitive flexibility, positive bias training), behavioural (e.g., behavioural activation), narrative (e.g., rescripting life stories), and acceptance-commitment-based strategies (e.g., cognitive defusion, valued-based committed action) may help reduce mental defeat. However, further development and evaluation of just-in-time interventions delivered during moments of heightened mental defeat are still needed.

Regarding the dynamic relationship between mental defeat and pain, neither networks showed a direct link: Pain did not predict later increases in mental defeat, nor did mental defeat predict subsequent pain. In fact, in our temporal network, pain ratings were not influenced only by prior pain (autocorrelation = 0.37). The absence of a direct effect from mental defeat to later pain aligns with earlier proof-of-concept work in healthy adults, where experimentally induced mental defeat (through an autobiographic memory of personally relevant defeating experience task) did not alter pain ratings or cold-pain threshold during a cold pressor task.[6]

The influence of mental defeat on functional outcomes also seemed indirect. The temporal network showed that mental defeat predicted greater subsequent attention to pain and stronger perceived impacts of pain on the self, relationships, and future, which in turn, predicts reduced physical activity engagement. Similarly, increased self-focussed thoughts and feelings were associated with greater perceived pain impact on daily routines, which again predicted lower subsequent physical activity engagement. These findings underscore several cognitive-evaluative pathways through which mental defeat can intensify the pain-related distress and contribute to poorer day-to-day functioning.[6]

Several limitations should be noted. First, the within-person design may have heightened our participants' symptom awareness, although this was mitigated by limiting surveys to 3 times per day with protected 2.5 hours downtime in between surveys. Our analysis focussed on relationships between variables (nodes) rather than absolute intensity of experiences, reflecting our research aims. Future studies interested in intensity changes should use an EMA design with a reactivity control condition.[31] Second, to balance data richness with participant burden, we used single-item proxy measures instead of validated multi-item questionnaires. This enabled in vivo assessments with low attrition, but may not fully capture complex constructs. For example, mental defeat—usually assessed with a 24-item questionnaire[45]—was measured using a single item, which may not capture its full impact on pain and behaviour. Nonetheless, post hoc analyses showed a moderate to strong correlation between baseline PSPS scores and average daily mental defeat ratings ($r = 0.52$, 95% CI 0.39, 0.64). Third, due to ESM constraints, no objective assessments of pain, medication use, or activity were performed. Future studies could incorporate wearables or monitoring devices although costs, burden, user-errors, and instrument validity and reliability must be considered. Fourth, attrition and missing data are inevitable in intensive ESM studies,[19] with chances of missing data increase with study length.[37] In our sample, no significant differences were found between completers and noncompleters, and missing data among included participants were relatively low (<17%) and handled using standard data imputation. We restricted our temporal analysis to within-day and data from the 2 waves of data collection were merged only after confirming stationarity across all variables (meaning stable distributions and autocorrelations of variables over time). Finally, generalisability of our findings may be limited as this study did not have the scale to support representative sampling. Participants were volunteers from clinical and community settings and lacked racial/ethnic diversity. In addition, the attentional and technological demands of the study mean that the current findings may be most applicable to individuals who are able to accommodate an additional burden alongside their usual pain management and to those who are more proficient with digital technology. Although all participants reported chronic pain for more than 3 months, medical records were not accessed, preventing classification by pain condition. Future research should consider embedding ESM studies of this kind within large-scale epidemiological surveys. Through data linkage, the ESM component can leverage the scale and representativeness of these surveys, while adding mechanistic depth through intensive, real-time data collection.

In conclusion, this study applied a novel network approach to uncover the dynamic role of mental defeat in shaping daily pain experiences. The contemporaneous network revealed that mental defeat is intertwined with people's cognitive, emotive, and behavioural responses to pain. In particular, it is most closely linked to attention to pain and perceived pain impact on future. The temporal network highlighted the possible impact of mental defeat through increased attentional focus on pain and more negative evaluation of pain's impacts on their daily routine, relationships, self-identity, and future. Notably, mental defeat operates distinctly from pain, stress, and mood. It is not just a byproduct of being in pain or feeling stressed/depressed but a distinct psychological driver that changes how a person experiences pain. Standard cognitive behavioural treatments typically focus on pain catastrophising and fear avoidance but do not always address the loss of self and identity that defines mental defeat. Interventions that target mental defeat or disrupt the self-reinforcing loop that reinforces mental defeat may offer clinical benefit, particularly in reducing pain-related suffering brought on by perceived threats to one's self and identity.

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NKYT conceived the research idea. NKYT and SPS secured funding for the project. JLG, PK, and KT were responsible for setting up the study, data acquisition, and supporting data analysis. JC and NKYT developed the data analysis plan for the study, conducted the data analysis, and led the data interpretation. NKYT, JC, and JLG drafted the original manuscript. KT, SB, CBM, TMP, and SPS provided critical reviews and further

development of the manuscript. All authors contributed to the study development and reviewed, commented, and approved the manuscript.

Program (R) code used in analysis is available via the OSF (https://osf.io/qpn5e/overview?view_only=25c-f306525654a82a3dc17a13a74fcb0) to any researcher for purposes of reproducing the results or replicating the procedure. Anonymised data set used for analysis is available upon reasonable request through the corresponding author. For the purpose of open access, the author has applied a Creative Commons Attribution (CC BY) licence to any Author Accepted Manuscript version arising from this submission.

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