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CLINICAL RESEARCH ARTICLE

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Development and proof-of-concept of a treatment target recommendation algorithm in the context of cognitive processing therapy

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ABSTRACT

Background: Cognitive Processing Therapy (CPT) is an effective, widely supported treatment for PTSD, but patient response varies considerably. Optimally targeting maladaptive trauma-related beliefs (stuck points) may significantly enhance treatment outcomes. This study evaluated the feasibility of developing a recommendation algorithm that helps clinicians identify specific patient-endorsed stuck points, which, when effectively restructured, could lead to greater reductions in PTSD symptoms.

Methods: Data were drawn from 898 veterans and service members participating in a two-week CPT-based accelerated PTSD treatment programme. Measures administered at pre-, mid-, and post-treatment included the Posttraumatic Cognitions Inventory (PTCI), PTSD Checklist for DSM-5 (PCL-5), and Patient Health Questionnaire (PHQ-9). Patients were clustered at pre- and mid-treatment using K-means based on their PCL-5 subscores and PHQ-9 and PTCI item endorsement profiles. Within each cluster, random forest and elastic net regression models identified PTCI items most predictive of PTSD symptom reductions. The algorithm's predictive utility was illustrated through simulated patient cases.

Results: Machine learning models identified specific PTCI items within each cluster that appeared most predictive of PTSD symptom reductions. Simulations indicated that targeting these algorithm-selected cognitions could yield an additional 5–7 points improvement on the PCL-5 by mid-treatment, with further improvements of 4–6 points thereafter. Overall, following the algorithm's personalised recommendations could theoretically result in approximately 11 additional points of symptom reduction on the PCL-5 beyond expected standard improvements.

Conclusions: This study demonstrates the feasibility of developing a data-driven recommendation algorithm that personalises CPT by identifying the most impactful stuck points to target. Prospective clinical trials are necessary to validate the algorithm's effectiveness, establish clinical utility, and facilitate implementation into routine care.

ARTICLE HISTORY

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PTSD; veterans; machine learning; precision medicine; cognitive processing therapy

PALABRAS CLAVE

TEPT; veteranos; aprendizaje automático (*machine learning*); medicina de precisión; terapia de procesamiento cognitivo

HIGHLIGHTS

- Algorithm recommends trauma-related beliefs to target in PTSD treatment.
- Machine learning models identify beliefs that predict PTSD symptom change.
- Patient simulations suggest up to 11-point greater PTSD reduction on the PCL-5.
- This approach offers a data-driven method to identify key treatment targets.

Desarrollo y prueba de concepto de un algoritmo de recomendación de objetivos terapéuticos en el contexto de la terapia de procesamiento cognitivo*

Antecedentes: La Terapia de Procesamiento Cognitivo (CPT) es un tratamiento eficaz y ampliamente respaldado para el TEPT; sin embargo, la respuesta de los pacientes varía considerablemente. Abordar de manera óptima las creencias desadaptativas relacionadas con el trauma (*stuck points*) podría mejorar significativamente los resultados del tratamiento. Este estudio evaluó la viabilidad de desarrollar un algoritmo de recomendación que ayude a los clínicos a identificar *stuck points* específicos reportados por el paciente que, al ser reestructurados eficazmente, podrían conducir a una mayor reducción de los síntomas de TEPT.

Métodos: Los datos se obtuvieron de 898 veteranos y militares en activo que participaron en un programa de tratamiento intensivo de dos semanas para el TEPT, basado en CPT. Las medidas administradas antes, durante y después del tratamiento incluyeron el Inventario de Cogniciones Postraumáticas (PTCI por sus siglas en ingles), la Lista de Verificación del TEPT para el DSM-5 (PCL-5) y el Cuestionario de Salud del Paciente (PHQ-9). Los pacientes fueron agrupados al inicio y a mitad del tratamiento mediante *K-means*, basándose en sus puntuaciones en las subescalas del PCL-5 y en los perfiles de respuesta a los reactivos del PHQ-9 y del PTCI. Dentro de cada grupo, modelos de *random forest* y de regresión *elastic net* identificaron los reactivos del PTCI con mayor capacidad predictiva sobre la reducción de los síntomas de TEPT. La utilidad predictiva del algoritmo se ilustró mediante casos de pacientes simulados.

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*Los términos *K-means*, *random forest* y *elastic net* se mantienen en su denominación original en inglés, ya que aluden a algoritmos específicos de aprendizaje automático (*machine learning*) estándar en la literatura científica internacional.

Resultados: Los modelos de aprendizaje automático identificaron reactivos específicos del PTCI dentro de cada grupo que resultaron ser los más predictivos para la reducción de los síntomas de TEPT. Las simulaciones indicaron que abordar estas cogniciones seleccionadas por el algoritmo podría generar una mejora adicional de 5 a 7 puntos en el PCL-5 hacia la mitad del tratamiento, con mejoras posteriores de 4 a 6 puntos. En general, seguir las recomendaciones personalizadas del algoritmo podría resultar, teóricamente, en una reducción de síntomas de aproximadamente 11 puntos adicionales en el PCL-5, más allá de las mejoras estándar esperadas.
Conclusiones: Este estudio demuestra la viabilidad de desarrollar un algoritmo de recomendación basado en datos que personalice la CPT al identificar los *stuck points* de mayor impacto. Es necesario realizar ensayos clínicos prospectivos para validar la eficacia del algoritmo, establecer su utilidad clínica y facilitar su implementación en la atención habitual.

Cognitive Processing Therapy (CPT) is a well-established trauma-focused cognitive treatment for posttraumatic stress disorder (PTSD; Department of Veterans Affairs, 2023; Resick et al., 2024). Research has demonstrated that individuals who receive CPT generally experience large reductions in PTSD symptoms (Asmundson et al., 2019), which can be maintained for many years following treatment (Resick et al., 2012). Although CPT is commonly delivered via weekly sessions, research has demonstrated that increasing the session frequency allows treatment to be completed in as little as one to three weeks (Galovski et al., 2022; Held, Kovacevic, et al., 2022; Held, Smith, et al., 2023), which is known as intensive, massed, or accelerated treatment. Research has shown these accelerated CPT-based PTSD treatments to also produce large symptom reductions that can be maintained (Held et al., 2024).

Despite its overall effectiveness, CPT outcomes can be highly variable (Held et al., 2021; Nixon et al., 2021). To address this variability, research has focused on the importance of training, supervision, and consultation to ensure therapists are sufficiently equipped to offer CPT with fidelity, which has been shown to result in better outcomes (Farmer et al., 2017; Marques et al., 2019). Yet, maintaining fidelity over time can be a challenge, with some clinicians exhibiting drift in their delivery of evidence-based treatment as time passed (Waller & Turner, 2016). Aside from fidelity, another challenge to providing effective CPT is the identification of optimal treatment targets. In CPT, these targets are maladaptive cognitions, which are referred to as stuck points (Resick et al., 2024). Cognitive restructuring of maladaptive cognitions has been shown to be associated with symptom change (Brown et al., 2019). However, research has also demonstrated that the order in which stuck points are targeted can impact treatment response (Farmer et al., 2017). In addition to prioritising assimilated (i.e. trauma-focused beliefs) prior to over-accommodated stuck points (i.e. present- and future-focused beliefs; Farmer et al., 2017; Resick et al., 2024), identifying the maladaptive beliefs that may be most associated with PTSD symptom severity may also be relevant for treatment. For example, cognitive theory posits that identifying the stuck points at the core of patients' traumatic experiences can lead to greater symptom reduction (Resick et al., 2024). Yet, identifying the cognitions that, when changed, result in the greatest impact on PTSD severity can be difficult as these cognitions are person-specific and differ for each patient. The identification of optimal treatment targets is a skill that clinicians tend to develop over time through training, consultation, and ongoing supervision.

To aid in the identification of stuck points, some clinicians ask their patients to complete existing self-report measures, such as the Posttraumatic Cognitions Inventory (PTCI; Foa et al., 1999). The PTCI lists a number of beliefs commonly held by trauma survivors and asks individuals to rate the degree to which they agree with each belief. Changes in belief strength on the PTCI have been shown to be associated with changes in PTSD severity (Brown et al., 2019), and clinicians often use such measures to prioritise beliefs that patients endorse most strongly. The prioritisation of highly rated beliefs can be especially challenging when patients rate several beliefs similarly high. Providing clinicians with additional data-driven guidance for selecting cognitions could be one way to improve this process.

The goal of this project was to evaluate whether it is possible to build a recommendation algorithm that may eventually help clinicians identify personalised stuck points that, when effectively restructured, may result in greater amounts of symptom change. To do so, we evaluated patients' PTCI and symptom profiles before the start of CPT and at mid-treatment, as patients' cognitions may change over the course of treatment, and identified cognitions for each profile that were associated with the greatest amount of PTSD symptom reduction to the next timepoint. We then simulated the performance of the algorithm using two patients, Joe and John, who were identical

in their demographic characteristics but differed based on the cognitions they endorsed. Evaluating the proof-of-concept is an important first step toward determining the possibility of having a treatment target recommendation system that could potentially help clinicians to identify stuck points associated with the greatest amount of change during CPT and ultimately help reduce the previously observed variability in PTSD treatment outcomes.

1. Method

1.1. Participants

For this study, data from 898 service members and veterans who completed a 2-week CPT-based accelerated PTSD treatment programme (ATP) were used. The average age of the sample was 45.90 years (SD = 10.46), and the majority of individuals identified as male (52.67%), and white (63.03%). Additional demographic characteristics can be found in Table 1.

1.2. Programme description

Treatment in the 2-week ATP was provided in a cohort format; individuals were assigned to either a combat trauma or a military sexual trauma (MST) cohort based on the index trauma they agreed to work on during CPT. Prior research has demonstrated comparable outcomes across both cohort types (e.g. Held et al., 2024; Held, Smith, et al., 2023). The ATP centred around two daily individual CPT sessions on most days, for a total of 16 CPT sessions over the 10-day treatment. Each CPT session was followed by dedicated time for the completion of homework assigned and complemented by different adjunctive services, such as psychoeducation and wellness activities. More information about the structure and outcomes of the programme can be found in Held, Smith, et al. (2023).

Table 1. Participant demographic characteristics.

Demographic variables		n	
		n	% or *M* (*SD*)
Sex			
	Male	473	52.67
	Female	425	47.33
Cohort Type			
	Combat	469	52.29
	MST	428	47.71
Race			
	White	566	63.03
	Black/African American	200	22.27
	Asian	21	2.34
	Native Hawaiian/Pacific Islander	11	1.22
	American Indian/Alaska Native	9	1.00
	Other	91	10.13
Ethnicity			
	Hispanic or Latinx	155	17.26
	Not Hispanic or Latinx	743	82.74
Military Branch			
	Army	463	51.62
	Navy	139	15.50
	Air Force	113	12.60
	Marine Corps	120	13.38
	Coast Guard & reserves	62	6.91
Age			44.58 (10.64)

1.3. Measures

1.3.1. Posttrauma cognition inventory (PTCI)

The PTCI (Foa et al., 1999) is a 33-item self-report measure designed to assess the strength of common trauma-related cognitions. Total scores range from 33 to 231, with higher scores indicating stronger trauma-related cognitions. In the 2-week ATP, the PTCI was administered pre-treatment and shortly before mid-treatment (Day 4). Cronbach's alpha for the PTCI in this sample ranged from .95 to .97.

1.3.2. PTSD checklist for DSM-5 (PCL-5)

The PCL-5 (Weathers et al., 2013) is a 20-item self-report measure designed to assess PTSD symptom severity based on the DSM-5 diagnostic criteria. The measures captures the four PTSD symptom clusters: Intrusions, Avoidance, Alterations in Cognition and Mood, and Hyperarousal. Total scores range from 0 to 80, with higher scores indicating more severe PTSD symptoms. Pre-treatment, individuals reported their symptoms for the past month. At mid- (Day 5) and post-treatment (Day 10), past-week symptom severity was reported. Cronbach's alpha in the current sample ranged from .90 to .94.

1.3.3. Patient health questionnaire (PHQ-9)

The PHQ-9 (Kroenke et al., 2001) is a 9-item self-report measure designed to assesses symptoms of depression experienced over the past two weeks. Total scores range from 0 to 27, with higher scores indicating more severe depressive symptoms. In the 2-week ATP, the PHQ-9 was administered at pre-treatment, mid- (Day 5), and post-treatment (Day 10). Cronbach's alpha in the current sample ranged from 84 to .87.

1.4. Analytic approach

Patients were initially clustered based on baseline PTCI and PHQ-9 items as well as PCL-5 subscores (i.e. intrusions, avoidance, alterations in cognitions and mood, and hyperarousal) using K-means clustering.[1] K-means clustering was used as an exploratory distance-based method to partition individuals into mutually exclusive clusters by minimising within-cluster variance based on Euclidean distances. This unsupervised learning approach assigns each observation to the nearest cluster centroid, providing classification based on overall similarity in the noted observed variables. The optimal number of clusters was determined by evaluating multiple criteria, including the average

silhouette width, gap statistic, and Calinski-Harabasz index, though clinical interpretability and theoretical relevance and convergence with other clustering methods, such as latent profile analysis, were also important considerations.

Following baseline determination of clusters, we explored which specific PTCI items whose changes during the first half of the treatment programme were most closely associated with the amount of PTSD severity change that occurred during this time. This was done separately for each cluster identified in the first step. We utilised both elastic net regression and random forest models to determine variable importance for PTCI items to better obtain representation from common statistical and machine learning approaches that are functionally different in how feature (i.e. variable) importance is determined. These machine learning approaches were also selected due to their ability to include a large number of potentially correlated predictors as well as our prior work with this population indicating the ability for these methods to effectively predict programme outcomes (Held, Schubert, et al., 2022). Five-folds cross-validation was used in model training for both approaches, though as our emphasis was on obtaining features determined to be most impactful in modelling rather than examining model accuracy, all data were used in training, rather than implementing a train-test split. Random forest models utilised 500 trees with gini splitting rule and permutation feature importance, elastic net models optimised over a grid of alpha and lambda values to maximise the area under the ROC curve. We then selected the two most important cognitions across the two model types to generate predictions of expected amount of PTSD severity improvement by mid-programme associated with a meaningful change in these PTCI items within each cluster. These models adjusted for change in the other PTCI items as well as baseline PTSD severity. Although other methods for generating predictions are certainly available, linear regression utilising these selected features as predictors of PCL-5 change was utilised for this step solely to ensure the greatest ease of interpretability for predictions of PTSD change per PTCI cognition change for illustrative purposes.

This process was then repeated at mid-treatment to determine the probable existing clusters at this timepoint and establish the PTCI items deemed most important within each to address for optimal change in PTSD severity by the end of the programme. Repeating the analyses at mid-treatment was deemed important as we assumed that cognition profiles might change as a result of CPT, which is designed to address these beliefs. Latent profile analysis was conducted in MPlus (Muthén & Muthén, 2023) and k-means and machine learning and statistical models were generated using R (R Core Team, 2024). All study procedures were approved by the Rush University Medical Center Institutional Review Board.

1.5. Simulated case examples

Simulated case examples were used as a proof-of-concept to illustrate how the recommendation algorithm might identify different cognition targets for individuals with similar demographic characteristics and baseline symptom severity but differing patters of trauma-related cognitions. Demographic variables and baseline PTSD and depression severity were held constant across cases to better isolate the influence of PTCI item endorsement on algorithm recommendations. The predicted PTSD symptom change was estimated assuming a two-point improvement on algorithm-identified PTCI items and sample-average change on all other items. These simulations are intended to demonstrate algorithm logic and interpretability prior to testing in real-world samples.

2. Results

Pre- to post-treatment reductions in PTSD severity were very large ($d = 1.27$, 95% CI: 1.19–1.36). The average amount of PTSD symptom change was 21.24 points ($SD = 16.25$). Similarly, effect sizes for amount of change in trauma-related cognitions was moderately large ($d = 0.71$, 95% CI: 0.61–0.80). Average amount of item-level PTCI change during the programme across all items was close to one point ($M = 0.92$, $SD = 2.05$).

We next considered fit criteria across K-means and LPA clustering methods, and ensuring that no cluster contained less than 5% of the sample, we examined the nature and makeup of generated clusters and determined that seven clusters were most appropriate at pre- and mid-treatment. As fit criteria preferences differed based on metric, clinical interpretability and consistency across the clustering methods was prioritised. The seven cluster solutions at pre- and mid-treatment appeared to provide sufficiently different PTCI item endorsements that reflected patterns frequently observed in clinical care (see Figures 1 and 2 and Supplemental Material).

Next, random forest and elastic net machine learning models were explored for each cluster to determine cognitions deemed most predictive of midpoint improvement in PTSD severity. Across all seven clusters the top feature (i.e. variable; in this case PTCI item) for each machine learning approach was within the top five features of the other approach. Thus, the top feature for each model type was chosen for this clinical prediction illustration. If the two models ranked the same feature as the most important

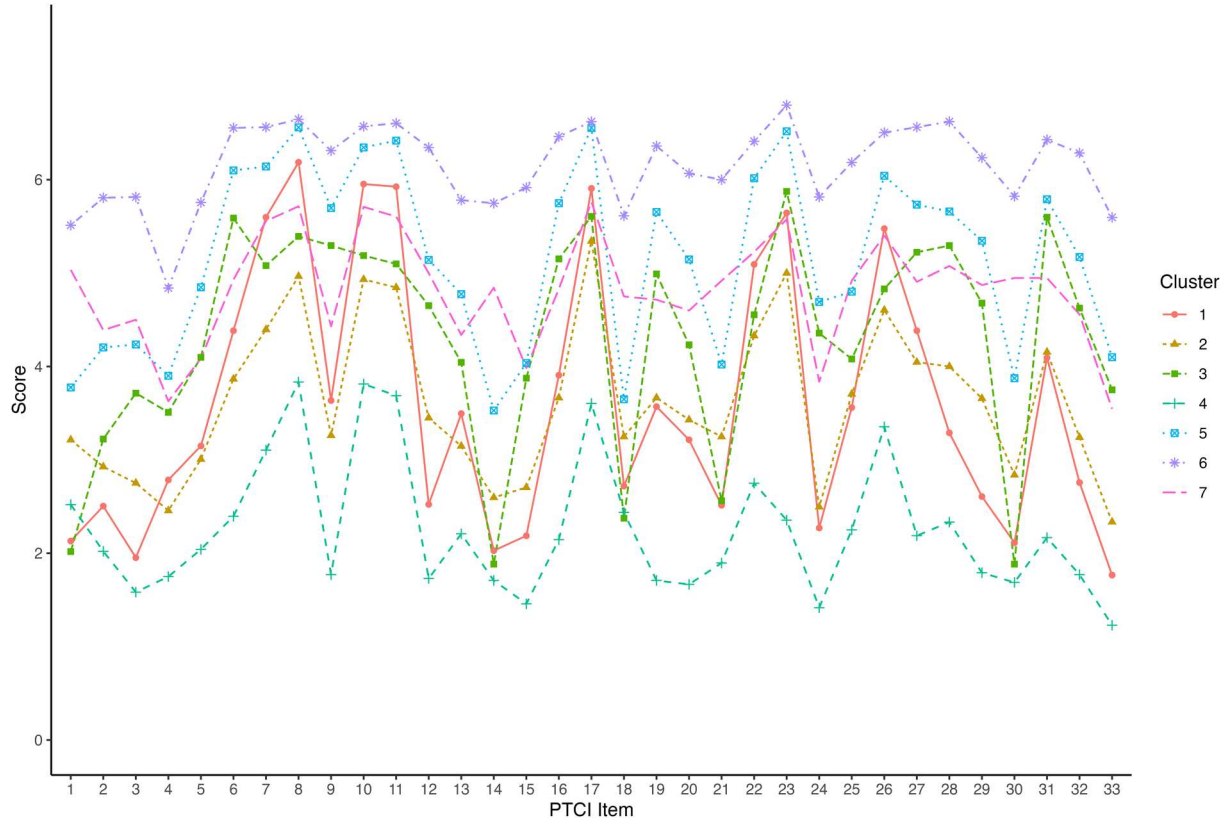

Figure 1. K-means-derived posttrauma cognition inventory profiles at baseline.

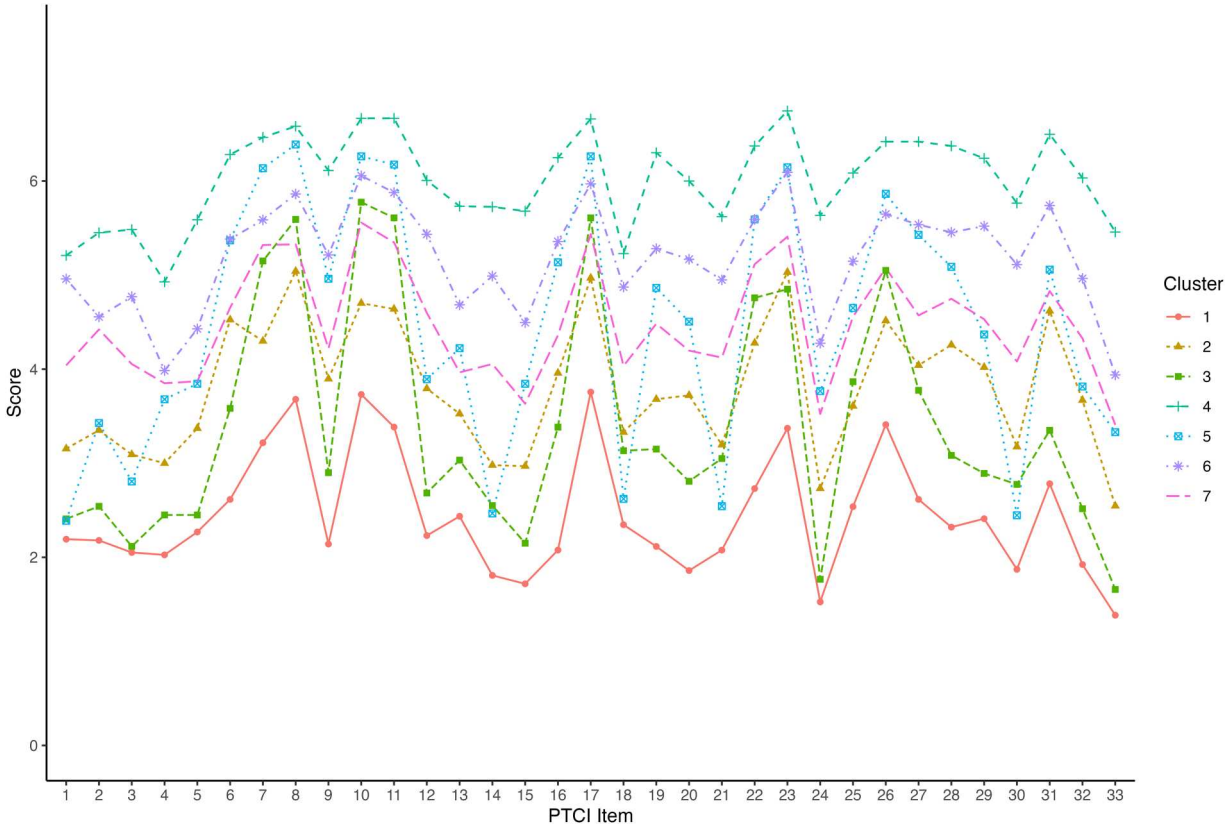

Figure 2. K-means-derived posttrauma cognition inventory profiles at mid-treatment.

this feature was chosen along with whichever second-ranked feature between the two models ranked highest in the other model types list as well.

General expectations for eventual clinical use of this algorithm would involve a participant filling out questionnaires on PTSD (PCL-5), depression (PHQ-9),

and trauma-related cognition (PTCI) severity at pre- and mid- treatment. In this context, symptom profiles (also referred to as symptom clusters or classes) represent patterns of symptom and cognition endorsement that are later formally identified using unsupervised analytic approaches. A determination regarding class would be made using generated posterior probabilities of class membership for the individual based on these pre-treatment scores. Based on the participant's cluster, the two cognitions that are most closely associated with improvement in PTSD severity from pre- to mid-treatment would be targeted during CPT. This procedure would then be repeated at mid-treatment for assessing the trauma-related cognitions to target for the second half of treatment. To illustrate how the algorithms may perform in clinical care, we provide two simulated case examples of Joe and John. Both Joe and John have the same demographic characteristics and pre-treatment symptom severity. They are both 43-year-old male combat veterans with pre-treatment PTSD and depression severity of 55 points on the PCL-5 and 17 points on the PHQ-9, respectively. We kept the demographics and pre-treatment symptom severity constant to demonstrate that the algorithm suggests different cognitions (i.e. PTCI items) to target during treatment. Joe and John only differ in their endorsement of negative posttrauma cognitions. Joe's endorsement of PTCI items most closely aligned with PTCI Cluster 2. John, on the other hand, endorses PTCI items more consistent with PTCI Cluster 4.

The algorithm suggested that if Joe and his clinician were to focus on PTCI items 8 ('I have to be on guard all the time') and 23 ('I feel isolated and set apart from others') during the first half of treatment, Joe would be expected to experience the most PTSD change by mid-treatment. Assuming average change on the other PTCI items, and that Joe would improve by two points on each of these two identified PTCI items by mid-treatment, he would be predicted to improve by 18.15 points on the PCL-5 by mid-treatment. However, if Joe improved on these items only as much as the average participant improvement during the first half of treatment, he would be predicted to improve by 12.54 PCL-5 points during this time. At mid-treatment Joe's trauma-related cognitions, depression, and PTSD severity scores were again examined, and he was determined to be most appropriately in Cluster 3 for the second half of treatment. Based on this, if Joe would improve by two points in PTCI items 16 ('I will never be able to feel normal emotions again') and 11 ('I have to be especially careful because you never know what can happen next') he would be predicted to improve by another 13.72 points on the PCL-5, compared to a predicted change of 8.47 if he only had the average amount of change in these two items during the second half of treatment.

For John, the items deemed most impactful for predicted PCL-5 change to mid-treatment were items 9 ('I feel dead inside') and 11 ('I have to be especially careful because you never know what can happen next'). Should John improve by two points on each of these two items by mid-treatment, assuming average change in the other PTCI items, we predicted that he would improve by 23.21 points on the PCL-5 during the first half of the programme, as opposed to 16.63 points if he improved only the programme average amount in these items. At mid-treatment his current scores on these measures are re-evaluated, and John was determined to best approximate a member of Cluster 7. Based on this, the algorithm recommended that PTCI items 8 ('I have to be on guard all the time') and 11 ('I have to be especially careful because you never know what can happen next') would be targeted. Should John improve by 2 points on each of these two items during the second half of the programme, John's predicted amount of PCL-5 change would be 11.97 points, rather than 7.98 points if these items were not specifically targeted and he experienced programme-average amounts of improvement in them.

3. Discussion

The primary goal of this study was to evaluate whether it is feasible to develop a predictive algorithm to help clinicians personalise CPT. Specifically, we aimed to identify particular cognitions, measured via the PTCI at pre- and mid-treatment, that, when targeted, might yield the greatest reduction in PTSD symptoms. Rather than using a general approach applied uniformly to all patients, we employed unsupervised machine learning techniques to generate distinct cognition profiles at both timepoints based on patients' differential PTCI item endorsements. We then identified optimal cognition targets within each profile that were predicted to yield the largest improvements in PTSD symptoms. The development of this recommendation algorithm represents an illustration of an initial step toward overcoming traditional 'one-size-fits-all' approaches by providing clinicians with data-driven, individualised recommendations.

To illustrate the potential practical application and utility of this algorithm, we simulated two case examples of Joe and John. These two simulated patients were identical in their demographic characteristics and initial clinical presentation; they differed only in their specific PTCI endorsement and symptom patterns and thus the cognition profiles to which they were matched. As a result, Joe's and John's therapists were recommended to address different cognitions that were predicted to produce the largest amount of PTSD symptom change when effectively addressed.

In these simulated examples, which assumed an achievable 2-point change on the recommended

PTCI items and the sample-average change for all other items, Joe was predicted to experience an additional PTSD symptom reduction on the PCL-5 of 5.61 points from baseline to mid-treatment, and 5.25 points from mid-treatment to post-treatment. Similarly, John was predicted to experience an additional 6.58-point PCL-5 reduction from baseline to mid-treatment, and 3.99 points from mid-treatment to post-treatment. Both simulated patients were predicted to experience substantially larger PTSD symptom reductions (10.86- and 10.57-point changes for Joe and John, respectively).

These simulated examples suggest that targeting person-specific cognitions may improve overall outcomes, although it will be critical to determine whether similar results can be obtained when the recommendation algorithm is tested prospectively with actual patients. The concept of identifying and addressing person-specific cognitions is central to CPT (Resick et al., 2024). Clinically, such identification typically occurs through therapist-patient conversations or patient-completed measures such as the PTCI, where clinicians often prioritise highly rated cognitions. Having a data-supported method to identify cognitions most closely associated with potential large PTSD symptom reductions for each individual could directly address clinicians' challenges in selecting the most impactful stuck points. This might be especially important when patients rate multiple cognitions similarly highly. The examples presented here also provide support for systematically differentiating cognition targets, even when patients present as clinically similar. Thus, if these simulated findings translate into actual clinical outcomes, recommendation algorithms such as the one presented here could offer clinicians a practical and accessible method to enhance the effectiveness of CPT.

Integrating recommendation algorithms into treatments like CPT may potentially reduce variability in outcomes (Held, Schubert, et al., 2022; Nixon et al., 2021) and enhance overall PTSD treatment effectiveness without substantially increasing implementation barriers. Unlike other novel therapeutic approaches currently being explored (e.g. integrating PTSD treatment and other psychotherapeutic interventions or complementing PTSD treatment with medical interventions such as transcranial magnetic stimulation; Saccenti et al., 2024; Sornborger et al., 2017), implementing recommendation algorithms would not require clinicians to undergo extensive training in new therapeutic modalities or to integrate complex adjunctive interventions into existing treatment models. Instead, clinicians would simply need brief training on an easy-to-use recommendation tool, including its limitations, and could then continue to provide CPT as usual. Importantly, such a recommendation algorithm is envisioned strictly as a decision-support tool to augment – not replace – the nuanced clinical judgment and therapeutic alliance that are foundational to effective CPT. We hypothesise that having access to recommendation algorithms may be especially beneficial for less experienced clinicians, who might still be refining their ability to identify optimal cognition targets.

Despite promising initial results, several important limitations must be acknowledged. First, the results from Joe and John represent simulated scenarios primarily designed as a proof of concept based on model predictions. Therefore, these illustrative examples alone cannot support broad generalisations about the recommendation algorithm's effectiveness in clinical practice. The assumption of average change in the non-targeted PTCI items, while illustratively useful, may not be plausible given the strong correlation between items. Prospective clinical trials are needed to rigorously assess whether following algorithm recommendations genuinely enhances PTSD symptom improvement beyond standard CPT and whether effectiveness varies by clinician experience. Second, the presented model was developed using data from a specific CPT-based ATP, which limits its generalizability. Its applicability to other populations, treatment settings, or CPT delivery formats requires validation with larger, more diverse samples with respect to demographics, trauma types, and comorbidities. Third, analyses relied exclusively on self-report measures (PCL-5, PTCI, PHQ-9). While validated and commonly employed in CPT research, incorporating clinician-administered assessments or objective biomarkers of symptom change could further strengthen future iterations of the recommendation algorithm. However, requiring clinical ratings or biological markers could reduce the accessibility and scalability of the algorithm in routine CPT settings, where time and resources are limited. Reliance on brief, commonly administered self-report measures may therefore enhance feasibility and uptake in clinical practice. Fourth, the clustering methods employed introduce inherent probabilistic uncertainty regarding both individual cluster assignments and the optimal number of clusters selected. While cluster solutions were informed by statistical indices and clinical judgment, these assignments represent probabilistic groupings reflecting general similarity patterns, not definitive classifications. Sample size differences and other factors could influence model accuracy across model types, potentially making predictions within some clusters more valuable than others depending on the approach. Thus, accuracy in real-world clinical use could vary, highlighting the need for ongoing empirical validation. Additionally, various statistical and machine learning approaches were used for feature selection and illustration in this application to provide eclectic and easily interpretable examples, though it is not expected that such an approach would necessarily be utilised in

the same way when implemented into clinical practice. Finally, the PTCI captures only a subset of potential cognitions and predominantly assesses over-accommodated cognitions. However, CPT research suggests that initially prioritising assimilated cognitions typically results in better outcomes (Farmer et al., 2017). In its current form, the recommendation algorithm presented here still requires clinicians to collaboratively identify underlying assimilated cognitions linked to the recommended over-accommodated cognitions. Future research should explore strategies for guiding clinicians in connecting these cognitions to enhance usability and alignment with established CPT protocols.

To address the aforementioned limitations, prospective studies evaluating the recommendation algorithm's effectiveness, usability, and acceptability from both clinician and patient perspectives will be essential. Future work should explicitly examine potential patient concerns regarding data privacy and security. Additionally, implementation challenges, such as data collection practices and technical support needs, must be systematically examined.

4. Conclusion

This study illustrates a potential step toward precision mental healthcare by simulating how predictive algorithms might personalise targeting specific cognitions within PTSD treatment. By identifying unique cognition profiles and their association with PTSD symptom trajectories, this approach underscores the need to tailor treatment strategies to the individual rather than relying solely on group-level data. The algorithm offers a potentially scalable framework for delivering personalised recommendations, addressing the heterogeneity inherent in PTSD presentations and responses to treatment. By providing clear, data-driven guidance to clinicians, the algorithm bridges the gap between complex computational methods and practical, patient-centred care. It is easy to envision the potential of such tools to enhance clinical decision-making which may result in improved patient outcomes and more efficient allocation of therapeutic resources. A concrete next step is to rigorously evaluate the presented algorithm with patients who receive CPT during the ATP.

Note

1. Latent profile analysis (LPA) was also explored in MPlus due to the advantages to this model-based, probabilistic approach. However, agreement in cluster assignment between K-means and LPA in baseline clustering was 95.32%, similar to other published work (Sinha et al., 2021). Due to the ease of automation in R and convergence between these approaches, K-means results are reported here. Examination of information criteria (AIC and BIC) using the approach as well as clinical rationale behind cluster solutions also guided selection of the number of clusters for K-means analyses.

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Author contributions statements using Credit

PH: Conceptualization, Investigation, Funding acquisition, Writing – original draft
DS: Formal analysis, Methodology, Writing – original draft
SP: Data curation, Writing – review & editing

Disclosure statement

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Data availability statement

The dataset used in the current study is not publicly available due to funder policy. Datasets can be obtained from the corresponding author upon reasonable request.

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