

Supplementary Materials

Music therapy intervention protocol

A standardised protocol was designed to ensure alignment across all music therapy (MT) delivery formats (one-to-one, small group, large group). All music therapists adhered to the protocol to reduce variability and minimize noise in the data. Music therapists were employed by the community care provider and received training to promote consistency and fidelity to the intervention framework. This included two face-to-face sessions led by the first author, during which therapists engaged with the intervention materials and had opportunities to clarify aspects of the procedure. The first author remained available throughout the intervention period to provide ongoing supervision and address any arising questions. An online forum was also created, with dedicated discussion threads for music therapists to facilitate peer support and sharing of experiences.

To define the core components of the MT sessions, a qualitative video analysis was conducted using three improvisational MT sessions involving older adults with varying degrees of cognitive functioning. This directly informed the structure and delivery of the MT protocol. The videos were sourced from the provider's internal MT archive. The analysis was performed during a workshop attended by an experienced music therapist, a music psychologist, and a cognitive neuropsychologist. Each session was reviewed in detail to identify salient therapeutic features, and a consensus list of elements was compiled. The following features were identified as characteristic of effective improvisational MT practice:

- Melody and pitch variation (e.g., transposing)
- Rhythm variation
- Tempo variation
- Timbre variation
- Dynamics
- Harmonic changes (e.g., mode shifts)
- Musical dialogue

- Use of silence
- Verbal dialogue/conversation
- Physical musical movement
- Physical non-musical movement
- Dance-like movement
- Physical contact
- Intermittent eye contact—in conjunction with the above

These elements were integrated through the improvisational and affect-matching approach used by the therapists (see Introduction in the main text), in line with established MT frameworks (Hsu et al., 2015; Franco et al., 2014). In this approach, therapists responded musically to clients' behaviours and implicitly considered their affective state (e.g., alertness, apathy, mood). Importantly, improvisation in MT differs from classical or jazz improvisation in that its goal is not aesthetic but therapeutic. It involves spontaneous, free-form music-making within a relational context, allowing participants to explore sound, gesture, and interaction without predefined structure or judgment (Hsu et al., 2015; Santi & Zorzi, 2016).

MT sessions were delivered in three formats: one-to-one, small-group, and large-group, each tailored to the specific dynamics of the setting while grounded in the same therapeutic principles. Across all formats, therapists employed improvisation, familiar songs, rhythmic activities, and singing to support meaningful and responsive musical engagement. The core therapeutic elements and modes of interaction remained consistent. What differed was the scale of the session, the degree of individual attention, and the nature of social interaction. In the one-to-one format, the therapist provided focused and individualised support. Musical activities, including improvisation, singing, and instrument play, were shaped in the moment according to the participant's responses and emotional state. This allowed for a high level of attunement and personal connection. In the small group format (four to eight participants), the therapist facilitated the same types of musical activity

within a shared setting. Participants were encouraged to respond musically to one another, promoting turn-taking, mutual responsiveness, and collaborative creativity, while still allowing space for individual expression. In the large group format (fifteen or more participants), sessions were structured to maximise inclusive participation and collective enjoyment. Therapists led familiar songs, call and response sequences, and rhythm-based exercises that supported stimulation and group cohesion, even when individual engagement was less prominent due to the size of the group.

Protocol outline (all formats)

1. Session planning: Therapists informed the community manager in advance of each session to communicate possible changes (therapist absence, change of the room, etc).
2. Resources and duration: All therapists used a standardised set of musical instruments, and a record of those used in each session was taken (see Table SM1). Sessions lasted ~40 min (slight flexibility may be present due to participants' health or contextual factors).
3. Participant accompaniment: In one-to-one and small group formats, therapists welcomed the participants to and from the session space. In large-group settings, staff assisted with transitions.
4. Orientation: Each session began with temporal and spatial orientation prompts, including the date, time, month, season, location, and town.
5. Therapeutic features: Therapists were instructed to incorporate the therapeutic elements identified in the video analysis, although no fixed sequence was required (see Figure SM1)
6. Opening and closing songs: Each session began and ended with standardized 'hello' and 'goodbye' songs selected from a shared database. During the initial month, therapists worked with participants to identify the specific songs that would remain consistent for each individual (or group) across all sessions, although the chosen songs could differ between participants. While the song identity remained fixed, therapists adjusted the musical delivery

(e.g., tempo, rhythm, dynamics) to match the participant's or group's arousal level and affect presentation.

7. Music selection: The main musical content was either selected by participants, based on memory or preference, or drawn from a curated database (see Table SM2). Choices were made with consideration of both familiarity and arousal modulation.
8. Session documentation: At the end of each session, in addition to clinical records, therapists completed a Participant Attendance Log (Table SM3).
9. Video recording: As a standard practice of the community provider, music therapists record their sessions with participant consent.

Robb et al. (2025) recently published reporting guidelines for music-based interventions, and to comply with their recommendations we have, in addition to the descriptions above, provided a checklist for the current protocol using their template (Table SM4).

Dynamic Bayesian Network (DBN) analysis

A Bayesian Network is a formal framework for representing the joint probability distribution of a collection of random variables, grounded in specific assumptions of conditional independence (Jensen, 1996; Koller & Friedman, 2009). It is structured as a directed acyclic graph, where each node denotes a random variable, and directed links signify probabilistic dependencies, with parent nodes influencing their children. Each variable is associated with a conditional probability distribution conditioned on its parent nodes, and together with the graph structure, these fully specify the Bayesian Network. When extended to capture temporal relationships among variables, the model becomes a Dynamic Bayesian Network (DBN), which allows the modeling of probabilistic dependencies across time steps.

To construct a DBN from our dataset, we used the R package bnstruct (Franzin et al., 2017), designed for structure and parameter learning in discrete/categorical data settings. This tool is particularly suited for datasets with missing values or limited sample sizes, common characteristics in clinical research. Bnstruct incorporates advanced algorithms for learning network structures and supports bootstrap resampling and probabilistic inference. It also enables the integration of domain knowledge by allowing the application of structural constraints. In our implementation, we permitted interdependence among variables measured at the end of the intervention phase, and allowed earlier measurements to influence later ones. The DBN structure was learned using the Maximum Minimum Hill-Climbing algorithm (Friedman et al., 2013; Tsamardinos et al., 2006), a hybrid method that merges constraint-based techniques with score-based search strategies to infer the optimal network topology from the data.

For this analysis, a set of primary variables was selected based on their relevance to the intervention and their contribution to cognitive and psychosocial functioning. These included the between-subject variable Group, four key demographic variables (Age, CRIq, CIRS total, and CIRS Comorbidity Index), and a series of cognitive and behavioural outcome measures derived from the test battery: Music Cognitive Test (MCT), Mini-Mental State Examination (MMSE), Verbal Fluency Test MCT version (VFT), Trail Making Test A (TMT-A), Tangle Figure Test (TFT) along with its subcomponents (Visual Errors, Repetition Errors, Semantic Errors, and Anomia), Wellbeing of Older People Scale (WOOP), Geriatric Depression Scale (GDS), and Pittsburgh Sleep Quality Index (PSQI). These variables were chosen for their contribution to significant main or interaction effects in the mixed-design ANOVA and their inclusion in the DBN model.

Structure learning algorithms in Bayesian networks require discrete variables to estimate conditional probabilities, but the dataset includes also continuous variables. Thus, these variables underwent tertile-based discretization (33rd and 66th percentiles), splitting each variable into three roughly equal-frequency bins. This approach ensures that each bin has approximately the same number of data points, it is robust to outliers and does not assume any underlying distribution (like

normality). The choice of 33rd and 66th percentiles (and not the median, or more percentiles) is a good trade-off for improving network learning, since too few bins (e.g., 2) may oversimplify patterns, and too many bins may lead to data fragmentation, where each configuration occurs only a few times, leading to unreliable probability estimates. Table SM5 reports the result of discretization for each variable, while the bootstrap and non-bootstrap Dynamic Bayesian Network describing the dependencies among variables over time is represented in Figure SM2.

The distribution of quantized variables is represented as barplots (see Supplementary Figures SM3-5): for each variable, the number of participants with a particular discretisation level is displayed.

Analysis adjusted for between-group differences in age (ANCOVA)

Although the mean age of the participants did not significantly differ between groups, the average age of the control group in the final sample was lower than that in the other groups (see Table 1 in the main text). Even though the difference was non-significant, groups were not truly equivalent in age, so it is possible that age differences could have influenced the observed effects. Therefore, we repeated the 2(Time) x 4(Group) ANOVA including Age as a covariate. The key assumptions were met, and outcomes are reported in Table SM6. The Time x Group interactions were broadly the same as in the main analysis, except the interaction was no longer significant on the TFT-V (but there was a main effect of Group). There was no longer a main effect of Time on the TMT-A, although the Time x Group interaction remained significant, and no main effect of Time on VF, TFT-S, or GDS. However, the age-adjusted planned comparisons (Table SM7) based on the estimated marginal means from the ANCOVA showed the same effects as the main analyses, with the exception that the small MT group showed a significant improvement on the TFT pre-post intervention (previously not significant).

References

- Ansdell, G., & Pavlicevic, M. (2005). Musical companionship, musical community. Music therapy and the process and values of musical communication. In D. Miell, R. MacDonald & D. Hargreaves (Eds.), *Musical Communication* (pp. 193). Oxford: Oxfordshire.
<https://doi.org/10.1093/acprof:oso/9780198529361.003.0009>
- Beaty R.E. (2015). The neuroscience of musical improvisation. *Neuroscience & Behavioral Reviews*, 51, 108-117. <https://doi.org/10.1016/j.neubiorev.2015.01.004>
- Biasutti, M., & Frezza, L. (2009). Dimensions of music improvisation. *Creativity Research Journal*, 21(2-3), 232–242. <https://doi.org/10.1080/10400410902861240>
- Biasutti, M. (2015). Pedagogical applications of cognitive research on musical improvisation. *Frontiers in Psychology*, 6, 614. <https://doi.org/10.3389/fpsyg.2015.00614>
- de Witte, M., Pinho, A.D.S., Stams, G.J., Moonen, X., Bos, A.E., & van Hooren, S. (2022). Music therapy for stress reduction: a systematic review and meta-analysis. *Health Psychology Review*, 16(1), 134-159. <https://doi.org/10.1080/17437199.2020.1846580>
- Faber, S., Brown, T., Carpentier, S., & McIntosh, A. R. (2025). Mapping multi-modal dynamic network activity during naturalistic music listening. *Imaging Neuroscience*, 3, imag_a_00413. https://doi.org/10.1162/imag_a_00413
- Franco, F., Swaine, J. S., Israni, S., Zaborowska, K. A., Kaloko, F., Kesavarajan, I., & Majek, J. A. (2014). Affect-matching music improves cognitive performance in adults and young children for both positive and negative emotions. *Psychology of Music*, 42(6), 869-887. <https://doi.org/10.1177/03057356145485>
- Franzin, A., Sambo, F., & Di Camillo, B. (2017). bnstruct: an R package for Bayesian Network structure learning in the presence of missing data. *Bioinformatics*, 33(8), 1250-1252. <https://doi.org/10.1093/bioinformatics/btw807>

- Friedman, N., Nachman, I., & Pe'er, D. (2013). Learning Bayesian network structure from massive datasets: The "sparse candidate" algorithm. *arXiv preprint arXiv:1301.6696*.
<https://doi.org/10.48550/arXiv.1301.6696>
- Hsu, M. H., Flowerdew, R., Parker, M., Fachner, J., & Odell-Miller, H. (2015). Individual music therapy for managing neuropsychiatric symptoms for people with dementia and their carers: a cluster randomized controlled feasibility study. *BMC Geriatrics*, *15*, 1-19.
<https://doi.org/10.1186/s12877-015-0082-4>
- Jang, S., & Kunde, L. (2021). A systematic review of music therapy interventions used to address emotional needs of older adults. *The Arts in Psychotherapy*, *76*, 1–11.
<https://doi.org/10.1016/j.aip.2021.101842>
- Jensen, F. V. (1996). *An introduction to Bayesian networks* (Vol. 210, pp. 1-178). London: UCL press.
- Koller, D., & Friedman, N. (2009). *Probabilistic graphical models: principles and techniques*. MIT press.
- Ma, G., & Ma, X. (2023). Music intervention for older adults: Evidence map of systematic reviews. *Medicine*, *102*(48), e36016. <https://doi.org/10.1097/MD.00000000000036016>
- Malekmohammadi, A., & Cheng, G. (2025). Music familiarization elicits functional connectivity between right frontal/temporal and parietal areas in the theta and alpha bands. *Brain Topography*, *38*(1), 2. <https://doi.org/10.1007/s10548-024-01081-z>
- Mangiacotti, A. M., A., Hsu, M. H., Barone, C., Van Puyvelde, M., Zandonà, A., Gabai, G., Biasutti, M., & Franco, F. (2024). Effects of one-to-one music therapy in older adults with cognitive impairment: A randomized controlled trial. *Psychology and Aging*, *39*(8), 960.
<https://doi.org/10.1037/pag0000861>

- Robb, S. L., Springs, S., Edwards, E., Golden, T. L., Johnson, J. K., Burns, D. S., ... & Perkins, S. M. (2025). Reporting Guidelines for Music-based Intervention: an update and validation study. *Frontiers in psychology, 16*, 1551920. <https://doi.org/10.3389/fpsyg.2025.1551920>
- Santi, M., & Zorzi, E. (Eds.). (2016). *Education as jazz: interdisciplinary sketches on a new metaphor*. Cambridge Scholars Publishing.
- Tsamardinos, I., Brown, L. E., & Aliferis, C. F. (2006). The max-min hill-climbing Bayesian network structure learning algorithm. *Machine learning, 65*, 31-78. <https://doi.org/10.1007/s10994-006-6889-7>
- Ward, E. V., Isac, A., Donnelly, M., Van Puyvelde, M., & Franco, F. (2021). Memory improvement in aging as a function of exposure to mood-matching music. *Acta Psychologica, 212*, 103206. <https://doi.org/10.1016/j.actpsy.2020.103206>

Supplementary Materials Tables**Table SM1***Music therapy instrument checklist*

Participant's identification code:																				
Sessions	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Standing Instruments:																				
Alto Metallophone																				
Alto Xylophone																				
Sonor trolley																				
Keyboard																				
Windchimes 27 bar																				
Timpani drum 16"																				
Crash cymbal 15"																				
Cymbal stand																				
Large instruments:																				
Mini bongos																				
Ocean drum 16"																				
Slit drum 6 tongues																				
Guitar																				
Hand-held instruments:																				
Plastic maracas																				
Wooden maracas																				
Micro Cabasa																				
Handcasta																				
Castanet on handle																				
Claves, wooden,																				
Wooden rhythm sticks																				
Pocket rattle																				
Tulip block																				
Woodblock																				
Double wooden agogo																				
Sleighbells																				
Triangle																				
Tambourine																				
Tambour																				
Egg shakers																				
Fish guiro & scraper																				
Beaters:																				
Single																				
Pair																				
Small																				
Large																				

Table SM2

Music database

1. A Nightingale Sang in Berkley Square – Nat King Cole
2. After The Ball – Charles K. Harris
3. Alexanders Rag Time Band – Irving Berlin
4. All The Nice Girls Like A Sailor – Traditional
5. Amazing Grace – Traditional
6. Angels Eyes – ABBA
7. April Showers – Al Jolson
8. Are You Lonesome Tonight – Elvis Presley
9. Ash Grove – Traditional
10. Barcarole Duet in The Tales Of Hoffmann – Offenbach
11. Beautiful Dreamer – Stephen Foster
12. Beside The Sea Side – Traditional
13. Blowing Bubbles – Traditional
14. Blue Birds – Traditional
15. Blue Danube – Johann Strauss II
16. Bobby Shafto – Traditional
17. Bohemian Rhapsody – Queen
18. Bring Me Sunshine – Arthur Kent / Johnny Burke
19. Bye Bye Blackbird – Ray Henderson / Mort Dixon
20. Camptown Races – Stephen Foster
21. Careless Whisper – George Michael
22. Charlie Is My Darling – Traditional
23. Chiquitita – ABBA
24. Clementine – Traditional
25. Coming Round The Mountain – Traditional
26. Coming Through The Rye – Robert Burns
27. Crazy Little Thing Called Love – Queen
28. Daisy Bell – Harry Dacre
29. Dancing Queen – ABBA
30. Do They Know It's Christmas – Band Aid
31. Don't Fence Me in – Cole Porter
32. Don't Look Back in Anger – Oasis
33. Don't You Want Me – The Human League
34. Dream of Jeannie With The Light Brown Hair – Stephen Foster
35. Drunken Sailor – Traditional
36. Eight Days a Week – The Beatles
37. Every Breath You Take – The Police
38. Fly Me to the Moon – Bart Howard
39. Get Back – The Beatles
40. Get Me To The Church On Time – Lerner & Loewe
41. Getting To Know You – Rodgers & Hammerstein
42. Gimme Shelter – The Rolling Stones
43. Gimme! Gimme! Gimme! (A Man After Midnight) – ABBA
44. Goodbye Dolly – Traditional
45. Goodnight Sweetheart – Ray Noble
46. Happy Wanderer – Friedrich-Wilhelm Möller
47. Hava Nagila – Traditional
48. Head Shoulders Knees And Toes – Traditional
49. Hello Dolly – Jerry Herman
50. Hello Peter – Traditional
51. Here Comes the Sun – The Beatles
52. Hey Jude – The Beatles
53. Hokey-Cokey – Traditional
54. How Much is That Doggie – Al Hoffman / Maurice Sigler
55. I Believe – Irving Berlin
56. I Could Have Danced All Night – Lerner & Loewe
57. I Have A Dream – ABBA
58. I Want to Hold Your Hand – The Beatles
59. I'll Be Your Sweetheart – Herman Darewski
60. I've Got Sixpence – Traditional
61. If You're Irish – Traditional
62. Imagine – John Lennon
63. Irish Eyes Are Smiling – Chauncey Olcott
64. Jamacia Farewell – Lord Burgess
65. John Brown's Body – Traditional
66. Just Like Starting Over – John Lennon
67. Karma Chameleon – Culture Club
68. Kiss Me Good Night Sargent Major – Traditional
69. Lambeth Walk – Noel Gay
70. Lassie From Lancashire – Traditional
71. Leaning on a Lamppost – Noel Gay
72. Let It Be – The Beatles
73. Let Me Call You Sweetheart – Leo Friedman
74. Lilli Marlene – Norbert Schultze
75. Little Brown Jug – Joseph Winner
76. Live Forever – Oasis
77. Loch Lomond – Traditional
78. Love A Lassie – Traditional
79. Magic Moments – Burt Bacharach / Hal David
80. Mamma Mia – ABBA
81. Match of the Day – Barry Stoller
82. May Be It's Because I'm A Londoner – Hubert Gregg
83. Men of Harlech – Traditional
84. Molly Malone – Traditional
85. Moon River – Henry Mancini
86. My Bonnie – Traditional
87. My Grandfather's Clock – Henry Clay Work
88. My Old Man Said Follow The Van – Charles Coborn

89. My Old Man's A Dustman – Lonnie Donegan
90. Now is The Hour – Traditional
91. Oh Dear What Can the Matter Be? – Traditional
92. Oh Suzanna – Stephen Foster
93. Old Bull And Bush – Traditional
94. Pack Up Your Troubles – George Henry Powell
95. Paint It Black – The Rolling Stones
96. Penny Lane – The Beatles
97. Power to the People – John Lennon
98. Quarter Masters Store – Traditional
99. Que Sera Sera – Doris Day
100. Rain Drops Keep Falling on My Head – Burt Bacharach
101. Red Red Robbin – Harry Woods
102. Relax – Frankie Goes to Hollywood
103. Satisfaction – The Rolling Stones
104. Show Me The Way to Go Home – Irving King
105. Side by Side – Harry Woods
106. Siegfried Line – Traditional
107. Somewhere Over the Rainbow – Judy Garland
108. Sunny Side Of The Street – Jimmy McHugh
109. Swing Low – Traditional
110. Tavern in The Town – Traditional
111. Tell Me Ma – Traditional
112. The Grand Old Duke Of York – Traditional
113. Three Little Birds – Bob Marley
114. Tip Toe Through The Tulips – Al Dubin
115. Tipperary – Jack Judge
116. Underneath The Spreading Chestnut Tree – Traditional
117. Uptown Girl – Billy Joel
118. Waltzing Matilda – Traditional
119. We Are the Champions – Queen
120. We'll Keep A Welcome – Mai Jones
121. When I Fall in Love – Victor Young
122. When I Grow Too Old To Dream – Sigmund Romberg
123. When The Saints – Traditional
124. When You're Smiling – Mark Fisher
125. Who's Your Lady Friend – Harry Castling
126. Wish Me Luck – Traditional
127. Wouldn't It Be Lovely – Lerner & Loewe
128. You Are My Sunshine – Jimmie Davis

Table SM3*Participant attendance log*

Care Home ID: _____

X = participant attended; **NA** = participant unavailable; **NU** = participant unwell; **R** = refused; **T** = technical/organisational problem;**TA** = therapist unavailable; **TU** = therapist unwell

ID PARTICI PANT (anonym)	Session																
	___/___	___/___	___/___	___/___	___/___	___/___	___/___	___/___	___/___	___/___	___/___	___/___	___/___	___/___	___/___	___/___	___/___

Table SM4

Intervention protocol checklist based on the Robb et al. (2025) reporting guidelines for music-based interventions (RG-MBI) template

Item number	Item
1	Brief Name MusiCare Project: Protecting Cognitive Functions and Wellbeing Using Music Therapy in an Aging Population.
2	Intervention Theory and/or Scientific Rationale The intervention was designed to support cognitive function and psychosocial wellbeing in healthy older adults through active, relational music making. Music listening and performance engage distributed neural networks linked to attention, working memory, executive control, sensory integration, and visuospatial processing (Beaty, 2015; Biasutti & Frezza, 2009). Neuroimaging work suggests that music-based engagement recruits networks involved in executive control and memory, and that repeated exposure can enhance functional connectivity and phase synchronisation across frontal, temporal, and parietal regions - processes relevant to cognitive integration and emotional regulation (Faber et al., 2025; Malekmohammadi & Cheng, 2025). Affect-matching was included because music that mirrors and supports the listener's emotional state can facilitate cognitive performance (especially attention/working memory) (Franco et al., 2014; Ward et al., 2021), and in music therapy (MT) this is operationalised as therapist shaping musical responses to align with the participant's moment-to-moment affect (Ansdell & Pavlicevic, 2005). Improvisation was used to promote rapid decision-making, sustained attention, sensorimotor coordination, and flexible responding within a safe relational context (Beaty, 2015; Biasutti, 2015). Familiar songs were incorporated to support engagement, autobiographical resonance, and arousal modulation, with potential downstream benefits for mood and cognitive performance (Ward et al., 2021; Malekmohammadi & Cheng, 2025). The protocol also targeted psychophysiological regulation: prior MT work integrating improvisation and affect matching has been associated with improved stress modulation (e.g., reduced cortisol/DHEA ratio; increased parasympathetic activity) (Mangiacotti et al., 2024), and evidence syntheses indicate music-based interventions can support wellbeing and reduce distress in older adults (de Witte et al., 2022; Ma & Ma, 2023). Finally, the group formats were motivated by the role of social context in later-life wellbeing, leveraging shared musical interaction to support belonging and social connectedness (Ansdell & Pavlicevic, 2005; Jang & Kunde, 2021; Ma & Ma, 2023).
3	Intervention Content Twenty weekly sessions (~40 minutes) were delivered over ~5 months. Across all formats, sessions followed shared core components: opening/closing 'hello' and 'goodbye' songs, temporal/spatial orientation prompts, and an interactive, improvisational and affect-matching approach that combined improvisation, familiar songs, rhythmic activities, singing, and instrument play. Therapists continuously modulated musical parameters (e.g., melody/pitch, rhythm, tempo, timbre, dynamics, harmony), incorporated periods of silence, and used verbal prompts/questions to facilitate attention, reflection, and dialogue. While therapeutic elements were standardised, no fixed within-session sequence was mandated; activities were tailored in-the-moment to participants' affect, engagement, and group dynamics (see Figure SM1)
3a	Music Selection The main musical content was participant-led (based on memory, preferences, and requests) and/or drawn from a curated music therapy database shared across therapists (Supplementary Table SM2). Selection prioritised familiarity and arousal modulation and was revisited iteratively as participants' preferences emerged. During the first month, participants (or groups) worked with therapists to identify consistent opening/closing songs that remained stable across sessions, with delivery adapted session-by-session (e.g., tempo/dynamics) to match arousal.
3b	Music Sessions integrated (i) live therapist-led and participant-involved singing of familiar repertoire (drawn from participant requests and the shared database), (ii) structured and semi-structured rhythmic activities, and (iii) relational improvisation/musical dialogue. Rather than using a fixed repertoire, therapists adjusted musical features (e.g., tempo, rhythmic density, melodic contour, dynamics, and mode) to match participants' arousal and affect, supporting

	affect-matching and engagement (Franco et al., 2014; Ward et al., 2021). Improvisation was used therapeutically as spontaneous, free-form music making within a relational context, supporting exploration of sound/gesture/interaction without performance goals (Hsu et al., 2015; Santi & Zorzi, 2016).
3c	Music Delivery Method Music was delivered live by HCPC-registered music therapists using voice and accessible instruments, with participants encouraged to sing, play, and move. When recorded music was used (e.g., for specific familiar tracks), therapists used a computer connected to a portable speaker (Tribit XSound Go), and controlled playback and volume in-session. Sessions took place in comfortable, well-lit, acoustically isolated community rooms, free from distractions. In one-to-one sessions, music making was shaped moment-by-moment through close therapist attunement. In small groups (4–8), therapists facilitated mutual responsiveness (e.g., turn-taking, shared rhythm), and in large groups (≥ 15) led inclusive activities (e.g., call-and-response, group singing, rhythm circles) to maximise collective participation.
3d	Materials A standardised set of instruments was available across sites and therapists. Instruments were organised in clusters (standing, large, and hand-held percussion/melodic instruments); a full item-by-item checklist is provided in Supplementary Table SM1. Therapists also used non-music technology for playback when needed (laptop/computer + portable speaker). Session documentation included completion of the Participant Attendance Log after each session (Supplementary Table SM3) and Instrument Check list form (Table SM1).
3e	Intervention Strategies Therapists used an improvisational and affect-matching framework to sustain attention, promote regulation, and support therapeutic interaction. Strategies included: musical dialogue (therapist responds to vocal/instrumental/bodily cues), deliberate variation in musical parameters (tempo, rhythm, dynamics, harmony), intentional pauses for listening/turn-taking, and verbal prompts/questions to scaffold reflection and narrative about the music experience. Across formats, the approach aimed to stimulate attention and facilitate dialogue with the therapist and, where applicable, between participants. Format-specific emphases: one-to-one sessions prioritised individualised attunement and personal exploration; small groups encouraged interpersonal musical responding, collaborative creativity, and mutual support; large groups used structured inclusive activities (call-and-response, rhythm-based exercises, group singing) to build cohesion and collective enjoyment.
4	Interventionist Five HCPC-registered music therapists delivered the intervention. Each had at least two years' experience working with older adults and received in-depth study-specific training. Participants remained with the same therapist throughout the intervention period.
5	Individual or Group Intervention Three delivery formats were implemented for comparison: one-to-one, small-group (4–8 participants), and large-group (≥ 15 participants).
6	Setting Sessions were delivered in community centre rooms that were comfortable, well-lit, and acoustically isolated, with minimal distractions. Where needed (e.g., large-group contexts), community staff support was limited to facilitating participant transitions to/from the session space.
7	Intervention Delivery Schedule Intervention exposure was 20 sessions delivered weekly over ~5 months, with each session lasting ~40 minutes. Pre- and post-intervention assessment took place up to two weeks before the first session and within one week after the final session. Both cognitive and wellbeing measures were administered; refer to the main manuscript Materials section for the full test battery.
8	Treatment Fidelity Fidelity was supported via standardised protocols across formats, therapist training sessions led by the first author, ongoing supervision availability during delivery, and an online peer-support forum. All therapists followed the same core components (orientation prompts, opening/closing songs, and shared therapeutic elements identified via video analysis of exemplar sessions). In addition to clinical notes, session documentation (attendance log) and a standardised instrument checklist were used to monitor delivery and resources across sessions.

Table SM5*Tertile-Based Discretisation Cut-Off Values for Continuous Variables*

	Percentile			
	0.00	0.33	0.66	1.00
Age	53.00	76.13	83.26	101.00
CRI_Tot	85.00	124.13	142.00	175.00
CIRST_Tot	0.00	5.00	8.00	18.00
MMSE	25.00	28.00	29.00	30.00
MCT	38.00	46.13	50.00	52.00
MCT_P	37.00	48.13	50.00	52.00
TMT_A	220.00	392.20	566.45	1125.10
TMT_A_P	188.00	351.13	509.78	1110.00
VF	1.00	14.00	20.00	33.00
VF_P	9.00	15.00	20.26	35.00
TFT	7.00	21.00	28.26	38.00
TFT_P	7.00	24.13	31.52	49.00
GDS	0.00	1.00	3.00	12.00
GDS_P	0.00	1.00	3.00	12.00
WOOP	25.00	35.00	40.00	45.00
WOOP_P	25.00	36.00	40.00	45.00
PSQI	1.00	10.00	14.00	28.00
PSQI_P	2.0	10.0	14.6	33.0

Note: MMSE, Mini Mental State Exam. CRIq, Cognitive Reserve Index questionnaire. CIRS, Cumulative Index score for physical health. MCT, Music Cognitive Test. TMT-A Trail Making Test parts A. TFT, Tangle Figure Test. VF, Verbal Fluency. GDS, Geriatric Depression Scale (short version). WOOP, Wellbeing of Older People Scale. PSQI, Pittsburgh Sleep Quality Index. Variables with ‘_P’ representing post-intervention.

Table SM6

ANCOVA outcomes for each measure as a function of Time (pre-post intervention) and Group (one to one, small-group, large-group, control).

Measure	Source of variance	SS	df	F	<i>p</i>	η^2
MCT	Time	0.297	1	0.114	.736	0.002
	Group	41.896	3	0.981	.408	0.049
	Age	68.826	1	4.836	.032*	0.078
	Time $\times$ Group	48.284	3	6.208	.001*	0.246
	Time $\times$ Age	0.056	1	0.022	.883	0.000
	Error(time)	147.783	57	—	—	—
TMT-A	Time	309.690	1	3.079	.085	0.051
	Group	2.326.380	3	1.232	.306	0.061
	Age	4.705.023	1	7.476	.008*	0.116
	Time $\times$ Group	1.264.850	3	4.192	.009*	0.181
	Time $\times$ Age	243.554	1	2.422	.125	0.041
	Error(time)	5.732.468	57	—	—	—
TFT	Time	78.792	1	6.114	.016*	0.097
	Group	705.776	3	2.248	.092	0.106
	Age	1.256.973	1	12.014	.001*	0.174
	Time $\times$ Group	146.875	3	3.799	.015*	0.167
	Time $\times$ Age	46.229	1	3.587	.063	0.059
	Error(time)	734.565	57	—	—	—
VF	Time	23.946	1	1.812	.184	0.031
	Group	846.541	3	6.078	.001*	0.242
	Age	229.541	1	4.944	.030*	0.080
	Time $\times$ Group	33.670	3	0.849	.473	0.043
	Time $\times$ Age	17.368	1	1.314	.256	0.023
	Error(time)	753.272	57	—	—	—
TFT_V	Time	7.813	1	1.156	.287	0.020
	Group	154.588	3	2.826	.047*	0.129

	Age	8.928	1	0.490	.487	0.009
	Time × Group	51.101	3	2.521	.067	0.117
	Time × Age	7.324	1	1.084	.302	0.019
	Error(time)	385.089	57	—	—	—
TFT_R	Time	0.384	1	0.194	.661	0.003
	Group	31.598	3	2.799	.048*	0.128
	Age	22.949	1	6.098	.017*	0.097
	Time × Group	15.595	3	2.629	.059	0.122
	Time × Age	0.401	1	0.203	.654	0.004
	Error(time)	112.703	57	—	—	—
TFT_S	Time	0.008	1	0.023	.881	0.000
	Group	0.683	3	0.509	.678	0.026
	Age	1.493	1	3.336	.073	0.055
	Time × Group	0.839	3	0.784	.508	0.040
	Time × Age	0.003	1	0.008	.927	0.000
	Error(time)	20.330	57	—	—	—
TFT_A	Time	0.593	1	1.652	.204	0.028
	Group	1.166	3	0.677	.570	0.034
	Age	0.162	1	0.282	.598	0.005
	Time × Group	2.021	3	1.878	.144	0.090
	Time × Age	0.520	1	1.449	.234	0.025
	Error(time)	20.449	57	—	—	—
GDS	Time	3.062	1	1.633	.207	0.028
	Group	13.285	3	0.485	.694	0.025
	Age	1.672	1	0.183	.670	0.003
	Time × Group	6.598	3	1.173	.328	0.058
	Time × Age	1.360	1	0.725	.398	0.013
	Error(time)	106.913	57	—	—	—
WOOP	Time	0.001	1	0.000	.990	0.000
	Group	211.424	3	1.496	.225	0.073
	Age	26.317	1	0.559	.458	0.010
	Time × Group	12.744	3	0.836	.480	0.042
	Time × Age	0.017	1	0.003	.954	0.000

PSQI	Error(time)	289.610	57	—	—	—
	Time	25.961	1	2.346	.131	0.040
	Group	445.621	3	2.098	.111	0.099
	Age	0.493	1	0.007	.934	0.000
	Time × Group	34.343	3	1.035	.384	0.052
	Time × Age	29.359	1	2.653	.109	0.044
	Error(time)	630.692	57	—	—	—

Note. MCT, Music Cognitive Test; TMT-A, Trial Making Test-A; TFT, Tangle Figure Test; TFT_V, Tangle Figure Test Visual Errors, TFT_R Tangle Figure Test Repetition Errors; TFT_S, Tangle Figure Test Semantic Errors; TFT_A, Tangle Figure Test Anomia; VF, Verbal Fluency; GDS, Geriatric Depression Scale (short version). WOOP, wellbeing of Older People Scale. PSQI, Pittsburgh Sleep Quality Index.

Table SM7*ANCOVA Bonferroni-corrected pairwise comparisons of outcome measures pre-post intervention*

	One-to-one MT (n=17)				Small-group MT (n=17)				Large-group MT (n=12)				Control (n=16)			
	Baseline mean (SD)	Post mean (SD)	<i>p</i> (η^2)	MD [95% CI]	Baseline mean (SD)	Post mean (SD)	<i>p</i> (η^2)	MD [95% CI]	Baseline mean (SD)	Post mean (SD)	<i>p</i> (η^2)	MD [95% CI]	Baseline mean (SD)	Post mean (SD)	<i>p</i> (η^2)	MD [95% CI]
MCT	48.89 (0.68)	49.24 (0.72)	.521 (.007)	0.36 [-0.75, 1.46]	47.04 (0.70)	49.00 (0.74)	<.001 (.175)*	1.96 [0.83, 3.08]	47.16 (0.81)	48.58 (0.86)	.035 (.076)*	1.42 [0.10, 2.74]	48.27 (0.73)	46.81 (0.78)	.017 (.096)*	-1.46 [-2.65, - 0.27]
TMT-A	47.83 (4.53)	39.05 (4.75)	.014 (.102)*	-8.78 [-15.67, - 1.88]	56.22 (4.61)	47.05 (4.84)	.011 (.107)*	-9.16 [-16.19, - 2.14]	49.09 (5.39)	44.70 (5.65)	.288 (.020)	-4.39 [-12.60, 3.81]	51.02 (4.86)	58.15 (5.09)	.059 (.061)	7.13 [-0.27, 14.53]
TFT	27.40 (1.74)	32.80 (1.98)	<.001 (.252)*	5.40 [2.93, 7.87]	24.04 (1.77)	26.75 (2.02)	.036 (.075)*	2.70 [0.19, 5.22]	22.77 (2.06)	29.39 (2.35)	<.001 (.264)*	6.63 [3.69, 9.56]	23.39 (1.86)	24.19 (2.12)	.550 (.006)	0.80 [-1.85, 3.44]
TFT_V	6.53 (0.77)	5.51 (0.94)	.259 (.022)	-1.02 [-2.80, 0.77]	5.07 (0.79)	4.96 (0.95)	.906 (.000)	-0.11 [-1.93, 1.71]	5.75 (0.92)	5.22 (1.11)	.618 (.004)	-0.53 [-2.66, 1.59]	1.80 (0.83)	4.21 (1.00)	.015 (.100)*	2.41 [0.49, 4.33]
TFT_R	1.33 (0.43)	1.75 (0.40)	.386 (.013)	0.42 [-0.55, 1.39]	2.26 (0.43)	1.83 (0.40)	.389 (.013)	-0.43 [-1.41, 0.56]	1.54 (0.51)	2.47 (0.47)	.112 (.044)	0.93 [-0.22, 2.08]	1.22 (0.46)	0.22 (0.42)	.058 (.062)	-1.00 [-2.04, 0.03]
TFT_S	0.58 (0.19)	0.05 (0.10)	.013 (.104)*	-0.53 [-0.94, - 0.12]	0.31 (0.20)	0.20 (0.10)	.588 (.005)	-0.11 [-0.53, 0.30]	0.32 (0.23)	0.16 (0.12)	.500 (.008)	-0.17 [-0.65, 0.32]	0.57 (0.21)	0.31 (0.11)	.250 (.023)	-0.26 [-0.70, 0.18]
TFT_A	0.18 (0.17)	0.41 (0.17)	.281 (.020)	0.22 [-0.19, 0.64]	0.21 (0.17)	0.11 (0.17)	.607 (.005)	-0.11 [-0.53, 0.31]	0.43 (0.20)	0.41 (0.20)	.957 (.000)	-0.01 [-0.50, 0.48]	0.63 (0.18)	0.14 (0.18)	.031 (.079)*	-0.49 [-0.93, - 0.05]
VF	19.97 (1.28)	21.97 (1.37)	.114 (.043)	2.01 [-0.49, 4.51]	18.38 (1.30)	21.19 (1.40)	.031 (.079)*	2.82 [0.27, 5.36]	15.02 (1.52)	15.43 (1.63)	.783 (.001)	0.41 [-2.56, 3.39]	14.81 (1.37)	15.06 (1.47)	.849 (.001)	0.26 [-2.43, 2.94]
GDS	2.25 (0.64)	1.29 (0.49)	.046 (.068)*	-0.96 [-1.90, - 0.02]	2.97 (0.65)	1.89 (0.50)	.028 (.082)*	-1.08 [-2.04, - 0.12]	3.61 (0.76)	1.75 (0.58)	.002 (.162)*	-1.85 [-2.98, - 0.73]	2.37 (0.69)	1.93 (0.53)	.385 (.013)	-0.44 [-1.45, 0.57]
WOOP	38.55 (1.30)	39.31 (1.18)	.329 (.017)	0.76 [-0.79, 2.31]	35.83 (1.32)	36.52 (1.20)	.381 (.014)	0.70 [-0.88, 2.28]	36.12 (1.55)	35.20 (1.40)	.323 (.017)	-0.92 [-2.76, 0.93]	37.76 (1.39)	38.40 (1.26)	.445 (.010)	0.64 [-1.02, 2.30]
PSQI	9.99 (1.42)	11.49 (1.67)	.193 (.030)	1.50 [-0.78, 3.79]	15.27 (1.45)	15.37 (1.71)	.933 (.000)	0.10 [-2.23, 2.43]	15.72 (1.69)	14.62 (1.99)	.422 (.011)	-1.10 [-3.82, 1.62]	11.93 (1.53)	13.62 (1.80)	.174 (.032)	1.69 [-0.77, 4.14]

Table SM8

Pathway	Step 1	Step 2	Step 3	Step 4
1	CIRS	WOOP	GDS	GDS_P
2	WOOP	PSQI	PSQI_P	
3	WOOP	WOOP_P		

Supplementary Materials Figures

Figure SM1

Examples of the order of features of MT sessions. All sessions incorporated the same therapeutic elements, but with no fixed sequence.

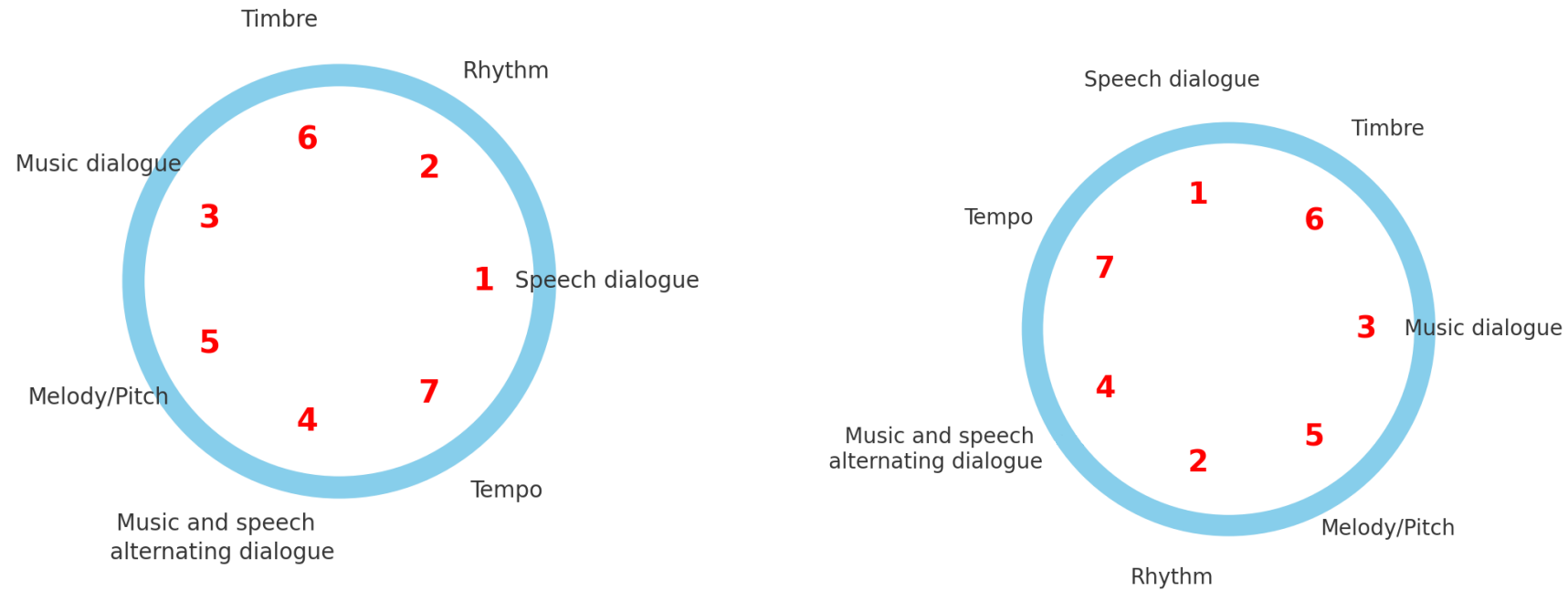
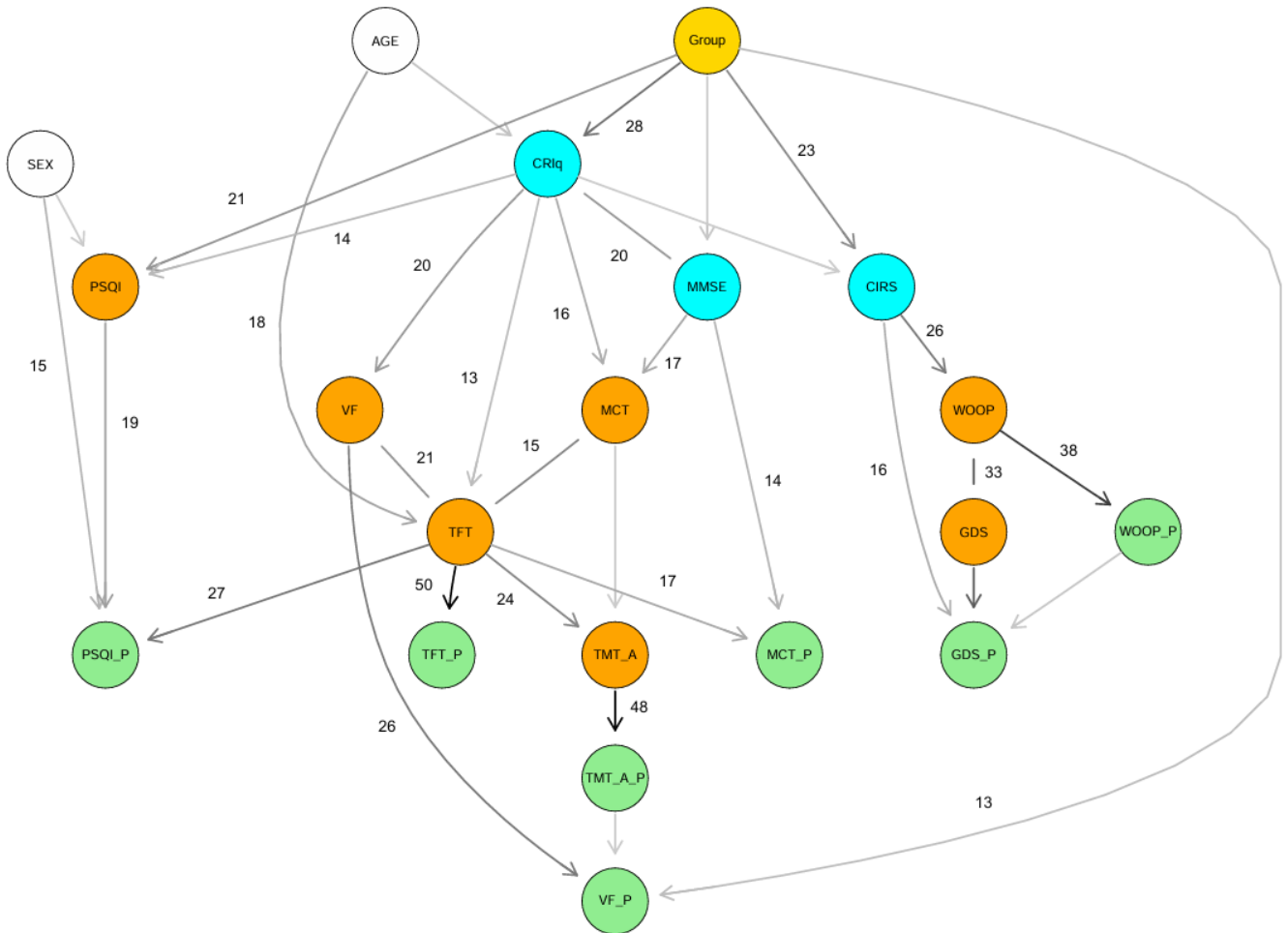
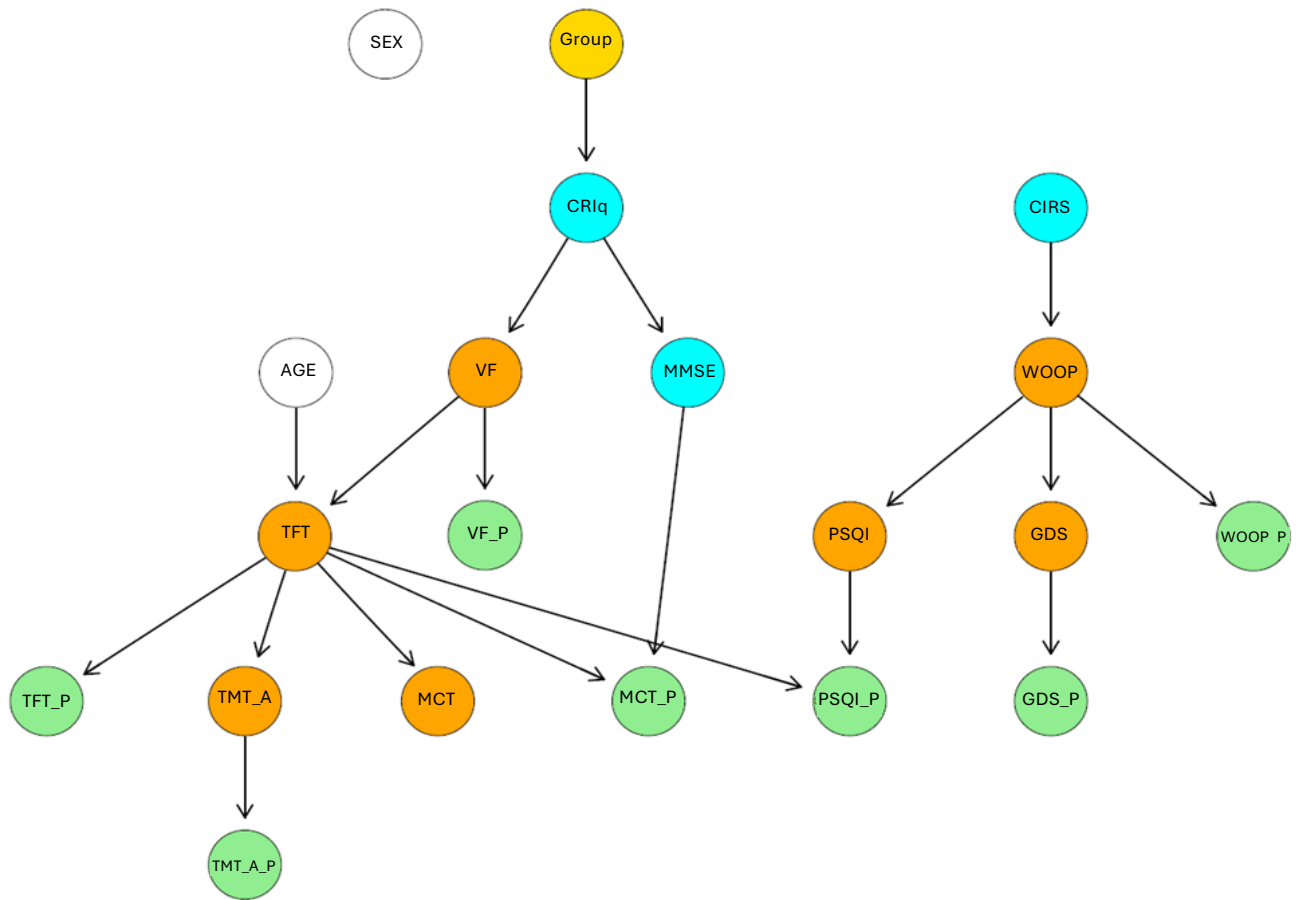


Figure SM2

A: **Bootstrap** Dynamic Bayesian Network describing the dependencies among variables over time. Structure learning from many random samples of dataset (with replacement). Edge thickness is proportional to the frequency of the specific dependency among resamples. The numbers on the edges indicate the number of bootstrap samples in which a given dependency was identified.



B. Non-Bootstrap Dynamic Bayesian Network describing the dependencies among variables over time. One-shot structure learning from the original data (no resampling).

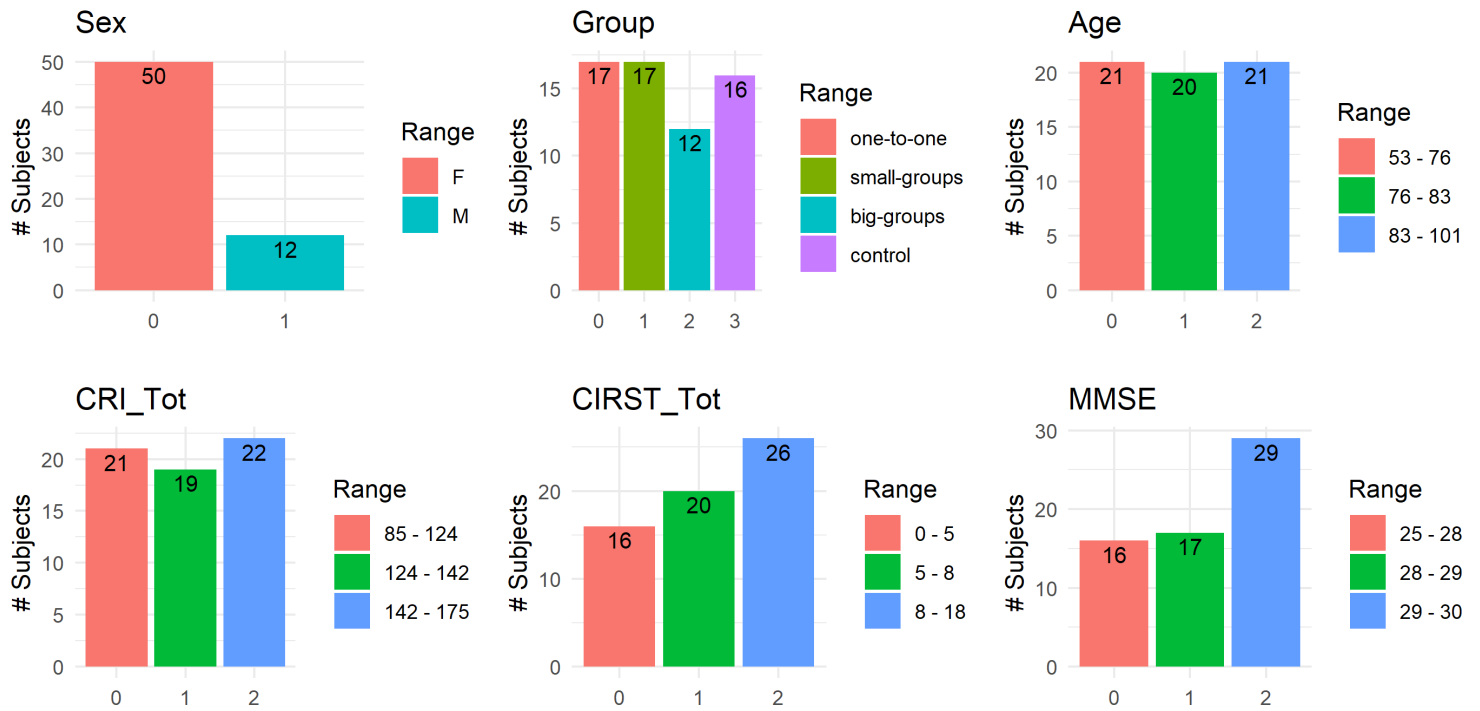


Note. White nodes = demographic variables; Light-Blue = Screening variables; Orange = variables of interest at pre- intervention period; Green = post-intervention period. MMSE, Mini Mental State Exam. CIRIq, Cognitive Reserve Index questionnaire. CIRS, Cumulative Index score for physical health. MCT, Music Cognitive Test. TMT-A Trail Making Test parts A. TFT, Tangle Figure Test. VF, Verbal Fluency. GDS, Geriatric Depression Scale (short version). WOOP, Wellbeing of Older People Scale. PSQI, Pittsburgh Sleep Quality Index. Variables with ‘_P’ representing post-intervention. Bootstrap learning (Figure SM2-A) produces robust networks, reducing the chance that random noise or outliers affect the learned structure, and avoiding overfitting to a single sample. Moreover, frequent edges are more likely to be real dependencies. Only dependencies appearing in at least 12 out of 50 resamples ($\geq 25\%$) are shown. Edge thickness is proportional to the frequency of the dependency across resamples. Non bootstrap learning (Figure SM2-B) leads to a deterministic

network, based on the original data without resampling; weights cannot be assigned to a DBN computed without bootstrapping, as they reflect how often each dependency appears across bootstrap rounds.

Figure SM3

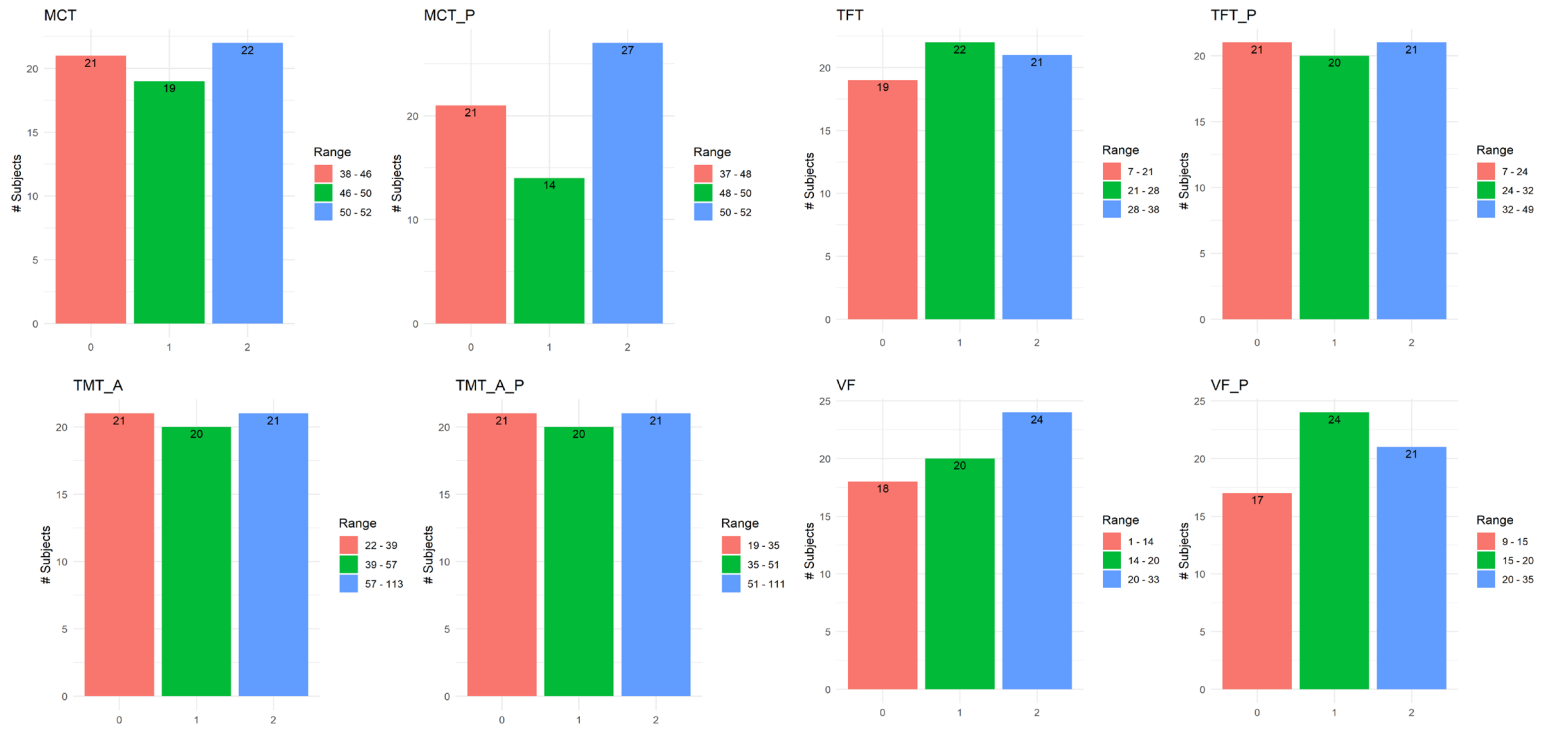
Distribution of Quantized Baseline Variables Across Participants for Demographic and Screening Variables



Note: CRIq, Cognitive Reserve Index questionnaire. CIRS, Cumulative Index score for physical health. Numbers above each bar indicate the number of participants in that discretisation level.

Figure SM4

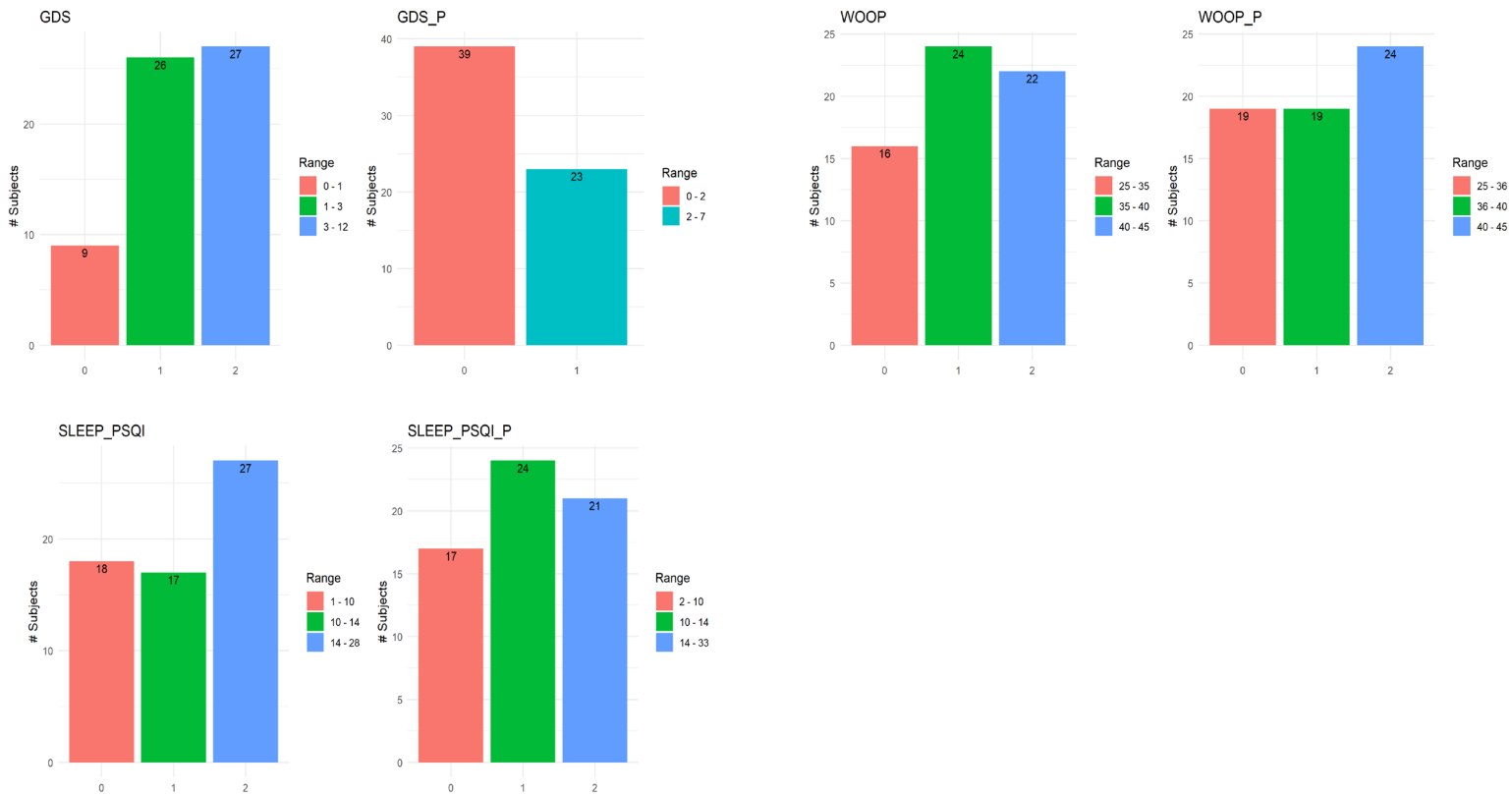
Distribution of Quantized Baseline Variables Across Participants for Cognitive Test Variables



Note: CRIq, MCT, Music Cognitive Test. TMT-A Trail Making Test parts A. TFT, Tangle Figure Test. VF, Verbal Fluency. Variables with ‘_P’ representing post-intervention. Numbers above each bar indicate the number of participants in that discretisation level.

Figure SM5

Distribution of Quantized Baseline Variables Across Participants for Behavioural Variables



Note: GDS, Geriatric Depression Scale (short version). WOOP, Wellbeing of Older People Scale.

PSQI, Pittsburgh Sleep Quality Index. Variables with ‘_P’ representing post-intervention. Numbers above each bar indicate the number of participants in that discretisation level.