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5 **Supplementary appendix**
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7 **Mapping Aboriginal mental health journeys through psychiatric care systems: a mixed-**
8 **methods study integrating lived experience with network analysis**
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68 **Supplementary Methods**

69 **Construction of the Clinical Interaction Network**

70 To construct the Clinical Interaction Network (CIN) we initially followed the methodology outlined by
 71 McCullough et al.¹

72 An undirected graph, G , is created upon a vertex set, V , where each $i \in V$ represents the various agents and
 73 information systems. Edges between two vertices i and j are constructed if the agents or information systems are
 74 present in the same interaction instance. However, edges must observe additional criteria to exclude certain
 75 forbidden edges. Information systems cannot be accessed directly by other information systems and can only be
 76 accessed by relevant clinical staff. For example, the My Health Record (MHR) is only accessible by agents
 77 belonging to the psychiatric team. Thus, edges involving information systems are restricted only to (a) agents that
 78 (b) have the appropriate clearance. Table 1 and Figure 1a illustrate this construction scheme with an example event
 79 log.

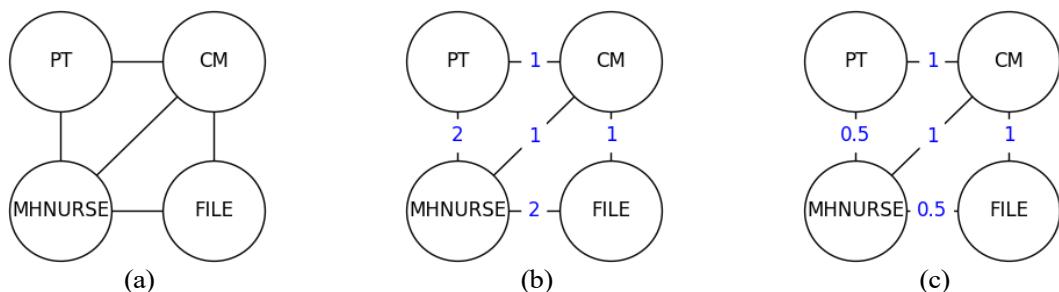
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Patient ID	Date	Time	Agents	Information Systems
1	31-01-2024	1230	MHNURSE, PT	FILE
1	31-01-2024	1430	CM, PT	
1	02-02-2024	0830	MHNURSE, CM	FILE
1	02-02-2024	0930	MHNURSE, PT	

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82 **Table 1: Example event log used in the construction of the Clinical Interaction Network (CIN).** This table
 83 provides an excerpt of the de-identified observational dataset collected at the Great Southern Mental Health
 84 Service (GSMHS), illustrating the key variables used to build the CIN. Each row represents a single recorded
 85 clinical interaction, identified by Patient ID and timestamped with date and time of occurrence. The Agents
 86 column lists the individuals or roles (e.g., PT = Patient; MHNURSE = Mental Health Nurse; CM = Case
 87 Manager) involved in the interaction, while the Information Systems column specifies any electronic or physical
 88 health record systems accessed during that encounter (e.g., FILE = patient file). Interactions may include direct
 89 patient contact, liaison activities, assessments, or interventions, and can involve multiple agents and systems in
 90 the same event. This format was applied consistently across the full dataset ($N = 1108$ interaction instances) to
 91 define network nodes and edges for subsequent CIN analysis, with edges representing co-occurrence of
 92 agents/systems within an interaction.

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95 **Figure 1: Example construction of a Clinical Interaction Network (CIN) from a sample event log**
 96 **(Table 1).** (a) Unweighted CIN - nodes represent agents or information systems with edges indicating co-
 97 occurrence in the same interaction instance. (b) Weighted by interaction frequency - edge weights reflect the
 98 total number of recorded interactions between each pair of nodes. (c) Weighted by reciprocal interaction
 99 frequency - edge weights converted to distances (reciprocal frequency) for shortest path and path length
 100 calculations, emphasizing shorter distances between frequently interacting nodes.

101 Abbreviations: PT = Patient; MHNURSE = Mental Health Nurse; FILE = Patient file in the health record system;
 102 CM = Case Manager

103 While this construction mirrors the approach by McCullough et al.¹, our methodology includes additional
 104 information into the network model due to a more extensive dataset. McCullough et. al.¹ analysed a total of $N =$
 105 213 interactions, whereas our dataset contains $N = 1108$ interactions, allowing edges to be defined with weights
 106 corresponding to the frequency of interactions. Consequently, a more nuanced analysis is available, distinguishing
 107 between frequent and infrequent interactions. The unweighted CIN represents all possible interactions, while the
 108 weighted CIN represents how frequently these interactions occur.

109 To use weighted centrality measures that utilise weighted path lengths and shortest distances, a notion of distance
 110 between nodes is required. Interactions with high frequencies should correspond to shorter path lengths, and

111 interactions with low frequency should correspond to longer path lengths. Thus, we define the distance between
112 two nodes as the reciprocal of frequency. Figures 1b and 1c demonstrate the extension of McCullough et al¹.s
113 CIN model with two additional layers of interaction frequency and distance.

114 This construction scheme minimises external assumptions, only limiting interactions to maintain feasible
115 interactions from an organisational standpoint. Nonetheless, some limitations exist due to the data collection
116 process

117 To collect data with minimal impact on clinical outcomes, interactions were observed with no additional clinical
118 information that may inform the severity or significance of an interaction. While the action field may be used to
119 give weighting to each interaction, we assume that each interaction is of equal weighting for simplicity. Thus, our
120 model is only able to describe structural features based on what interactions are present and the frequency they
121 occur, not the nature of the interaction.

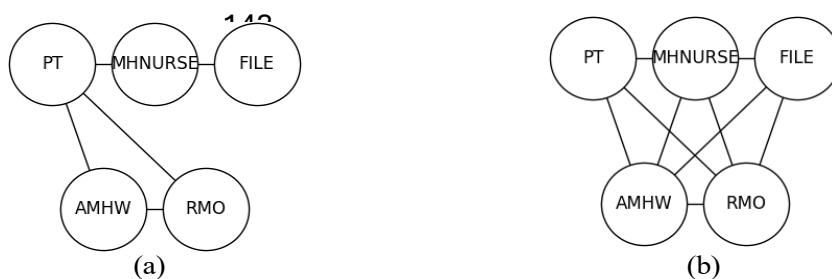
122 Events with a large number of agents, such as team meetings, are unlikely to have every agent interacting between
123 each other equal significance. Information about individual interactions is lost for simplicity in data collection.
124 The network model assumes that every possible interaction occurs with equal significance, thus over-representing
125 the total number of interactions present. Similarly, information systems may exhibit an artificially higher
126 connectivity as we assume that every agent capable will always access an information system. Table 2 and Figure
127 2b illustrate this effect with an example interaction instance. Figure 3 shows that most interaction instances have
128 two or fewer agents per interaction instance. Thus, the over-representation of interactions is minimal and unlikely
129 to impact the overall structure of the CIN significantly.

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Patient ID	Date	Time	Agents	Information Systems
1	31-01-2024	1230	PT, MHNURSE, RMO, AMHW	FILE

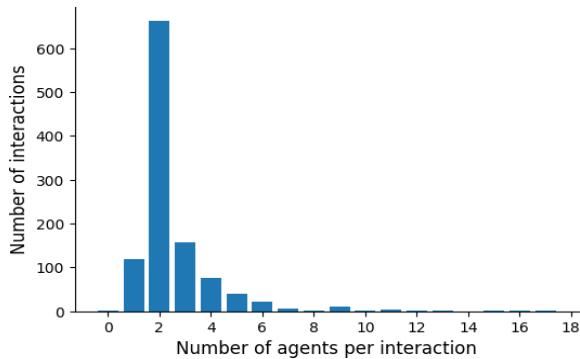
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133 **Table 2: Example event log entry illustrating potential over-representation of interactions in clinical**
134 **communication networks.** This example shows a single logged instance in which MHNURSE conducts a
135 routine patient observation and simultaneously accesses the patient’s file. Concurrently, an AMHW and a RMO
136 are present to inform the patient of a discharge plan. Although these are separate tasks with distinct purposes,
137 standard event logging records them within the same time frame and may therefore capture them as a single
138 interaction. In network analyses that do not distinguish between task context or communication intent, such an
139 event may artificially inflate the perceived strength of connections between staff roles. This highlights the
140 importance of filtering and categorizing event logs to avoid misinterpretation of collaboration patterns.

141 Abbreviations: PT = Patient; MHNURSE = Mental Health Nurse; RMO = Resident Medical Officer; AMHW =
142 Aboriginal Mental Health Worker; FILE = Patient file in the health record system



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148 **Figure 2: Comparison of theoretically expected vs. modeled CINs from an example event log interaction.** (a) CINs
149 that are expected to arise from the interaction described in Table 2, based on the assumption that all temporally co-
150 occurring events represent a potential link between participating agents. In this example, the agents are PT, MHNURSE,
151 RMO, and AMHW, with FILE representing the patient’s electronic medical record. All possible dyads implied by the
152 raw interaction data are shown, assuming equal significance of all co-present agents. (b) CINs generated using our
153 construction scheme, which applies feasibility constraints such as restricting information system access to relevant
154 clinical staff and assuming complete interaction between all eligible agents within an event. These methodological
155 decisions can remove or add edges compared to the idealized model in (a). Differences between (a) and (b) illustrate how
156 construction rules affect inferred connectivity and consequently network metrics.

157 Abbreviations: PT = Patient; MHNURSE = Mental Health Nurse; RMO = Resident Medical Officer; AMHW =
158 Aboriginal Mental Health Worker; FILE = Patient file in the health record system.



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Figure 3: Distribution of agents per clinical interaction. Histogram of 1,108 recorded interactions for 19 Aboriginal patients at the GSMHS showing the number of agents involved per event. Most interactions involved one or two agents - typically the patient and a single clinician - with progressively fewer multi-agent events. This pattern indicates a predominance of dyadic encounters and minimal inflation of pairwise links from multi-party events in constructing the CIN. Agent categories include patients, clinical staff, external providers, and family members. x-axis = number of agents; y-axis = count of interactions.

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Surrogate Testing

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We introduce the main ideas motivating surrogate testing to detect nonlinearity in time series analysis ^{2,3}. A surrogate ensemble is produced that preserves certain characteristics of the original time series (such as the mean or variance). These surrogates are constructed using either typical or constrained realizations. Typical realizations preserve characteristics by estimating parameters of the original time series and use a generative process to form surrogate data reflecting these parameters. This is in contrast to constrained realizations which contain exactly preserved characteristics by modifying the original process, typically from randomization and shuffling algorithms.

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An appropriate discriminating statistic sensitive to non-linearity is then applied to the surrogate ensemble and original time series. In the framework of hypothesis testing, the null hypothesis being scrutinized asks whether the nonlinearity of the time series can be attributed solely to randomization. If the original time series is indeed statistically significant, the null hypothesis is rejected, meaning that the randomization with preserved characteristics cannot explain the nonlinear behavior. If the original time series is not significant, the null hypothesis cannot be rejected ³.

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By starting with the simplest null hypotheses (such as random noise) and working towards increasingly complex surrogates, a hierarchy of null hypotheses can be created that iteratively exclude specific characteristics as being explanatory for the nonlinear behavior of the time series ². Here, we extend this idea from time series to graphs and apply it to CINs.

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Graph randomization

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The first typical realization scheme available is the Erdős-Rényi model which requires an edge probability parameter p to be estimated from the original network ⁴. By specifying the number of nodes, each edge is then constructed with probability p to produce networks with binomial degree distribution. To produce networks with a prescribed degree sequence, the configuration model may be used ⁵. This model works by initializing nodes with half-edges corresponding to the degree sequence. Two nodes are then chosen at random to connect their two half-edges until all half-edges are resolved. To maintain uniform sampling of nodes, half-edges may be connected to form self-loops and multi-edges. Self-loops and multi-edges may be removed to produce a simple graph, but the resulting degree sequence is no longer exact.

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A constrained alternative to the configuration model is the double-edge swap (DES) which modifies the original network by shuffling edge connectivity ⁶. This algorithm first selects two edges with distinct endpoints (i, j) and (u, v) . Node pairing is then swapped to generate two new edges (i, u) and (j, v) . The two old edges (i, j) and (u, v) are removed with new edges (i, u) and (j, v) inserted if both edges are not already present in the graph. If this criterion is invalid, a new edge pair is selected until the required number of swaps is achieved. Since node degree is preserved at each step, the DES preserves both degree sequence and node degree. An additional constraint is also typically enforced to ensure connectivity of the network is maintained in each swap. Similarly to McCullough et al. ¹, we can also impose additional criteria to maintain the constraints in agent and information system interactions for use on the CIN.

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Using this scheme on the unweighted CIN, we can interpret randomized surrogates as alternate CINs with

randomized communication channels. Considering the weighted CIN, surrogates can be generated by performing the DES and randomly reassigning edge weights. Surrogates are interpreted as networks with randomized communication channels and frequency of interactions. Ideally, the total interaction frequency of each node, represented by the node strength, should be preserved to maintain realism in CIN interpretation. However, attempts to preserve global node strength were unsuccessful and only local node strengths of specified nodes could be achieved. Therefore, we only looked at surrogate testing on the unweighted CIN.

Surrogate 1: The Double-Edge Swap

We used the surrogate testing to examine whether important agents in the CIN have favorable position due to their specific connectivity. We chose closeness to measure agent importance as it is robust to small perturbations in connectivity, making differences in closeness values indicative of major structural differences ⁷. Using 500 randomly generated networks, each with 2000 successful edge swaps, closeness values of the Mental Health Nurse, Consultant Psychiatrist, Psychiatric Registrar and AMHW are tested against the original CIN. Since the degree of each node is identical in the surrogate ensemble, the null hypothesis for this test stipulates that high closeness of the important nodes can be fully attributed to high degree. Figure 4 shows that all four agent nodes have lower closeness values than each surrogate on average and were thus nonsignificant at any level.

Therefore, the null hypothesis cannot be rejected.

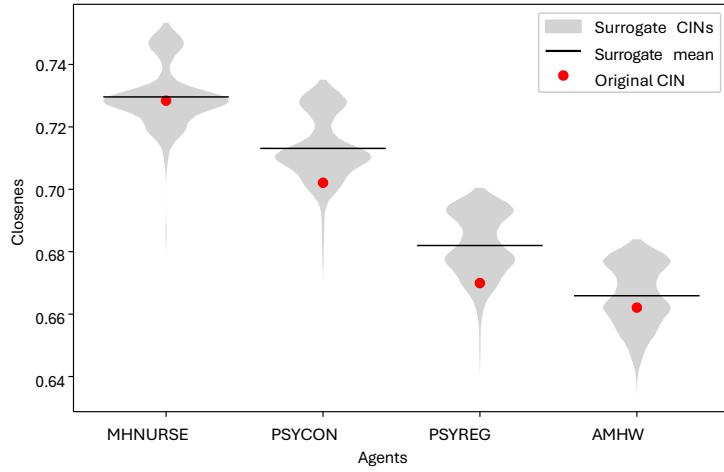


Figure 4: Violin plots of closeness centrality for key clinical agents. Violin plots show the distribution of closeness centrality from 500 surrogate Clinical Interaction Networks (CINs) generated using the connected Double-Edge Swap (DES) algorithm with 2000 successful swaps. Results are shown for the Mental Health Nurse (MHNURSE), Consultant Psychiatrist (PSYCON), Psychiatric Registrar (PSYREG), and Aboriginal Mental Health Worker (AMHW), who were identified as important agents in the original CIN. Horizontal markers indicate the mean of each surrogate distribution (black line), and the value for the original CIN is overlaid (red point). For all four agents, the original CIN values lie within the surrogate distributions and are consistently lower than the surrogate means, indicating that their observed closeness can be explained by degree alone under this null model. However, because the DES randomization disrupts the intrinsic separation between external agents and hospital staff - producing surrogate networks with more direct connectivity across these groups - the DES constitutes an imperfect surrogate model for the CIN.

While the surrogate networks have less structure than our original CIN, they are also subject to fewer restrictions on connectivity. Thus, surrogates will not exhibit the same dysconnectivity between external agents and hospital staff. Agents in the surrogate ensemble need not disperse information through the Patient node and may connect directly to hospital staff, reducing average path length and explaining the higher closeness. Hence, this surrogate test is flawed as the DES produces networks that are infeasible when considering limitations in how agents may interact. We thus required an alternate network randomization scheme that can preserve these structures.

Community Preserving Connected Double-Edge Swap

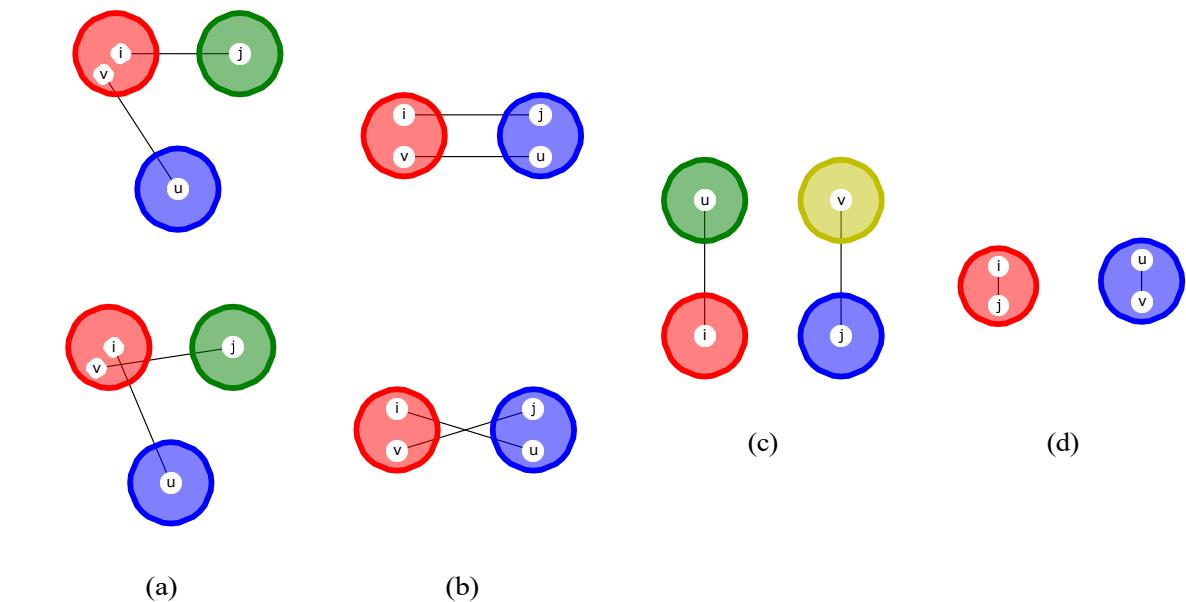
The DES could be modified with additional constraints to preserve the intrinsic separation between external agents and hospital staff. However, we aimed to develop a modified algorithm that can be applied to other networks more generally. Namely, we describe an algorithm that preserves the number of connections within and between node groups. While the groups found in the CIN were not communities, we call this algorithm the

269 community preserving double-edge swap (CP-DES) to highlight its potential use for networks with strong
 270 community structure.

271 Currently, there is an absence of graph randomization schemes that preserve global community structure. The
 272 most similar existing study proposed a method for generating community preserving attribute graphs to reflect
 273 online social networks. However, this study aimed to produce accurate depictions based on online social
 274 network data rather than a randomization scheme. Another study examined hypergraph randomization schemes
 275 that preserved local clustering structure, which is limited to preserving local connectivities rather than global
 276 community structures. These distinctions make the CP-DES algorithm, which uniquely focuses on both
 277 randomization and community preservation, the first of its kind.

278 Given a graph G with communities $\{C_n\}_{n=1}^{n=N}$ partitioning the vertex set, we define the block network B , which
 279 has nodes representing each community C_n with weighted edges between nodes representing the number of edges
 280 that span between communities.

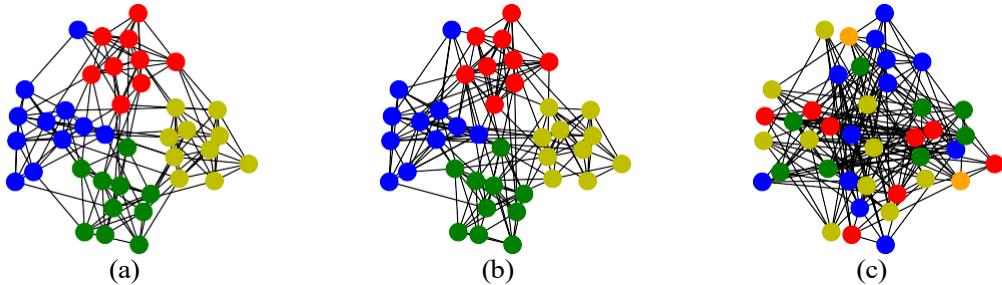
281 The algorithm similarly starts by selecting two edges from G given as (i, j) and (u, v) . Each node belongs to a
 282 community denoted as C_i, C_j, C_u and C_v . While we picked edge pairs to guarantee each node is distinct, we
 283 placed no restriction on the uniqueness of each community. The two selected edges are represented in the block
 284 network B as the edges (C_i, C_j) and (C_u, C_v) . We replaced the selected edge pair with a new edge pair (i, u) and
 285 (j, v) if the edge pair is not already present in the network. Additionally we ensured that connectivity between and
 286 within communities before and after the swap remains the same. Namely, the edges (C_i, C_j) and (C_u, C_v) must
 287 both be accounted for by the edges (C_i, C_u) and (C_j, C_v) . Figure 5 illustrates several examples of valid and invalid
 288 swaps with this community preserving criterion. Since community connectivity is preserved, graph connectivity
 289 is also preserved, so the additional connectivity constraint of the DES is absorbed into the community preserving
 290 criterion. If any of the two criteria is invalid, a new edge pair is selected until the prescribed number of edge swaps
 291 is reached. Since intra-community and inter-community edges are preserved at each step, the algorithm preserves
 292 the connectivity of the block network, thus preserving community structure.



300 **Figure 5: Illustration of community-preserving double-edge swaps.**

301 (a) Example with three distinct communities (denoted by differently colored node groups) where two edges are rewired
 302 in a way that maintains the original distribution of intra-community and inter-community edges. (b) Similar example
 303 with two communities, showing a valid swap that preserves the structural relationships between communities. (c)
 304 Example with four communities where selected edge pairs cannot be validly swapped without altering the community
 305 structure, resulting in an invalid configuration. (d) Example with two communities where a proposed swap is invalid
 306 because it changes the proportion of edges connecting nodes within versus between communities. Nodes are colored
 307 according to community membership, and solid lines represent edges before swapping, while dashed lines represent
 308 rewired edges. A swap is considered “valid” only if the rewiring does not change the number of edges within each
 309 community or between any pair of communities.

311 A synthetic network was generated with community structure to test the algorithm, as shown in Figure 6a. DES
 312 and CP-DES are then used to generate two randomized networks before using maximum modularity to detect
 313 communities. Figure 6b shows that CP-DES randomizes local connectivity while preserving community structure.
 314 Contrarily, Figure 6c shows DES destroys community structure with a low modularity value of $M = 0.25$.



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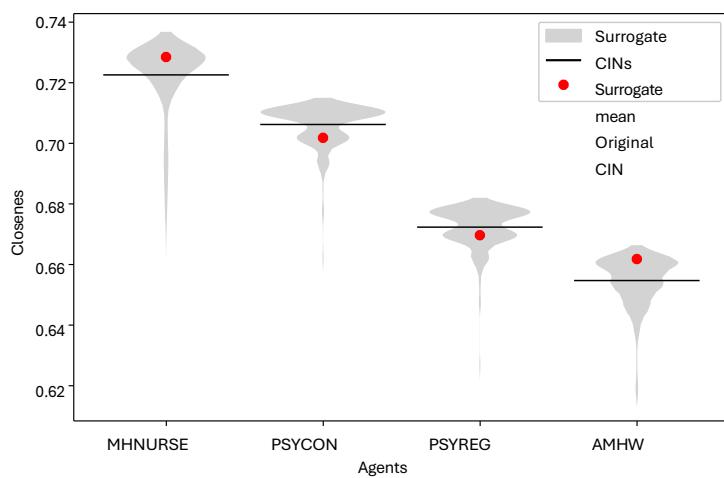
317 **Figure 6: Synthetic network randomization comparison.** (a) Synthetic network with four intrinsic
318 communities (modularity $M = 0.48$) used to illustrate the effect of different randomization schemes on
319 community structure. Node colors denote community membership; edges represent connections within and
320 between communities. (b) Example of the proposed Community Preserving Double-Edge Swap (CP-DES)
321 algorithm applied to the synthetic network with 1000 successful swaps ($M = 0.48$). The CP-DES randomizes
322 local connectivity while exactly preserving the number of intra- and inter-community edges, thereby
323 maintaining the original community structure. (c) Standard Double-Edge Swap (DES) applied to the same
324 network with 1000 successful swaps ($M = 0.25$). The DES preserves the degree sequence but not the between-
325 /within-community connectivity, leading to the destruction of global community structure and markedly reduced
326 modularity.

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328 **Surrogate 2: The Community Preserving Double-Edge Swap**

329 We partitioned the CIN into artificial communities. Namely, C1 contains external agents, excluding the Patient;
330 C2 contains the Patient, Mental Health Nurse, and Patient File; C3 contains hospital staff with a core number of
331 10; and C4 contains the remaining hospital staff with a core number less than 10. Using these communities, the
332 CP-DES generates 500 surrogate networks with 1000 successful edge swaps. These surrogates thus represent
333 randomized CINs that maintained feasible organizational and hierarchical structures but otherwise have
334 randomized connectivity. The original CIN is compared to the surrogate ensemble using the closeness centrality
335 of the most important hospital staff, as shown in Figure 7. The Consultant Psychiatrist and Registrar have
336 closeness values less than the surrogate networks (18th and 32nd percentile), whereas The Mental Health Nurse
337 has higher closeness (67th percentile). Therefore, as all three agents had non-significant closeness, we cannot
338 reject the null hypothesis that degree and community position can explain their high importance.
339 However, AMHW has closeness significantly higher than in the surrogate networks (top 99th percentile),
340 suggesting that their high closeness cannot be attributed solely to their degree and positions in their respective
341 communities. Therefore, we surmise that the unique connectivity of the AMHW is responsible for their high
342 closeness.

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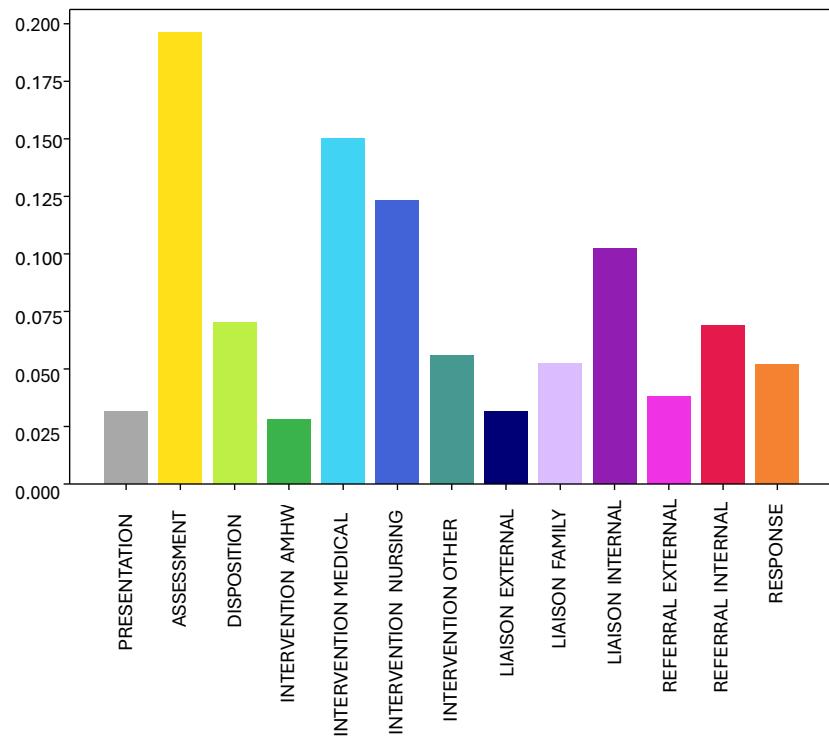
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373 **Figure 7: Distribution of closeness centrality for key clinical roles in the community-preserving double-
374 edge swap (CP-DES) surrogate networks.** Violin plots show the distribution of closeness values computed from
375 500 CP-DES surrogate networks (each generated by performing 1000 successful edge swaps while preserving
376 degree sequence and inter-community connectivity). Grey horizontal bars indicate the mean surrogate closeness
377 for each role; black horizontal lines show the observed closeness in the CIN. The Consultant Psychiatrist
378 (PSYCON) and Psychiatric Registrar (PSYREG) had closeness values at the 18th and 32nd surrogate percentiles,
379 respectively, and the Mental Health Nurse (MHNURSE) at the 67th percentile - none significantly different from
380 the CIN.

373 the surrogate ensemble. In contrast, the Aboriginal Mental Health Worker (AMHW) exceeded the 99th percentile,
374 indicating a level of centrality not explained by degree or community position alone. The AMHW's observed
375 value was a clear outlier relative to its surrogate distribution (cf. Fig. 4).

377 **Symbolic Sequence Construction and Analysis**

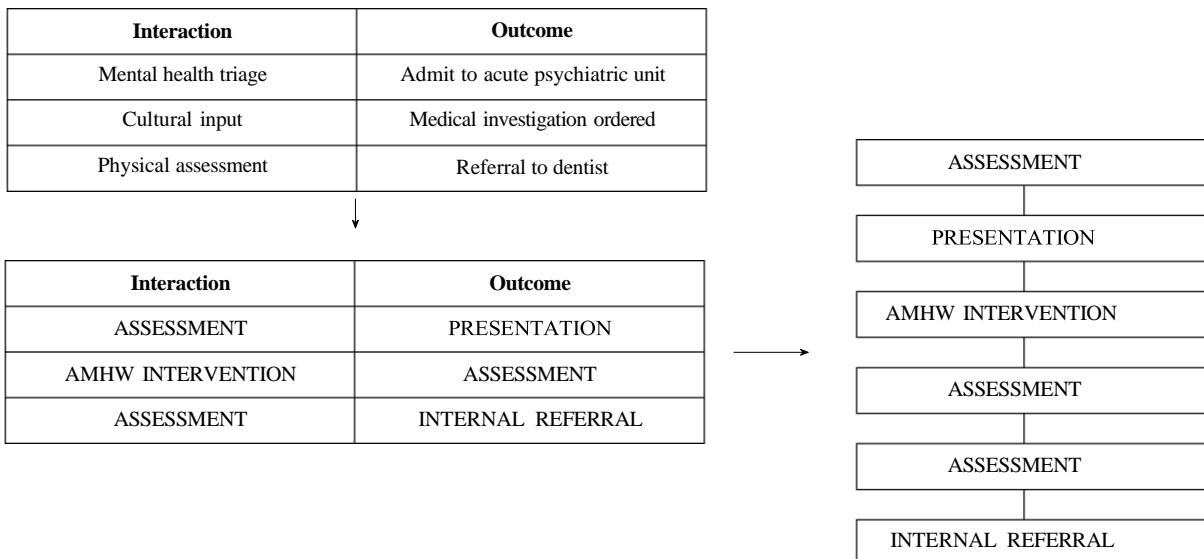
378 The most relevant entries to represent the clinical trajectories of each patient are the Interaction and Outcome
379 columns. These columns describe the actions initiating each event and the actions that arose after that. Actions
380 in both columns were coarse-grained into thirteen distinct symbols, as shown in Figure 8. We hereon refer to
381 these as action symbols. Events occur irregularly in time as clinical interactions do not occur at regular intervals
382 but rather only when clinical events occur. While trajectories may be modelled as irregularly sampled time
383 series, we disregard the varying time intervals between each symbol and model each trajectory as symbolic
384 sequences. Rather than examining global temporal patterns and timings between actions, we focus on local
385 temporal patterns in action symbol transitions. We hypothesize that the existence and non-existence of particular
386 action symbol transitions allow for the categorization of patient trajectories.



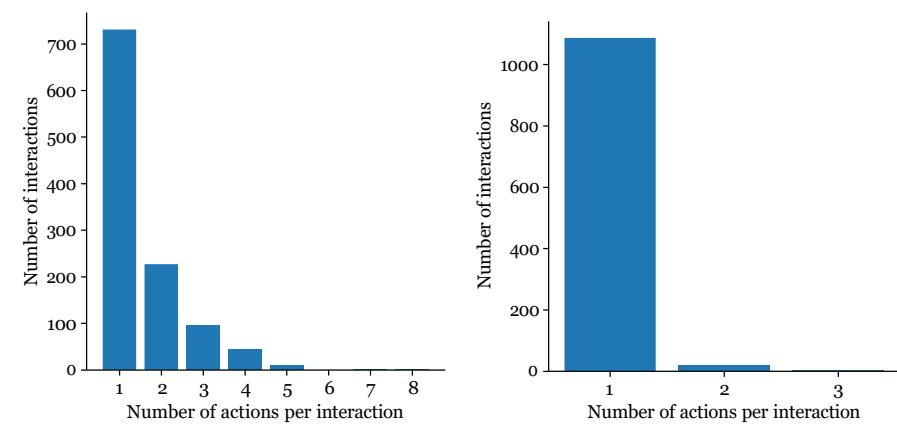
413 **Figure 8: Probability distribution of action symbols across all recorded clinical interactions.**

414 The histogram displays the overall relative frequencies of the 13 coarse-grained action categories derived from
415 the Interaction and Outcome fields in the event log for the 19 observed Aboriginal mental health patients at the
416 GSMHS. Action labels are presented on the x-axis (PRESENTATION, ASSESSMENT, DISPOSITION,
417 INTERVENTION AMHW, INTERVENTION MEDICAL, INTERVENTION NURSING, INTERVENTION
418 OTHER, LIAISON INTERNAL, LIAISON EXTERNAL, LIAISON FAMILY, REFERRAL INTERNAL,
419 REFERRAL EXTERNAL, RESPONSE), with bar heights indicating their relative frequency. This distribution
420 informed subsequent entropy and transition-matrix analyses.

421 Since data collection was transcribed chronologically, the two action columns were concatenated and flattened
422 to produce a single sequence of action symbols. Figure 9 demonstrates this process. In doing so, entries with
423 multiple interactions or multiple outcomes may lose causal information linking the two columns. For instance,
424 two inter- actions and two outcomes within a single event should all exhibit transitions for a total of four
425 transitions. However, our model only captures the single transition between the last interaction and the first
426 outcome recorded. Figure 10 shows that most events contain one interaction and one outcome, justifying the
427 small effect of this assumption.



446 **Figure 9: Symbolic sequence construction scheme.** Actions documented in the Interaction and Outcome
 447 columns of the clinical event log are course-grained into thirteen distinct action symbols (e.g., Assessment,
 448 Presentation, Nursing Intervention, Referral). The resulting symbols from both columns are concatenated
 449 chronologically and flattened into a single sequence to represent each patient's clinical trajectory. This
 450 transformation captures local temporal patterns in clinical pathways by encoding transitions between successive
 451 actions. While causal information linking multiple interactions and outcomes within a single event may be
 452 partially lost, this process provides a consistent framework for symbolic sequence analysis and subsequent
 453 construction of transition matrices across patients.



463 **Figure 10: Histograms of action count in the (a) interaction and (b) outcome columns.** Histograms
 464 summarizing the number of recorded actions per event log entry for the Interaction and Outcome columns in the
 465 GSMHS dataset. Each event instance was coded into one or more coarse-grained action symbols representing
 466 presentations, assessments, interventions, liaison, referrals, disposition, and response behaviors. The majority of
 467 events contained a single recorded action, reflected in the peak at one action per entry in both distributions. A
 468 smaller proportion of entries contained two actions with very few involving three or more. This indicates that
 469 most clinical interactions were documented as a simple one-to-one mapping between an initiating action and an
 470 outcome, supporting the simplifying assumption used in symbolic sequence construction (i.e., concatenating
 471 Interaction and Outcome into a single sequence). These distributions suggest minimal over-representation of
 472 transitions was introduced by the modelling approach.

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474 Due to the lack of global temporal information in our symbolic sequence, methods such as symbolic recurrence
 475 analysis and symbolic dynamic time warping are unavailable ^{9,10}. Instead, we looked at probabilistic and
 476 statistical methods to analyze our symbolic sequences. Information theory is frequently used to quantify the
 477 complexity and uncertainty within a time series ¹¹. By considering the probability distribution of symbols $p(x)$ as

478 a random variable X over the symbolic alphabet $x \in \mathcal{X}$, time series are represented by their associated probability
479 distributions. Regime changes and dynamics are encapsulated by changes in distribution characteristics. For instance,
480 the Shannon entropy, given by

$$481 \quad H(X) = - \sum_{x \in \mathcal{X}} p(x) \log(p(x)),$$

483 quantifies the potential information gained from a new observation of the random variable. Intuitively, probability
484 distributions have low entropy when probability distributions are heavily skewed towards a particular value, reducing
485 the uncertainty in observation. Contrarily, more uniformly dispersed distribution have higher entropy as each symbol
486 is equally likely to be observed. Variants of entropy are related to the Lyapunov exponent of dynamical systems,
487 indicating their ability to detect regime change ¹².

488 We utilized Ferriera and Zhao's community detection technique for its ability to create arbitrarily shaped
489 clusters ¹³. Ferriera and Zhao propose k -nearest neighbors and ϵ -nearest neighbors for network construction.
490 Both methods are shown to work accurately with ϵ -nearest neighbors performing marginally better. Thus, we
491 used ϵ -nearest neighbors to take only edges between nodes if their distance is less than the minimum threshold
492 ϵ . Greedy modularity maximization community detection is used to cluster nodes. Each symbolic sequence is
493 used to construct its probability distribution, with the entropy of each distribution displayed alongside a
494 visualization of the corresponding symbolic sequence in Figure 11.

495 Looking at the entropy values shown in Figure 11, one significant observation is the variation in predictability
496 across patients. For example, Patient 9 has a lower entropy, indicating a more predictable trajectory dominated
497 by a smaller subset of service actions. In contrast, Patients 1 and 18 exhibit higher entropy, reflecting a broader
498 and more diverse range of action symbols. Figure 11 reflects this observation as Patient 9 has lower entropy,
499 while Patients 1 and 18 have higher entropy. Generally, entropy correlates with symbolic sequence length for
500 sequences less than 100 symbols. This likely suggests that short sequences have low entropy due to their
501 inability to fully populate their probability distributions.

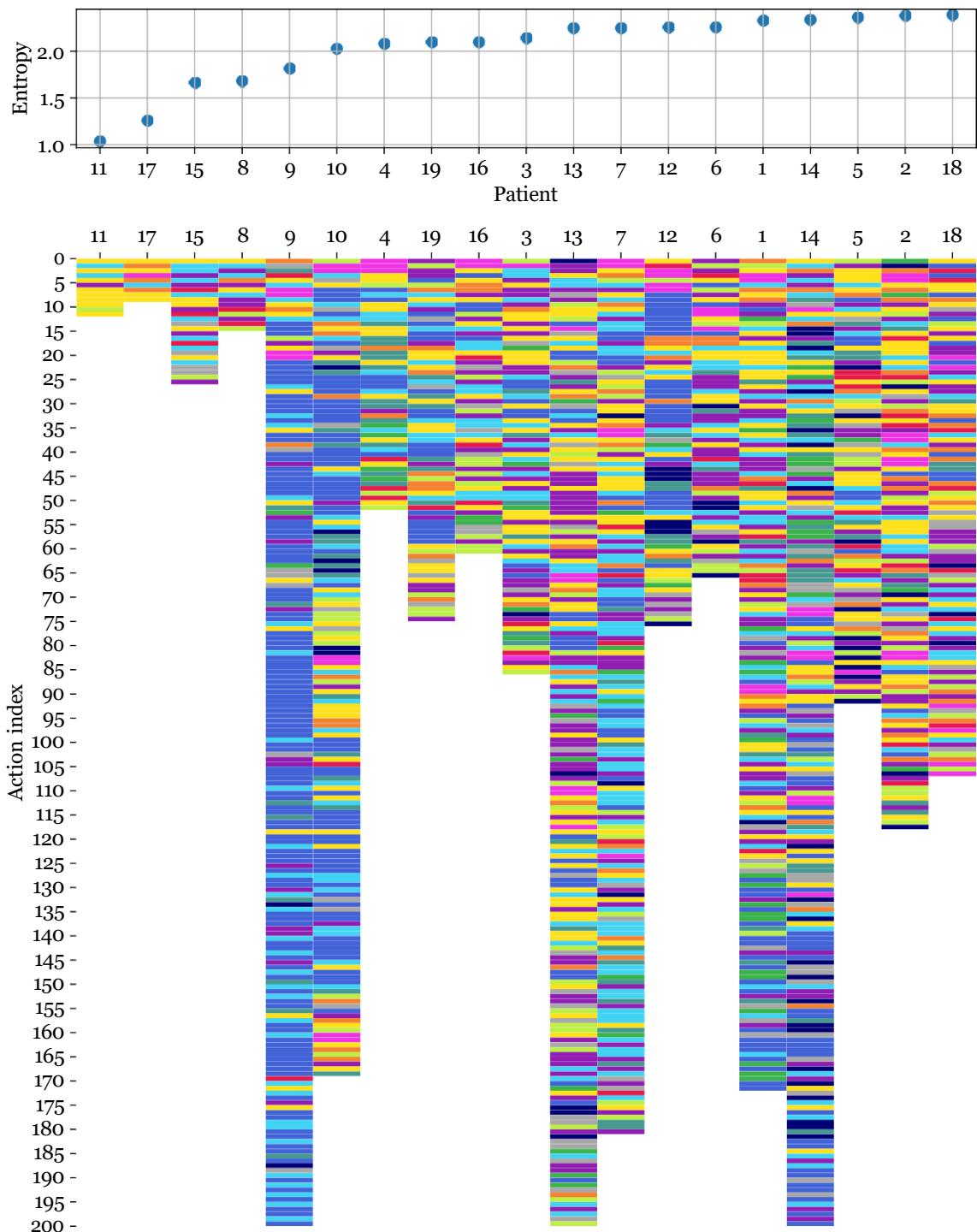
502 For the six trajectories with significant size, namely Patients 1, 7, 9, 10, 13 and 14, entropy indicates the
503 predictability of each distribution. Distributions with low entropy, such as Patient 9, are more predictable as they
504 require a smaller subset of service actions. Contrarily, distributions with high entropy, such as Patient 14,
505 require a broader, more holistic spectrum of action types. However, this notion of predictability does not
506 necessarily correlate with the actual predictability of a patient's trajectory. For instance, patients with more
507 uniform distributions may still have predictable trajectories if common cycles exist in their trajectory. This
508 limitation highlights the main issue in looking at probability distributions alone: temporal information is not
509 captured.

510 To address the absence of local temporal information, transition matrices are constructed for each patient using
511 the frequency of observed transitions. Namely, a transition matrix

512 $T_{n=1}^{n=19}$ has entries $T_{n=1}^{n=19}(i,j)$ corresponding to the proportion of transitions from action symbol

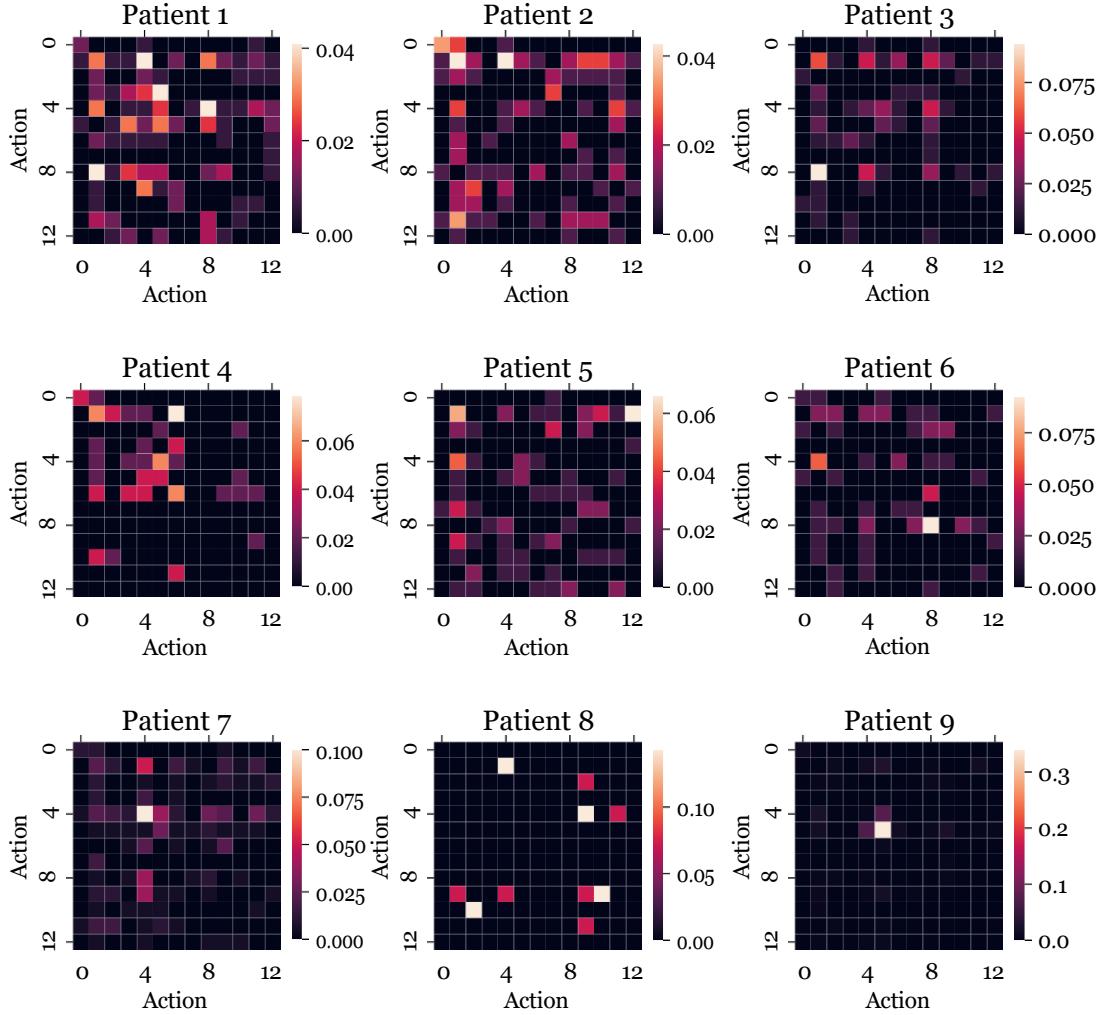
513 $i \rightarrow j$. Transition matrices for each patient are shown in Figures 12 and 13. Patients 9, 10, 12 and 19 all share a
514 characteristic transition along the main diagonal corresponding to Nursing Intervention \rightarrow Nursing Intervention.
515 The main diagonal transition exists due to the high proportion of Nursing Intervention, as frequently occurring
516 action symbols are more probable to transition to themselves. Patients 11 and 13 also exhibit this characteristic
517 transition along the main diagonal due to their high proportion of a singular action symbol. Across all
518 trajectories, only five transitions were unaccounted for, indicating that almost all transitions are possible and
519 present in this dataset. The Assessment \rightarrow Medical Intervention transition occurred in all patients except for
520 Patient 16. Similarly, Assessment \rightarrow Assessment and Medical Intervention \rightarrow Assessment occurred in all but
521 two patients.

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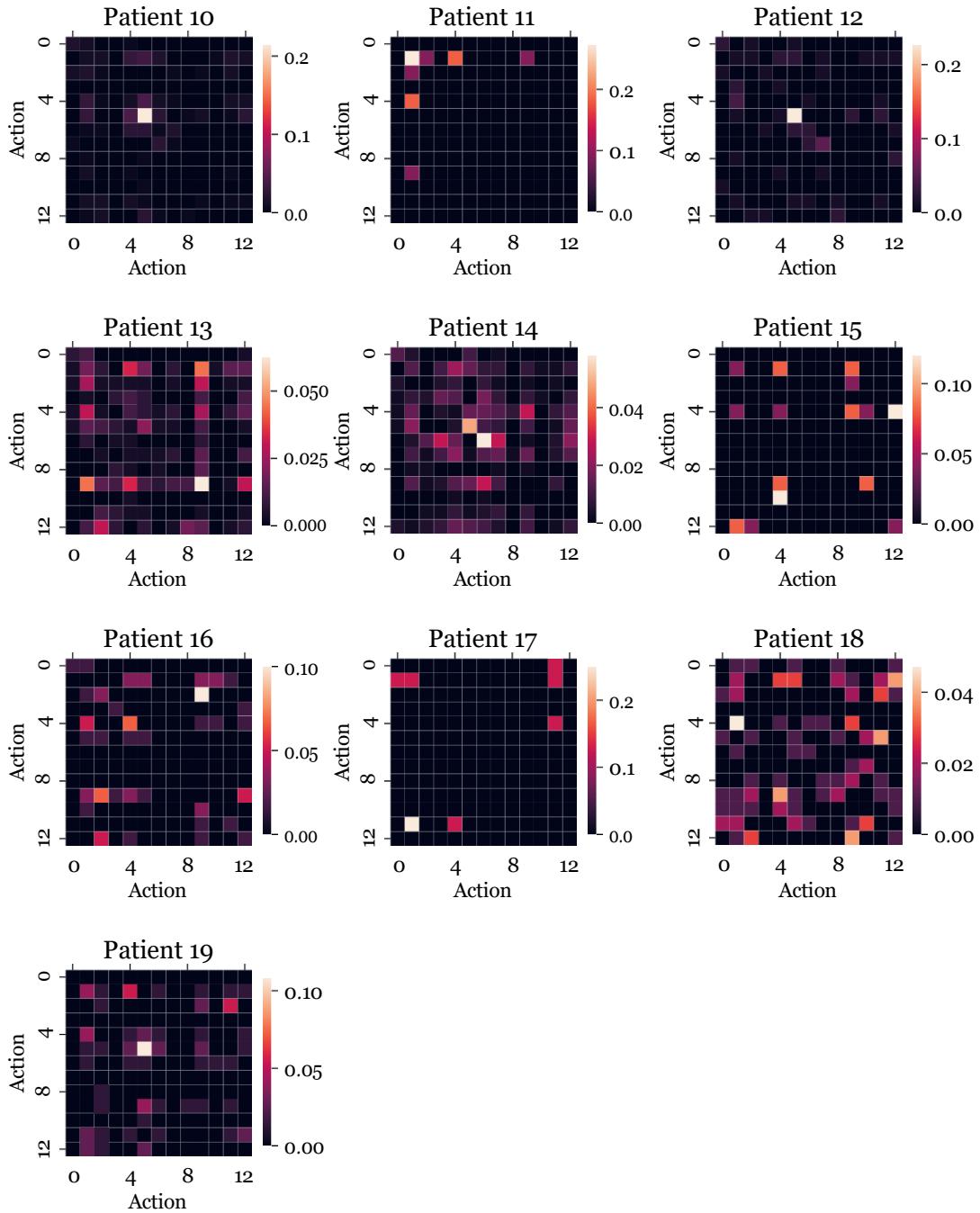
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Figure 11: Patient-specific entropy and symbolic sequence trajectories. (Top) Shannon entropy of action-symbol probability distributions calculated for each patient's symbolic sequence. Lower entropy values indicate highly skewed sequences dominated by a small number of actions, whereas higher entropy values correspond to more balanced distributions across action types. (Bottom) Visual representation of symbolic sequences for all 19 patients, where each vertical line denotes an event coded into its respective action symbol. Sequences are ordered from left to right by increasing entropy to illustrate the spectrum of predictability across patients, ranging from trajectories dominated by single action types (e.g., repeated nursing interventions) to those with diverse and complex patterns of care actions.



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Figure 12: Transition matrices of Patients 1 to 9. Each heatmap represents the patient-specific transition matrix $T(n)$, where entry $T_{i,j}$ corresponds to the relative frequency of transitions from action symbol i to action symbol j . Action symbols were derived by coarse-graining interaction and outcome data into thirteen categories (Presentation, Assessment, Disposition, Intervention - AMHW, Medical, Nursing, Other, Liaison - External, Family, Internal, Referral - External, Internal, and Response). Brighter intensities indicate higher transition probabilities. Patterns show considerable heterogeneity across patients. For example, Patient 9's trajectory is dominated by self-transitions along the Nursing Intervention diagonal, reflecting repeated nursing actions, whereas Patients 1 and 7 demonstrate more distributed transitions across assessment, intervention, and disposition categories. The presence and frequency of these local temporal action sequences provide a basis for clustering patients and identifying characteristic clinical pathways.

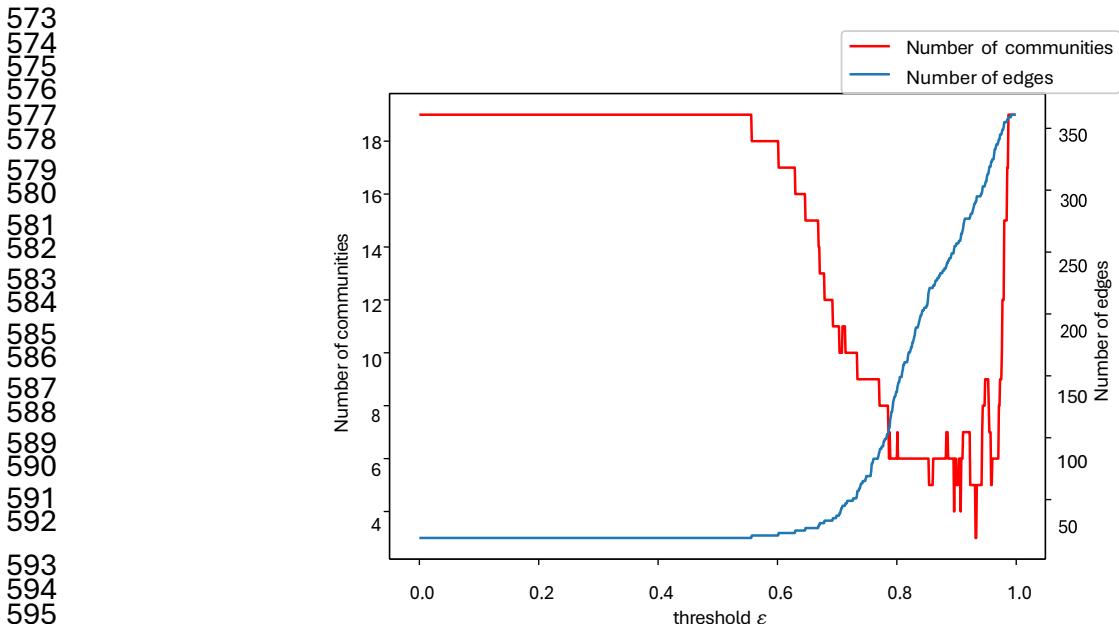


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Figure 13: Transition matrices of Patients 10 to 19. Patient-specific transition matrices $T(n)$ are shown, where entry $T_{i,j}$ represents the proportion of observed transitions from action symbol i to action symbol j . Action symbols (Presentation, Assessment, Disposition, Interventions - AMHW, Medical, Nursing, Other, Liaison - External, Family, Internal, Referrals - External, Internal, and Response) were derived by coarse-graining observed interaction and outcome events. Brighter intensities denote higher transition probabilities. Several patients, including Patients 10, 12 and 19, exhibit strong self-transitions along the Nursing Intervention diagonal, reflecting repeated cycles of nursing actions, while Patient 13 shows a similar concentration linked to a dominant action category. In contrast, patients with broader matrices (e.g., 14 and 18) demonstrate more diverse transitions across assessments, dispositions, and referrals, indicative of complex or cyclical care pathways.

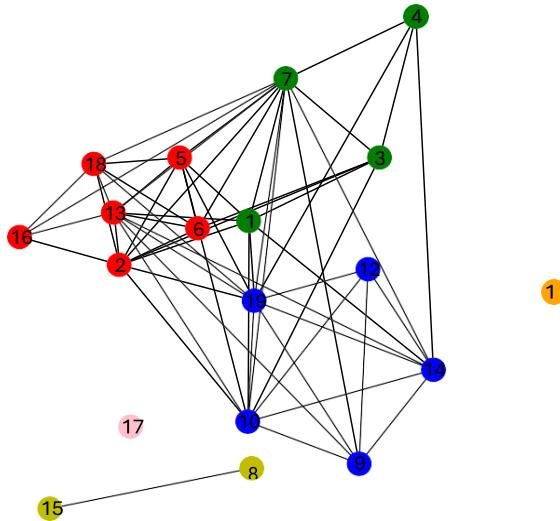
559 We construct A distance matrix D by taking pairwise Jaccard distances between transition matrices. Namely,
 560 $D_{n,m} = d_J(T(n), T(m))$ for $n, m = 1, 2, \dots, N = 19$. Choice of ϵ is made by varying ϵ between D_{\min} and
 561 D_{\max} . As ϵ is increased, the network becomes more densely connected until the network is complete and forms
 562 one whole community, thus maximizing modularity. Thus, we cannot choose ϵ to maximize modularity. Instead,
 563 we increase ϵ only until an appropriate number of communities can be distinguished. Further increasing ϵ will
 564 only increase the density of edges, allowing for less discrimination between unique topological connectivities.
 565 Figure 14 shows that at $\epsilon \approx 0.55$, increasing ϵ causes singleton nodes to start forming detectable communities. At
 566 $\epsilon \approx 0.8$, community detectability stops increasing rapidly. Thus, we choose $\epsilon = 0.8$ as our threshold. The
 567 resulting communities are shown in Figure 15.

568 Patients 8, 15, 11 and 17 correspond to the four symbolic sequences with least length. Therefore, it is no surprise
 569 that these four patients were grouped singularly or with one other node. As stated previously, the short symbolic
 570 sequences do not necessitate enough symbols for a fully populated transition matrix, making them further away
 571 from every other patient. For the remaining three clusters, we examine presentation to determine any
 572 correlation.



596 **Figure 14: Distance threshold (ϵ) against number of communities and number of edges.**

597 The figure shows the effect of varying the community detection threshold parameter ϵ on the connectivity and
 598 clustering of symbolic patient trajectories. The x-axis represents the distance threshold ϵ used in the ϵ -nearest
 599 neighbors construction, while the left y-axis (blue line) shows the number of detected communities and the right
 600 y-axis (orange line) shows the total number of edges in the constructed network. As ϵ increases from the minimum
 601 pairwise Jaccard distance between transition matrices (D_{\min}) to the maximum (D_{\max}), the number of
 602 communities decreases, and the network becomes progressively denser. At low ϵ , patients are isolated into many
 603 small or singleton communities due to sparse connectivity. Around $\epsilon \approx 0.55$, patients begin to aggregate into larger
 604 communities, and by $\epsilon \approx 0.8$ the number of new communities stabilizes while edges continue to accumulate. On
 605 this basis, $\epsilon = 0.8$ was selected as an appropriate threshold for community detection, as it maximizes cluster
 606 interpretability without collapsing the network into a single undifferentiated community.



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608 **Figure 15: Detected communities of symbolic sequences using ϵ -nearest neighbour clustering ($\epsilon = 0.8$).** Each
 609 node represents an individual Aboriginal patient's symbolic sequence, constructed from observed clinical
 610 interactions and outcomes. Pairwise distances between patients were computed using Jaccard similarity on their
 611 transition matrices, and a network was formed by linking patients whose distance fell below the ϵ threshold
 612 ($\epsilon = 0.8$). Community detection with modularity maximisation identified six clusters, visualised here by node
 613 colour. Patients within the blue, green, and red clusters demonstrate stronger internal similarity in their transition
 614 structures than between-cluster connections, suggesting shared patterns in disposition and referral transitions
 615 within these groups. Smaller singleton or two-patient clusters (green, pink, orange) typically correspond to
 616 patients with very short symbolic sequences, limiting the number of observable transitions. These patterns suggest
 617 that while overall separation between clusters was limited, patients within each group shared more closely aligned
 618 clinical trajectories and disposition behaviours than with patients in other clusters.
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621 Modes of presentation are identified from the Presentation column of the dataset and shown in Table 3. Of the
 622 three remaining clusters of size 2 or greater, only the blue cluster has highly associated presentation types, with 3
 623 of 5 presenting by themselves and 3 of 5 presenting with a police officer or ambulance. However, the red and
 624 green clusters contain a spectrum of presentations with no clear correlation. Thus, the clusters identified cannot
 625 be solely attributed to the presentation of each patient, and the presentation of a patient cannot be solely attributed
 to these clusters. We aim to quantify some of the structural features that are characteristic to these clusters.

Patient	Self	Associate	External Referral	Police and Ambulance
1	Self	AMHW, Family		Police
2	Self	AMHW	GSAHS	
3				Transport officer
4			RFDS	
5			GSMHS, PALM	
6	Self	Family		Ambulance, Police
7	Self	Family	GP	
8			GP, OCCP	
9	Self	Family	GP	Police
10	Self			Transport officer
11			GP	
12				Transport officer
13	Self,	AMHW, Family	GSAHS, GP TFMHS	Police
14	Self		TFMHS	Ambulance, Police
15			GP	
16	Self			Transport officer
17			GP	Ambulance
18				TFMHS
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859 **Table 3: Patient presentation modes.** Modes of presentation to the GSMHS for each participating Aboriginal

860 patient (N = 19). Presentations were classified into four main categories: (i) Self – the patient presented
 861 independently; (ii) Associate – the patient was accompanied by family members, friends, or Aboriginal Mental
 862 Health Workers; (iii) External Referral – the patient was referred or transferred from another health service (e.g.,
 863 GP, Great Southern Aboriginal Health Service (GSAHS), Royal Flying Doctor Service (RFDS), or other mental
 864 health services); and (iv) Police and Ambulance – the patient was brought in by emergency services. Several
 865 patients had multiple presentation pathways across different episodes, and categories are listed as reported in the
 866 event log data.

867 Abbreviations: GSAHS = Great Southern Aboriginal Health Service; RFDS = Royal Flying Doctor Service;
 868 GP = General Practitioner; OCCP = Occupational Physician; TFMHS = Transferred/referred from mental health
 869 service.

870 **Supplementary Tables**

Characteristic	Qualitative (n=7)	Quantitative (n=19)
Age, years (mean \pm SD)	44.0 \pm 17.8	38.4 \pm 15.9
Male, n (%)	3 (42.9)	9 (47.4)
Female, n (%)	4 (57.1)	10 (52.6)
Diagnosis, n (%)		
Psychotic Disorder	2 (33.3)	6 (31.6)
Mood Disorder	3 (42.9)	8 (42.1)
Anxiety Disorder	1 (14.3)	2 (10.5)
Organic Disorder	0 (0.0)	1 (5.3)
Personality Disorder	2 (28.6)	6 (31.6)
Psychosocial Problem	3 (42.9)	12 (63.1)
Alcohol and Drug Problem	3 (42.9)	11 (57.9)
Stress/Trauma Problem	3 (42.9)	5 (26.3)

866 **Table S1:** Demographic and clinical characteristics of study participants in quantitative (n=19) and qualitative
 867 (n=7) analyses. The figure displays distributions for mean age (\pm SD), gender (n and %), and primary psychiatric
 868 diagnoses (n and %). Participants may have multiple diagnoses; therefore, percentages within diagnosis categories
 869 may total more than 100%.

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Question	Answer (Yes/Partially/No/Unclear)
Did the research respond to a need or priority determined by the community?	Yes <ul style="list-style-type: none"> This research aims to contribute to improving mental health care for Aboriginal and Torres Strait Islander peoples, addressing a community priority identified through close consultation with Aboriginal community partners (Greater Southern Aboriginal Health Planning Forum and an Aboriginal Reference Group) and researchers. The need for culturally safe mental health care was re-affirmed through the co-design of our broader research program ¹⁴.
Was community consultation and engagement appropriately inclusive?	Yes <ul style="list-style-type: none"> This research was conducted in close collaboration with Aboriginal community partners and researchers, both before the commencement of the project and continuously throughout its implementation. An iterative co-design and consultation process was carried out with local Aboriginal organizations, including the Great Southern Aboriginal Health Planning Forum and an Aboriginal Reference Group.
Did the research have Aboriginal and Torres Strait Islander research leadership?	Yes <ul style="list-style-type: none"> This research is led by Aboriginal and Torres Strait Islander researchers, with an Aboriginal executive team and Aboriginal lead investigators.
Did the research have Aboriginal and Torres Strait Islander governance?	Yes <ul style="list-style-type: none"> This research ensured that Indigenous governance and decision-making were central to the management and interpretation of the data, guided by an Aboriginal-led research team and Aboriginal research partners, with oversight from an Aboriginal Reference Group.
Were local community protocols respected and followed?	Yes <ul style="list-style-type: none"> By following consultations with local Aboriginal organizations Interviews employed yarning as a method of data collection.

	<ul style="list-style-type: none"> Gender considerations were adhered to through the employment of a female and male worker who led the yarning. Interviewers received specialized training in culturally appropriate engagement and reflexivity. Non-Indigenous participants involved in the research benefited from mentoring and training, including the completion of the Dance of Life program by Professor Helen Milroy ¹⁵ and participation in the Social and Emotional Wellbeing Gathering. Recruitment of participants was conducted in close collaboration with the treating team and local AMHWs who additionally offered advice on communicating with potential participants in a way that aligned with cultural safety practices. Participants could choose their interview location, including the Great Southern Mental Health Service, the Rural Clinical School in Albany, or the Albany public library
Did the researchers negotiate agreements in regard to rights of access to Aboriginal and Torres Strait Islander peoples' existing intellectual and cultural property?	<p>Yes</p> <ul style="list-style-type: none"> Aboriginal people have ownership over the data, demonstrated through the Aboriginal leadership team.
Did the researchers negotiate agreements to protect Aboriginal and Torres Strait Islander peoples' ownership of intellectual and cultural property created through the research?	<p>Yes</p> <ul style="list-style-type: none"> This research was conducted within an Indigenous knowledge framework, empowering Aboriginal and Torres Strait Islander peoples to preserve, manage, safeguard, and advance the knowledge generated from this research.
Did Aboriginal and Torres Strait Islander peoples and communities have control over the collection and management of research materials?	<p>Yes</p> <ul style="list-style-type: none"> Through the Aboriginal Participatory Action Research (APAR) approach. Participants provided written informed consent and were aware of their right to withdraw at any time without consequences. The researchers implemented rigorous data security protocols to protect participants' identities and maintain confidentiality, with all data aggregated and de-identified. Findings were first shared with the Aboriginal research team and community partners for review and feedback prior to any external dissemination. A feedback loop was offered to participants, allowing them the opportunity to review and provide input on the interpretation of the data.
Was the research guided by an Indigenous research paradigm?	<p>Yes</p> <ul style="list-style-type: none"> This research employed APAR and integrated Aboriginal perspectives and values throughout the study.
Does the research take a strengths-based approach, acknowledging and moving beyond practices that have harmed Aboriginal and Torres Strait peoples in the past?	<p>Yes</p> <ul style="list-style-type: none"> The project aims to improve cultural safety in mental health services, by privileging the voices and knowledges held by Aboriginal peoples. Provisions were made for referrals to appropriate support agencies in case of participant distress during interviews.
Did the researchers plan and translate the findings into sustainable changes in policy and/or practice?	<p>Yes</p> <ul style="list-style-type: none"> The results from this project aim to inform a Cultural Safety Framework.
Did the research benefit the participants and Aboriginal and Torres Strait Islander communities?	<p>Yes</p> <ul style="list-style-type: none"> The results from this research aim to improve cultural safety of mental health services. It is possible that the local service will adopt recommendations based on the findings of this paper.
Did the research demonstrate capacity strengthening for Aboriginal and Torres Strait Islander individuals?	<p>Yes</p> <ul style="list-style-type: none"> Two Aboriginal people were employed to lead the yarning interviews and were invited as authors on this paper.
Did everyone involved in the research have opportunities to learn from each other?	<p>Yes</p> <ul style="list-style-type: none"> Continuous collaboration, consultation, and training between researchers and Aboriginal partners/community members facilitated opportunities for mutual two-way learning.

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Table S2. Quality Appraisal Tool for Aboriginal and Torres Strait Islander Studies: Evaluation of Our Study's Criteria Fulfillment

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Questions
• Can you tell me a little about how you were referred to the great southern mental health service? ○ Probe: who was the referral made by? ○ Follow up question: is this the first mental health service you have been referred to?
• Once you were referred, what sort of contact did you have with the service? ○ Probe: how frequent was the contact? ○ Probe: how did they contact you or your family? ○ Follow up question: what were your experiences of this initial contact?
• Have you been to an appointment yet? ○ probe: do you have plans to attend an appointment? ○ Follow up question: what are the reasons you have not attended an appointment?
• Is there anything that could be changed to help you attend an appointment?
• Who have been your main supports in your mental health care? (if they have been to an appointment)
• What were your feelings of going to speak with a psychologist/psychiatrist?
• What have your experiences been like with the staff at the hospital?
• Do you feel this service understands your culture? ○ Probe: what does the service do or not do to show you this? ○ Probe: have you had access to an Aboriginal mental health worker?
• Is there anything you would like to see improved about the service?
• Do you feel mental health services understand Aboriginal people and their culture? ○ Probe: can you give me an example? ○ Probe: can you describe what happened?
• How would you like culture to be recognised through mental health services? ○ Probe: what do services do well for cultural safety ○ probe: what do services do badly?
• What are some of the cultural principles that services need to be respectful of? ○ (question for family members and carers): Are there additional cultural considerations for families and carers in mental health services?
• How can mental health services build cultural safety? ○ Prompt: things that promote, enhance and empower consumer and clinicians' culture

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The Central Role of Culture in Mental Health and Wellbeing

- *'And my history, what people don't understand is that as Aboriginal people, we've got spiritual, cultural and then there's mental health. I've been through the three of them. Spiritual is my everyday life. Cultural is my everyday life because I'm Aboriginal. Mental health is affected when people don't believe me that what I'm going through is cultural or spiritual.'* (P16, female)
- *'I believe it's my journey that I've asked my ancestors to take me on to heal. And it was a disrespect to my ancestors for doing it in the first place. And like as blackfellas we never had tobacco, drink, drugs, whatever. But then we didn't have all this other society stuff either, too. And that's not saying that – we just got to get back to basics where we feel really good. And back out on country, doing things on country, yeah.'* (P7, female)
- *'I had a mental breakdown, and I was scared about opening up to the doctors and stuff down here [in Albany] because I've had a bad experience. They listened to everything that I had to say. They didn't judge me. They didn't say to me... They didn't say that my feelings weren't valid. They didn't say to me that anything that I've told them weren't valid. They listened to me. They didn't judge me because down here, they have more of understanding of Aboriginal people than Perth. That's what it comes down to.'* (P16, female) *'There needs to be more Aboriginal people working in mental health. You need to be direct about how Aboriginal people don't give eye contact. [...] And if you don't give eye contact, it doesn't mean that it's bad body language. They need to have cultural awareness. If there's no Aboriginal workers, there needs to be cultural awareness that we find eye contact intimidating.'* (P16, female)
- *'And I don't believe that there should be women and men in the same ward. There should be a woman's section and a man's section.*

[Interviewer] [...] So you're saying not mixed? [...]

No, not mixed, because we go to sleep in the same corridor as well as men's. That's against our culture. (P2, female)

- *'I know there's one thing that I don't like there, is sometimes when they come and check on you during the night, they look through that little hole and they point the torch at you. Now, they point that torch straight in your eyes. And we know as blackfellas, what can happen too this*

light comes straight in your eyes, wakes you up, and the spirit comes through, right. So that happening is really quite disturbing. Not only does it wake you up, but the belief and the cultural stuff that we know, that happens.' (P7, female)

- *'Because blackfella way, maybe sometimes we're not meant to talk about our private lives. We don't say what's going on at home because a lot of time blackfellas be like, "Now don't go telling these wadjellas [Noongar word for whitefellas] what we're talking about. You don't tell no one our business.' (P16, female)*

'The kinship stuff'

- *'And I said, "Well, actually yes, because yeah, I'd like to be able to talk about some deeper stuff here that I really can't talk with people who aren't getting it." [...] Yeah, because there's a whole thing there about, yeah, our Indigenous families that... some people just don't get. Like the size of them and how many funerals we have to go to.' (P14, female)*
- *'Yeah, I think I had a little thing when I was about in my 20s when my Nan passed, it was only short [...] then all the way up to 2020 when I started taking the tablets that I'm on now because I, it kind of hit me pretty hard but it was the fallout plus the anxiety and just everything that I suppose or going way back to when I was a young fellow because that's where I did my mental health. I suppose with counselling and stuff has worked all that stuff out that it was triggers from way back when I was a kid that carried all the way through.' (P8, male)*
- *'But it's not good at the moment because my kids aren't with me at this time. DCP have taken my baby and it's a 12-month order. So now I don't have any of my kids with me and I'm just an emotional wreck.' (P16, female)*
- *'He doesn't have nothing to do with it. He does not condone us on drugs. So, I'm going to fix myself before I get acknowledged by my father.' (P2, female)*
- *'I knew something had to change in my life. I knew I had to do something. I've only just started having these psychotic episodes. And I didn't fight my whole life to have my beautiful girls and to get a house and everything, from everything that I've been through, to end up a vegetable. I didn't. And I won't. And [...] knowing that my children were going to be looked after by my aunty, who they respect, and who is a lovely lady, that made all the difference for me to be able to sit in here [inpatient at mental health] and relax – or not relax, but sit in here and spend time and get things moving to make it all better, for me to get better, sorry.' (P7, female)*
- *'And if I do talk about some of the trauma, and they start saying things like, "Cut off your family," and I'm like, "all right, there are some cultural problems here, we can't talk anymore. Thank you anyway." Because that's a different mentality. Granted a valid option, not one I have chosen, and it is a cultural thing because my family, we have this... you know, there's reasons why we're all like we are, there's a reason why things happened as they happened. [...] All stemming from the research of colonisation, right? [...] So, cutting them off is not something I want to do. Boundaries, good, moving to a different town, also good.' (P14, female)*

Trauma and stress

- *'And the only way I was engaged to mental health is because my parents brought me in when I first had a nervous breakdown, when my child was moved out of my care and after the tragedy, death of my [family member] being [killed] down here.' (P2, female)*
- *'I knew I was struggling but also too there was just the signs were popping up like oh I suppose not suicidal thoughts but just thoughts of had enough and just wanted to, didn't want to harm myself but just couldn't kind of cope there' (P8, male)*
- *'[...] if I was brought here in an ambulance, or the back of a police truck or whatever, if that AMHW was there straightaway, then I would feel safer. Because at the end of the day, I mean, ambulances have beautiful people, but at the end of the day, policemen frighten me. What they will produce, or how they were formed to eradicate half castes¹, right from the word go, is not nice. If you come into the back of the thing, if AMHWs were right there, then it feels safer. They would be able to calm us a bit more, have more of an understanding of what's been going on with us.' (P7, female)*

¹The term *half-caste* was historically used in Australia to describe individuals of mixed Aboriginal and non-Indigenous heritage. is now accepted as an offensive term.

'Because the spaces that we want don't exist yet. This place where you can come and just go, "I don't have to explain my whole culture to you. I don't have to explain anything.'" (P14, female)

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Box S1: Participant quotes illustrating key themes from qualitative interviews Selected participant quotations are presented, exemplifying key themes from qualitative interviews exploring Aboriginal peoples' experiences accessing the GSMHS in Kinjarling (Albany). Participant identifiers are provided to ensure authenticity while maintaining anonymity.

Characteristics	Proposed Strategies for Implementation	
	Community Mental Health Service	Inpatient Unit
People who listen, understand and do not judge	More AMHWs and involvement as early on as possible. Ongoing cultural training for all staff aiming to deepen understanding and appreciation of Aboriginal ways of life moving beyond cultural 'awareness and knowledge' to 'acknowledgement' of Aboriginal experiences. Working together with non-Aboriginal champions within the service.	Developing culturally safe self-referral protocols. Involvement of AMHWs during ED presentations. Cultural training for all ED staff. Training on trauma-informed care for all ED staff on the impact of Police involvement in involuntary admissions. On-going cultural training for all ward staff aiming to deepen understanding and appreciation of Aboriginal ways of life moving beyond cultural 'awareness and knowledge' to 'acknowledgement' of Aboriginal experiences. Working together with non-Aboriginal champions within the service.
Trauma-informed care		
Culturally-safe environment	Calm waiting room area allowing patients to have their own personal space.	Separate gender wards. Cultural activities including cooking (e.g. damper) and Aboriginal art. Promote healing by facilitating connection to the land, outside the boundaries of the hospital (e.g. walks to the beach, activities on Country)

916 **Table S4: Characteristics of Culturally Safe Mental Health Services and Proposed**
917 **Strategies for Implementation in a Community Mental Health Service and Inpatient Unit**
918 Aboriginal Mental Health Workers (AMHWs); Emergency Department (ED).

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924 Supplementary Figures

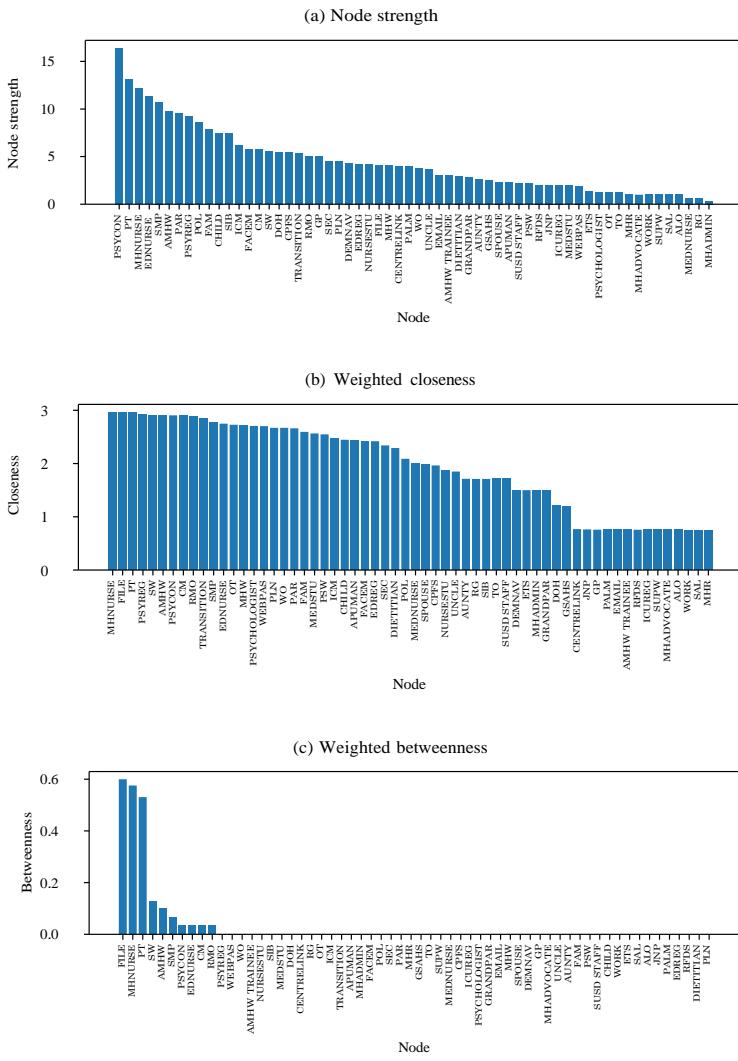


Figure S1: Weighted centrality measures of the Clinical Interaction Network.

Three metrics are shown for each node: (a) node strength, reflecting cumulative interaction frequency; (b) weighted closeness centrality, representing the inverse of average shortest path distances weighted by interaction frequency; and (c) weighted betweenness centrality, indicating the degree to which a node lies on the shortest weighted paths between other nodes. Key nodes such as the Mental Health Nurse, Patient File, and Aboriginal Mental Health Worker (AMHW) display high centrality across these metrics, highlighting their pivotal roles in care coordination and information flow within Aboriginal psychiatric service delivery at GSMHS.

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974

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