Deriving and Presenting Insights from Experience Sampling Method (ESM) Data Through Network Visualization

Adam Gajdos[1]

Supervisor(s): Dr. Willem-Paul Brinkman[1]**, Esra de Groot**[1]

[1]**EEMCS, Delft University of Technology, The Netherlands**

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Name of the student: Adam Gajdos
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Thesis committee: Dr. Willem-Paul Brinkman, Esra de Groot, Prof.dr.ir. Inald Lagendijk

Abstract

Experience Sampling Method (ESM) has emerged as a technique for capturing real-time mental health data in natural environments, offering advantages over traditional retrospective assessments by reducing recall bias and providing contextual understanding of emotional patterns. Despite its benefits, ESM remains underutilized due to limited tools for transforming complex datasets into interpretable insights for clinicians and patients. This study developed and evaluated a network graph visualization to represent behavior-emotion relationships from ESM data. Six mental health practitioners evaluated the system through structured surveys assessing usability, clinical relevance, and interpretive capability. Participants rated visualization intuitiveness at 3.8/7 and visual design at 3.2/5. Comparative evaluations were mixed, with participants rating the approach as better (n=2), equivalent (n=2), worse (n=1), or much worse (n=1) than traditional methods. Despite usability challenges related to visual complexity and dynamic node movement, participants successfully extracted clinically relevant behavior-emotion patterns. Color coding was the most effective design element, while interactive filtering functionality was crucial for pattern recognition. Network visualization shows potential for making ESM data more accessible to mental health practitioners, though design refinements addressing visual complexity and temporal dynamics integration are needed to improve clinical utility.

1 Introduction

Mental health monitoring and intervention have traditionally relied on retrospective assessments conducted in clinical settings, often weeks or months apart. This approach suffers from limitations, including recall bias, lack of contextual information, and inability to capture the dynamic nature of psychological states as they unfold in daily life [5]. Experience Sampling Method (ESM) - a technique for collecting real-time psychological data through repeated brief surveys in natural environments - represents an approach to mental health data collection that addresses these limitations by capturing experiences and symptoms in real-time within participants' natural environments [5; 20].

Central to effective mental health intervention is understanding the complex relationships between daily behaviors, environmental situations, and emotional responses. Traditional clinical assessments often capture these elements in isolation, missing the critical interconnections that drive psychological well-being [15]. For instance, a patient might report experiencing anxiety without clinicians understanding which specific behaviors (such as poor sleep or social isolation) or situations (such as work stress or family conflicts) consistently precede or co-occur with anxious states. This relational understanding is crucial for developing targeted interventions - helping clinicians identify behavioral patterns that could be modified and enabling patients to recognize situational triggers they can learn to manage. ESM's strength lies not just in its real-time data collection, but in its ability to capture these behavior-emotion and situation-emotion relationships as they naturally unfold in daily life.

The importance of ESM extends beyond mere data collection improvements. Studies have consistently demonstrated that ESM enables real-time symptom monitoring, reduces recall bias [5; 20], provides rich contextual understanding of how environmental factors influence mental health [4], and facilitates early detection of relapse symptoms [5]. Importantly, ESM enables the identification of behavior-emotion and situation-emotion relationships that might be beneficial for effective mental health care. Studies indicate that patients using ESM tools report substantial improvements in self-awareness, self-insight, and self-management capabilities [19; 20], specifically through developing better understanding of how their daily activities and environmental contexts connect to their psychological well-being [8; 4]. This relational insight is expected to empower both clinicians and patients: clinicians could potentially design more targeted interventions based on identified behavioral triggers and emotional patterns, while patients could develop the self-awareness needed to recognize and modify problematic behavior-emotion cycles in their daily lives.

Despite these benefits, a critical implementation gap persists between the promise of ESM and practical adoption in clinical practice [3; 22; 1]. Current research reveals several barriers to widespread ESM utilization. Mental health professionals face time constraints that prevent thorough analysis of rich ESM datasets during clinical sessions [3; 22]. Existing visualization tools, while technically sophisticated, present accessibility challenges. For instance, ESMvis [6] provides comprehensive ESM data visualization capabilities but requires R programming knowledge, which would likely make the tool inaccessible to most clinicians and end-users who typically lack programming expertise. Similarly, recent analyses of popular mental health applications reveal a gap between data collection capabilities and meaningful insight generation [1]. Current approaches focus predominantly on displaying raw data through basic timeline visualizations and scatter plots, rather than identifying and presenting actionable insights about behavior-emotion relationships [22; 12]. This limitation is particularly problematic because the therapeutic value of ESM lies precisely in revealing these relational patterns - understanding which behaviors consistently precede negative emotions, which situations trigger specific emotional responses, and which positive activities reliably improve mood states. Without tools that can effectively visualize and communicate these relationships, clinicians cannot leverage ESM data for treatment planning, and patients miss opportunities for developing self-management strategies based on their personal behavior-emotion patterns.

The literature identifies several critical unanswered questions in ESM implementation. Although recent work has explored personalized feedback mechanisms [9; 12], limited understanding remains regarding how to effectively visualize complex temporal and contextual relationships within ESM data for non-technical users. Furthermore, despite the recognition of the need for user-friendly analysis tools [23; 3], there is not enough research to design intuitive visualization methods that can present meaningful patterns in behavior-emotion relationships to both clinicians and patients.

Given the importance of behavior-emotion and situation-emotion relationships for mental health intervention, and the current gap in visualization tools that can effectively reveal these patterns, there is a need for approaches that can transform complex ESM datasets into insights about these relationships. Such tools would enable clinicians to quickly identify intervention targets and help patients develop awareness of their personal psychological patterns.

This research addresses the following question: *How can meaningful insights be derived and presented from ESM data to reveal relationships between behaviors/situations and emotions/feelings?* Specifically, the investigation focuses on how to design intuitive visualizations that make complex ESM data patterns accessible to mental health clinicians and patients without specialized analytical expertise, while ensuring clinical relevance and actionability of the derived insights.

The main contributions include: (1) the development of a network graph visualization system designed to intuitively represent behavior-emotion relationships from ESM data, (2) evaluation of whether this approach can improve accessibility and interpretability compared to existing approaches through structured usability assessments with mental health practitioners using comparative analysis between the network visualization and traditional data tables/charts, measuring both quantitative usability metrics and qualitative insights regarding clinical utility, and (3) exploratory design insights for ESM data visualization in mental health applications, based on initial practitioner feedback. Through user-centered design principles and evaluation with mental health practitioners, the study demonstrates that complex ESM data can be transformed into actionable insights accessible to both clinicians and end-users.

The remainder of this paper is structured as follows. Section 2 presents the related work done regarding visualizing ESM data and applying network graphs to various health domains. Section 3 presents the methodology for developing and evaluating the visualization system. It also describes the network graph visualization approach and implementation. Section 4 presents evaluation results regarding usability and clinical relevance. Section 5 concludes with directions for future work in ESM data visualization. Section 6 showcases the responsible approach taken during the research.

2 Related Work

2.1 Network Visualizations in Mental Health Context

Traditional approaches to mental health data analysis often examine symptoms and behaviors in isolation, limiting understanding of the complex interconnected dynamics that characterize psychological well-being [2]. Network theory offers a perspective by conceptualizing mental health phenomena as dynamically interconnected systems where symptoms, behaviors, and environmental factors influence each other through complex pathways [2].

The application of network visualizations to mental health data has demonstrated potential for revealing patterns that remain hidden in traditional statistical analyses [7; 14]. These approaches enable identification of central nodes - variables with disproportionate influence on the overall system - and critical pathways that may represent intervention targets [10]. However, existing tools like ESMvis [6], while technically sophisticated, primarily focus on temporal trends of individual variables rather than the relational structures that are for clinical understanding and intervention planning.

This represents a potential opportunity in ESM research, where the rich data collected includes multiple aspects of experience that could potentially benefit from network-based analysis. ESM data is collected frequently over time and captures many different dimensions, suggesting it could be well-suited for network visualizations that aim to show how behaviors and emotions relate to each other, how context influences people, and where interventions might be most effective - insights that standard charts and graphs cannot reveal as clearly.

2.2 Visualization Design Principles for Clinical Data

The development of effective ESM data visualization requires consideration of the tension between data complexity and interpretive clarity. Key principles for balancing analytical depth with intuitive understanding have been established in clinical data visualization, particularly when targeting non-technical users such as mental health practitioners.

Visual encoding strategies - the methods used to translate data into visual elements such as colors, shapes, sizes, and positions - for clinical data must account for the cognitive load imposed on practitioners who may lack specialized data analysis training. Research in medical informatics has demonstrated the importance of consistent visual metaphors, clear hierarchical organization, and interactive features that support both overview and detail-on-demand exploration patterns [21; 11].

3 Methodology

3.1 Research Approach

This research employs a user-centered design methodology [17; 13] to address the gap between sophisticated ESM data collection and practical clinical implementation. The approach integrates iterative design principles with domain expert collaboration to ensure that visualization solutions align with the real-world needs of mental health practitioners and the clinical realities of ESM data interpretation.

The methodology unfolds through three interconnected phases, each building upon insights from the previous stage. The initial phase involves analysis of ESM data structures and patterns, examining how temporal, emotional, behavioral, and contextual dimensions interact within real-world datasets. This understanding is complemented by a literature review of existing ESM visualization approaches and mental health informatics research, identifying limitations and opportunities for innovation.

The second phase centers on the iterative design and development of a network graph visualization system. This phase prioritizes the translation of complex relational patterns into accessible visual representations that effectively communicate behavior-emotion connections without requiring specialized analytical expertise. The design process emphasizes clinical utility, incorporating interactive elements such as dynamic filtering and contextual highlighting to support exploratory analysis and clinical interpretation.

The final phase involves evaluation with mental health practitioners through structured usability assessments and clinical relevance evaluations. This evaluation framework captures both quantitative usability metrics and qualitative insights regarding the tool's potential for enhancing clinical practice and patient care. The feedback ensures that the final visualization approach addresses identified barriers to ESM adoption while maintaining scientific accuracy and clinical applicability.

3.2 Identified Concerns and Challenges in ESM Data Visualization

Through semi-structured interviews with 3 mental health practitioners and analysis of existing ESM visualization tools, several design requirements were identified for ESM data visualization in mental health contexts:

Accessibility Requirements: The visualization must be interpretable by mental health practitioners without specialized data analysis training or programming knowledge. This requirement directly addresses the limitations identified in existing tools like ESMvis [6], which require R programming expertise and thus remain inaccessible to most clinicians.

Relational Emphasis: Unlike traditional ESM visualization approaches that focus on temporal trends of individual variables, the system must prioritize the visualization of relationships between behaviors, situations, and emotions. This requirement emerges from the clinical need to understand behavior-emotion patterns for effective intervention planning [4].

Clinical Utility: The visualization must present actionable insights that directly support clinical decision-making and patient self-awareness development. This includes the ability to quickly identify intervention targets, behavioral triggers, and emotional patterns that can inform treatment planning.

Cognitive Load Management: The interface must balance comprehensive data representation with cognitive accessibility, avoiding information overload while maintaining analytical depth. This requirement is informed by principles from medical informatics research on clinical decision support systems.

Workflow Integration: The tool must support both exploratory analysis and focused investigation, accommodating different analytical needs and expertise levels among potential users in clinical settings.

3.3 Network Graph Visualization Development

This section describes the development of the network graph visualization system designed to transform complex ESM datasets into visual representations that reveal behavior-emotion relationships without requiring specialized analytical skills.

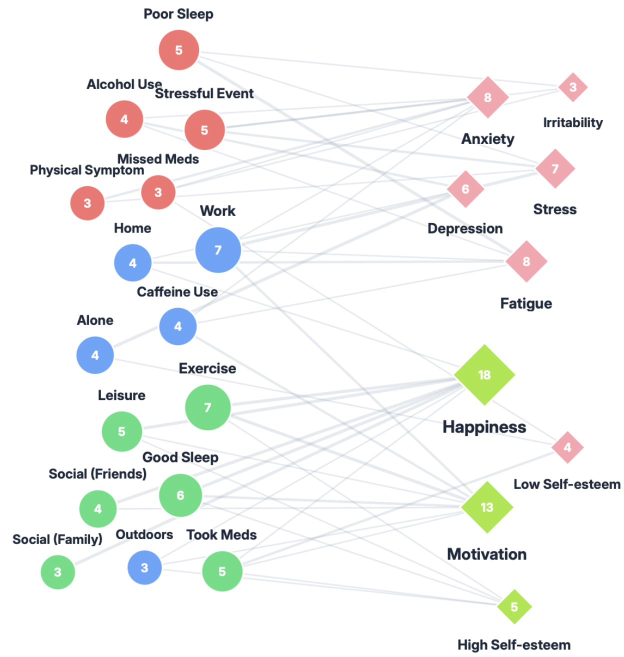

Figure 1: The directed network graph displays relationships between behaviours/contexts and emotional states extracted from ESM data. Nodes represent either behaviours (circles) or emotions (diamonds), while edges indicate correlations between them.

Visualization Design Framework

The visualization framework employs distinct visual cues to represent different data elements based on the design requirements identified above. The system represents ESM data as a network where behaviors and emotions appear as connected nodes, with behaviors shown as circles positioned on the left side of the visualization and emotions appearing as diamonds on the right side (Figure 1). This spatial separation is designed to provide visual clarity about the different types of variables while maintaining their relational connections.

The categorization system uses color coding to convey affective valence: positive behaviors (Exercise, Social interactions, Leisure) appear in green, negative behaviors (Poor Sleep, Alcohol Use, Stressful Event) appear in red, and neutral behaviors (Work, Home, Caffeine Use) appear in blue. Emotions follow a similar categorization, with positive emotions (Happiness, Motivation) displayed in light green and negative emotions (Anxiety, Depression, Stress) in pink. This color scheme is designed to enable rapid pattern recognition and support intuitive understanding of the data's emotional landscape.

Node sizing reflects frequency patterns within the dataset, with larger nodes indicating behaviors or emotions that occur more frequently. This encoding is intended to allow users to quickly identify prominent patterns and the most significant elements within their ESM data. Edge representation utilizes thickness to indicate relationship strength, with thicker connections representing more frequent co-occurrences between behaviors and emotions, enabling users to immediately identify the strongest behavior-emotion associations.

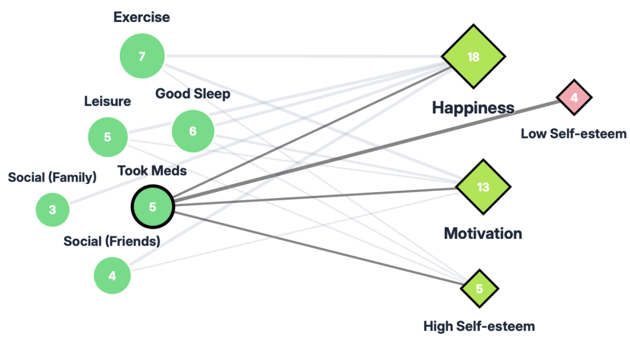

Figure 2: Filtered view, reducing visual complexity of the network, graph showing positive behaviors. Here, only positive behaviors (green circles) and positive and negative emotions (diamonds) are displayed along with their interconnections.

Interactive Functionality

The system incorporates interactive features designed to enhance analytical utility while maintaining simplicity. Six filtering options enable users to explore all connections or focus on specific subsets: positive behaviors, negative behaviors, neutral behaviors, positive emotions, or negative emotions (Figure 2). When a filter is applied, the system automatically displays only the relevant nodes and their connections, reducing visual complexity and enabling focused analysis.

Hover interactions provide additional contextual information by highlighting selected nodes and their connections. When users move their cursor over a node, the system emphasizes that node and all its relationships, making it easy to trace connections between specific behaviors and emotions without losing the overall network context.

Technical Implementation

The system processes ESM data by analyzing co-occurrences between behaviors and emotions within the same time periods. The algorithm calculates frequency patterns and correlation strengths, then generates the network layout using force-directed positioning that automatically arranges nodes to minimize visual clutter while maintaining clear separation between behaviors and emotions.

The interface adapts to different screen sizes and includes a comprehensive legend (Figure 3) explaining the visual encoding. Color coding, node shapes, and size scaling are documented for users to understand how to interpret the visualization without external guidance.

Design Rationale and Clinical Integration

The network approach addresses key limitations identified in existing ESM tools [23; 4] by potentially making behavior-emotion relationships more apparent through spatial positioning and visual connections rather than requiring complex statistical interpretation. Network visualizations have been

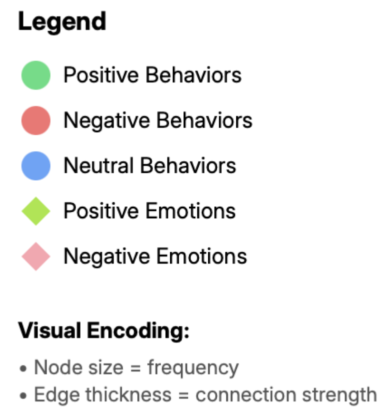

Figure 3: Comprehensive legend and visual encoding guide for the network visualization guiding users to easily interpret the visualization independently without external documentation.

shown in other domains to effectively reveal relational patterns that may be less obvious in traditional statistical presentations [2; 14; 7]. The categorical filtering system accommodates different analytical needs while maintaining interface simplicity, supporting both comprehensive data exploration and targeted analysis [18; 16].

The design aims to prioritize clinical utility by focusing on potentially actionable insights that could support treatment planning and patient self-awareness development. The intention is that practitioners could more quickly identify patterns such as which behaviors consistently connect to positive emotions or which situations tend to precede negative emotional states, though this effectiveness remains to be evaluated through the user study. This type of pattern recognition is intended to support the development of targeted interventions and could potentially enable patients to recognize behavioral patterns and situational triggers they might learn to manage.

The complete interface layout, demonstrating the integration of all visualization components including the network graph, filtering controls, and legend, is shown in Appendix A.

3.4 Evaluation Framework

This study employed a cross-sectional, mixed-methods evaluation design with six mental health professionals recruited through purposive sampling. Participants participate in an evaluation consisting of three distinct blocks, each targeting specific aspects of the visualization's effectiveness and practical applicability.

Participant Demographics and Background: Six mental health practitioners and researchers participated in the evaluation study. The sample included three mental health practitioners (psychologists, psychiatrists, counselors), two researchers in psychology/mental health, and one university student in a psychology/mental health related field. Regarding familiarity with ESM data, two participants reported being ”very familiar” with regular use in practice or research, three were ”somewhat familiar” having encountered it previously, and one was ”not familiar” with ESM data. For network visualizations, one participant was "very familiar," four were "somewhat familiar," and one was unfamiliar.

Materials and Procedure
A synthetic ESM dataset spanning 365 days with behavioral variables (exercise, sleep, social interactions, etc.) and emotional variables (happiness, anxiety, depression, etc.) was created to ensure ethical compliance while maintaining clinical realism. The network visualization was accessible via web link throughout the evaluation.

Three-block structured questionnaire:

- **Background information:** (3 questions) - professional role, ESM familiarity, network visualization experience
- **Usability and Intuitiveness Assessment:** (8 questions) - intuitiveness (1-5 scale), comprehension speed, design quality (1-5 scale), comparative rating vs. traditional methods, with supporting open-ended explanations
- **Visual Design Evaluation:** (4 questions) - initial reactions, interpretation capability, pattern recognition, desired features (all open-ended)

Procedure: Remote evaluation via Qualtrics platform with integrated visualization access. Participants: (1) provided informed consent and background information, (2) freely explored the network visualization, (3) completed structured assessment comparing network approach to traditional methods, and (4) provided detailed feedback on clinical utility and interpretability.

The study received institutional ethical approval with emphasis on voluntary participation, anonymity protection, and secure data handling. No personal identifiers were collected, and all data was stored on encrypted servers.

Qualitative Analysis Procedures: Open-ended responses were analyzed through a dual coding approach with two independent evaluators to ensure reliability. Initial open coding identified themes related to usability, clinical utility, and design effectiveness. A second evaluator validated these themes, achieving substantial intercoder agreement (Cohen's $\kappa = 0.81$). The coding scheme is detailed in Appendix B.

Key limitations: Small sample size limits generalizability; synthetic dataset may not capture full complexity of real-world ESM data; remote evaluation format may not reflect actual clinical usage contexts; potential ordering effects in comparative assessments.

4 Results

4.1 Usability and Intuitiveness Assessment

Participants' ratings of visualization intuitiveness revealed mixed but generally positive responses. On a 7-point scale (1=Very confusing, 7=Very intuitive), ratings ranged from 3 to 5, with a mean of 3.8 (SD=0.75). Three participants rated the visualization as neutral (3-4 on the scale), while three found it moderately intuitive (4-5 on the scale). No participants rated the visualization as either very confusing or very intuitive.

Regarding comprehension speed, four participants reported understanding the visualization "quickly" (within 30 seconds), while two required "moderate" time (1-2 minutes). No participants reported immediate understanding or slow comprehension, suggesting the visualization achieved reasonable accessibility without being immediately self-evident.

4.2 Visual Design Evaluation

Visual design elements received mixed evaluations on a 5-point scale (1=Very poor, 5=Excellent), with ratings ranging from 2 to 4 and a mean of 3.2 (SD=0.75). Participants identified specific design challenges that influenced their ratings. One participant noted: "The fact that they are moving when you open or change the tab makes it very chaotic and takes effort to understand. I like the legend, but I always find something confusing if a different figure (e.g. a circle or a square) is used for a same sort of construct."

Color coding received the most positive feedback, with multiple participants identifying colors as the most effective visual element. However, concerns emerged regarding specific color choices, with one participant questioning: "I don't get it why you'd use pink for a negative emotion." Shape differentiation created interpretation challenges, as another participant explained: "having similar shapes for different domains makes a bit difficult to get. You have to first study the legend in detail."

The dynamic movement of nodes upon loading was consistently identified as problematic. Participants described this as "very chaotic" and expressed desire for static positioning, with one stating: "I'd like it to stand still and not move when you open a tab."

4.3 Comparative Assessment with Traditional Approaches

When compared to traditional data tables or charts, the network visualization approach received varied evaluations. On a 5-point scale (Much worse to Much better), two participants rated it as "Better," two as "About the same," one as "Worse," and one as "Much worse." This distribution suggests the approach offers advantages for some users while creating barriers for others.

Participants identified specific advantages of the network approach, particularly its ability to reveal interconnections. One participant noted it shows "the interconnectedness between domains" that traditional charts might miss. Another explained the visualization as showing "different types of normative behavior and their association to emotions."

However, significant disadvantages were also identified. The primary concern involved visual complexity, with one participant describing it as "very chaotic, lines crossing each other, creates a barrier to take the time to understand." This participant questioned whether researchers prioritize "a fancy visualization over easily understandable visualization."

4.4 Pattern Recognition and Clinical Insights

Participants demonstrated ability to extract meaningful patterns from the visualization despite usability challenges. When asked to identify specific insights about behavior-emotion relationships, participants provided clinically relevant observations. One participant noted: "positive emotions are related to positive and negative behaviors, while negative emotions are related to negative and neutral behaviours."

The filtering functionality was identified as crucial for pattern recognition. One participant explained that "the selection of domains made it easier to understand, if you don't use the selection tool it is rather messy." This suggests that while the complete network view may be overwhelming, the interactive filtering capabilities successfully support focused analysis.

However, participants also identified limitations in the insights available. One researcher noted missing temporal information: "For ESM, you would want to see the daily variability here which I miss." This feedback highlights the tension between revealing relational patterns and maintaining the temporal richness that is central to ESM data analysis.

4.5 User Interaction and Feature Requests

Participants' initial interactions with the visualization revealed common exploration patterns. Multiple participants immediately attempted to manipulate the node positions, with one stating: "Tried to move the figures, to 'break' them down in order to have more space and see how the lines lie." This suggests users intuitively expected interactive manipulation capabilities beyond the provided filtering options.

The most frequently requested additional feature was temporal information integration. Participants expressed desire to see "time" and "daily variability" incorporated into the visualization. Other requested improvements included static node positioning to reduce visual chaos and enhanced node manipulation capabilities to support user-driven layout optimization.

Edge thickness and node sizing, intended to convey relationship strength and frequency patterns, created interpretation challenges rather than supporting understanding. One participant noted that "Node sizes and edge thickness made it more difficult to understand/spot patterns," suggesting these visual encodings may require refinement or alternative representation approaches.

4.6 Interpretation and Explanation Capability

When asked to explain the visualization concisely, participants demonstrated reasonable comprehension despite noted usability issues. Explanations included: "The network shows me that exercise and social activities have the strongest connections to happiness, which validates what we often recommend clinically." Participants also demonstrated ability to identify actionable insights from the visualization. One explained: "I can quickly spot that poor sleep connects to multiple negative emotions." Another stated: "The filtering feature helps me focus on specific patterns - like seeing only positive behaviors helps identify what we should be encouraging more of."

These responses indicate that participants could extract the core purpose of the visualization - revealing behavior-emotion relationships - even when struggling with specific visual design elements. The variety and clinical relevance of their interpretations suggest the fundamental concept of network representation for ESM data has merit, though implementation details require refinement. Importantly, participants' ability to translate visual patterns into clinical insights demonstrates the visualization's potential for supporting evidence-based intervention planning.

4.7 Design Element Effectiveness

The evaluation revealed clear hierarchies in visual element effectiveness. Participants consistently rated colors as the most successful design element, followed by shapes, then layout. The legend received positive feedback as a necessary reference tool, though participants noted the need to "study the legend in detail" before achieving full comprehension.

The spatial separation between behaviors and emotions was implicitly successful, as participants could correctly identify and describe the different node types and their relationships. However, the crossing lines between domains created visual complexity that hindered rather than supported pattern recognition, with multiple participants describing the visualization as "messy" or "chaotic" in its default state.

5 Discussion and Conclusion

This research addresses a gap in the implementation of ESM data for clinical practice by introducing a network graph visualization designed to enhance interpretability and clinical utility. The developed visualization method translates complex relational patterns between behaviors, situations, and emotions into insights, providing a foundation for improved intervention strategies and patient self-awareness. Evaluation results indicate that, despite initial usability challenges primarily associated with visual complexity and dynamic layout movements, mental health practitioners successfully extracted meaningful behavior-emotion relationships, demonstrating the inherent value and potential of the network visualization approach. Additionally, the visualization's reliance on color coding as the primary distinguishing feature may create accessibility barriers for users with color vision deficiencies, who comprise approximately 8% of the population and may struggle to differentiate between the red-green color scheme used for positive and negative elements.

The strengths of this study lie in its user-centered design methodology, iterative development informed by clinical needs, and usability evaluation, yielding valuable guidelines for designing clinically relevant visualizations of complex ESM datasets. Participants identified clear advantages of network representations, especially the interactive filtering feature, highlighting its capability to clarify relationships otherwise hidden in traditional visualization methods. Nonetheless, usability feedback underscores the importance of refining visual encodings and static positioning for improved cognitive clarity and immediate interpretability.

Future work should focus on addressing the identified usability concerns, particularly exploring stable node placement algorithms to reduce perceived visual chaos and integrating temporal dynamics to capture variability inherent in ESM data. Further research should also incorporate longitudinal studies to evaluate the visualization's effectiveness in real-world clinical settings, exploring how it directly influences intervention outcomes and patient engagement over extended use. By continuing to refine visualization approaches and emphasizing actionable insights, future developments can further bridge the gap between sophisticated data collection methods and practical clinical applications, enhancing ESM's adoption and utility in mental health care.

6 Responsible Research

This study prioritized ethical standards and methodological integrity throughout the research process. Data collection employed a two-stage approach: an anonymized original ESM dataset containing no private information provided the foundation for understanding real-world patterns, while a synthetic dataset was created for visualization development and evaluation. This approach maintained clinical relevance while eliminating privacy risks.

The evaluation with six mental health practitioners followed transparent consent procedures. All participants were fully informed about the study purpose and data handling, with participation being entirely voluntary. No personal identifiers, contact details, or IP addresses were collected, ensuring complete anonymity. Data was stored exclusively through Qualtrics' secure platform, and anonymous quotes may be used in scientific publications.

The study acknowledges potential limitations that may introduce bias, including the small sample size limiting generalizability and potential biases in how the network visualization represents behavior-emotion relationships. Additionally, participants' varying familiarity with different analytical approaches may have influenced comparative evaluations. Given the mental health context, the design process prioritized clinical utility while avoiding potentially misleading representations that could impact patient care decisions.

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A Full View of the Visualisation

You can access the survey at the following link: https://graph-visualisation.fly.dev

B Coding Scheme

Table 1: Coding Scheme and Inter-coder Reliability Results

Main Category	**Code**	**Description**	**Cohen's Kappa**
Usability Issues	Visual Chaos	Movement problems, crossing lines, overwhelming layout	0.85
	Design Confusion	Shape differentiation issues, legend complexity	0.78
	Interaction Limitations	Missing manipulation capabilities	0.80
	Cognitive Load	Information overload, complexity barriers	0.82
Design Elements	Color Effectiveness	Positive feedback on color coding	0.76
	Shape Clarity	Circle vs diamond differentiation	0.74
	Layout Organization	Spatial arrangement of behaviors/emotions	0.79
Positive Aspects	Filtering Utility	Value of interactive filtering options	0.88
	Relationship Clarity	Ability to show interconnections	0.81
	Legend Helpfulness	Effectiveness of visual encoding guide	0.73
Clinical Utility	Pattern Recognition	Ability to identify behavior-emotion patterns	0.83
	Intervention Planning	Support for treatment decision-making	0.77
	Patient Insights	Potential for self-awareness development	0.80
	Actionable Information	Clinical relevance of revealed patterns	0.79
Comparison vs Traditional	Advantages Over Charts	Benefits compared to tables/graphs	0.82
	Disadvantages	Limitations compared to traditional methods	0.84
	Contextual Preference	When network vs traditional is preferred	0.75
Feature Requests	Temporal Integration	Desire for time-based information	0.87
	Static Positioning	Request for non-moving node placement	0.91
	Enhanced Interaction	Additional manipulation capabilities	0.78
Overall Agreement	**All categories combined**	**Comprehensive coding reliability**	**0.81**