Visualizing Experience Sampling Method Data to Support Mental Health Symptom Identification and Intervention Planning

Exploring Visualization Strategies for Clinical Insight

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Abstract

The Experience Sampling Method (ESM) is increasingly recognized for its ability to capture fine-grained, real-time insights into individuals' emotional and behavioral states in their everyday environments. While the utility of ESM in clinical contexts has been well-documented, its integration into practical tools for mental health professionals remains underexplored. This study investigates how meaningful insights can be derived and presented from ESM data to assist clinicians in the identification of mental health symptoms and intervention planning. A series of prototype visualizations, in the form of line charts, pie and bar charts and network diagrams, were developed and then evaluated for usefulness, user-friendliness and intuitiveness by a total of 8 participants. Results suggest that no single visualization is sufficient on its own, but that a combination of temporal, contextual, and relational visualizations provides a more complete view of a patient's emotional patterns. While bar charts were preferred for clarity and comparison, pie charts were appreciated for quickly identifying dominant factors by a few participants. Network diagrams, though initially less intuitive, were still valued when paired with descriptive captions. These findings support the potential of multi-format visual tools to assist clinicians in extracting meaningful insights from ESM data.

Additional Key Words and Phrases: ESM, data visualization, human-computer interaction, user evaluation, online surveys, mental health, context, prototypes

1 Introduction

The Experience Sampling Method (ESM) is a technique used to collect real-time, in-the-moment data on an individual's thoughts, feelings and behavior in their current environment. By asking participants to report on their experiences multiple times per day, throughout multiple consecutive days, ESM enables the capture of dynamic psychological processes that would be difficult to observe through potentially biased retrospective reports or occasional clinical assessments [Myin-Germeys et al. 2018]. This momentary assessment approach has proven particularly valuable in mental health research for detecting emotional variability, contextual influences, early warning signs of relapse or symptom exacerbation and other interesting patterns [van Os et al. 2017] that are difficult to capture with traditional methodologies.

In recent years, there has been growing interest in the use of ESM within clinical contexts, particularly to support collecting insights into patients' experiences, symptom monitoring and giving personalized patient feedback or treatment [Bos et al. 2019]. Clinicians and researchers alike have emphasized the potential of ESM to provide granular, valid data that can complement traditional diagnostic approaches and aid in more individualized treatment plans [Weermeijer et al. 2024]. However, despite this potential, ESM remains underutilized in day-to-day clinical practice. One of the most cited challenges is the lack of intuitive, accessible tools that translate raw ESM data into meaningful insights that clinicians, often without strong data science backgrounds, can easily interpret and act upon [Weermeijer et al. 2024].

When ESM is used, it is often too impractical to oversee tens or even hundreds of time-stamped entries per patient, making it infeasible to manually review and extract patterns from the data without some form of intelligent summarization or visualization. Furthermore, most tools developed for ESM visualization are research-oriented prototypes that do not explicitly incorporate the needs of clinicians from a human-computer interaction or software design perspective [Weermeijer et al. 2024]. Moreover, other studies state that existing tools should be more thoroughly tested with end-users [Bringmann et al. 2021]. As a result, there remains a gap between what ESM can offer in theory and what is currently usable in a real setting.

This study aims to address this gap by exploring which types of visualizations are most beneficial to clinicians when identifying mental health symptoms from ESM data and thus, when planning a personalized intervention, and offering some understanding into what clinicians can realistically work with. A series of conceptual prototype visualizations were created using a prototyping tool to explore how insights from ESM data can be presented effectively, in order to support clinical interpretation without needing a technical background.

The research question of this study is, therefore, the following: *How to present meaningful insights from ESM data to identify mental health symptoms and support intervention planning?*. However, this study will also be addressing the following questions:

- What kinds of insights from ESM data are most relevant for mental health assessment?
- How can these insights be visualized interactively and understandably for users with minimal technical background?
- How useful are the derived visualizations for clinical staff in a real-world scenario?

Ideally, the perceived usefulness and intuitiveness of the visualizations would be evaluated through open-ended surveys conducted by mental health professionals, but their limited availability meant the surveys were also open to psychology students and students in other fields, in order to gather perspectives both from a clinical standpoint and from the viewpoint of users less familiar with such work. The outcome of this research is intended to inform future development of ESM-centered visualization tools that can aid mental health professionals in practice.

2 Related Work

This section outlines the approach used to investigate how meaningful insights can be visualized from ESM data for the purpose of identifying mental health symptoms. It begins by identifying which types of insights are considered relevant in clinical contexts based on prior research, and then it details the design decisions made for visualizing these insights, using prior, documented evaluations of visualization preferences among mental health professionals.

2.1 Relevant ESM Insights

As previously stated, the raw volume and granularity of ESM data present challenges for practical clinical use. To address this, prior work has identified several categories of insights that are particularly relevant for clinicians in symptom identification and, subsequently, intervention planning.

Mood variability, or the extent to which the average emotional states fluctuate throughout consecutive days [Toenders et al. 2024], is an informative pattern. It has been shown to reflect emotional instability, which is a central feature in several disorders, including borderline personality disorder and mood disorders [Abitante et al. 2024]. Kuppens et al. [2007] shows that greater variability is associated with higher psychological distress and difficulties in emotion regulation. Emotional inertia, the degree to which emotional states persist over time, offers complementary information. High inertia, especially in negative affect, has been linked to depression, anxiety and reduced emotional flexibility [De Longis et al. 2022; Kuppens et al. 2010].

Contextual factors are a dimension that is mentioned in most momentary assessment studies. ESM studies consistently show that certain environments and activities correlate strongly with changes in affect [Habets et al. 2022; Myin-Germeys et al. 2018]. For instance, emotional distress may be more likely during work-related tasks or other specific activities. Understanding how symptoms manifest across contexts allows clinicians to identify environmental triggers and act accordingly. Closely related are social presence effects: how being alone, or with certain people, influences emotional states. Research suggests that social environments can either alleviate or exacerbate symptoms, depending on the individual's relationships and interpersonal functioning [Bos et al. 2019; Brown et al. 2007; Oorschot et al. 2013] . For example, individuals with interpersonal sensitivity may report heightened negative affect when around family members [Hepp et al. 2017]. This study only considered these two type of contextual factors for the sake of simplicity, inspired by the Leuven clinical study [Heininga et al. 2019].

Lastly, feedback loops and temporal dependencies, how one emotional state may influence another at future time points, represent an advanced but clinically meaningful insight. Studies show that such dynamic emotional interplays (e.g., anxiety leading to later sadness or anger) can help clinicians anticipate symptom escalation or emotional spirals [Hall et al. 2024; van Os et al. 2017]. While modeling these dependencies often requires more complex statistical tools, their clinical value lies in understanding patterns that are not obvious in cross-sectional assessments.

Together, these insights form the basis for the visualization prototypes developed in this study. They were selected not only for their documented usefulness, but also for their clinical interpretability and potential to support decision-making in real-world settings.

2.2 Exploration of Visualization Techniques

The visualization formats selected for this study were informed by previous research on the preferences of practitioners as well as the nature of the ESM-derived insights targeted. According to Weermeijer et al. [2024], while clinicians working with mental health data cannot currently envision how they would like to visualize ESM data, they showed a clear preference for familiar and interpretable visual forms, namely time series, pie charts and bar charts. Network visualizations and pictograms, while occasionally used in exploratory settings, were considered more ambiguous and less intuitive by most participants in their study. Similarly, Hall et al. [2024] reported that network diagrams were generally perceived as less intuitive by clinicians, particularly in settings where they were used with patients. This demanded that the visualizations were understandable not only to clinicians but also to patients with varying levels of health and data literacy. Furthermore, participants in this study were given dedicated training sessions to familiarize themselves with the models before using them. This is an important distinction from this project, where the visualizations are purely addressed to clinicians and not patients and no prior training will be provided, because it calls for a more simplistic approach that needs to be understood with minimal hints.

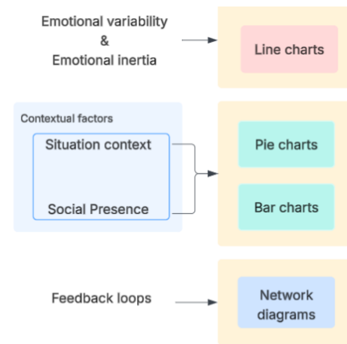

Fig. 1. Design choice for each ESM insight

Despite this, network diagrams were included in this study for visualizing feedback loops (patterns of emotional and behavioral states) because of their unique ability to represent potential cyclical associations and directional relationships that other chart types cannot easily capture. Their inclusion, while tentative, is grounded in the assumption that clinicians may still find them useful if the communicated insight is relevant and difficult to convey otherwise, especially if such format will be more appropriately designed. This was tested in the user evaluation stage.

To represent emotional trends such as mood variability and emotional inertia, a line chart format was chosen, a type of visualization that is established in literature for tracking temporal changes and supporting comparative analysis [Javed 2010]. An **alternative** considered during the design process was the heatmap, which can also be applied in time-based data analysis. However, heatmaps may pose interpretability challenges. Visualizations that rely on chromatic channels and contrast effects have limitations when conveying information [Ware 2012], and, because the amount of visualizations incorporated in this study would have been too high for a reasonable online survey, only line charts were ultimately included to support the intended reasoning tasks.

Contextual factors were shown using pie charts and bar charts (Figures 4 and 5), in order to examine which categorical representation is more intuitive and useful for end-users. While pie charts can give an intuitive sense of proportions and illustrate well simple splits (e.g., showing exactly one half or one quarter), bar charts are far better for comparative precision [Croxton and Stryker 1927]. Including two types of formats a choice made for the study to account for differences in both the preferences of practitioners and task-specific suitability.

To clearly communicate the pairing of insights with visualization types, Figure 1 provides an overview of the mapping between each targeted ESM insight and the corresponding visual formats chosen for this study. Mood variability and emotional inertia are intended to be captured within a single line chart. This approach aligns with time series-based data and is visible in previous work [Trull et al. 2008; van Genugten et al. 2022].

The visual representation of contextual factors will feature side-by-side pie or bar charts, each representing the distribution of a chosen emotion's intensity across different activity contexts and social presences respectively. This format aims to allow practitioners to directly compare how the same emotional state relates to both dimensions simultaneously.

3 Methodology

This section details the methodology employed in this project, beginning with the development of the prototype visualizations and concluding with the evaluation approach. It first describes the choices made in the implementation process of the prototypes, including the final visual designs that were shared with participants. Following this, the section describes the survey used to evaluate the prototypes and lastly, it briefly outlines the intended approach for analyzing the qualitative responses collected during the evaluation.

3.1 Development of Prototypes

The development of the prototype visualizations was guided by the data–task–user triangle [Miksch and Aigner 2014], which highlights the importance of aligning data structures and representations with the specific tasks and cognitive needs of the target user. In this study, the user is the mental health professional, the data is based on possible patient input from ESM surveys and the primary task is to interpret emotional and contextual patterns that may indicate the onset or presence of mental health symptoms.

Each type of visualization was created to fulfill a distinct interpretive function:

- **Network diagrams** were designed to highlight both temporal and associative feedback loops between reported emotional and/or contextual states. These diagrams display directional relationships (e.g. transitions from one emotion to another), with arrows representing sequences from one state at a point in time (an ESM survey) to another state at an immediate point in the future (e.g. the next ESM survey) and line weight indicating the amount of correlation between these states. They allow clinicians to identify upstream emotional states that may lead to critical behaviors and use that understanding to intervene early. This can also create awareness for the patient, who may not be knowledgeable in their own emotional dynamics.
- **Line charts** provide a temporal overview of mood variability and emotional inertia. Clinicians can add or remove emotion lines based on their focus, allowing comparison of multiple emotional states over time. When consecutive ESM entries share the same common factors (e.g., social presence and/or activity), they are highlighted visually with a dotted rectangle to help clinicians detect patterns across time segments. An option to turn this feature off is shown in the prototype.
- **Pie charts** and **bar charts** allow for analysis of emotional states within their context. These visualizations support custom filtering: the clinician selects the variable of interest (e.g., anxiety) and sets score ranges (e.g., 4–7) to view the distribution of relevant emotional states across different settings (e.g., household, job-related) or social presences (e.g., alone, with family).

3.2 User Evaluation Procedure

To assess the usefulness, clarity and complementarity of the developed visualizations, an exploratory user evaluation was conducted in the form of an online survey. The goal was to determine whether the visualizations could help users identify mental health symptoms from the designed prototypes. Due to the challenges of reaching out to experts in the field (mental health professionals), the survey was open to psychology students and students in other fields as well. The survey consisted of open-ended questions, aiming to extract detailed feedback on usability, utility and possible improvements. The full set of questions is provided in Table 1.

Participants were presented with a scenario in which they played the role of a clinician reviewing a patient's ESM data collected over a two-week period. The patient had completed several daily surveys reporting on mood, emotional states, environmental context and clinically relevant symptoms. The participant's task was to explore a few static visualizations (a network diagram, contextual bar and pie charts and a line chart, displayed together in the same place, **in this order**) and reflect on how these might support the process of forming a preliminary understanding of the patient's emotional tendencies. The decision to present the network diagram **first** was intentional. As it displays temporal emotional patterns (e.g., early signs of distress escalating into harmful behavior), it can encourage participants to begin exploring the scenario by identifying a problematic emotional state or sequence and then inspect how that emotion is expressed across time (line chart) and context (bar / pie charts) to support intervention planning. There is no specific motivation behind the ordering of the line chart and bar / pie charts and it should not affect the participants' thinking process.

In addition to the aforementioned set of questions from Table 1, participants were also asked to report basic background information, including their age range, gender, professional background (mental health professional, psychology student, student in another field), and their familiarity with ESM data.

The survey, including reading the background information of this study and the scenario, viewing the visualizations, and completing the questions, was expected to take approximately 15 minutes or negligibly longer, depending on the depth of the participants' responses.

3.3 User Demographics

The survey was completed by a total of 8 participants: 4 psychology students and 4 students from other fields. All participants were between 21 and 25 years old. Table 2 summarizes the demographic breakdown.

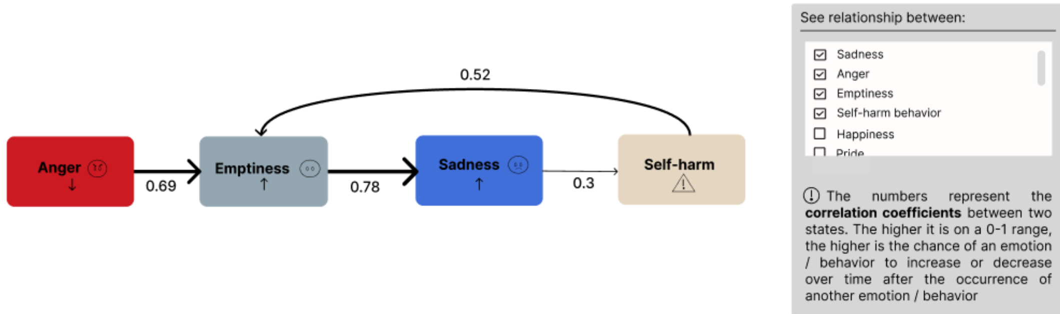

Fig. 2. Example of a network diagram with four nodes and a cyclical relationship. Each variable is accompanied by a representative icon and each node is color-coded distinctly to support recognition and visual differentiation. Underneath the directional edges, correlation coefficients were added to indicate the strength of association between states. Smaller arrows were used to present the behavior of each mood (e.g., after multiple consecutive ESM surveys of anger decreasing, a period of increased feelings of emptiness is followed)

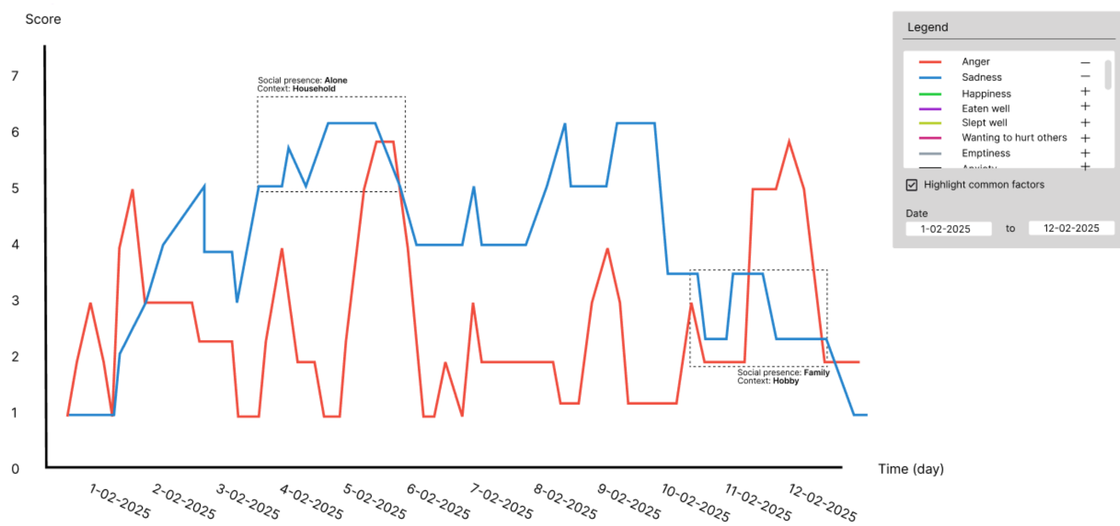

Fig. 3. Example of a line chart with two modeled emotional states.

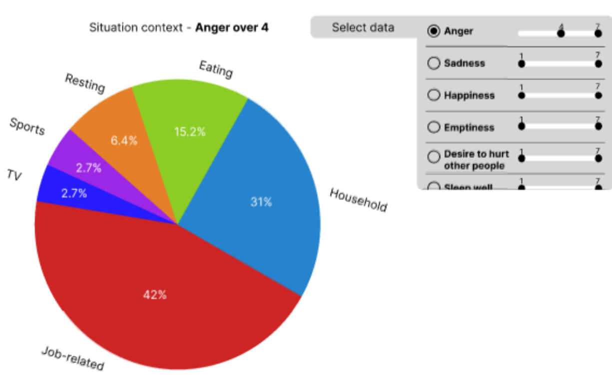

Fig. 4. Example of a pie chart showing the distribution of the situation context for the **anger** variable.

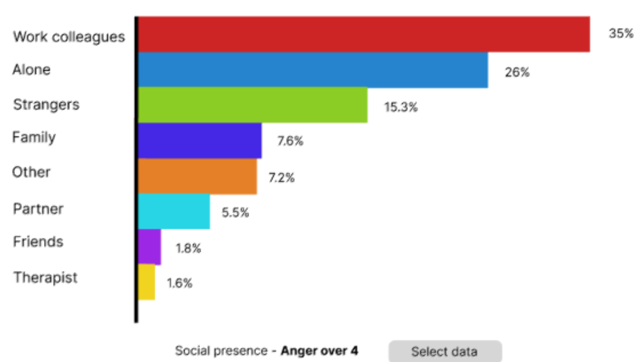

Fig. 5. Example of a bar chart showing the distribution of the social presence for the **anger** variable.

Number	Question
1	Which of the visualizations helped you most in identifying potential symptoms or concerning patterns? Why?
2	When viewing the contextual factors (pie charts and bar charts), did you find one more helpful than the other? If so, why? If not, you can simply say there is no difference.
3	Do you feel that any of these visualizations (or all of them together) would support you in planning an intervention or tailoring therapy for a patient? If so, how? If not, why not?
4	In what ways do these visualizations work together? (e.g., Do you see them as complementary?). Please explain briefly.
5	If you were to use a tool like this in practice, what changes (visual, interactive) would make it more effective for you? If possible, detail the changes for each visualization.
6	Was there any visualization that you found confusing, unnecessary, or less helpful? Please explain briefly.

Table 1. Open-ended questions used in the online survey.

Background	Total	Female	Male
Psychology Students	4	4	0
Students in other fields	4	1	3

Table 2. User demographics

Regarding familiarity with ESM, all psychology students reported being somewhat familiar with ESM data, whereas the students from other fields indicated no familiarity at all.

3.4 Analysis and Data Preparation

Open coding was initially conducted on a per-question basis to preserve the contextual relevance of participant responses. After all responses were coded, recurring patterns across questions were identified and clustered into themes, following the principles of thematic analysis outlined by Braun and Clarke [2006].

The coding process was split into two phases. In the first phase, the open coding strategy was applied to independently label participant comments with relevant concepts and topics. Each response was coded for one or more concepts, with multi-coding permitted to capture nuanced feedback. In the second phase, to enhance the reliability of this process and reduce individual bias, a second coder independently applied the same coding scheme, and they were also encouraged to add more codes if deemed necessary.

Finally, inter-coder agreement was quantified using Cohen's Kappa. This reliability measure showed near perfect agreement, with an average Cohen's Kappa of 0.861. A full list of the per-question codes, alongside their individual Cohen's Kappa coefficients is provided in Appendix A.

4 Responsible Research

This study was conducted with respect to ethical considerations and responsible research practices. Approval for this study was granted by the university's Ethics Board (ID = 5405) prior to data collection. The survey was distributed through the Convergence academic collaboration between TU Delft, Erasmus University Rotterdam and Erasmus MC, as well as through the researcher's own network.

All participants were provided with clear information about the purpose of the study, its voluntary nature and the measures taken to ensure data anonymity and confidentiality. No personally identifiable information, IP addresses, or contact details was recorded. Informed consent was obtained from each participant before beginning the survey and how their responses would be used and stored subsequently was also announced.

This study raises broader societal implications around the use of data-driven visualizations in mental health contexts. Such tools can support clinicians in identifying patterns, but they also risk misinterpretation or misuse if not properly designed. Therefore, the focus should fall on the importance of transparency and interpretation when working with sensitive data in a clinical setting. Moreover, due to the nature of this study, while it is reproducible given the same responses, coding scheme and analysis methods, it is only **partially replicable**, as similar themes or responses may arise in future studies with comparable participant groups, but individual responses will naturally vary.

5 Results

This section presents a thematic summary of the responses, with selected quotes included to provide further context for the thematic findings. A more comprehensive view of participants' quotes can be found in Appendix B.

Complementarity Across Visualizations

Participants described how different visualizations enabled distinct types of insights. Rather than treating the visualizations individually, several respondents reflected on the value of using them in combination.

In summary, line charts allowed users to track mood fluctuations over time, contextual pie and bar charts supported understanding of environmental triggers and identifying the most affecting factors, and network diagrams revealed connections between emotional states. One participant explained, *"In the feedback loop I understood how the moods interact and predict each other. In the contextual factors, I understood more about where these moods came from and in the mood variability one I understood how intense are some emotions and when that happened"*. Another focused on the relationship between temporal patterns and context: *"The mood variability score would not tell us much without the contextual factors."*

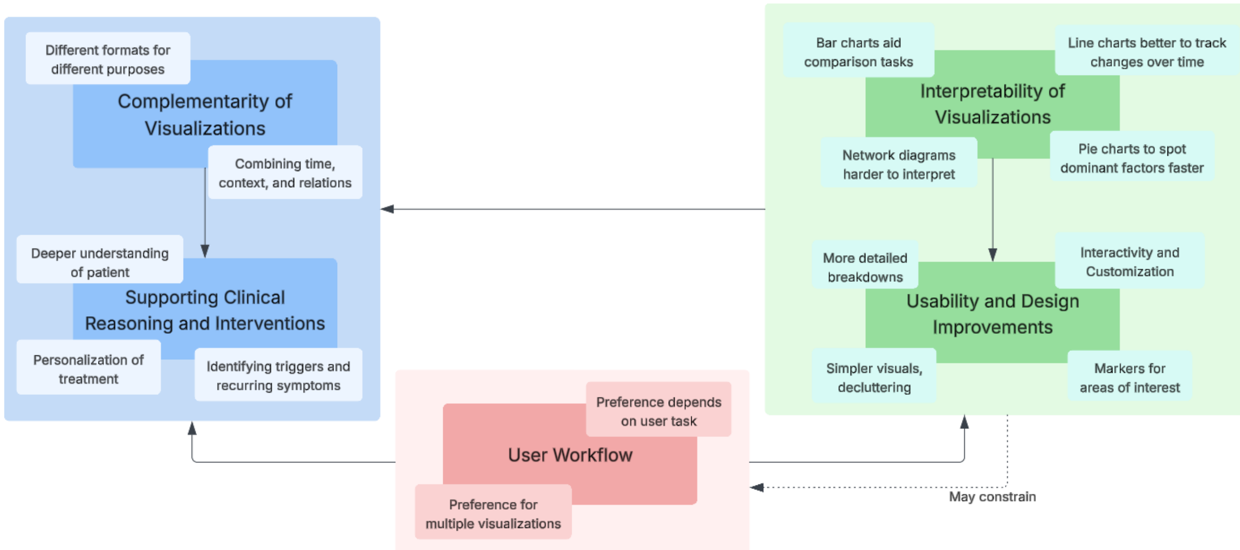

Fig. 6. The five identified themes and their respective sub-themes. Directional full arrows portray how one theme or collection of themes may affect another theme or collection of themes, while directional dashed arrows indicate whether one theme or collection of themes may constrain another theme or collection of themes.

This combination of perspectives, three participants described, is what allows for a comprehensive picture of a person's emotional dynamics.

Interpretation of Visualizations

The ease with which participants could interpret the visualizations varied depending on format, complexity, and their intended use. Simpler visuals such as bar and pie charts were praised for their clarity by three participants. Bar charts, in particular, were described as more effective for making comparisons or for other tasks, such as ordering values. One participant explained, *"I find the bar chart much easier than the pie chart… the small differences between values are more visible."*

Pie charts were described as more intuitive when it came to quickly assessing the dominant contextual factor: *"I like the pie charts… if I want to see which contextual factor is more present, I can spot the biggest one easily."*

Line charts were largely seen as helpful for understanding mood fluctuations over time. However, concerns were stated if too many variables were shown, potentially leading to visual clutter. *"The third visualization is rather clunky, especially if we were to add more emotional states"*, one participant noted.

Network diagrams generated mixed responses. While some respondents considered them easy to understand and valuable for clinical interpretation, others described them as harder to interpret and complex. One participant stated, *"The first one (network diagrams) needed more in-depth reading to understand what the numbers on the arrows meant."*. Another proposed an alternative design, based on personal preference: *"I would use a circle technique, for all the correlation relations to be more clear and diverse."*.

Overall, participants were generally satisfied with the current designs, but improvements were suggested, as described in the following section.

Usability and Design Improvements

Participants provided a range of suggestions aimed at improving both the readability and interactivity of the visualizations. These suggestions included the removal of less important data points ("*For both pie and bar charts I would remove the factors that obtained really low scores to 0*"), higher interactivity such as hover functions that expand to more detailed breakdowns, and highlighting dangerous emotional states or sequences of emotional states in the network diagrams.

One participant proposed greater flexibility in contextual visualizations: *"Upon clicking a bar in the situational context chart, it would expand to outline all the moods."* Another suggested adding markers to the line chart, but also wished for the possibility of zooming into the visualization and comparing multiple simultaneously: *"I would add markers for significant events or interventions to see their impact on mood and allow zooming into specific time frames and comparing mood trends side-by-side."*

Several respondents also noted that some elements might be confusing for patients, suggesting incorporating more descriptive captions if visualizations are shared in clinical discussions.

Supporting Clinical Reasoning and Intervention Planning

Several participants indicated that the visualizations, especially when used in combination, could support the process of identifying symptoms and planning tailored interventions. Their reasoning often focused on the ability to uncover helpful patterns and influencing factors on the patient's mood.

One respondent described this: *"The visualizations show the factors most active in the patient's life... I can suggest a plan to focus on the factors that affect daily functionality."*. Another stated, *"They all give relevant information about emotional states and contextual factors in which these emotional states occur and which emotional states influence each other. These... can inform us about when and what needs to be implemented in a possible intervention."*

In the same manner, one participant expressed their intention to use these visualization to guide their discussion with their patients: *"These graphs also help me understand what are the possible causing factors of mood variability and discuss that with the client."*.

User Workflow

Participants expressed that the usefulness of a visualization depended on their goal or workflow. As one participant noted, *"If I want to see which contextual factor is more present, I would prefer the pie chart as I can spot easily the biggest one."*. Then, they expanded more on this subject, *"For analyzing more data, I feel like I can visualize it better with a histogram because I can compare better the variables."*.

In addition to individual preferences, several participants noticed the value of using multiple visualizations together. One respondent noted, *"All visualizations helped (in identifying symptoms), but regarding different aspects,"* suggesting, as previously noted in Results, that each type of visualization contributes to the overall assessment process. Another participant, with a non-clinical background, stated, *"I also hope psychologists are looking at more than one visual in order to make decisions."*.

Some participants also discussed how certain visualizations might function independently, while others worked better in combination. For example, one participant observed, *"The first visualization (network diagram) could work independently as it shows causal chains between different moods, while the second (bar or pie charts) and third (line chart) could work together."*. The consensus was that using multiple visualizations would benefit most workflows in clinical practice.

6 Discussion

This study aimed to investigate what kinds of visualizations are most beneficial for clinicians in identifying mental health symptoms in ESM data and how such visualizations might support intervention planning. The findings suggest that a single visual format may not be sufficient to fully convey the nature of self-reported ESM data. Rather, participants focused on the importance of combining several perspectives (temporal, contextual, relational) to extract clinically meaningful insights, and they described how each fulfilled a distinct role within a bigger system. This may be a sign that clinicians benefit from a complementary set of visualizations, each designed to highlight a different aspect of the patient's data.

Although studies on ESM-based tools such as Bringmann et al. [2021]'s ESMvis do not explicitly argue for multi-visualization tools, their use of distinct visual formats to convey different types of insights suggests an implicit recognition of the value of combining multiple visual perspectives within the same system. This observation suggests that tools supporting multiple visualizations may be better suited to capture the complexity of ESM data.

Participants found these visualizations useful for both identifying symptoms and planning interventions or guiding client discussions. The network diagrams, for example, encouraged clinicians to think about early-stage emotional symptoms and preventative interventions, which may suggest a more proactive clinical approach. While further empirical validation is needed, the results suggest that integrating multiple types of visualizations may support clinicians in developing a more actionable understanding of ESM data.

The results also expand on recent findings by Weermeijer et al. [2024] and Hall et al. [2024], who identified limitations in visual clarity and user experience when it comes to network diagrams. In the present study, while participants acknowledged the network diagrams as less intuitive, many still saw value in them, especially when they were clearly labeled and descriptions of visual elements were provided.

In terms of chart preferences, participants stated that bar charts were better suited for tasks involving comparisons, while pie charts offered faster visual overviews of dominant variables. This aligns with the findings of Croxton and Stryker [1927], which shows the superiority of bar charts in enabling higher accuracy in data extraction, but which also affirms that pie chart formats have their own usefulness in giving users a sense of simple proportions. In the context of clinical practice, giving clinicians control over what visualization format they can interact with depending on their task may be the way of designing tools going forward.

6.1 Limitations

Several limitations must be acknowledged that affect the interpretation and generalizability of the findings.

Firstly, the participant pool consisted exclusively of students rather than actual mental health professionals. While psychology students offered clinically informed perspectives, their feedback cannot fully represent the needs, constraints, and decision-making processes of experienced professionals working in real clinical settings. Professionals might prioritize different visualization features based on different workflows or time pressure during sessions. The lack of practicing clinicians, the intended end-users, raises questions about whether the perceived usefulness of the visualizations included in this study holds true in practice.

Secondly, the small sample size (N=8) limits the generalizability of the results. With only four psychology students and four students from other fields, the study cannot properly capture the full range of user perspectives. A larger, more diverse participant pool should increase the reliability in the findings and allow for a better analysis.

Finally, the evaluation used static rather than interactive prototypes, which may have simplified the usability assessment. In practice, the cognitive demands when exploring all types of interactions with such tools might reveal different challenges or general insights than those identified in this study.

6.2 Future Work

Looking forward, these findings suggest several directions for both research and implementation. Future work should focus on developing interactive systems that improve the clarity and understanding of these types of visualizations through dynamic features. Although not directly assessed through the survey, the relationships between the themes identified in this study could reveal interesting insights if tested further. Based on observed patterns and participant reasoning, a conceptual model was created to visualize how themes such as user workflow, interpretability and design usability may interact to influence clinical reasoning and the perceived value of combining multiple visualizations (Figure 6). This model is not intended as a conclusive scheme, but as a reflection of intuitive connections observed throughout the analysis. Future research could investigate the validity of these relationships, for example by exploring whether usability constraints or workflow demands actually shape clinicians' reasoning in practice.

Participants expressed wanting to see functionalities such as customizable filters and line charts which can be zoomed in or which have visual markers for significant life events. These could improve the interpretability of an ESM-based tool to task-specific clinical needs. Moreover, such systems should be evaluated for both usability and their actual impact on clinical decision-making. Future evaluations should involve a larger and more diverse group of participants, ideally including the intended end-users of such tools, mental health professionals, who can offer professional perspectives on the tools' applicability and relevance.

Additionally, while the study focused on a selected set of insights (emotional variability and inertia, environmental factors and feedback loops), these proved to be sufficient for extracting preliminary findings for mental health symptom identification and intervention planning. Nevertheless, other insights may also be clinically relevant (e.g., time-of-day effects), and future studies may explore how these can be visualized and interpreted effectively.

7 Conclusion

To answer the research question, this study found that combining temporal, contextual, and relational visualizations is generally perceived to be more effective by participants for identifying mental health symptoms in ESM data and for reasoning about potential interventions. The findings indicate that while each visualization type offers distinctive clinical insights, their true power is shown when integrated into a cohesive framework. The line charts' ability to track emotional fluctuations over time, the bar or pie charts' clarity in revealing environmental triggers, and the network diagrams' ability to expose dynamic relationships between emotions can contribute to a more comprehensive clinical assessment than relying on a single type of visualization alone.

Acknowledgment

This thesis made limited but acknowledged use of generative AI to support the research and writing process. AI assistance was used in three main ways: (1) identifying relevant literature, which was then verified and reviewed independently; (2) refining the academic tone and structure of specific sections, based on my own drafts and notes; (3) receiving suggestions for improvements regarding the clarity, coherence and flow of the writing. All content and final decisions about wording and interpretation were made by the author.

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A Codes Table

Questions	Codes	Cohen's Kappa
Which of the visualizations helped you most in identifying potential symptoms or concerning patterns? Why?	Mood variability - able to track changes over time	1.0
	Contextual factors - ease of understanding	1.0
	Feedback Loops - able to identify how moods influence each other	1.0
	Preference for multiple visualizations for the bigger picture	1.0
When viewing the contextual factors (pie charts and bar charts), did you find one more helpful than the other? If so, why? If not, you can simply say there is no difference.	No perceived difference	1.0
	Bar charts easier to read	1.0
	Bar charts easier to compare	1.0
	Bar charts support better labelling and ordering	1.0
	Pie charts easier for proportions	1.0
	Depends on the task	1.0
Do you feel that any of these visualizations (or all of them together) would support you in planning an intervention or tailoring therapy for a patient? If so, how? If not, why not?	All visualizations helped	0.238
	Reveals helpful patterns about patient	1.0
	Identify factors influencing the patient's mood	0.351
	Integration of mood and context	0.794
In what ways do these visualizations work together? (e.g., Do you see them as complementary?). Please explain briefly.	Useful independently and in combination	1.0
	Complementary as each visualization shows different aspect	0.314
	Provide a complete picture	0.238
If you were to use a tool like this in practice, what changes (visual, interactive) would make it more effective for you? If possible, detail the changes for each visualization.	Highlighting important regions of interest	0.619
	Decluttering	1.0
	Data customization	1.0
	Improved comparison between many emotional states	1.0
	More detailed breakdowns	0.741
	Alternative visual design	1.0
	General satisfaction	1.0
	Dynamic features	1.0
Was there any visualization that you found confusing, unnecessary, or less helpful? Please explain briefly.	Feedback loops - less intuitive	0.771
	Mood variability - scales bad with more emotional states	1.0
	Feedback loops - arrows below moods are confusing	0.771
	All are easy to understand	1.0
General	Misinterpreted question	1.0

Table 3. Coding scheme used for each question.

B Participant Quotes

Background	Theme	Quotes
Student in other field	Complementarity Across Visualizations	"I believe the visualizations are complementary: the first one is used to detect feedback loops between certain emotions, while the second shows us how environment and the people involved affect the patient."
Psychology student		"Yes, I believe they are better when used together. For example, the mood variability score would not tell us much without the contextual factors. I believe every information is necessary for a complete picture"
Student in other field	Interpretation of Visualizations	"I liked the bar charts. Personally I find them easier to read and much more easier to compare their dimensions in a bar chart format (e.g. see that Eating is about half the size of Household)."
Psychology student		"The last one (mood variability line chart) helped me most in identifying potential symptoms. The evaluation becomes accurate when the mood is tracked daily. If the potential symptoms are not constantly active it may not be a clinical concern but more of a personality trait."
Psychology Student	Supporting Clinical Reasoning and Intervention Planning	"...they all give relevant information about emotional states and contextual factors in which these emotional states occur + which emotional states influence each other. These factors taken together as a whole can inform us about when and what needs to be implemented in a possible intervention/therapy session."
Psychology Student		"...I consider all of them helpful, especially the last one (mood variability chart) because based on the results I can interpret potential or existing concerns. The visualizations show the factors that are most active in the patient's life. If so, I can suggest a plan to focus on the factors that affect daily functionality."
Student in other field	Usability and Design Improvements	"I liked the bar charts, and I would expand on them. I would also add a bar chart of all the available moods associated with the context. E.g. upon clicking a bar in the situational context, mood X chart, it would expand to a new chart outlining all the moods. I would also add an additional variability chart. For a lot of people, activities are generally repetitive on a weekly basis... It might also be useful to be able to compare individual weeks to showcase improvement or lack thereof."
Psychology student		"...To make them (bar charts) more effective, I would add color coding for different categories or severity levels. Adding animation to reflect changes over time could also help visualize progress dynamically... For mood variability graphs, I would add markers for significant events or interventions to see their impact on mood and allow zooming into specific time frames and comparing mood trends side-by-side."
Student in other field		"...if each visualization is provided with an explanation along with it (at least a caption), I think they are easy to understand."
Student in other field	User Workflow	"I believe the first two visualizations would help me in planning an intervention by understanding the patient's environment in different settings, and how it influences their emotional state."
Psychology student		"I like more the pie charts, but again, depending on context. If I want to see which contextual factor is more present, I would prefer the pie chart as I can spot easily the biggest one. For analyzing more data, I feel like i can visualize it better with a histogram because I can compare better the variables"

Table 4. Participant quotes