Visualizing Experience Sampling Data to Enhance Clinical Insights into Mental Resilience

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A Thesis Submitted to EEMCS Faculty Delft University of Technology,
In Partial Fulfilment of the Requirements
For the Bachelor of Computer Science and Engineering
June 22, 2025

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Final project course: CSE3000 Research Project
Thesis committee: Dr. Willem-Paul Brinkman, Esra de Groot, Dr. Inald Lagendijk

Abstract

Understanding mental resilience-how individuals recover from stressors-is a critical focus area for mental health practitioners. To support this, the Experience Sampling Method (ESM) can be utilized, which offers rich, real-time data for tracking emotional dynamics. However, visualizing these data in an informative and actionable way remains a challenge. This study presents a set of visualizations designed to depict emotional recovery trajectories by focusing on mood, emotions, types of stressors and the influence of coping activities. To assess whether the developed visuals are interpretable and useful to mental health professionals, a survey-based evaluation was conducted. Afterwards, thematic analysis was applied in order to analyze and present the results. What was highlighted in the results is that easy-to-interpret visuals, such as line graphs and heatmaps, were more likely to be considered intuitive and clinically relevant. Moreover, visualizations that incorporated contextual or emotional details were regarded as more insightful and valuable for guiding therapy.

1 Introduction

Understanding how individuals respond to and recover from stress is a central concern in the field of mental health [23]. Mental resilience-the capacity to return to a stable emotional baseline after a stressor-is a key indicator of psychological well-being [21]. Moreover, failing to recover properly is a strong indicator of underlying mental illnesses [10]. As such, mental health practitioners are increasingly seeking ways to better assess and interpret the resilience capabilities of their patients [23]. However, visually presenting the dynamics of this recovery process remains a challenge, as it requires methodologies that can account for temporal and contextual variability in emotional states [23].

In recent years, advances in technology have enabled new ways of collecting data about an individual's mental health, one of which is the Experience Sampling Method (ESM). ESM provides a valuable framework for collecting in-the-moment data about individuals' emotions and behaviors throughout the day [11]. Unlike traditional retrospective reports, ESM allows for fine-grained insights into emotional fluctuations and the context encompassing them [13]. However, despite its potential, the barrier remains in making the resulting data interpretable and actionable for mental health practitioners [16].

The increasing usage of data visualizations has sparked interest in applying visual tools to mental health data to improve understanding and communication between practitioners and patients [4, 17]. However, existing tools typically focus on visualizing general symptom trends or mood dynamics, rather than the specific process of mental resilience [4, 17]. Moreover, while ESM data have been used in prior studies [23] to evaluate mental resilience capabilities, the focus was not in visualization. As a consequence, there is a gap that separates research on the tools used for effective visualization of ESM data and the specific demands of optically presenting the process of mental resilience.

This research is motivated by the need to develop and evaluate visualization techniques that can translate ESM data into meaningful representations of mental resilience. Hence, the research question it seeks to explore is the following: *How can we present meaningful insights from ESM data on an individual's mental resilience after stressful events?*

The goal of this study was to contribute to the design of intuitive and clinically relevant tools that help mental health professionals gain deeper insights into emotional resilience patterns of their patients. Specifically, this work explored how various forms of data visualizations, ranging from line graphs to box plots and heatmaps, can be employed to support the interpretation of emotional recovery trajectories. To assess the practical value of these visualizations, a qualitative evaluation was conducted with mental health practitioners, focusing on their perceived interpretability, usefulness, and potential application in therapeutic contexts.

2 Related Work

This section outlines the prior literature based on which the visualizations for mental resilience were developed. Firstly, it provides an overview of existing tools within the scope of ESM data visualization. Then, it presents studies that highlight which aspects of mental resilience are important to clinicians. Lastly, it analyses the practicality of various visualization techniques for presenting ESM data.

2.1 Existing tools

This subsection presents visualization techniques for ESM data found in literature. In particular, three different tools are described which are parts of complete projects that focus not only on the visualization of data, but also on the deployment of applications, the collection of ESM data and their analysis. Since this study is only concerned with the visualization of ESM data, the focus for this overview is on that aspect.

One tool is ESMVis [4], which aims to replace summary statistics of traditional ESM apps, such as averages, with visualization techniques, in order to provide insights and descriptive feedback on the data. This tool is utilizing data gathered using ESM questionnaires that require users to rate their experiences on a scale. Then, the gathered data are visualized using three distinct plots. These include a box-plot with the variation of all collected variables, a line graph that presents the overall trajectory of selected variables and a dynamic circle figure, which displays all the data collected by an individual at once.

Moreover, FRED [17] is another tool that aims to provide personalized and dynamic visual feedback based on collected data. Hence, the first plot presented is a scatter plot with variables related to positive mood and sleep on the y-axis (Happy, Relaxed, Rested) plotted against a Likert scale ranging from 1 (not at all) to 7 (very much) on the x-axis. Additionally, bar charts are showcased which visualize the context of individuals' daily lives, including the distribution of the time spent on different activities or places. Furthermore, time series display how positive mood, negative mood and tiredness fluctuate within a time period. Finally, contemporaneous networks are visualized, highlighting the correlations that exist between different variables.

HowNutsAreTheDutch [9] is a crowd-sourcing initiative aimed to present mental health data of individuals and in particular how they relate to the general population. Consequently, the generated visualizations focused both on individual-level data and on aggregated data across all participants. Personalized plots included bar charts and spider plots that compare the ESM statistics of individuals to the general public and network graphs that indicate connections between variables of everyday lives that could be captured using the questionnaires, like emotional states and activities. Visualizations for the complete study sample were comprised of scatter-plots that exhibit the relationship between positive and negative affect on the general population and bar charts showing statistics of mental health symptoms across the users.

2.2 Literature on Mental Resilience

This subsection highlights key aspects of mental resilience identified in the literature, which informed the design and focus of the visualizations developed in this study.

Firstly, Zietse et al. [23] highlighted the importance of the total duration between the stressful event and the time it stops affecting an individual. Moreover, the same study also emphasized that the resilience process is often non-linear, as fluctuations in one's mood appear during the recovery. Hence, factors such as how quickly and smoothly someone recovers from stressors can provide insights on how resilient they are.

Also, studies such as the one conducted by Velozo et al. [19] demonstrate that affective recovery, the process through which an individual's emotions return to a neutral baseline after a stressful event, can serve as a meaningful indicator of psychological vulnerability, as delayed emotional recovery has been associated with increased risk for developing depressive symptoms.

In addition, a paper by Almeida [1] explains that emotional recovery varies significantly across different types of stressors. This suggests that, in clinical settings, special attention should be given to those stressors that overwhelmingly affect an individual.

Furthermore, research by Sherman et al. [18] places great value on the effect of post-stressor activities for effective mental resilience. Their findings propose that engagement in meaningful activities can buffer the negative impact of stressful events.

2.3 Visualization Techniques

This subsection gives an outline of the selected visualization techniques for this project, along with the rationale behind their use.

Line graphs were employed to depict changes in overall mood and specific emotions over time following stressful events. Prior research has indicated that line graphs are the preferred visualization tool to depict temporal data [2]. Additionally, they are an intuitive tool even to non-experts and they allow viewers to quickly recognize trends and patterns [14].

Error bars and hover-enabled details were utilized to enhance the precision and interpretability of the line graphs. Relevant literature suggests that incorporating uncertainty values into visualizations is crucial for informed decision making [8]. Moreover, providing textual details of data points can increase the confidence in understanding the graph [16].

Box plots were used in order to present the variation in recovery time per stressor type. They were selected for their effectiveness in summarizing distributional characteristics and highlighting variability across groups [22]. Also, box plots allow for the direct comparison of data gathered from different categories [22].

Finally, a heatmap was selected to visualize how recovery time from stressors is affected as a function of both stressor type and post-stressor activities. Relevant literature suggests that heatmaps are a suitable tool to convey the correlation between two variables [2]. Additionally, this format enables quick identification of patterns and interactions among the parameters through color gradients [6].

3 Methodology

This section presents the methodology of the study, beginning with the development of visualizations designed to capture essential aspects of emotional resilience. Then, it details the qualitative evaluation procedure, which involved gathering feedback from mental health professionals to assess the clarity, interpretability, and perceived clinical usefulness of the proposed visual tools. Finally, it outlines the thematic analysis conducted on the survey's responses, in order to gather meaningful insights.

3.1 Development of Visualizations

To support the interpretation of ESM data on mental resilience by mental health professionals, four visualizations were developed. Each visualization aims to address key aspects of the resilience process, including recovery speed, emotional granularity, and context-specific effects. All visualizations were developed using Python's matplotlib[1] library by utilizing synthetic data.

Line Graph Visualizing Average Mood Rating Around Stressors

The first visualization, shown in Figure 1, is a line graph that depicts the average trajectory of an individual's mood over time relative to stressful events. This graph highlights the emotional recovery process by visualizing how mood levels fluctuate before and after the appearance of stressors.

The horizontal axis represents the number of hours relative to the reported stressor (with 0 indicating the time when the stressor occurred), while the vertical axis shows the average mood rating across multiple such events. In addition, a dotted horizontal line shows the individual's baseline mood value, which is the average mood level prior to the occurrence of the stressor.

In a more detailed version (Figure 2), error bars indicate the standard deviation at each time point, and hover-enabled annotations display precise values of the time and mean mood

[1] https://matplotlib.org/

rating, along with an uncertainty range (Error) for the calculation of the average mood. These design features allow mental health professionals to assess both the general recovery pattern and its variability.

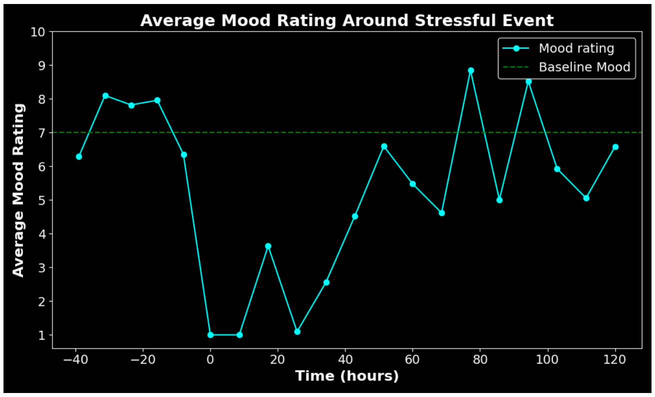

Figure 1: Average mood rating over time, showing recovery after a stressful event.

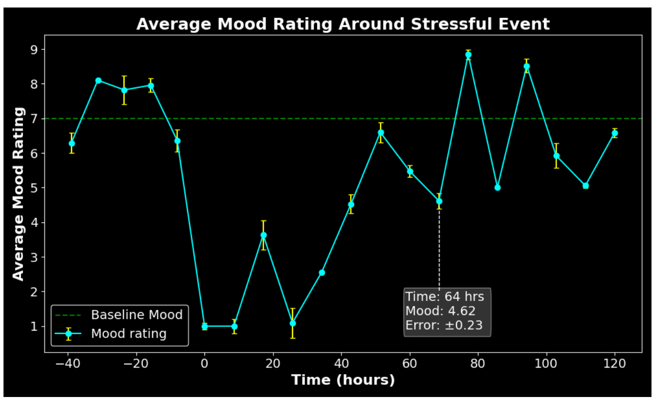

Figure 2: Average mood rating over time with uncertainty information. Error bars indicate the standard deviation at each time point. In interactive versions, hovering over a point displays additional information such as time and mood rating.

Line Graphs Visualizing Average Intensity of Specific Emotions Around Stressors

The second visualization, shown in Figure 3, uses multiple line graphs to represent the trajectory of distinct negative emotions over time, preceding and following a stressor. This approach highlights emotional granularity, enabling clinicians to identify which specific emotions are most reactive or persistent after stressors.

In each graph, the horizontal axis shows the time relative to the stressor, while the vertical axis indicates the average rating for each emotion, on a scale of 1 - 10.

Box Plots Showing the Variation of Recovery Time by Type of Stressor

The third visualization, presented in Figure 4, is a set of box plots comparing emotional recovery times across different categories of stressors. Recovery time is defined as the time interval between the occurrence of a stressor and the moment at which the reported mood returns to baseline [19]. Each box plot displays the median recovery time (central line), inter-quartile range (box edges) in which half of the values belong, whiskers extending to 1.5 times the inter-quartile range, and outliers as individual points.

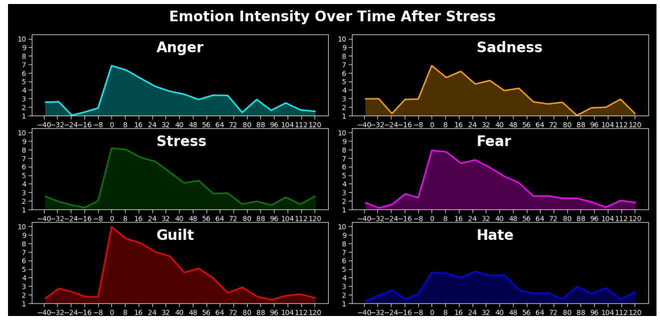

Figure 3: Emotion-specific recovery trajectories over time, illustrating the variation in intensity and recovery speed for different negative emotions.

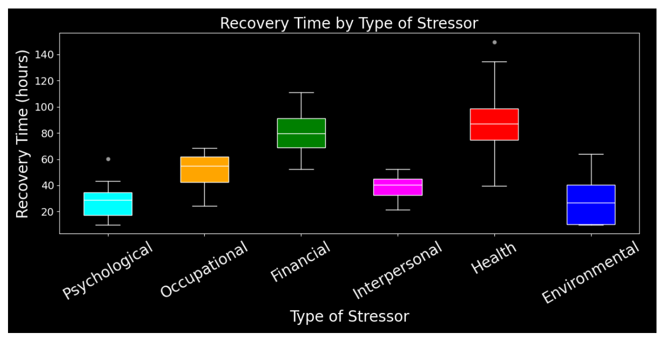

Figure 4: Box plots showing recovery time distributions for different stressor types. Each box displays the median, inter-quartile range, and outliers.

Heatmap Visualising Improvement in Recovery Time by Stressor Type and Post-Stressor Activities

The fourth visualization, shown in Figure 5, is a heatmap that explores the relationship between coping activities, stressor types and emotional recovery time. It presents the average change in recovery time (in hours) for each combination of stressor type and coping activity, compared to the average recovery time of the individual. This visualization highlights how specific activities may help or hinder emotional recovery depending on the stressor context.

Activities such as walking, talking, journaling, and scrolling are plotted along the vertical axis, while stressor types are shown along the horizontal axis. Positive values indicate longer recovery times (i.e., less effective coping), while negative values reflect improved recovery. Also, this heatmap makes use of a color gradient, in which greener values indicate boost in recovery, while more red values show worsened recovery.

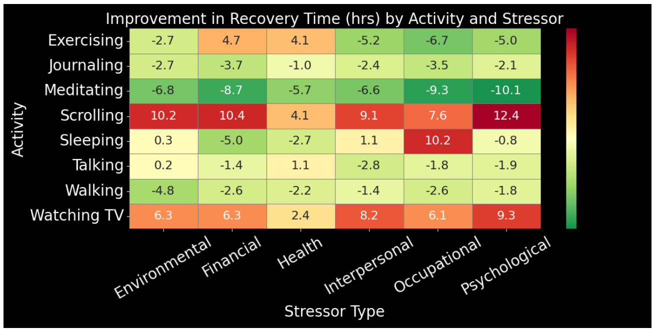

Figure 5: Heatmap showing the average improvement or worsening in recovery time across different stressor-activity combinations, compared to the average recovery time of the individual.

Together, these visualizations offer multiple different perspectives on emotional resilience. They highlight not only the overall dynamics of recovery, but also how these are shaped by emotion type, stressor category, and post-event behavior.

To make these visualizations usable in clinical practice, certain data must be collected through well-structured ESM questionnaires. For instance, the first visualization requires participants to regularly rate their overall mood, while the second requires separate ratings for distinct emotions. The third and fourth visualizations rely on additional context: participants must indicate the nature of stressful events (e.g., categorize the stressor), and report any coping activities they engaged in afterward. Designing an ESM instrument to gather this information consistently is essential to enable accurate, personalized feedback based on these visualizations.

3.2 Evaluation Method

An evaluation was conducted to assess whether the developed visualizations provide clear, meaningful and actionable insights for mental health practitioners. By utilizing the Qualtrics[2] platform, an online survey was devised, which included open ended questions aimed to capture the opinions of respondents on the visualizations.

The target group of the survey was practicing mental health professionals, such as psychologists or psychiatrists. However, due to difficulties in reaching a sufficient number of such respondents, the survey was also open to university students from related fields. In order to find enough respondents for the survey, it was shared among groups of university students and mental health practitioners, which were kindly asked to complete it.

Before accessing the survey, the respondents were instructed to give approval for their responses to be used for the purposes of this research project. The survey was completely anonymous and did not collect any personal information that did not relate to the objective of the evaluation. Furthermore, if an open-ended response included personally identifiable information, such data were removed to ensure anonymity.

In the beginning of the survey, participants were asked to fill out details concerning their professional or academic role and their familiarity with ESM data. Afterwards, they were presented an introduction, in which the purpose of the project was explained. Following this, they were prompted to fill out the survey as if they were using the plots in a therapeutic context.

The survey included questions that focused on two main pillars. First, they were aimed to understand whether the respondents were able to interpret the meaning of the graphs correctly. Second, they wanted to investigate whether each of the visualizations could be useful in therapeutic contexts. A complete list of all questions can be found in Table 1

The survey was completed by five participants, which included two mental health practitioners and three university students in fields related to mental health. Additionally, the respondents had varying levels of expertise with ESM data, with two being very familiar, one being somewhat familiar and two not having any previous experience with them. A detailed overview of their characteristics is presented in table 2

3.3 Data Analysis

The qualitative data collected through open-ended survey responses were analyzed using thematic analysis, a method elaborated by Braun and Clarke [3] for identifying and interpreting patterns of meaning within textual data. Thematic analysis involves a systematic process of coding qualitative data and organizing these codes into broader themes that capture recurring ideas across the dataset.

The process began with a familiarization phase, during which all responses were read multiple times to develop an overall understanding of the data. Then, a total of 39 codes were manually generated to label meaningful segments of text. This part was completed with a "theory-driven" approach [3], in which the data were analyzed with the study's objectives in mind, specifically to explore the interpretability and clinical usefulness of the visualizations.

After the initial coding, an inter-coder reliability check [12] was conducted to ensure the consistency and trustworthiness of the coding scheme. A second coder independently applied the codebook to the same set of answers and agreement between the two coders was assessed using Cohen's Kappa. The average Cohen's Kappa for the set of codes was 0.85, which is considered acceptable in most situations [12].

For transparency reasons, the coders' positionality is shared in this paper. More specifically, both coders were university students who study and conduct research on computer science.

The codes, along with their Cohen's Kappa values, can be found in Table 3 of Appendix A.

Following the coding, related codes were grouped into candidate themes that captured broader patterns in the data. These themes were focused around answering the study's research question. A semantic methodology was chosen for this task, in which the focus for the themes was on the explicit messages conveyed by the participants, instead of trying to uncover underlying meanings.

Then, an iterative process of reviewing and refining the themes was undertaken, in order to make sure that each theme accurately represented the coded data. Once the themes were

[2] https://www.qualtrics.com/

Table 1: Survey Questions

#	Question
1	What do you understand from the line graph? What does the trajectory suggest to you about the individual's emotional recovery?
2	In what situations can the error bars and hovering details be important when interpreting the graph?
3	In what ways is it important to distinguish each different emotion, instead of viewing a general mood score?
4	What does the box plot reveal to you about how the individual reacts to different types of stressors?
5	What insights do you gain from this heatmap about the effectiveness of different activities in promoting emotional recovery?
6	Which of these four visualisations would you consider using in a therapeutic setting? Please explain your answer.
7	What else would you like to be visualised or what would you change in these visualisations to make them more effective in therapy?

Table 2: Survey Participants by Familiarity with ESM data and Background

Background / Familiarity with ESM	**Not Familiar**	**Somewhat Familiar**	**Very Familiar**
Mental Health Practitioner	1	0	1
University Student in Related Field	1	1	1

finalized, they were given descriptive names that reflect on the meaning of each theme.

As the creators of this method mention, it is important to support the resulting themes with representative quotes by the participants. These quotes help illustrate the key findings of the analysis while preserving the original language and intent of the respondents, enhancing the credibility and authenticity of the results.

The final set of themes is presented in the results section.

4 Results

This section provides the results of the survey, in terms of comprehensibility, usefulness and potential improvements of each visualization. This includes the outcome of the thematic analysis conducted on the received responses, with the derived themes presented per visualization. To develop a stronger connection between the collected data and the subsequent analysis, the themes are supported by quotes extracted from the responses.

Line graph visualizing recovery is helpful but limited

The general consensus among the participants about the line graph which presents mood recovery is that it is an easy to interpret visualization that can give a general impression about the resilience process, but does not give enough details to prompt a therapeutic discussion or intervention. Respondents were able to understand the speed and mood fluctuations that occur through a resilience process (*"This is a nice graph to visualize fluctuations in mood levels, until recovery"*). Furthermore, they appreciated the inclusion of the baseline mood value, as it is a way to argue that the individuals have recovered from stressors completely (*"It's also helpful that the baseline is clearly marked, so I can compare how long it takes for their mood to stabilize"*). However, they also highlighted limitations that hinder its usefulness in therapeutic contexts. More specifically, some respondents agreed that this visualization is helpful to investigate general emotional patterns, but in order to foster meaningful discussions with the patients or targeted interventions, further context should be added to the visualization (*"The visualization is helpful as a broad narrative tool", "A general mood score can mask important emotional dynamics"*).

Hovering details and error bars provide data informed judgments but their usefulness is debated

The details that appear when hovering above data points and the error bars appear to enhance clarity and accuracy in graph interpretation, but their practicality in clinical contexts is not clear to some experts. Respondents were able to extract exact values at specific time points through the hovering details, which was deemed important in therapy settings (*"hovering details are important to show exact values, as precision is important in therapy"*). On the other hand, opinions about the usefulness of error bars were mixed. Some of the respondents considered them helpful, as they represent the precision of mood responses at each time (*"The error bars can be used to determine how precise a reported mood rating was at a certain time point."*). Also, it was mentioned that large error bars result in less confidence when interpreting the graph (*"If the error bars are large we should be cautious about interpreting the average too confidently"*) and that they can help distinguish between values that represent consistent emotional responses and values that are affected by outlier responses (*"it tells us whether a sharp drop or rise in mood is a strong, consistent response or just based on a few outlier responses"*). On the contrary, some answers found no usefulness of the error bars in clinical settings (*"no idea what the error bars could be used for"*), or argued that this feature is not intuitive to be understood by non-experts in data analysis and visualization (*"may be less intuitive for clients unless well-explained"*).

Emotion-specific graphs can foster discussions with clients

It was widely agreed by the survey participants that viewing how an individual's emotions are affected after a stressful event is useful in clinical settings. Particularly, it was argued that discussing specific emotions with the clients is more relevant and can provide more meaningful insights compared to a general mood score (*"it is always more relevant to discuss any specific mood in a therapeutic session"*). Consequently, practitioners may use these graphs to help their patients gain emotional awareness and to provide tailored interventions (*"help clients build emotional awareness by distinguishing between feelings", "you can implement more targeted intervention strategies"*). As a possible modification of this graph, it was noted that practitioners would like to select which emotions to visualize, instead of viewing some predefined ones (*"I would like to be able to choose which emotions to view here"*).

Box plots offer insight into impact by stressor type but may not be suitable for clinical settings

Participants generally saw box plots as valuable tools for identifying how different stressors affect emotional recovery, but their appropriateness for therapeutic contexts was questioned. All of them highlighted the usefulness of boxplots in understanding the recovery time of different stressor types. One respondent focused on the capacity of this visualization to reveal which stressor types yield prolonged effects, which can encourage specific therapeutic focus and interventions (*"helpful for pinpointing which stressors are the most emotionally taxing, and it could guide both therapeutic focus and coping strategies tailored to the individual"*). Others recognized how the structure of the box-plot can be utilized in therapy, with some arguing that the visualization of variability in the responses aids interpretation, as high variability can mean that the individual has a less predictable response to a stressor (*"wide variability indicating unpredictably disruptive events"*). Also, it was mentioned that outliers may be extreme scenarios that can be discussed in therapy (*"The outliers could reflect particularly distressing experiences that might need to be explored in therapy"*). Despite these strengths, participants raised concerns about the box plot's suitability in clinical settings. Some described the format as less intuitive and suggested that, without clear contextual information, the visualization might be difficult for clients or practitioners to interpret accurately (*"I think it should give some more context on the specific occurrences of each stressor"*). Another, questioned whether it would be realistic to collect sufficient data from a single person to generate valuable plots, as the individual would have to report numerous stressors for that to happen. (*"I am not sure how long it would take to gather enough data to have a meaningful graph like this"*).

The heatmap is a practical and intuitive tool for therapy

Participants overwhelmingly viewed the heatmap as easy to interpret, visually clear, and therapeutically useful. It was mentioned that the effect of post-stressor activities was understandable through the heatmap, especially through the color gradient (*"I like the color coding as it is intuitive to understand"*). Moreover, several respondents indicated the practicality of the heatmap in therapeutic contexts, as it can be a helpful tool when discussing with the client (*"handy in recovery when discussing de-stressing activities with a client"*). In detail, it was said that it can prompt conversations on their engagement in post-stressor activities and support patients in making evidence-based decisions on which activities to pursue after a stressful event (*"could help clients make informed choices"*). Finally, one person expressed that it would be a more complete visualization if, additionally, the aggregated effect of an activity across all stressor types was displayed (*"in the heatmap show the aggregated effect of each activity"*).

Suggested enhancements to the visualization of Mental Resilience

After reflecting on the developed visualizations, respondents were asked to provide any additional aspects of mental resilience they would find useful to be presented. One desire was to visualize changes in resilience over time, especially how the speed of recovery might evolve with repeated stressors (*"how recovery speeds up or slows down across repeated stressors"*). Another, emphasized on the need to be able to filter based on the perceived intensity of stressors, allowing them to focus specifically on more significant or high-impact events (*"filter based on how stressful the event was"*). Lastly, one participant noted that they would appreciate being able to view the resilience process for each individual stressful event, including the context and the duration of its emotional impact (*"visualizations about each specific recovery from a stressor"*).

5 Discussion

This section discusses the key findings that emerged through thematic analysis on the survey's responses, while contrasting on the expectations that were formed based on literature. Additionally, it reflects on the limitations and future improvements of the research.

5.1 Discussion of Results

The line graph showing mood recovery after stressors was generally deemed intuitive, understandable and helpful in gaining a general picture about what trajectory a person' mood tends to follow after stressful events. This aligns with prior literature [2] that highlights the suitability of line graphs for visualizing temporal patterns, particularly for ESM data. However, this visualization was not successful in providing actionable insights to the respondents, hence its usage in a clinical context would be restricted. Even though previous research [23] has emphasized the return to baseline as a key indicator of emotional resilience, without information about contextual factors, this visualization does not provide sufficient insight to support therapeutic decision-making.

Similarly, error bars and hover-enabled details on the line graph were seen as improving precision and interpretability, but their usefulness in clinical settings was less consistent. On one hand, these features were recognized as enhancing clarity and supporting data-informed judgments, reinforcing the motivation behind their use [8, 16]. This precision was appreciated by some respondents, especially in therapeutic contexts where nuance matters. However, despite these benefits, the practical utility of these elements in therapy was contested, with some respondents questioning the intuitiveness of error bars to non-experts. So, while features like error bars support interpretive depth, they may reduce confidence among users less familiar with statistical representations [5].

The plots emphasizing on emotional granularity were evaluated as suitable to be used in therapeutic scenarios. More specifically, the respondents highlighted the importance of being able to distinguish between specific emotions in a visualization, since it can foster dialogue, enhance self-awareness and guide personalized interventions. This is on par with existing research [19] that argues about the importance of differentiating among distinct emotions in clinical contexts.

Moreover, responses related to the box plots shared the opinion that understanding which stressors cause prolonged effects on an individual might allow them to provide specialized care towards those stressful events. The importance of distinguishing between stressors is also supported by the relevant literature [1]. On the other hand, the appropriateness of the box plot as a visualization technique was debated. Some argued that it served as a useful tool to compare the data collected through different stressors, which is also the motivation for its usage based on other studies [22]. However, some respondents were not certain about its intuitiveness to non-experts and whether it would be feasible to collect sufficient data from individuals to produce meaningful insights.

Finally, the heatmap was widely viewed as one of the most practical and intuitive visualizations for therapeutic use. Respondents shared the opinion that using a heatmap with a well defined color gradient makes the relationship between two variables visually intuitive and easy to understand. This view also reinforced the literature [2, 6] advocating the use of heatmaps for the visualization of two-dimensional data. Additionally, the participants noted that the heatmap could be used to foster discussions about the individual's engagement to post-stressor activities and help them understand which activities aid their recovery process. Literature [18] and respondents alike agree that participation in meaningful activities is important after stressors.

Across all visualizations, two main general discussion points can be extracted. Firstly, the simplicity and intuitiveness of each feature was crucial in interpreting the plots. Graphs with clear visual characteristics, such as the color gradient in the heatmap or the straightforward layout of the line graph, were more consistently understood and appreciated. Conversely, visualizations that introduced more technical features, like error bars or box plots, were met with mixed reactions. Secondly, participants repeatedly emphasized the importance of actionable information. Tools that presented how specific emotions vary or incorporated context, such as post-stressor activities, were more likely to be deemed useful in therapeutic contexts, as they can prompt discussions and provide practical insights.

5.2 Limitations

Despite the promising results, this study has several limitations. First, the difficulty in approaching and pursuing mental health professionals to take part in the survey meant that the number of opinions collected was relatively small, which affected the variation of the responses and constrained the ability to generalize the feedback. Also, even though the use of synthetic data is a good option for development, they may not fully capture the variability of real ESM datasets [7]. Furthermore, the visualizations were not tested on actual patients, meaning that their practical effectiveness and usefulness in supporting therapeutic decision-making remain unproven.

5.3 Future Improvements

Future improvements on the research could focus both on the visualizations and the evaluation procedure. More specifically, by taking into consideration the feedback received through the survey, many new features could be added to the visualizations. These can include a presentation of how the recovery process changes through repeated stressors, which is based on research [15] indicating that individuals can become more resilient through continuous adversities. Also, contextual information can be provided for each specific occurrence of a stressful event, as it is common in therapy settings for particular circumstances to be discussed [20]. On the evaluation side, future studies could test these visualizations in more ecologically valid contexts, such as through real case studies involving individuals in therapy. In order to achieve this, the visualizations would have to be integrated into full scale mental health applications, such as the ones presented in the related work section [4, 17, 9].

6 Responsible research

The research procedure presented in this paper was conducted in accordance to certain standards that ensure the ethical integrity of the project. Moreover, ethical approval for the project was obtained from TU Delft's Human Research Ethics Committee (Approval ID: 5405). This section presents the measures that were taken in order to guarantee that the creation of the visualizations, the survey procedure and the subsequent data analysis were carried out with responsibility. Then, the ethical implications of the project are discussed.

The development of the visualizations using Python's Matplotlib library was achieved using synthetic ESM data. As a result, no data emerging from real patients are being presented in this study, securing that no individual's mental health information is being exposed. Moreover, all design choices were sufficiently supported by existing literature, which was used to explain both the factors related to mental resilience and the choices of visualization techniques.

The evaluation survey was only completed by those professionals or students that were willing to voluntarily do so. Before filling in the questionnaire, they were asked to provide consent for their responses to be used in a scientific setting for the purposes of this research project. Additionally, they were informed that the data collected are completely anonymous, as there will be no gathering of names, contact details or IP Addresses. These measures were utilized to respect the privacy and volition of each responder.

The analysis of the received data was objective and reflected only the views and opinions of those who completed the questionnaire. In this manner, all responses were included in the analysis, regardless of whether or not they aligned with the expected outcomes. Moreover, the thematic analysis method used to understand the responses was documented clearly, ensuring that the results were as accurate and reliable as possible.

While the visualizations developed in this project aim to support clinical understanding of individuals' mental resilience, their use may present important ethical considerations. One such concern is the risk of over-reliance on these visualizations when drawing clinical conclusions, without integrating them with broader therapeutic expertise. For example, it is possible that these visualizations neglect important factors that may interfere with the resilience process and which should be discussed in therapy. Moreover, measures must be taken to avoid misinterpretation of visuals by clinicians or patients, which would possibly lead to inaccurate conclusions and misguided interventions.

7 Acknowledgment of Generative AI Use

Generative AI and more specifically ChatGPT was utilized in the Research Project by providing help both in the research process and in the writing of this paper.

In particular, it served as a valuable tool for finding prior literature, in combination with looking up in relevant databases. For this task, the queries included, for example, "Find papers that talk about ESM visualization tools" or "Find papers that talk about the important factors of mental resilience".

Additionally, it was a valuable tool to help me get started with writing this paper, especially due to the fact that I was not able to use my dominant hand for a significant period of the course, as I underwent a surgery. Hence, in the beginning, some sections were written using support from ChatGPT. However, since regaining the ability to use my hand, these were recreated to match the tone and characteristics of my writing.

Finally, ChatGPT was used in order to get insights on how to produce Latex code. Examples for this included questions on how to generate tables, or how to structure text nicely.

8 Conclusion

The main contribution of this study was the development of a wide range of visualizations designed to effectively convey the process of mental resilience of individuals, as captured by ESM data. These visualizations included a line graph that presents how the average of mood ratings collected via ESM questionnaires fluctuate in the hours after a stressful event, as well as a graph that emphasizes on emotional granularity and shows how different emotions vary after stressors. Furthermore, a box plot chart is incorporated that shows the variance in recovery times after different types of stressors. Finally, a heatmap was created that shows the way post-stressor activities affect the recovery time of each category of stressors.

While the visualizations were developed based on prior literature on mental resilience and ESM tools, a survey was required to understand the views of mental health professionals on the usefulness and clinical relevance of these tools. The results indicated that visualizations that succeeded in providing rich information and context, while remaining intuitive and easily interpretable were the most likely to be utilized in therapeutic settings.

Concluding, this study reinforces the potential of using valuable visualization techniques to provide actionable insights for mental health practitioners, through ESM data.

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A Thematic Analysis Codes

Table 3: Codes Generated from Survey Responses through Thematic Analysis and Intercoder Agreement

Visualization Aspect	Code Description	Cohen's Kappa
Line Graph	Understand recovery process	0.79
	Understand fluctuations in recovery process	0.64
	Baseline marking is helpful	1.00
	Can understand resilience abilities	0.65
	Helpful but general tool	1.00
	Risk of oversimplification	1.00
Hovering Details	Helpful to see exact values	1.00
Error Bars	Not useful in clinical context	1.00
	Show variability in mood ratings	0.79
	Large error bars give less confident interpretations	1.00
	Distinguishing consistent vs. outlier responses	1.00
	Less intuitive	0.48
Error Bars & Hovering Details	Data informed judgment	1.00
Emotion-Specific Graphs	Discussing specific emotions is more relevant	0.72
	Provide targeted interventions	1.00
	Want to choose which emotions to view	1.00
	Builds emotional awareness	0.00
Box Plots	Understand recovery time of stressor types	1.00
	Understand which stressor types cause prolonged effects	0.38
	Variability aids interpretation	0.65
	Outliers can be discussed in therapy	0.65
	Provide therapeutic focus in certain stressors	1.00
	Tailor coping strategies	0.65
	High variability means unpredictable response	1.00
	Need context on specific occurrences	1.00
	May not have enough data	1.00
	Less intuitive	1.00
Heatmap	Helpful when discussing with client	0.84
	Efficient and visually pleasing	1.00
	Understand the effect of different coping mechanisms	0.72
	Prompt discussions about engagement in activities	0.65
	Intuitive color coding	1.00
	Helps patients make informed choices	1.00
	Practical in therapy	0.54
	Easy to interpret	1.00
	Show aggregated effect of each activity	1.00
Other Suggestions	Show improvement in resilience	1.00
	Filter based on stress intensity	1.00
	Visualize specific recoveries	1.00