Triaging and Risk Automation System for Mental Health (Project TRAS-Me)

Background

NUS Health and Wellbeing (HWB), established in 2021, aims to enhance the university's focus on mental wellbeing by offering comprehensive and accessible psychological services to over 17,000 staff members. Throughout the years, numerous cases have presented complex mental health challenges, including suicide and self-harm risk. Identifying these risks early is a critical challenge due to the high case volume and the subtle signs of distress. Without timely identification, early interventions are delayed, increasing the risk potential for adverse outcomes. Having efficient systems is a priority as it helps to flag high-risk individuals and ensure they receive immediate care and support for their safety. At the same time, addressing this gap is crucial to improving clinical outcomes for clients.

Innovation Overview

Since 2024, NUS HWB has developed a novel data-driven workflow that enhances the identification, visualisation, notification, and prioritisation of suicide and self-harm risks within its staff-facing services (see Figure 1). By integrating data analytics, natural language processing, and programming languages (i.e., Python), the workflow enables quicker identification of at-risk staff, allowing for a more proactive approach to care.

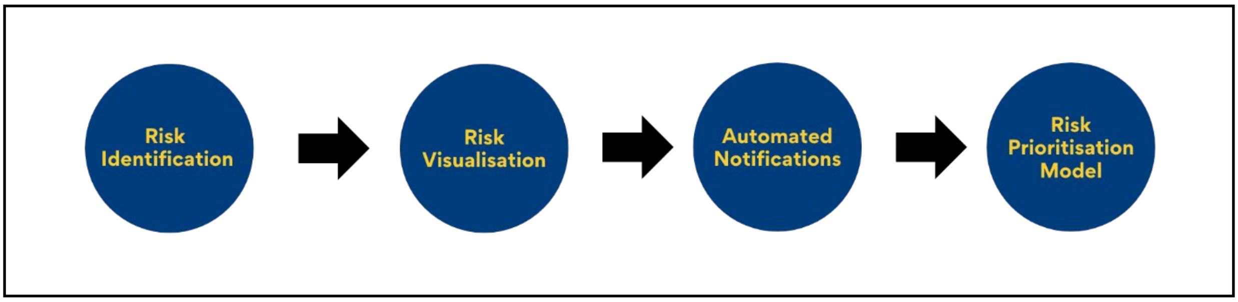

Figure 1. *HWB's Four-Step Process of Analysing Risk.*

Innovation Description

Step 1: Risk Identification

In the pre-intake phase, we adopt a dual approach to risk identification by integrating both quantitative and qualitative methods. The Outcome Questionnaire-45 (OQ-45) serves as our primary tool for gathering structured, objective data on mental health functioning, assessing domains such as symptom distress, interpersonal relationships, and social roles.

Complementing this, we utilise Natural Language Processing (NLP) techniques, including Bidirectional Encoder Representations from Transformers (BERT)-based models, to analyse unstructured client communications, such as initial reasons for appointments. BERT, an advanced NLP model, helps us understand the emotional tone and context of a client's language. At HWB, this capability is harnessed to develop an emotional profile for each client based on the textual information provided during the initial appointment request (see Figure 2).

This combination allows us to identify signs of distress and risks, offering a more comprehensive understanding of a client's emotional state.

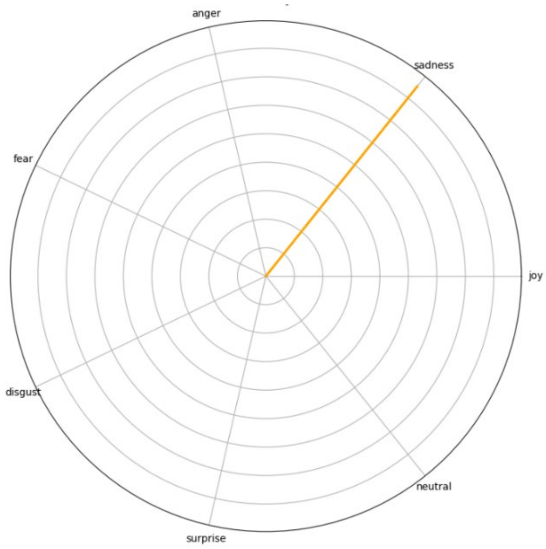

Figure 2. Sample *BERT Emotion Profile*.

Step 2: Risk Visualisation

In many clinical services, suicidal and self-harm risk is often assessed through qualitative methods, with risk levels reported using descriptive terms or numbers (Lolita & Cook, 2015). However, these self-reported responses, such as indicating that suicidal thoughts occur *"Frequently"* can be highly subjective and challenging to interpret consistently across cases. The lack of systematic interpretation impedes decision-making leading to variability in clinical assessments and delayed interventions.

To overcome this challenge, we have developed an in-house, Python-based automated solution that visually generates and represents risk levels (see Figure 3) immediately after a new case is logged. This offers a clear data-driven snapshot of a client's mental health status before the first session, enabling our clinical team to make informed and timely decisions. Our solution integrates real-time data from *Qualtrics* via Application Programming Interfaces (APIs), drawing on responses from clinical self-report tools like the OQ-45. For every client, we also compare their scores against standardised clinical thresholds, validated through research, to assess risk with greater consistency, accuracy and reliability.

Our solution has also incorporated visual cues such as colour-coded indicators (e.g., green for below clinical cut-offs, red for above), enhancing the clarity of the risk assessment and making it easier for clinicians to understand and prioritise critical cases. This solution improves risk evaluation efficiency and clinical outcomes by ensuring that high-risk clients receive immediate attention and interventions.

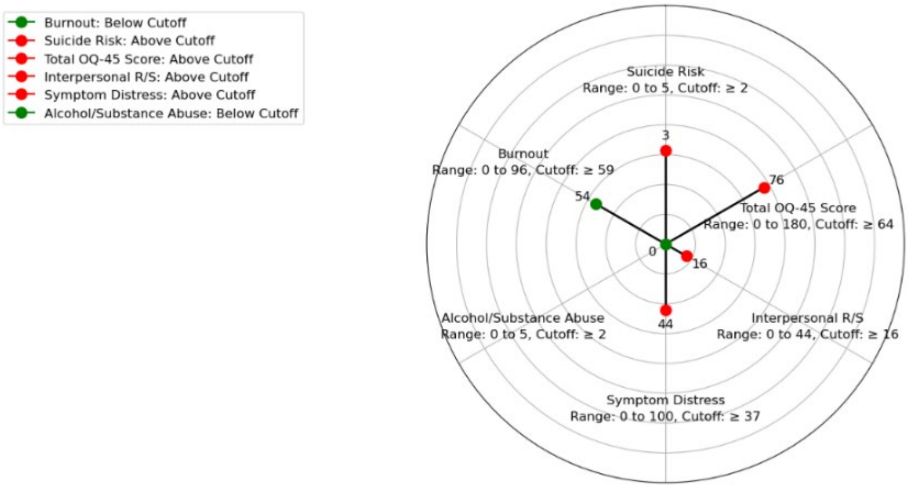

Figure 3. *Sample Visual Representation of Risk*.

Step 3: Automated Notifications

In addition to generating visual risk assessments, we have implemented a 24/7 automated flagging system for cases with significant self-harm or suicide risk using open-source webhooks. Flagged cases are automatically forwarded to a dedicated Microsoft Teams chat, where clinical leads can collaborate on decision-making for high-risk cases during regular working hours (see Figure 4). To ensure critical cases are also addressed outside working hours, our system leverages *Qualtrics'* in-built personalised auto-reply feature, which directs cases to appropriate services—such as SOS Singapore—via automated responses to *Qualtrics* submissions that meet a certain risk threshold (see Figure 5). This process minimises the risk of delayed responses, enhancing overall client safety.

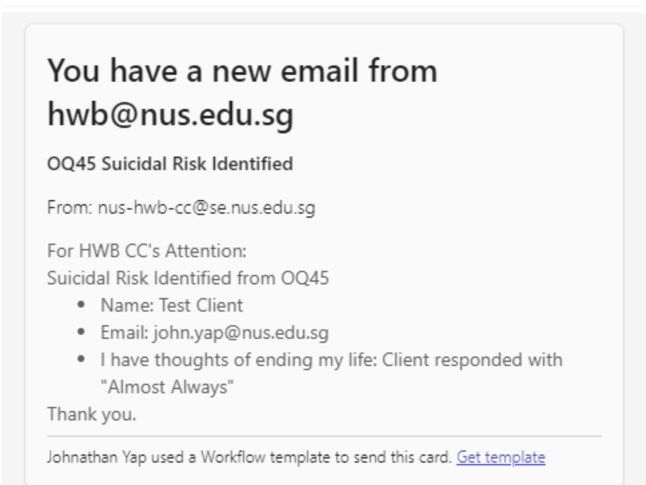

Figure 4. *Automated Risk Notifications*

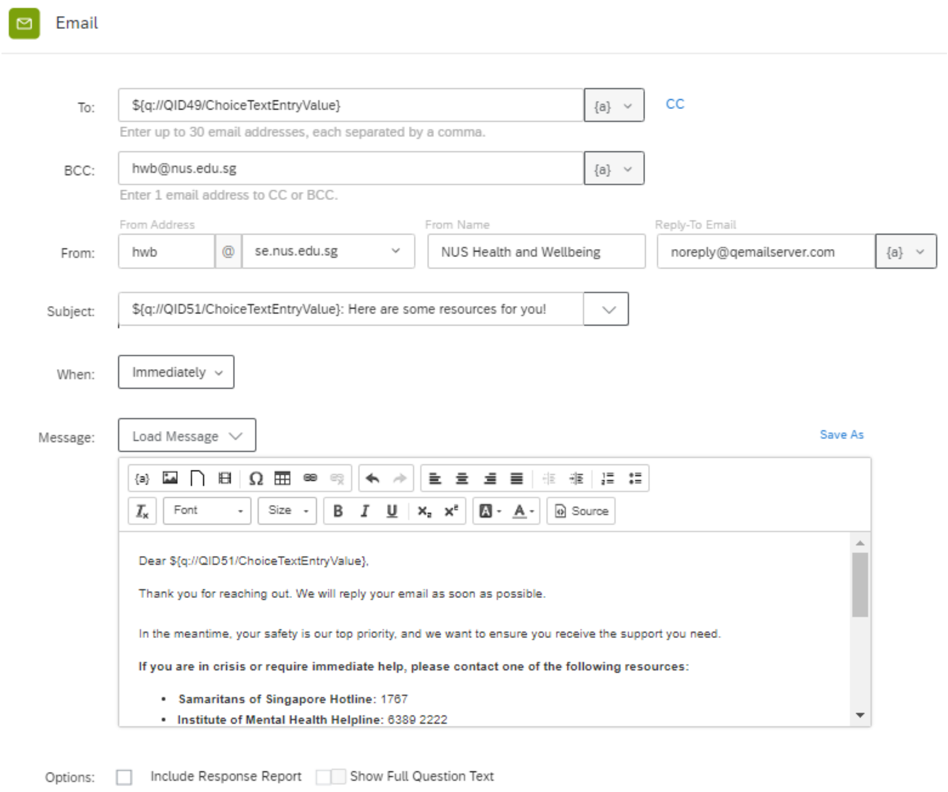

Figure 5. *Qualtrics' auto-reply workflow*

Step 4: Risk Prioritisation Model

We developed a Python model designed to efficiently prioritise and allocate resources based on key risk factors. The model computes a composite *Priority Score* by incorporating three critical weighted components: suicide risk, self-harm risk, and the OQ-45 total score (see Figure 6). Each risk factor is essential for assessing the urgency of cases, and thus, suicide risk and self-harm risk are assigned equal weight to reflect their critical importance. The OQ-45 score (normalised) serves as a tiebreaker, distinguishing cases with similar risk levels.

$$\boxed{\text{Priority\_Score} = (\text{Suicide\_Risk\_Value} \times w_{\text{suicide}}) + (\text{Self\_Harm\_Risk\_Value} \times w_{\text{self-harm}}) + (\text{Normalized\_OQ-45} \times w_{\text{OQ-45}})}$$

Figure 6. *Priority Score Formula*

The model ranks cases by priority based on combined risk scores, ensuring timely attention for individuals with the most acute needs. Qualitative risk categories (High, Moderate, Low) are mapped to numerical values for easy computation, which are then combined using predetermined weights to produce an overall *Priority Score*. To enhance accuracy, we introduced a tiebreaker based on appointment request time, prioritising earlier submissions among cases with identical Priority Scores. This approach ensures fair and timely handling of requests, especially during high-demand periods.

Our methodology enables dynamic, data-driven resource allocation, helping to optimise response times. We validated the model by simulating 500 cases, capturing a realistic distribution of risk levels and appointment requests (see Figure 7). The prioritisation algorithm effectively identified and re-ranked cases with higher risk factors, particularly ensuring that "High" risk cases for suicide and self-harm receive immediate attention.

	Case_ID	Suicide_Risk	Self_Harm_Risk	OQ-45	Appointment_Request_Time	Priority_Ranking
0	194	High	High	179	2024-09-23 12:41:37.739830	10.000000
1	110	High	High	178	2024-09-21 12:41:37.739215	9.985099
2	376	High	High	175	2024-08-27 12:41:37.741180	9.940397
3	33	High	High	175	2024-09-03 12:41:37.738639	9.940397
4	239	High	High	175	2024-09-20 12:41:37.740155	9.940397
...	...	...	...	...	...	...
495	71	Low	Low	16	2024-09-11 12:41:37.738922	1.134106
496	175	Low	Low	11	2024-09-15 12:41:37.739684	1.059603
497	107	Low	Low	11	2024-09-20 12:41:37.739182	1.059603
498	378	Low	Low	9	2024-09-13 12:41:37.741195	1.029801
499	223	Low	Low	7	2024-09-01 12:41:37.740039	1.000000

500 rows × 6 columns

Figure 7. *Python Simulation of Risk Prioritisation (dummy data)*

Impact & Relevance

Since implementing the data-driven workflow, HWB has significantly reduced the time to identify high-risk cases from ~1 day to under an hour. This improvement ensures that clients presenting with suicide or self-harm risk receive timely intervention, enhancing safety and minimizing the likelihood of adverse outcomes. Additionally, this approach is also scalable, offering a replicable framework that can be adapted by other institutions or clinical services, allowing for more proactive risk management in diverse settings.

References

Lotito, M., & Cook, E. (2015). A review of suicide risk assessment instruments and approaches. *Mental Health Clinician, 5*(5), 216-223.

Matero, M., Idnani, A., Son, Y., Giorgi, S., Vu, H., Zamani, M., ... & Schwartz, H. A. (2019, June). Suicide risk assessment with multi-level dual-context language and BERT. In *Proceedings of the sixth workshop on computational linguistics and clinical psychology* (pp. 39-44).