A trajectory-based analysis of heterogeneity in sentiment changes among help-seekers in text-based counselling

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Abstract

Background: Online text-based counselling services are becoming increasingly popular. However, their text-based nature and anonymity pose challenges in tracking and understanding shifts in help-seekers' emotional experience within a session. These characteristics make it difficult for service providers to tailor interventions to individual needs, potentially diminishing service effectiveness and user satisfaction.

Objective: This study sought to identify distinct within-session sentiment trajectories among help-seekers in online text-based counselling and examine key predictors of trajectory membership.

Methods: A total of 6,207 counselling sessions were randomly extracted from an online text-based counselling service in Hong Kong. A Latent Class Trajectory Analysis (LCTA) of help-seekers' in-session sentiment was conducted using a Growth Mixture Model (GMM) to identify latent groups of help-seekers exhibiting specific sentiment trajectories. Sentiment scores of help-seeker messages, labelled by ChatGPT, served as the primary variable for trajectory modelling. Subsequently, a multinomial logistic regression was performed to identify variables associated with class membership.

Results: The GMM identified three distinct sentiment trajectories as the best fit: i) Steady Improvement (18.9%), ii) Deterioration (18.0%), and iii) Dip-Then-Rebound (63.1%). Compared to the Dip-Then-Rebound Class, help-seekers in the Deterioration Class were more likely to report suicidal ideation, present with family or physical health-related concerns, have an unknown gender status, access the service through the anonymous channel, depart from the session prematurely, and have shorter session durations.

Conclusions: We identified three distinct trajectories of help-seekers' in-session sentiment. Identifying the most likely trajectory at an early stage in the session could potentially help counsellors adjust their approaches, thereby improving the effectiveness of text-based counselling and enhancing help-seeker satisfaction.

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Keywords: Text-based counselling; Latent class trajectory analysis; Sentiment analysis; Growth Mixture Model

Introduction

The demand for mental health services has surged in recent years [1], driving the rapid expansion of online text-based counselling [2]. This modality reduces barriers commonly associated with traditional face-to-face services [3], by allowing help-seekers to communicate with counsellors in real-time at any location, often anonymously, which may lower stigma and increase openness in disclosing concerns [4].

Despite its benefits, the anonymity inherent in text-based counselling poses challenges in gathering useful help-seeker information and accurately assessing therapeutic progress [[5], [6]]. Additionally, the lack of non-verbal cues in text communication can lead to misunderstandings and hinder counsellors from readily evaluating the severity of issues [7]. These difficulties highlight the need for alternative approaches to better understand help-seekers' emotional processes and improve the effectiveness of counselling services [8].

Natural language processing (NLP) integrates linguistics and artificial intelligence (AI) to analyse human language recorded in text or audio [9]. Within NLP, sentiment analysis focuses on classifying expressed emotions (e.g., positive, neutral, or negative) [10]. In the context of counselling research, sentiment analysis can i) serve as a supplementary tool for tracking help-seekers' emotional status and therapeutic process [10], ii) offer an objective indicator of session outcomes that circumvents the recall bias inherent in self-report methods, and iii) efficiently process large vast volumes of text. Prior research [e.g., [10], [11], [12]] has recommended employing sentiment analysis to track help-seekers' moment-to-moment shifts in emotional experiences and investigate how these shifts relate to counselling outcomes.

Recent studies have applied sentiment analysis to gain insight into the counselling process. For instance, Syzdek [13] used the *syuzhet* package in R [14] to label the sentiment of both client and therapist message as positive, neutral, or negative across twenty psychotherapy sessions. A hierarchical linear model revealed that client sentiment trended more negatively within each session but became more positively over multiple sessions, and that clients and therapists seemed to mirror each other's sentiment. However, a lack of formal outcome measures prevented the exploration of the sentiment-outcome relationship.

Althoff and colleagues [15] analysed crisis helpline interactions using the Linguistic Inquiry and Word Count (LIWC) tool to label help-seeker messages as positive, neutral or negative. Help-seekers' post-session self-reported feelings ("Better," "Same," or "Worse") served as a proxy for session quality. Sessions with response "Better" were coded as high-quality sessions, and sessions with feedback "Same" or "Worse" were coded as low-quality sessions. The authors found that help-seekers tended to start sessions with high-level negativity, but the sentiment became more positive over time for both high- and low-quality sessions.

Despite these achievements, previous studies relied on lexicon-based approach (e.g., *syuzhet* package and LIWC), which tends to overlook context-dependent nuances in language [12]. In addition, while research has demonstrated that help-seekers' sentiment can fluctuate throughout a session, less attention has been given to the underlying factors that drive or contribute to these emotional shifts. Help-seekers are not a homogeneous group; their emotional trajectories are likely shaped by individual characteristics and contextual factors. Identifying predictors of sentiment trajectory membership is crucial because certain help-seekers—such as those reporting suicidal ideation or accessing services anonymously—may be at higher risks of deterioration and may require different intervention strategies [5].

A few studies found that in-session sentiment changes are associated with various clinically meaningful indicators and demographic differences. Stamatis et al [16] demonstrated that text sentiment patterns are prospectively associated with symptoms of depression, generalized anxiety, and social anxiety, with distinct linguistic markers characterizing each condition. This underscores the importance of accounting for presenting issues when modelling emotional shifts. Similarly, Eberhardt et al [10] found that sentiment trends in psychotherapy sessions were significantly correlated with self-reported distress levels, highlighting the relationship between distress levels and unique sentiment trajectories. Demographic characteristics have been linked to differences in emotional expression and engagement in the counselling process. Efe at al [17] found that linguistic markers exhibited gender differences, with female users more frequently using negative emotion words, which were predictive of psychiatric symptoms. Further investigation into the clinical and demographic factors associated with sentiment changes could extend the utility of sentiment analysis, ultimately enhancing counselling practices.

In this study, we aimed to identify distinct sentiment trajectories among help-seekers and examine how psychological profiles (e.g., presenting problems, baseline level of distress), demographic characteristics (e.g., gender), and help-seeker behaviours (e.g., session duration, means of access) influenced the evolution of their sentiments. By uncovering latent sentiment trajectory classes and identifying predictors of trajectory membership, we seek to develop more tailored interventions and service planning strategies to improve counselling effectiveness and help-seeker satisfaction.

To achieve this, we applied Latent Class Trajectory Analysis (LCTA) to identify distinct sentiment trajectories in Open Up, an online text-based counselling service in Hong Kong. Fu et al. [12] reported that GPT-3.5 and GPT-4 significantly outperformed both lexicon-based and other machine learning methods in classifying text sentiment from Open Up. Building on this finding, we used GPT-4 to label each help-seeker message. Subsequently, multinomial logistic regression was employed to identify which variables—including demographic information, presenting problems, and distress levels—predicted membership in each trajectory class. By integrating advanced NLP techniques with trajectory analysis, this study sought to enhance our understanding of help-seekers' in-session emotional shifts and their implications for effective online counselling.

Methods

Data Source

This study analysed counselling transcripts from Open Up, a 24/7 online text-based counselling platform in Hong Kong providing support to youth with various issues, including mental health problems, family relationship, and academic pressure [18]. Ethical approval was obtained from the Human Research Ethics Committee, the University of Hong Kong (reference number: EA230548). Before using the service, users consented to data usage for research by accepting the Terms of Service. Counsellors provided written consent.

As illustrated in Figure 1, we initially extracted 222,005 counselling sessions from 10 November 2021 (when a pre-session survey was introduced) to 30 June 2024 (our chosen cutoff for data analysis).

We excluded 149,739 sessions (67.4%) with fewer than four message exchanges between the counsellor and help-seeker, as these were too brief for sentiment analysis. This exclusion left 72,266 valid sessions (32.6%).

Next, we excluded non-first time visit sessions, retaining 25,371 sessions (35.1% of 72,266) in which help-seekers used Open Up for the first time. Focusing on first-time visits prevents potential confounds introduced by repeated sessions, in which counsellors may already know help-seekers' profiles and presenting problems. Over multiple visits, help-seekers may also become more comfortable or adopt different communication patterns, and counsellors might tailor their approach based on prior interactions. By restricting the analysis to first-time visits, we ensure that i) all sessions represent an initial point of contact without prior counsellor knowledge, ii) help-seekers' emotional trajectories are observed from a more uniform "starting point," and iii) the independence of observations is maintained. This approach increases the clarity and comparability of the data when examining sentiment trajectories and associated outcomes. We then removed 947 sessions (3.7% of 25,371) that were non-Cantonese, resulting in 24,424 valid Cantonese first-time sessions.

Among the 24,424 sessions, we included only those with pre-session survey that provided information about help-seekers' primary concerns, level of psychological distress, and suicide ideation. This retained 15,518 (63.5% of 24,424) sessions.

Taking into consideration of computational and resource constraints, we randomly selected 40% of these sessions using Python package *pandas* (version 1.5.3; Python Software Foundation). Specifically, the sample method was applied with the fraction parameter set as 0.4 and the fixed random seed assigned as 42 to ensure reproducibility. These 6,207 sessions constituted the final dataset for trajectory modelling.

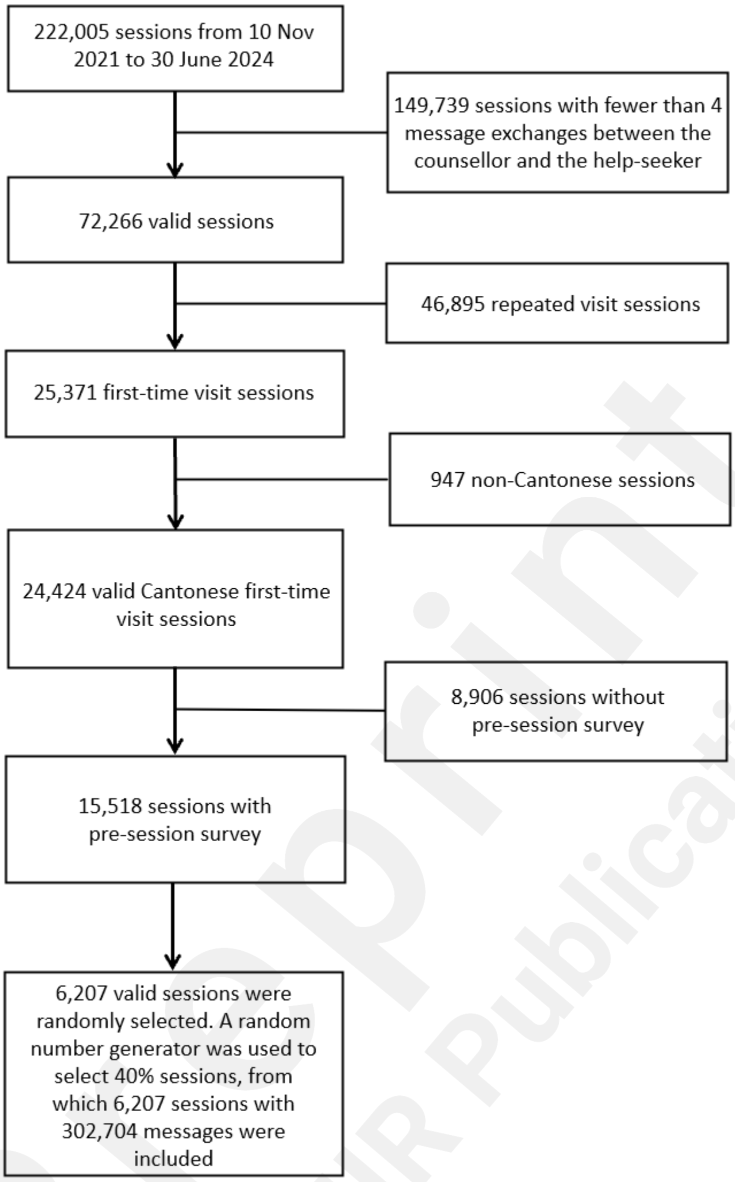

Figure 1. Data inclusion

Measurements

Pre-session survey for help-seekers' psychological distress profile

The pre-session survey contained eight questions that assessed help-seekers' psychological distress. It included three components: i) the help-seeker's primary concern, ii) severity of psychological distress, and iii) self-harm and suicide ideation.

Primary concern was assessed with the question, "What is the issue that concerns you the most?" Respondents were given 14 options to choose from: 1) mental health, 2) family relation, 3) intimate relationship, 4) interpersonal relationship, 5) study, 6) career, 7) traumatic experience, 8) physical health, 9) personal development, 10) sexual orientation/gender-related distress, 11) addictive behaviour, 12) social unrest, 13) covid-19, and 14) others. Help-seekers can only choose one option. For analysis, the primary issue was treated as a categorical variable (coded 1 to 14).

Psychological distress was measured using the 6-item Kessler Psychological Distress Scale (K6). The K6 is a widely used tool for screening psychological distress [20]. It measures the frequency of six distress-related symptoms over the past month, including feelings of nervousness, hopelessness, restlessness, depression, worthlessness, and fatigue [21]. The K6 has been shown to have strong reliability and validity to screen for psychological distress among young people in Hong Kong [[22], [23]]. Each of the six items was scored from 0 to 4, yielding a total possible score of 0 to 24 (with higher scores indicating greater distress).

Self-harm and suicidal ideation were accessed with one question, "In the past two weeks, have you had thoughts about hurting or killing yourself? The response was treated as a binary variable (Yes = 1, No = 0).

Help-seeker behaviours

Variables related to help-seekers' behaviours were collected:

1) **Communication Channel**
The mode by which help-seekers accessed the service was recorded as "Anonymous channel" (coded as "1") i.e., the web portal, where no personal identifier was available, or "Non-anonymous channel" (coded as "0"), including WhatsApp, Facebook Messenger, or WeChat, where help-seekers might have identifiable information such as their account numbers.

2) **Repeated Help-seeker**
This variable indicated whether the help-seeker used Open Up again after their first visit, with one-time help-seekers coded as "0" and repeated help-seekers coded as "1".

3) **Premature Departure**
This measured whether the help-seeker ended the session abruptly without indicating their intention to leave or establishing a mutual agreement with the counsellor to terminate the session. A session was coded as "1" if the help-seeker departed prematurely; otherwise, it was coded as "0".

4) **Queue Time**
The time (in minutes) a help-seeker waited in the queue before a counsellor picked up the session.

5) **Session Duration**
The time (in minutes) from when the help-seeker was connected to a counsellor until the end of the session.

Counsellors' post-session summary for help-seekers' demographic information

After each session, counsellor recorded basic demographic information about the help-seeker, including age group (e.g., secondary school student, university student, non-student youth, middle-aged, unknown), and gender (male, female, unknown). Age group was coded as "1" for secondary school students, "2" for university students, "3" for non-student youth, "4" for middle-aged individuals, and "5" for unknown. Similarly, gender was coded as "1" for male, "2" for female, and "3" for unknown.

Sentiment label

The sentiment scores of help-seeker messages, labelled by ChatGPT, served as the primary variable for trajectory modelling. Following Fu et al [11], GPT-4 was used to label each help-seeker message as positive, neutral, or negative, given its high accuracy in classifying Cantonese counselling messages. The labelling was conducted using the OpenAI GPT-4 API via Python package *openai* (version 1.23.2; Python Software Foundation). The model's parameter setting is outlined in Table 1, which followed those of Fu et al [11].

Table 1. GPT-4 prompt settings.

model	**GPT-4**
prompt	"Is the sentiment of this Cantonese text positive, neutral, or negative? Respond with a sentiment label only."
max_token	8,192
engine	gpt-4
temperature	0.0

A systematic review of sentiment analysis indicates that positive texts are often coded as 1, neutral texts as 0 and negative texts as -1 [24]. This study followed the same scoring approach.

Statistical analysis

Average sentiment score for each epoch in each session

To analyse sentiment changes over the course of each counselling session, we split sessions into five equal segments (hereafter referred to as "epochs") based on the total number of message exchanges. The decision was informed by prior studies that analysed counselling stages and session progression [e.g., [15], [25], [26]]. For instance, Pérez-Rosas et al [25] explored the change of linguistic features (e.g., linguistic alignment between the counsellor and the help-seeker, sentiment features, topics discussed during the session) as a counselling session progressed. They split each session into five stages of nearly identical number of message exchanges between the counsellor and the help-seeker [25]. We opted for a similar approach that allowed us to approximate the session progression without assigning messages into specific stages and ensured all sessions were structured consistently, which could increase the efficiency of trajectory modelling and improve the interpretability of trajectories.

After dividing each session into five equal epochs, we computed an average sentiment score for each epoch. Mathematically, for the j-th epoch of the i-th session, the average sentiment score $S_{i,j}$ was given by:

$$S_{i,j}=\frac{1}{N_{i,j}}\sum_{k=1}^{N_{i,j}} s_{i,j,k}$$

where $N_{i,j}$ is the number of messages in the j-th epoch of the i-th session. $s_{i,j,k}$ was the sentiment score of the k-th message in the j-th epoch of the i-th session.

Latent Class Trajectory Analysis

The Growth Mixture Model (GMM) was employed to model the help-seekers' sentiment trajectory throughout the session. We chose GMM due to its ability to capture heterogeneity in patterns of change and allow for random effects of individual differences [27]. Each latent class comprises sessions with similar patterns of sentiment change. To account for the non-linear nature of counselling dynamics including sentiment change [28], we included quadratic terms in our model. For each latent class C, the estimated score S is:

$$g(S)=b_0^c+b_1^c X+b_2^c X^2$$

where b_0^c is the random intercept for class C, so it is the sum of the mean intercept of that class and the random error ϵ_i for each session i. X and X^2 represent the linear and quadratic terms of the epoch, respectively. b_1^c and b_2^c are the estimated slopes for the linear and quadratic terms, respectively.

Because sentiment scores naturally range from −1 to 1, a beta link function was applied to ensure predictions remained within these bounds.

The GMM estimated the likelihood of each session belonging to each latent class; each session was then assigned to the class with the highest likelihood.

GMM was implemented using R package *lcmm* (version 2.1.0; R Core Team; [29]). GMM was fitted iteratively with the number of latent classes from 1 to 6. The optimal number of classes was selected based on the lowest Akaike's Information Criterion (AIC), the lowest Bayesian Information Criterion (BIC) and the highest maximum log-likelihood.

Associations of variables with trajectory class

Multinomial logistic regression was applied to identify variables associated with trajectory class membership. The membership of latent groups of sentiment trajectory derived from the GMM was treated as the outcome variable. Predictors included help-seekers' psychological distress profile (i.e., K6 distress scores, primary issue, suicidal ideation), help-seekers' behaviours (e.g., communication channel, premature departure), and help-seekers' demographic information (i.e., age group, gender). Regression was conducted using Python package *statsmodels* (version 0.13.5;

Python Software Foundation; [30]). The resulting coefficients and p-values of the predictors were evaluated for statistical significance and interpretation of their relationships with different sentiment trajectory classes.

Results

Data descriptives

The randomly selected 6,207 sessions contained a total of 302,704 messages, including 151,668 messages from help-seekers. As exhibited in Table 2, GPT-4 labeled 13,777 (9.1%) of these help-seeker messages as positive, 100,536 (66.3%) as negative, and 37,355 (24.6%) as neutral.

Table 2. Number and percentage of messages with each sentiment label.

Sentiment label	Sentiment score	Messages in total n (%)	Help-seeker messages n (%)
Positive	1	29,452 (9.7)	13,777 (9.1)
Negative	-1	135,292 (44.7)	100,536 (66.3)
Neutral	0	137,960 (45.6)	37,355 (24.6)

Table 3 presents the help-seekers characteristics for the 6,207 sessions. A total of 1,965 help-seekers (31.7%) reported mental health as their primary concern. Help-seekers reported a mean K6 score of 14.53 (SD = 4.61), indicating moderate distress. In the past two weeks, 2,123 help-seekers (34.2%) had thoughts of self-harm or suicide.

Regarding demographics, 2,097 help-seekers (33.8%) were identified as non-student youth, and 3,460 (55.7%) were female. Most help-seekers (84.0%) accessed Open Up via the web portal. Furthermore, 2,380 help-seekers (38.3%) returned to Open Up after their initial visit, while 1,773 (28.6%) left the session prematurely. On average, help-seekers waited 13.04 minutes (SD = 14.71) for a counsellor and sessions lasted 63.31 minutes (SD = 30.89).

Table 3. Descriptives of help-seeker characteristics.

Characteristics		Mean (SD) or *n* (%)
Primary concern	Mental health	1,965 (31.7%)
	Family relationship	564 (9.1%)
	Intimate relationship	953 (15.4%)
	Interpersonal relationship	475 (7.7%)
	Study	434 (7.0%)
	Career	640 (10.3%)
	Traumatic experience	237 (3.8%)
	Physical health	132 (2.1%)
	Personal development	303 (4.9%)
	Sextual orientation/Gender distress	53 (0.9%)

	Addictive behaviour	53 (0.9%)
	Social unrest	29 (0.5%)
	Covid-19	44 (0.7%)
	Others	325 (5.2%)
K6 score		14.53 (4.61)
Self-injury or suicidal ideation	Yes	2,123 (34.2%)
	No	4,084 (65.8%)
Age group	Secondary school student	1,452 (23.4%)
	University student	914 (14.7%)
	Non-student youth	2,097 (33.8%)
	Middle-aged	570 (9.2%)
	Unknown	1,174 (18.9%)
Gender	Male	1,305 (21.0%)
	Female	3,460 (55.7%)
	Unknown	1,442 (23.3%)
Communication channel	Anonymous portal	5,212 (84.0%)
	Non-anonymous portal	995 (16.0%)
Repeated help-seeker	Yes	2,380 (38.3%)
	No	3,827 (61.7%)
Premature departure	Yes	1,773 (28.6%)
	No	4,434 (71.4%)
Queue time		13.04 (14.71)
Session duration		63.31 (30.89)

Growth Mixture Model for help-seeker sentiment

As shown in Table 4, a three-class GMM was selected based on multiple criteria including AIC, BIC and maximum log-likelihood. Parameter estimates for the three-class model are provided in the Supplementary Table 1.

Table 4. Fit indices of different solutions.

Number of classes	AIC	BIC	Maximum log-likelihood
1	17167.18	17214.31	-8576.59
2	15742.33	15816.40	-7860.17
3	**15131.36**	**15232.36**	**-7550.68**
4	15155.75	15283.68	-7558.87
5	15786.11	15940.98	-7870.05
6	15255.12	15436.93	-7600.56

Figure 2 illustrates the in-session sentiment trajectories for the three latent classes. Among the 6,207 sessions, 1,171 sessions (18.9%) were clustered as Class 1, which was labelled as the “Steady Improvement Class”. This class displayed stable sentiment from the first epoch to the second epoch, followed by a gradual increase from the second to the fifth epoch.

Class 2, the “Deterioration Class”, consisted of 1,119 sessions (18.0%). This class is characterised by a decline in sentiment scores from the first epoch through the third epoch, followed by a relatively flat trajectory from the third to the fifth epoch.

Class 3, the “Dip-Then-Rebound Class”, consisted of 3,917 sessions (63.1%). This class reflects a more typical sentiment trajectory of help-seekers in counselling. Help-seekers showed increasingly negative sentiment from the first to the second epoch, a plateau from the second to the third epoch, an uptick from the third to the fourth epoch, and a more pronounced improvement in sentiment from the fourth to the fifth epoch.

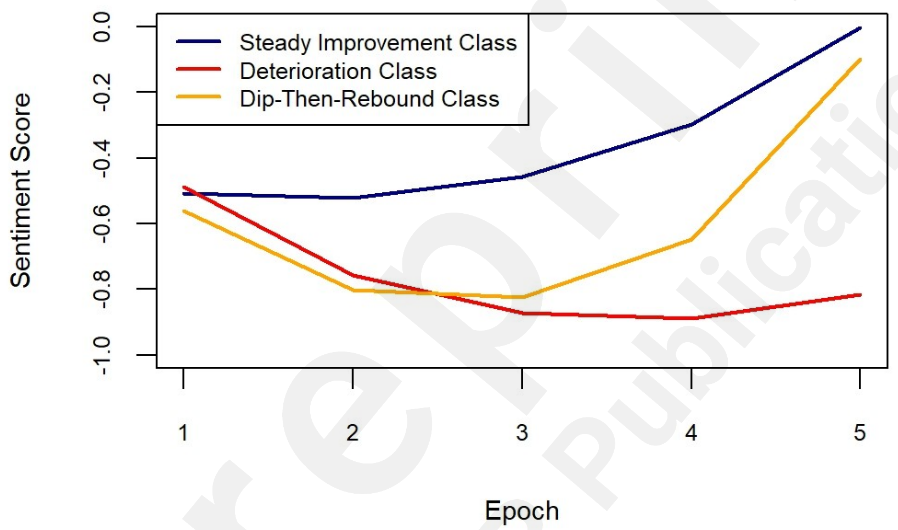

Figure 2. Three-class growth mixture model for help-seeker sentiment.

Association of variables with trajectory class

Steady Improvement Class vs. Dip-Then-Rebound Class

The Dip-Then-Rebound Class, which was the largest of the three, was used as the reference group in the multinomial logistic regression. As exhibited in Figure 3 and the Supplementary Table 2, compared with the Dip-Then-Rebound Class, help-seekers in the Steady Improvement Class were less likely to report “Family relationship” (OR=0.59, 95% CIs [-0.80, -0.25], p<0.001), “Intimate relationship” (OR=0.65, 95% CIs [-0.66, -0.21], p<0.001), or “Interpersonal relationship” (OR=0.68, 95% CIs [-0.66, -0.11], p=0.007) as their primary concern. They were more likely to be secondary school (OR=1.62, 95% CIs [0.29, 0.67], p<0.001) or university students (OR=1.34, 95% CIs [0.08, 0.51], p=0.007). Moreover, they were less likely to access the service via the anonymous portal (OR=0.71, 95% CIs [-0.51, -0.16], p<0.001), reported lower K6 scores (OR=0.82, 95% CIs [-0.27, -0.13], p<0.001), and had shorter session duration (OR=0.92, 95% CIs [-0.16, -0.02], p=0.014). They were also more likely to recontact the service after their first visit (OR=1.20, 95% CIs [0.04, 0.32], p=0.011).

Deterioration Class vs. Dip-Then-Rebound Class

Compared with those in the Dip-Then-Rebound Class, members of the Deterioration Class were more likely to report suicidal ideation (OR=1.28, 95% CIs [0.07, 0.42], p=0.006), and cite “Family relationship” (OR=1.56, 95% CIs [0.17, 0.73], p=0.002) or “Physical health” (OR=1.67, 95% CIs [0.02, 1.01], p=0.041) as their primary concern. These help-seekers were also more likely to have unknown gender information (OR=1.32, 95% CIs [0.04, 0.51], p=0.021), and access the service via the anonymous channel (i.e., web portal) (OR=1.30, 95% CIs [0.03, 0.49], p=0.025) They were much more likely to depart prematurely (OR=9.76, 95% CIs [2.12, 2.43], p<0.001), and had shorter session duration (OR=0.77, 95% CIs [-0.34, -0.17], p<0.001).

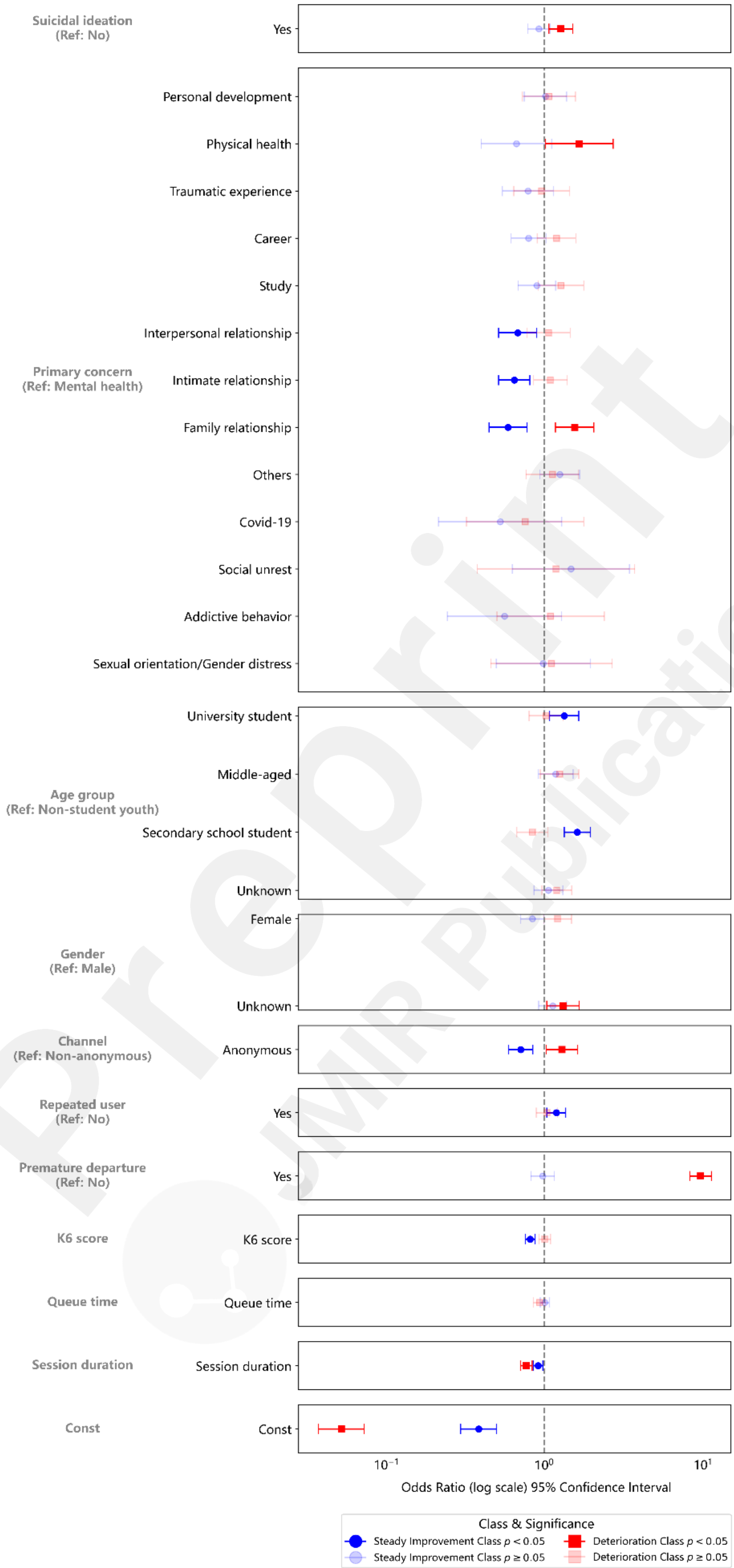

Figure 3. Multinomial logistic regressions of trajectory class membership using variables for a three-class growth mixture model of help-seeker sentiment

Discussion

This study identified three distinct in-session sentiment trajectories among help-seekers using a text-based counselling service. The three classes—Steady Improvement (18.9%), Deterioration (18.0%), Dip-Then-Rebound (63.1%)—demonstrate significant heterogeneity in how help-seekers' emotional states evolve during a session. Moreover, several help-seeker characteristics were associated with membership in each class, sentiment trajectories can serve as an indicator for understanding and tailoring interventions within online counselling contexts. These findings address a gap in the literature regarding practical methods for monitoring help-seekers' psychological states and the counselling process under conditions of high anonymity [[5], [6], [7], [8]].

Interpretation of the three trajectories

Help-seekers in the Steady Improvement Class exhibited stable sentiment in early stages (i.e., the first three epochs), followed by a gradual improvement thereafter. Their relatively lower psychological distress scores support the notion that they enter the service with less urgent concerns. For counsellors managing multiple sessions simultaneously, early identification of this stable-to-positive trajectory could permit more efficient resource allocation. Shorter sessions or timely referrals may suffice if the help-seeker's needs do not require intensive intervention.

In contrast, help-seekers in the Deterioration Class exhibited continuously worsening of sentiment throughout the session. This pattern was associated with more frequent suicidal ideation, higher likelihood of family or physical health-related issues, and a high rate of premature departure. As suggested by Xu et al [31], premature departure could indicate dissatisfaction with the counselling session. Taken together, this class might represent a potential mismatch between help-seeker needs and the interventions provided. Additionally, these help-seekers were more likely to access the service via the anonymous communication channel (i.e., web portal), and less likely to disclose their gender, which can undermine the counsellor's ability to tailor support. Early detection of such negative trends could enable counsellors to potentially shift their strategies or provide specialized resources before sentiments deteriorate further.

The largest group, the Dip-Then-Rebound Class, displayed a more typical counselling progression where the help-seeker initially expressed increasing negativity during initial problem exploration but rebounded in later phases, likely reflecting effective therapeutic engagement [12]. This pattern indicates that, for the majority of help-seekers, text-based counselling can help improve their affect—and potentially reflecting successes in addressing their presenting issues—over the course of a single session.

Practical applications and future directions

The findings have significant practical applications. Specifically, our approach lay the groundwork for predictive tools that could monitor in-session sentiment and forecast which pattern a help-seeker might follow. Such tools could enable counsellors to respond proactively in real time.

For example, Table 5 highlights three exemplar sessions—one from each trajectory—showing how counsellors could adapt their strategies based on emerging sentiment patterns. The help-seekers in the three sessions expressed a similar level of negativity in the first epoch of each session. In the session representing the Steady Improvement Class, detecting a reduced negativity by the second epoch may prompt the counsellor to conduct and close the session more quickly, especially if they judge the help-seeker's concerns and distress to be relatively mild. In the session depicting the Deterioration Class, heightened negativity observed by the fourth epoch could trigger escalating the case to a more experienced counsellor or suggesting immediate external support. In the session showcasing the Dip-Then-Rebound Class, noticing the rebound in sentiment around the fourth epoch indicates alignment with typical counselling protocols, as the help-seeker appears to benefit from interventions.

Future predictive model might track real-time, message-by-message sentiment rather than segmenting sessions into discrete epochs, thus providing just-in-time assistance for counsellors. By identifying likely trajectory earlier, counsellors can be more proactive and adaptive in their intervention strategies, ensuring appropriate and timely support.

Table 5. Sample Open Up sessions illustrating potential application of sentiment trajectories.

Epoch	Steady Improvement Class		Deterioration Class		Dip-Then-Rebound Class	
	Summary	Sentiment score	Summary	Sentiment score	Summary	Sentiment score
1	The help-seeker shared guilt and confusion over a recent breakup.	-0.778	The help-seeker expressed initial frustration and fatigue due to a combination of work stress and post-Covid symptoms.	-0.667	The help-seeker expressed sadness due to various stressors.	-0.750
2	Negativity decreased as the help-seeker felt relieved after venting. The counsellor showed empathy and reassurance.	-0.556	Negativity increased as the help-seeker described long commute and the increasing work pressure.	-0.714	Negativity peaked as the help-seeker showed feelings of hopelessness and doubts about their ability.	-1.000
3	Negativity continued to decrease as the help-seeker began to minimize	-0.556	The help-seeker showed increasing helplessness about balancing	-0.833	Negativity remained low, and the counsellor started to guide the help-seeker	-1.000

	the severity of their concern. The counsellor continued to validate emotions and reassure the help-seeker.		health, workload, and financial stress, despite the counsellor’s proposed solutions, such as contacting school counsellors.		to consider alternative perspectives.	
4	Negativity significantly reduced as the help-seeker exhibited confidence in managing her issue independently. The counsellor affirmed the help-seeker’s ability and constantly showed emotional support.	-0.111	The help-seeker explicitly expressed feelings of sadness and hopelessness, blaming themselves for their current situation. The counsellor suggested seeking professional therapy but struggled to reduce the help-seeker’s distress.	-0.857	Negativity began to decrease as the help-seeker agreed on the proposed suggestions and expressed gratitude to the counsellors.	-0.400
5	The help-seeker demonstrated readiness to solve the problem and positivity.	-0.111	The help-seeker’s distress remained unresolved despite the counsellor’s efforts.	-0.857	Sentiment turned positive as the help-seeker felt optimistic about their future.	0.600

Although this study provided valuable insights into help-seekers' emotional processes in text-based counselling, it also has several limitations that warrant attention in future research. First, while ChatGPT was highly accurate and computationally effective for labelling sentiments, its use of only three broad sentiment categories (positive, neutral, and negative) lacks granularity. Future studies could explore more advanced sentiment analysis models that captures arousal or emotional intensity, potentially leading to deeper insights and more precise interventions. Second, the dataset was limited to help-seekers aged 11-35 from a specific online text-based counselling service in Hong Kong, which might limit the generalizability of the findings to other populations and contexts. Further implementation and validation of this model in diverse settings are needed to enhance its broader applicability. Third, only first-time visit sessions were included for analysis, which warrants future investigation on sentiment changes within repeated visit sessions. As Open Up was designed to primarily provide single-session intervention, the decision to only include first-time visits ensures that the analysis aligns with and is representative of the service's scope and exclude potential confounding factors arising from recontacts. Although this criterion focused our analysis on first-session experiences, it also highlights the need for future research that could incorporate subsequent repeated visits. This could allow us to assess sentiment changes across repeated sessions [15], examine between-sessions dynamics and longer-term outcomes over multiple counselling engagements, and better understand repeated help-seekers' profiles. Finally, this study did not analyse the counsellor's sentiment trajectory. As counselling is an interactive and reciprocal process, examining both counsellor and help-seeker sentiments in tandem could yield richer insights into the counselling relationship and outcome efficacy.

Conclusion

This study used a Growth Mixture Model and identified three latent groups of help-seekers with distinct in-session sentiment trajectories in an online text-based counselling platform in Hong Kong: Steady Improvement, Deterioration, and Dip-Then-Rebound. Multinomial logistic regression revealed help-seeker characteristics associated with each trajectory. Specifically, the Deterioration Class was characterised by more suicidal ideation, higher proportions of family or physical health-related issues, a higher tendency to withhold demographic information and prematurely exit the session. These findings could inform the future development of predictive models that dynamically track help-seekers' emotional states in real-time, enabling counsellors to adapt interventions swiftly and appropriately and, ultimately, enhance the effectiveness of online text-based counselling.

Author contribution

FU Z conceptualized the study. FU Z was responsible for data inclusion work. FU Z and Hsu YC pre-processed the data, ran GMMs and logistic regression, conducted statistical analysis, and interpreted the results. Chan CS and Yip PSF arranged the resources for this study. FU Z and Hsu YC wrote the original manuscript. FU Z, Hsu YC, Chan CS and Yip PSF reviewed and edited the manuscript. This study was supervised by Chan CS and Yip PSF. All authors had full access to the data in this study and had final responsibility for the decision to submit for publication.

Data availability

Due to its sensitivity, the counselling transcript data are not publicly available but can be accessed with permission from the corresponding authors.

Code availability

The codes of this study are available in GitHub repository: https://github.com/iharrisonfu/sentiment_trajectory.git.

Conflicts of interests

None declared.

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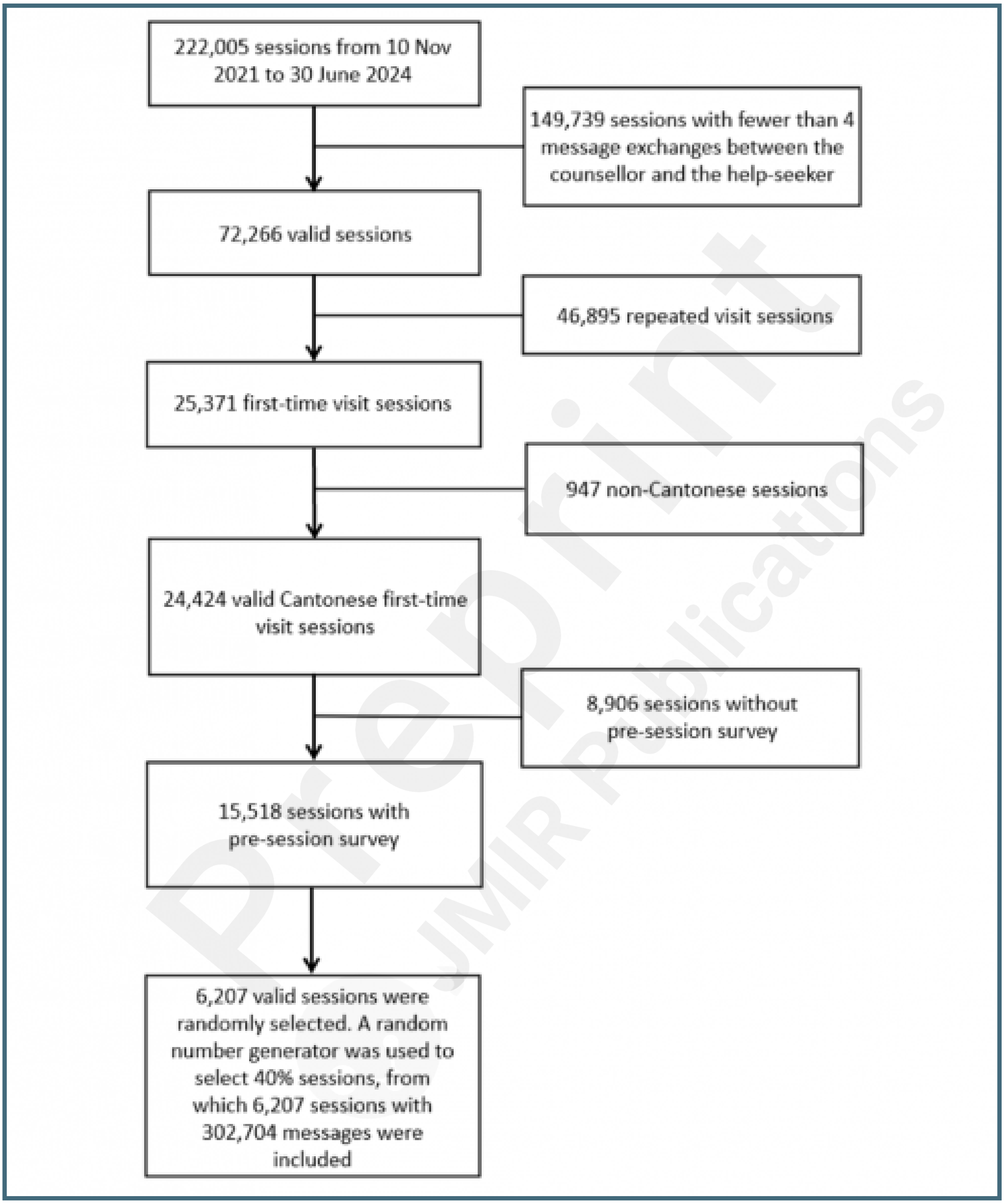
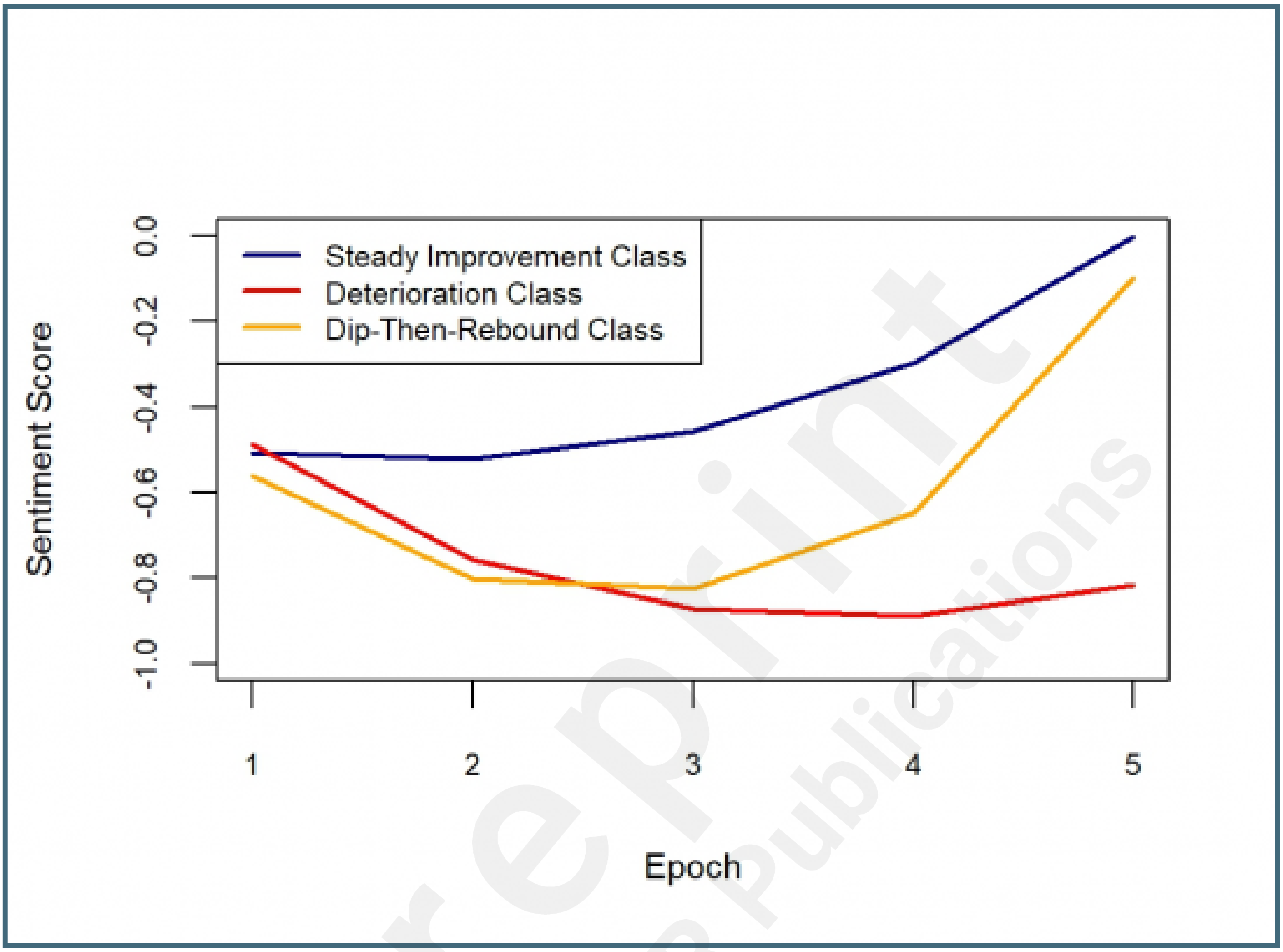
Supplementary Files

Figures

Data inclusion.



Three-class growth mixture model for help-seeker sentiment.



Multinomial logistic regressions of trajectory class membership using variables for a three-class growth mixture model of help-seeker sentiment.

Multimedia Appendixes

Supplementary materials.
URL: http://asset.jmir.pub/assets/880a33f71296ef195fcedb5b0f5eb534.docx