

**Online Treatment of adolescent sleep problems:
A text mining analysis of written feedback from CBT-I therapists**

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Abstract

Chronic insomnia in adolescents presents challenges to their well-being. Cognitive Behavioural Therapy for Insomnia (CBT-I) has shown effectiveness in adults, but its application in adolescents is still being explored. Internet-based CBT-I offers accessibility, potentially helping reluctant adolescents seek help. However, the impact of therapist feedback in this setting is unclear. This study investigates therapist feedback in adolescent Internet-based CBT-I, exploring topics, sentiments, and therapist differences. Data from seven Dutch-speaking CBT-I therapists for adolescents were analysed using text mining techniques. The dataset comprises feedback from 78 adolescent clients in six weekly CBT-I consultations, totalling 586 messages. Term Frequency-Inverse Document Frequency (TF-IDF) analysis and a word cloud revealed frequent terms. A three-topic model was chosen due to higher interpretability for human raters. Latent Dirichlet Allocation (LDA) was used for topic modelling and identified three topics: sleeping duration and quality, sleep habits and patterns, and sleep tracking. Topic identification was supported by ChatGPT. Sentiments were analysed using the NRC emotion lexicon to match relevant text excerpts. Therapists predominantly addressed fear in their feedback, with some also expressing anticipation, joy, and surprise, possibly while addressing clients' fears and concerns related to sleep. Variations among therapists highlighted individualized approaches. Future research should investigate AI feedback, treatment outcomes, and protocol-based vs. free-form feedback in Internet-based CBT-I for adolescents to personalize therapy and enhance outcomes. This research highlights the importance of text mining techniques, such as LDA and LiLaH, in analysing therapists' written feedback in online CBT-I for adolescents with insomnia.

Keywords: Cognitive Behavioural Therapy, Insomnia, Adolescents, Text-mining, Topic Modelling, Sentiment Analysis, Natural Language Processing

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Introduction

Chronic insomnia is the most common sleep-wake disorder in adolescents (Dewald-Kaufmann et al., 2019; Johnson et al., 2006). According to the DSM-5-TR classification criteria, individuals who experience difficulties in falling asleep, staying asleep, and not feeling rested when waking up for 3 or more days a week, for at least 3 months, despite having sufficient opportunity to sleep, may be diagnosed with chronic insomnia (American Psychiatric Association, 2022). Due to insomnia other mental disorders such as anxiety, depression, or attention deficit hyperactivity disorder (ADHD) can be exacerbated or caused and daytime functioning impaired (Gregory & Sadeh, 2016). Furthermore, it can impair family functioning and the parent's sleep (Lunsford-Avery et al., 2021).

For adults, CBT-I is the first line of treatment (Morgenthaler et al., 2006). It consists of a combination of behavioural (e.g., bedtime routine, sleep hygiene) and cognitive (modification of thoughts) pattern changes through therapy. In adults, CBT-I is effective and has a clinically meaningful effect on sleep. Compared to pharmacotherapy it does not have the drawbacks of dependence and habituation (Dewald-Kaufmann et al., 2019). Over the past ten years, several studies have indicated that CBT-I could also be a viable treatment option for adolescents, however, there is currently no consensus statement on the matter (Dewald-Kaufmann et al., 2019; Lunsford-Avery et al., 2021). A recent randomized controlled trial (RCT) found that adolescents in the CBT-I condition improved significantly in sleep efficiency, sleep onset latency, wake after sleep onset, and total sleep time compared to the control group (de Bruin et al., 2015).

Cognitive behavioural therapy for insomnia (CBT-I) has been linked to reduced fear of sleep and improved insomnia symptoms (Kanady et al., 2018; Sunnhed & Jansson-Fröjmark, 2014), while cognitive models of insomnia emphasize negative cognitive activity, dysfunctional beliefs about sleep, and counter-productive safety behaviours as contributing to insomnia maintenance (Harvey, 2002). CBT-I may also be associated with reductions in depression and anxiety (Ballesio et al., 2021). Building a strong therapeutic alliance and trust between therapist and client have shown benefits in therapy outcomes (Iwakabe et al., 2000), with the therapeutic relationship being

identified as an essential aspect of therapy (Luong et al., 2020). Clients' preference for positive CBT and the steeper learning curve experienced during positive CBT have been demonstrated (Geschwind et al., 2020). In CBT supervision and training, deliberate use of observational methods, such as video review and feedback, can enhance skill development (Gonsalvez et al., 2016). Competence feedback in CBT has been found suitable for improving therapeutic competencies (Weck et al., 2017; Murr et al., 2020), and receiving client feedback can enhance client outcomes and counsellor self-efficacy (Reese et al., 2009).

Cheng (2009) found that adolescents are reluctant to seek help for psychological problems at public mental health services. Internet CBT-I is broadly accessible and can overcome adolescents' reluctance to seek treatment (de Bruin & Meijer, 2017). A study by de Bruin et al. (2015) demonstrated in a randomized controlled trial that Internet CBT-I can be as effective as group therapy in adolescents. Internet CBT-I exists in different forms and modalities but not much is known about what exactly influences its effectiveness (de Bruin & Meijer, 2017). However, previous research, such as the study conducted by Okiishi et al. (2006), demonstrates significant differences between therapists in terms of treatment efficiency and effectiveness. Okiishi et al. (2006) analysed data from over 5,000 clients seen by 71 therapists and found that top-ranked therapists have clients with better outcomes compared to bottom-ranked therapists, highlighting the impact of individual therapists on client outcomes.

In internet-delivered CBT therapists typically guide participants via email once a patient has completed one of the several intervention modules (Provoost et al., 2019). The therapist bases their feedback on the client's input, the feedback prompts, and feedback instructions (Mol et al., 2018). A six-week longitudinal study investigating the impact of therapeutic feedback in adolescent Internet CBT-I revealed that emphasizing sleep-related knowledge enhancement is related to improved treatment outcomes (de Bruin & Meijer, 2017). However, factors such as forging therapy integrity and forging a positive attitude showed negative relations with sleep outcomes, and the length of therapeutic feedback and participation in chat sessions did not have a significant impact on treatment outcomes (de Bruin & Meijer, 2017). On the other hand, Mol et al. (2018) found that in blended CBT for depression adhering to feedback instructions, namely short feedback (sentences or one paragraph) sent within 3 days after each completed online

session, has a negative effect on future session completion. The existing literature suggests that the impact of therapeutic feedback in various forms of internet-based therapy, such as CBT-I and blended CBT for depression, varies in terms of its effects on treatment outcomes and session completion, highlighting the need to further explore the role and characteristics of written feedback in guiding and enhancing therapeutic interventions.

Despite the comprehensive history of psychological text analysis, there is a growing need for research into the application of text mining techniques, such as sentiment analysis and topic modelling, as tools to assess a patient's emotional state or therapist feedback (Veiga, 2019; Provoost et al., 2019). Manual content analysis of increasingly large amounts of text data is indeed laborious and time-consuming, making it challenging to analyse and extract meaningful insights efficiently (Antons et al., 2020). Topic modelling is a powerful technique that can be applied to analyse psychotherapy sessions as texts and extract meaningful topics from the data (Atzil-Slonim et al., 2021). It enables researchers to identify the topics discussed in therapy sessions, examine their associations with clients' functioning levels and alliance ruptures, and explore the relationship between changes in topics and treatment outcomes (Atzil-Slonim et al., 2021).

A study conducted by Atzil-Slonim et al. (2021) utilized topic modelling, specifically Latent Dirichlet Allocation (LDA), to analyse transcripts of 873 therapy sessions from 58 clients treated by 52 therapists. The researchers aimed to identify the topics discussed in the sessions and investigate their relevance to clients' functioning and the occurrence of alliance ruptures. They also explored whether changes in these topics were associated with changes in treatment outcomes. The results of the study demonstrated the effectiveness of topic modelling in extracting meaningful topics from psychotherapy textual data. The model achieved accuracy rates ranging from 65% to 75% in identifying the topics discussed. These identified topics provided valuable insights into the therapy process and outcomes.

Veiga (2019) conducted an exploratory study applying sentiment analysis to a psychotherapy session. When using the National Research Council Canada (NRC) lexicon, they concluded the lexicon is insufficient to properly represent the nuance or the

variety of emotions evoked in a therapeutic context (Veiga, 2019). The most numerous emotion identified was Trust (68), closely followed by Joy (64) and Anticipation (63). Fear was found 36 times, Sadness 28, and Anger 27. Disgust and Surprise have the smaller frequency count with 22 and 20 ratings, respectively. Veiga (2019) did not specify which type of psychotherapy was applied and which DSM-5 disorder was being treated. Provoost et al. (2019), on the other hand, conducted an automated sentiment analysis on online CBT patient texts showing that existing text mining algorithms for the Dutch language perform nearly equal to human assessment in distinguishing between positive, neutral, and negative sentiment. The suggestion for further research, in this case, was conducting a sentiment analysis of empathic feedback instead of patient texts (Provoost et al., 2019). The subsequent findings could then act as a benchmark for therapists on how to give feedback in guided CBT online therapy.

CBT-I has been proven successful in treating adolescents with insomnia in supervised internet therapy, and its effects are similar to CBT-I in group therapy. However, there is a lack of research exploring the potential of common text-mining techniques to gain insights into the topics and sentiments underlying therapist feedback in online CBT-I for adolescents. Therefore, this study aims to investigate the written feedback provided by online therapists in CBT-I for adolescents. From this standpoint, the following research questions are formulated:

1. What topics are sleep therapists discussing in written feedback?
2. What sentiments do therapists express in their feedback?
3. Are there differences between therapists in expressed topics and sentiments in their feedback?

Method

Design

The study utilized an exploratory design in which feedback transcripts from treatment sessions from an RCT were analysed for topics, sentiments, and differences between therapists.

Materials

Feedback transcripts

The dataset used in this study consists of written feedback transcripts from seven Dutch-speaking therapists given to 78 adolescent clients in six weekly CBT-I consults. The feedback transcripts were obtained from previous studies conducted by de Bruin et al. (2014, 2015, 2016, and 2017) focusing on CBT-I. In these studies, participants were recruited through various channels such as newspaper articles, electronic newsletters, and websites for youth health care professionals in the Netherlands. The inclusion criteria for participants were based on self-reports and assessments of insomnia complaints using standardized questionnaires. Exclusion criteria included factors such as age outside the range of 13 to 19, indications of other psychological disorders, sleep disorders other than insomnia, and lack of chronicity or severity of symptoms. Participants were randomized to face-to-face group CBTI or individual Internet CBTI (Bruin et al., 2014, 2015, 2016, and 2017).

In the internet condition, each participant was guided by a personal sleep-psychotherapist throughout the treatment (Bruin et al., 2014, 2015, 2016, and 2017). The therapists were trained in online conversation skills and received group supervision with an experienced sleep therapist. Participants in the internet condition could log on to a website where, at a fixed time of day, once every week, a consult was made available to them. A day before the consultation the therapists wrote their personalized feedback because at that time all the details from the sleep logs and answered questions from the previous week became available. These consultations included exercises, movies, questionnaires, automated feedback, personalized bedtime advice, and written feedback from a sleep therapist. During each consultation, participants in the internet condition were provided with a comprehensive overview of their personal sleep variables data from the sleep logs, along with automated feedback that was tailored based on their responses to the evaluation questionnaire completed the day before. This feedback was generated without direct input from a therapist and provided personalized guidance and information (Bruin et al., 2014, 2015, 2016, and 2017).

Additionally, the first page of each consultation included a concise written personalized feedback paragraph from the sleep therapist (Bruin et al., 2014, 2015, 2016, and 2017). The sleep therapists averaged 81.43 personalized feedback sessions per therapist with an average length of 352.0 words and a standard deviation of 104.6 words. This paragraph introduced new bedtime advice and offered further comments on

participants' evaluations of previous exercises, ensuring that the feedback remained relevant to their progress and individual needs. Based on the intervision and supervision the guidelines for the feedback were further developed to keep the differences between therapists' feedback minimal. Concluding each consultation, the last page consisted of a summary of the techniques introduced during the session. Additionally, participants in the internet condition had the option to schedule a 15-minute chat session with their therapist after the second session to address any specific concerns or further discuss their progress. These chat sessions aimed to enhance therapy commitment early in the treatment and improve adherence and outcomes (Bruin et al., 2014, 2015, 2016, and 2017).

Table 1

Feedback sessions of the therapists

	Feedback sessions	Average words per session
Therapist 1	35	134
Therapist 2	121	384
Therapist 3	211	388
Therapist 4	197	316
Therapist 5	197	342
Therapist 6	96	324
Therapist 7	23	225

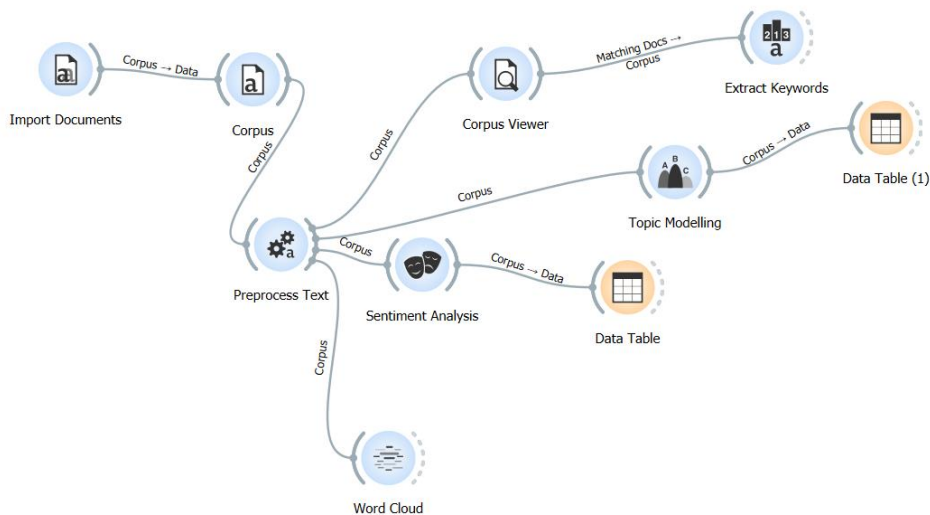
Orange

For this study, the Orange Data Mining Platform version 3.34.0 was utilized. Orange is an open-source platform developed with C++ providing a graphic user interface for Python (Orange, n.d.). It offers support for conducting analysis and processing routines for various data mining and machine learning approaches by connecting analysis modules into a visual workflow, or *pipeline*. The pipeline used in this study, depicted in Figure 1, encompassed keyword extraction, word cloud generation, topic modelling, and sentiment analysis.

The keyword extraction process involved identifying and extracting significant terms from the written feedback of therapists to their adolescent CBT-I clients. These extracted keywords provided insights into the important themes and concepts discussed by sleep therapists. The data was analysed using the Term Frequency-Inverse Document Frequency (TF-IDF) method, which calculates the importance of a term based on its frequency in a document and its rarity across all documents in the corpus. The word cloud generation technique visually represented the extracted keywords, with word size indicating their frequency of occurrence. This approach offered a concise overview of the most prominent terms and concepts addressed in the therapists' feedback. It helps readers quickly identify the key themes in the feedback data and provides a high-level understanding of the content being discussed. Topic modelling was employed to categorize the feedback into distinct topics or themes. Sentiment analysis was performed to assess the emotional tone expressed by therapists in their feedback.

Figure 1

Orange Pipeline



Analysis

The text data used in this study had certain limitations that required careful handling. Specifically, some of the text entries were found to have missing therapist names and contained errors. To address these issues, manual corrections were performed on the text data. These corrections involved adding therapist identifiers, rectifying errors, and deleting texts that were perceived as drafts or irrelevant to the study. The manual correction process was carried out in consultation with dr. Ed de Bruin, the first supervisor of this study, who oversaw the original studies from which the feedback data were obtained.

Text pre-processing involves cleansing unstructured text data for use in natural language processing, such as a text mining algorithm (Anandarajan et al., 2019). It typically consists of several steps to prepare the text for analysis. These steps include:

1. Removing punctuation and special characters.
2. Converting all text to lowercase or uppercase to ensure consistent processing.
3. Removing stop words, which are common words like "a" and "the" that do not provide meaningful information.
4. Tokenization, which involves splitting the text into individual words or tokens. For example, the sentence "Je inslaaptijden waren inderdaad wat lang. Vervelend lijkt me dat om zo lang wakker te liggen!" would be tokenized into ["Je",

"inslaaptijden", "waren", "inderdaad", "wat", "lang", "Vervelend", "lijkt", "me", "dat", "om", "zo", "lang", "wakker", "te", "liggen"]. Each word becomes a separate unit for further analysis.

5. Stemming or lemmatization, which involves reducing words to their base form for easier analysis. In the case of the word "slapen," which means "to sleep" in Dutch, it can be stemmed or lemmatized to "slaap" by removing the "-en" suffix. This process helps reduce words to their base or root form, facilitating analysis and comparison in text analysis tasks.

By performing these pre-processing steps, the unstructured text data is transformed into a structured format that is better suited for subsequent analysis techniques like topic modelling or sentiment analysis. Pre-processing enhances the quality of the data and facilitates the identification of meaningful patterns and insights. The text was pre-processed using the Orange pre-processing widget with specific settings. In the widget, the following transformation options were selected: lowercase conversion, removal of accents, parsing HTML, and removal of URLs. For tokenization, the "Word Punctuation" method was chosen. In terms of filtering, the Dutch stop words, numbers, and a regular expression filter (with the "%" symbol added to the predefined regular expression) were applied. Then word clouds were created for each therapist as an exploratory tool to observe the most frequent tokens before jumping into more advanced types of text analysis (Orange, n.d.). No additional meaningless words were added to the removal list based on this word cloud.

In this study, the unsupervised machine learning technique of Term Frequency-Inverse Document Frequency (TF-IDF) was used in the data analysis software Orange to find the ten most frequently used terms in the online feedback provided by therapists to their adolescent clients undergoing CBT-I. TF-IDF is a numerical statistic that reflects the importance of a word in a document or a corpus, by considering the frequency of the word and the rarity of the word in the corpus (Bafna et al., 2016). The most frequently used terms were then visually represented in a word cloud, which is a graphic representation of words where the size of each word indicates its frequency of occurrence in the dataset.

Topic modelling was applied to find hidden semantic structures (i.e., topics) from text documents (Haagen, 2022). This was done using the "Topic Modelling" widget. This widget provides the user with the option to define a corpus of text and subsequently identify the underlying topics automatically, using techniques such as Latent Dirichlet Allocation (LDA) (Jelodar et al., 2019). LDA is one of the most common topic modelling algorithms based on the bag-of-words (BoW) model in which a text is presented in such a way that grammar and syntax are disregarded making feature extraction possible (Blei et al, 2003; Harris, 1954). This is important as the machine learning algorithm cannot work with the raw text directly but rather with vectors and numbers and each word counts as a feature (Brownlee, 2019; Goldberg, 2017). LSI (Latent Semantic Indexing) is another popular topic modelling algorithm, but in this study, LDA was chosen over LSI due to its ability to handle large amounts of text data and provide meaningful topic representations (Liu, 2011). LDA has been widely used in various text mining applications and has shown promising results in topic extraction (Liu, 2015).

To determine the optimal number of topics in the topic modelling analysis, this study compared coherence scores and log perplexity scores displayed in the output of the "Topic Modelling" widget provided by Orange (n.d.). Coherence scores serve as a measure of the interpretability and meaningfulness of the topics generated by the algorithm, allowing researchers to select the number of topics that yields the highest coherence score. Typically, coherence scores are computed for a range of topic numbers, and the number of topics that results in the highest coherence score is chosen as the optimal number of topics. Coherence scores are typically scaled between 0 and 1, with higher scores indicating better coherence. While a coherence score above 0.5 is generally considered high, the interpretation of coherence scores can vary depending on the specific dataset and research context.

The log perplexity scores provide insight into the quality of the LDA model by measuring the degree of uncertainty in predicting the observed data. Lower log perplexity scores indicate better model fit and a more accurate representation of the underlying data. The resulting topics were then presented along with the corresponding keywords associated with each topic. To facilitate the interpretation and labelling of the generated topics, the assistance of ChatGPT version 3.5, a language model developed by

OpenAI (n.d.), was utilized. ChatGPT provides advanced natural language processing capabilities and can assist in topic identification and labelling. With the help of ChatGPT, the LDA-generated topics were labelled based on the ten prominent keywords associated with each topic. The most frequent and indicative words and phrases within each topic were identified and used to label and describe the underlying theme or concept discussed by the sleep therapists in their written feedback.

Based on the analysis of the data table output from the topic modelling, the scores for each topic per therapist were examined to identify the differences between therapists in terms of the topics discussed in their feedback. Rather than conducting separate topic modelling analyses for each therapist or calculating the average loadings of therapists on the topics, the focus was on determining the topics addressed by individual therapists using the scores obtained from the topic modelling analysis. This approach allowed for insights into the specific topics discussed by different therapists in their feedback.

Sentiment analysis (SA), also known as opinion mining, is the process of extracting and identifying people's emotions or opinions from text or speech (Medhat et al., 2014). There are two approaches to SA, namely supervised machine learning, which is an algorithm trained using labelled training data, and unsupervised machine learning, which is a type of machine learning algorithm that allows the model to learn and find patterns in data without any labelled input or guidance from humans (Usama et al., 2019). The unsupervised machine learning approach involves providing the model with a dataset without any specific instructions on how to categorize or group the data. Instead, the model searches for patterns, similarities, and differences within the data to create its own structure and classification system. This approach is often used in exploratory data analysis and can help identify hidden patterns or relationships in large datasets (Usama et al., 2019). Supervised machine learning often outperforms unsupervised lexicon-based SA (Eisenstein, 2016). Nevertheless, in this study, the unsupervised lexicon-based SA was chosen because the aim was to identify the topics and sentiments discussed by therapists in their online feedback for adolescent clients undergoing CBT-I. With unsupervised machine learning, the algorithm is not given any predefined categories or labels, and instead, it is left to discover patterns and groupings within the data on its own. This makes it ideal for exploratory analysis and for identifying themes and topics that may not have been previously recognized or defined. Additionally, unsupervised

machine learning allows for a more objective and unbiased analysis of the data, as it is not influenced by any preconceived notions or assumptions about the data.

In this study, lexicon-based SA was done based on the LiLaH Emotion Lexicon of Dutch as the feedback analysed was in Dutch and this lexicon covers more entities than other existing ones. The lexicon was created by two researchers from the University of Antwerp manually correcting an automatic translation of the NRC Emotion Lexicon (Ljubešić et al., 2020). Eight fundamental emotions (anger, fear, anticipation, trust, surprise, sadness, joy, and disgust) and two sentiments (negative and positive) are listed in the NRC Emotion Lexicon and therefore also in the LiLaH Emotion Lexicon (Ljubešić et al., 2020). The scores in the LiLaH sentiment analysis represent the association of specific sentiments and emotions with the therapists' feedback. The scores can range from 0 to 1, with 0 indicating no association and 1 indicating a strong association (Ljubešić et al., 2020).

To obtain text excerpts aligned with specific sentiments and provide the context for those sentiments, the NRC emotion lexicon served as the basis for the LiLaH sentiment analysis tool. As a dedicated LiLaH lexicon was not available, the Dutch translation of emotions in the NRC lexicon was examined, and words related to each sentiment were selected. These Dutch words representing different sentiments were then used to search the text file containing the feedback provided by the sleep therapists. While the LiLaH sentiment analysis tool provided sentiment scores for the entire feedback, it did not provide the actual concrete text excerpts under each sentiment. Therefore, to analyse sentiments within their contextual framework, a manual process was employed. The identified Dutch words representing different sentiments were used to search the therapist's feedback, and if a match was found between the entered word and the text, the corresponding text excerpt, along with the identified word, was included in the results. The decision to perform this manual process outside of the Orange platform was due to the tool's limitations in providing detailed text excerpts under each sentiment.

Results

Table 1 shows the ten most frequently used terms in online feedback provided by therapists for adolescent clients undergoing CBT-I. The table reveals that the terms

"week" (week) and "uur" (hour) were the most frequently used, followed by "wakker" (awake) and "hebt" (have). Other frequently used terms include "slaap" (sleep), "bed" (bed), "bedtijden" (bedtimes), "goed" (good), "minuten" (minutes), and "dagboekjes" (diaries). These results provide insight into the language used by therapists in their feedback and suggest that topics related to sleep duration and quality were commonly discussed.

Table 1

The Ten Most Frequently Used Terms in Online Feedback according to TF-IDF

Term	TF-IDF
week	0.419
uur	0.343
wakker	0.258
hebt	0.236
slaap	0.227
bed	0.200
bedtijden	0.197
goed	0.177
minuten	0.157
dagboekjes	0.138

Note. TF-IDF (Term Frequency-Inverse Document Frequency) is a numerical statistic that represents the importance of a term in a document within a collection or corpus of documents. It combines two factors: term frequency (TF) and inverse document frequency (IDF). The TF-IDF value ranges between 0 and 1, with higher values indicating greater importance.

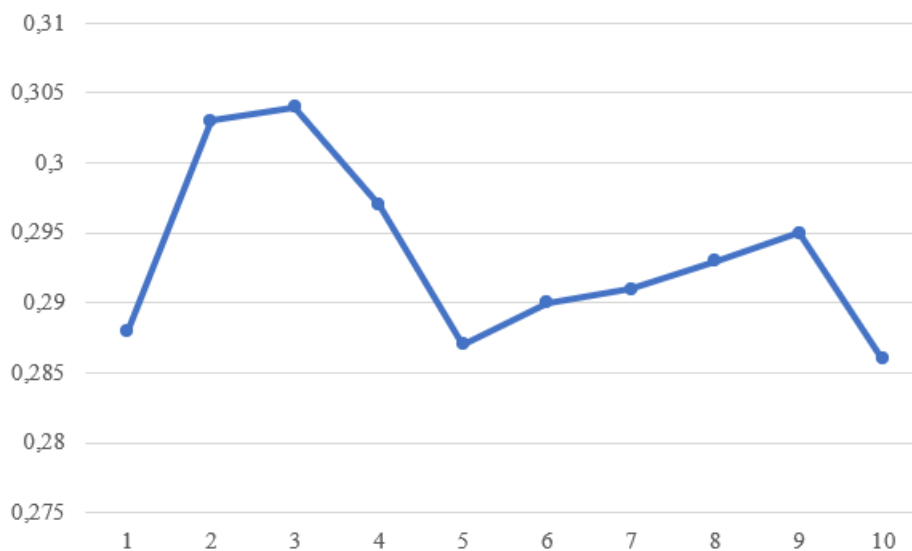
Topic modelling

The coherence scores for up to ten topics resulting from the topic modelling analysis are provided in Figure 3. In this study, the coherence score is highest for the model with 3 topics (0.304) and lowest for the model with 10 topics (0.286). The coherence scores for the models with 2, 4, 5, 6, 7, 8, and 9 topics fall between these two values, ranging from 0.287 to 0.295.

Based on the coherence scores, it can be concluded that the highest level of coherence is achieved when using three topics. As the number of topics increases beyond three, the coherence scores gradually decline. Therefore, if the interpretability and coherence of the topics are of utmost importance, it is recommended to select three topics. This conclusion is however based solely on the coherence scores and does not consider the log perplexity values or their implications.

Figure 3

Coherence scores in relation to the number of topics for LDA analysis



As seen in Figure 4, the log perplexity scores decreased as the number of topics increased from 1 to 4, indicating that these models provided an increasingly better fit to the data. However, the scores began to increase again at 5 topics and continued to fluctuate between 76.422 and 78.449 as the number of topics increased.

The lowest log perplexity score of 76.154 was achieved with a 4-topic model, which had a relatively low score compared to the other models. However, the 3-topic model had an almost similar score of 77.424 and had the highest coherence score, suggesting that it may be the most accurate representation of the underlying data.

Overall, the log perplexity scores in Figure 4 provide additional support for the 3-topic model identified in the coherence analysis as the most optimal for representing the topics being discussed by sleep therapists in their written feedback. These findings suggest that the 3-topic model provides the best balance between model fit and interpretability, allowing for meaningful insights into the concerns and needs of sleep therapists and their patients. Nevertheless, the 3-topic model did not yield keywords that were easily interpretable by human judgment, therefore ChatGPT was utilized to label the topics.

Figure 4

Log perplexity in relation to the number of topics for LDA analysis

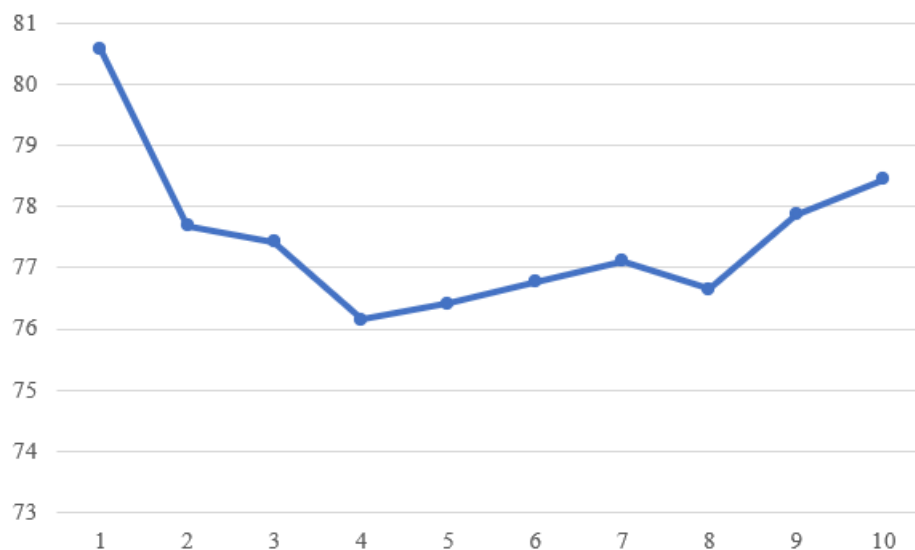


Table 2 presents the keywords associated with each of the three topics generated from the LDA analysis. These topics are represented by a combination of frequently occurring words and phrases that are indicative of the themes or ideas discussed by sleep therapists in their written feedback.

Table 2

Topic	Topic keywords
1	Uur, bed, goed, we, min, week, gemiddeld, kun, hebt, wakker
2	Week, uur, slaap, hebt, bed, wakker, goed, bedtijden, minute, tijd
3	Week, hebt, uur, goed, slaap bedtijden, wakker, we, houden

With the help of ChatGPT version 3.5, the analysis revealed three main topics that therapists discussed in their feedback (see Appendix). The first topic was labelled as sleeping duration and quality, which was characterized by keywords such as "hour," "bed," "good," "minute," "week," "average," "wake up," and "able to." This suggests a focus on the amount and quality of sleep that the individual is getting.

The second topic, identified by ChatGPT, was sleep habits and patterns, which was characterized by keywords such as "week," "hour," "sleep," "bed," "wake up," "good," "bedtimes," "minute," and "time." This suggests a focus on the individual's sleep habits and patterns, such as the time they go to bed and wake up.

The third topic, also identified by ChatGPT, was sleep tracking and monitoring, which was characterized by keywords such as "week," "hour," "sleep," "bedtimes," "good," "wake up," "keep," and "we." This suggests a focus on monitoring and tracking sleep habits and patterns to adjust for better sleep.

Sentiment Analysis

Table 3 presents the results of the LiLaH sentiment analysis per therapist. The results indicate that all seven therapists addressed fear in their feedback, with therapist 3 having the highest fear score of 0.479, while therapist 2 had the lowest fear score of 0.115. Therapists 5, 6, and 7 also addressed fear in their feedback, with scores of 0.308, 0.393, and 0.143, respectively. Empty cells in the table indicate that specific sentiment was not present in the feedback of those therapists.

Furthermore, the analysis revealed that therapist 3 expressed other sentiments in their feedback as well. Therapist 3 had a score of 0.009 for anticipation, indicating the

presence of expressions related to anticipation in their feedback. Additionally, therapist 3 also expressed joy and surprise, both with a score of 0.009.

There were no expressions of anger, disgust, sadness or trust detected in the feedback. Two therapists expressed negative sentiments, with therapist 2 having a score of 0.013 and therapist 5 having a score of 0.028. Additionally, therapist 3 expressed a positive sentiment with a score of 0.034.

Table 3

LiLaH sentiment analysis per therapist

	Therapist 1	Therapist 2	Therapist 3	Therapist 4	Therapist 5	Therapist 6	Therapist 7
Positive			0.034				
Negative		0.013			0.028		
Anger							
Anticipation			0.009				
Disgust							
Fear	0.444	0.115	0.479	0.228	0.308	0.393	0.143
Joy			0.009				
Sadness							
Surprise			0.009				
Trust							

Fear

When examining the therapists' feedback to adolescent clients, several expressions related to fear were identified. These fear-related expressions were correlated with specific words derived from the NRC lexicon, indicating fear as follows:

1. "bang" (afraid)
2. "spanning" (tension)
3. "zorgen" (concerns)
4. "moeite met inslapen" (difficulty falling asleep)

The therapists' feedback to the adolescent clients included the following text excerpts that exhibited expressions of fear:

- "Ik ben bang dat ik niet zal kunnen leren" (I'm afraid I won't be able to learn). Therapists encouraged clients to explore disturbing thoughts that made them feel tense.
- "Ik kan me echter voorstellen dat je bang bent dat je dan nog minder slaap krijgt" (However, I can imagine that you're afraid that you'll get even less sleep). Therapists acknowledged clients' concerns about getting less sleep.
- "Misschien ben je soms zelfs een beetje bang voor deze veranderingen omdat je dan overdag meer tijd hebt die je zelf moet invullen" (Perhaps you're sometimes even a little afraid of these changes because then you'll have more time during the day that you need to fill on your own). Therapists recognized that clients might feel apprehensive about changes and the need to fill their daytime.
- "Je zegt zelf dat je bang bent dat je weer moeite met inslapen hebt als je eerder naar bed gaat" (You yourself say that you're afraid you'll have trouble falling asleep again if you go to bed earlier). Clients expressed their fear of having trouble falling asleep again if they go to bed earlier.

By identifying these fear-related indicators and providing corresponding text excerpts, it becomes evident that fear plays a significant role in the therapists' feedback to adolescent clients.

Less Prominent Emotions (Anticipation, Joy, Surprise)

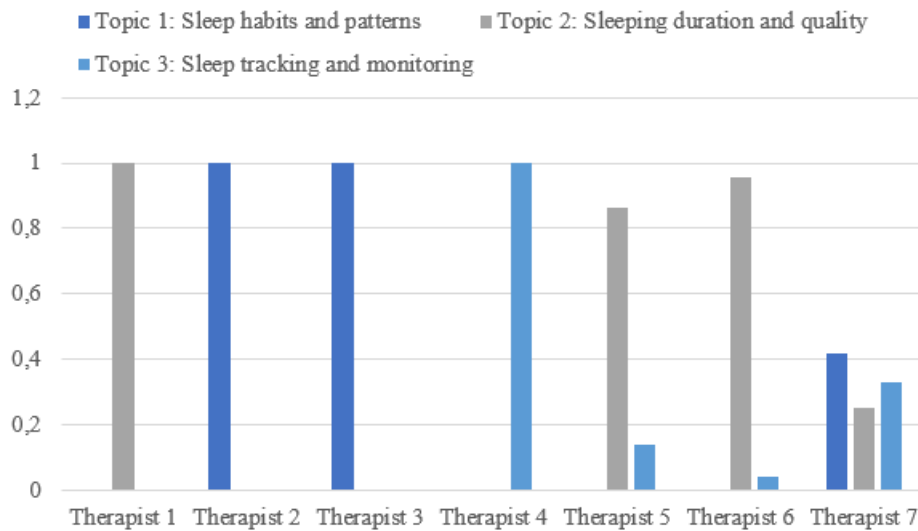
In addition to fear, other emotions were also evident in the therapists' feedback to adolescent clients. These emotions included anticipation, joy, and surprise. For anticipation, the therapists used various words and phrases, such as "gespannen" (anxious), "wachten" (await), "verjaardag" (birthday), and "wekken" (arouse). They acknowledged clients' feelings of anticipation and anxiety, mentioned waiting for the

next session, wished them a happy birthday in advance, and noted the arousing effect of certain drinks. The therapists also expressed joy in their feedback, using words like "prestatie" (achievement), "grappig" (funny), "streven" (aspiring), and "mooi" (beautiful). They praised clients for their achievements, commented on funny observations, acknowledged the presence of useful tips, and highlighted improvements. Lastly, the therapists conveyed surprise through words such as "ongeluk" (accident), "compliment" (compliment), "anders" (differently), and "ramp" (disaster). They advised clients on avoiding accidents, complimented their progress, emphasized the importance of good sleep hygiene, and discussed potential disasters if certain thoughts or behaviors persisted.

In Figure 5, the distribution of topics across different therapists is presented. Therapist 1 primarily focused on Topic 2, which revolves around sleeping duration and quality. Therapists 2 and 3 primarily discussed Topic 1, which relates to sleep habits and patterns. Therapist 4 predominantly addressed Topic 3, which pertains to sleep tracking and monitoring. Therapists 5 and 6 predominantly focused on Topic 2, with some mention of Topic 3. Lastly, therapist 7 covered all three topics in their feedback. These findings provide insights into the varying topical preferences and emphases of individual therapists when providing written feedback for adolescent insomnia through Cognitive Behavioural Therapy for Insomnia (CBT-I).

Figure 5

Topics per therapist



Discussion

This study aimed to investigate the written feedback provided by online therapists in CBT-I for adolescents. The study utilized text-mining methods to extract the relevant concepts in the written feedback of therapists to their adolescent CBT-I clients. The analysis revealed three main topics that sleep therapists discussed in their written feedback, addressing sleep duration and quality, sleep habits and patterns, and sleep tracking and monitoring. Moreover, sentiment analysis provided insights into the emotions expressed by therapists in their feedback. The analysis revealed that therapists expressed both positive and negative sentiments, with a stronger emphasis on negative emotions. Fear emerged as the most prominent negative emotion addressed by the therapists, while positive emotions were less prevalent, with only one therapist expressing positive sentiments.

Topic modelling

In terms of the topic modelling analysis, three interpretable topics related to sleep therapy discussions were identified: sleep duration and quality, sleep habits and patterns, and sleep tracking and monitoring. These findings align with previous research that suggests cognitive-behavioural therapy for insomnia (CBT-I) targets the regulation of sleep-wake rhythms, sleep hygiene, and cognitive and behavioural factors influencing sleep (de Bruin et al., 2015; Dewald-Kaufmann et al., 2019). The therapists' feedback appears to closely align with the key dimensions addressed in CBT-I interventions for

adolescents, indicating that their discussions revolve around the relevant areas targeted by CBT-I when addressing insomnia in this population.

However, it is important to consider why therapists predominantly demonstrate these specific topics. One possible reason is that these topics are indeed core components of CBT-I. By discussing sleep duration and quality, sleep habits and patterns, and sleep tracking and monitoring, therapists may be reinforcing the principles and strategies emphasized in CBT-I interventions. Adherence to these components is expected to contribute to improved sleep outcomes in adolescents based on previous research (de Bruin & Meijer, 2017).

On the other hand, it is worth noting that adherence to rigid feedback instructions may not always be necessary. Studies, such as the one by Mol et al. (2018) on blended CBT for depression, suggest that flexibility in providing individualized and readable communication can have positive effects on patient outcomes in therapy. Although this study did not focus specifically on insomnia, it raises the possibility that allowing therapists to tailor their feedback according to individual needs and preferences might be beneficial.

Another aspect to consider is the potential absence of certain CBT-I components in therapists' feedback. For example, while relaxation techniques are often included in CBT-I interventions (de Bruin et al., 2015), their presence may not have been strongly reflected in the identified topics. Exploring the reasons behind the observed topic prevalence and potential missing elements could contribute to a more comprehensive understanding of therapists' feedback practices in online CBT-I for adolescents.

Sentiment Analysis

The findings of the LiLaH sentiment analysis and the NRC lexicon revealed that fear is a predominant emotional tone expressed by all therapists in their feedback to adolescents undergoing Cognitive Behavioral Therapy for Insomnia (CBT-I). The therapists' feedback contained text excerpts where clients expressed fear of not being able to learn or having trouble falling asleep again, demonstrating how therapists acknowledged and validated these fears. The presence of fear-related expressions in the therapists' feedback further supports the notion that fear is a central concern in the

treatment of adolescent insomnia. Cognitive restructuring, a standard element of CBT-I, may be at play in addressing fear-related concerns. Cognitive restructuring aims to change negative thought patterns and beliefs about sleep, which can trigger autonomic arousal and emotional distress (Harvey, 2002). Previous research on CBT-I has shown that it can reduce fear of sleep and worry in individuals with insomnia (Kanady et al., 2018; Sunnhed & Jansson-Fröjmark, 2014; Ballezio et al., 2021). However, the specific impact of therapists' feedback on fear reduction in adolescents with insomnia has not been specifically studied.

While the study focused on fear, it is worth noting that the emotional tone of therapists' feedback can impact therapy outcomes. A supportive and validating emotional tone in feedback can enhance therapeutic progress and contribute to improved treatment outcomes (Peluso, 2018). Conversely, negative emotional tones might hinder progress and negatively influence the therapeutic alliance. In Veiga's (2019) study, which was not specific to insomnia treatment, the most frequent emotions identified were Trust, followed by Joy and Anticipation. However, in the present study, no expressions of anger, disgust, sadness, or trust were detected in the therapists' feedback specific to adolescent insomnia treatment. The absence of expressions related to trust in the therapists' feedback suggests a potential area for improvement in CBT-I for adolescents with insomnia.

Building a good working alliance and establishing trust between the therapist and the client is beneficial in therapy outcomes (Iwakabe et al., 2000). The trust-based therapeutic relationship can foster a sense of safety, openness, and collaboration, which may positively impact treatment outcomes (Luong et al., 2020). Addressing fears directly in therapy feedback while also nurturing a sense of trust may contribute to therapeutic progress. However, further research is needed to understand the effectiveness of addressing fears and enhancing trust in therapy feedback for adolescents with insomnia.

In summary, the present study highlights the prevalent expression of fear in therapists' feedback in the treatment of adolescent insomnia. It suggests that addressing fear through cognitive restructuring techniques is an important aspect of CBT-I. Furthermore, the absence of trust-related expressions in the therapists' feedback suggests a potential area for improvement in CBT-I interventions.

Differences between therapists

The findings of the topic modelling, the LiLaH sentiment analysis, and the NRC lexicon shed light on research question 3: Are there differences between therapists in expressed topics and sentiments in their feedback? The analysis revealed variations in the topics and sentiments expressed by therapists, indicating that each therapist has a unique approach to their interactions with adolescent clients.

These differences observed among therapists are noteworthy, considering the training and regular interventions they received, as mentioned in the studies from which the feedback was obtained (de Bruin et al., 2014, 2015, 2016, and 2017). In the context of cognitive-behavioral therapy for insomnia (CBT-I) training and intervention is important. Competence feedback, video feedback, and clinical supervision have been shown to improve therapists' competencies, self-reflection, and performance in CBT (Weck et al., 2017; Gonsalvez et al., 2016; Murr et al., 2020). Additionally, receiving client feedback has been found to enhance client outcomes and counsellor self-efficacy (Reese et al., 2009).

While therapists receive training and engage in regular interventions, our findings highlight distinct variations in the topics and sentiments expressed in their feedback. These variations highlight the individual therapeutic approaches and emphases among therapists, allowing for treatment tailoring to meet the specific needs of adolescent clients. This aligns with the study by Mol et al. (2018), which suggests that flexibility in adhering to rigid feedback instructions and allowing for more individualized and readable communication may positively impact patient outcomes in therapy. Therefore, recognizing and leveraging these differences among therapists can contribute to tailoring treatment approaches to better meet the specific needs of adolescent clients, potentially enhancing client care and improving the overall quality of psychotherapy outcomes.

One of the therapists' written feedback that stood out due to the presence of various emotions was incorporated into the master thesis discussion. Despite having the highest fear score, the therapist skilfully integrated positive sentiments, joy, surprise, and anticipation. This contradictory combination reflects their nuanced approach to addressing different emotions in therapy. They validated clients' fears and anxieties, providing guidance to alleviate anxiety, while also explicitly addressing anticipation and

celebrating clients' achievements, creating a more motivating and uplifting therapeutic experience (Geschwind et al., 2020). This aligns with clients' preferences for positive elements in therapy, emphasizing the benefits of incorporating positive emotions and validating a range of client emotions. By considering clients' perspectives and integrating positive CBT, therapists can create a more engaging and effective therapeutic experience.

Previous research has emphasized the impact of therapist differences on treatment outcomes (Okiishi et al., 2006). Despite the training and regular interventions, the observed variations in topics and sentiments expressed by therapists indicate that individual therapists play a significant role in shaping the therapeutic process and potentially influencing treatment outcomes. This emphasizes the importance of ongoing monitoring and professional development, allowing therapists to reflect on their feedback practices and continuously refine their skills to improve the quality of psychotherapy outcomes.

In conclusion, our study demonstrates differences between therapists in the topics and sentiments expressed in their feedback to adolescent clients and suggests that these can be detected by automated text-mining techniques. The results suggest that individual therapist factors should be considered alongside standardized training to optimize the therapeutic process and improve treatment outcomes for adolescents.

Text mining

The use of text mining in this study proved to be a valuable and efficient tool for analysing the written feedback of therapists in Cognitive Behavioural Therapy for Insomnia (CBT-I) for adolescents. Manual content analysis of large amounts of text data can be time-consuming and laborious, but text mining techniques, such as sentiment analysis and topic modelling, allowed for a comprehensive exploration of the therapists' feedback, providing meaningful insights efficiently (Antons et al., 2020).

The application of topic modelling, specifically Latent Dirichlet Allocation (LDA), enabled the extraction of relevant concepts and topics related to sleep therapy, revealing the emphasis on sleep duration, quality, habits, patterns, tracking, and monitoring by therapists. Additionally, sentiment analysis unveiled the presence of both

positive and negative sentiments expressed by therapists in their feedback, reflecting the complexity of emotions in the therapeutic context (Veiga, 2019).

Text mining techniques have also demonstrated their value in psychotherapy analysis in previous research by Atzil-Slonim et al. (2021) and Provoost et al. (2019). Atzil-Slonim et al. (2021) effectively used topic modelling to identify meaningful topics discussed in therapy sessions and explore their associations with clients' functioning and treatment outcomes, providing valuable insights into the therapy process and outcomes. Provoost et al. (2019) successfully conducted an automated sentiment analysis on online CBT patient texts, showing that existing text mining algorithms perform nearly equal to human assessment in distinguishing between positive, neutral, and negative sentiment, making sentiment analysis a useful tool for evaluating therapists' feedback and its emotional tone in guided CBT online therapy.

Despite these valuable insights, it is essential to acknowledge that sentiment analysis using existing lexicons may have limitations in accurately representing the nuances and variety of emotions evoked in a therapeutic context (Veiga, 2019). Therefore, further research is warranted to develop more refined lexicons that can better capture the emotional complexity of therapeutic interactions.

In conclusion, text mining techniques have proved to be a valuable asset in analysing therapists' written feedback in CBT-I for adolescents, providing valuable insights into therapist practices and offering a foundation for enhancing CBT-I interventions for adolescent sleep problems. The application of text mining techniques in psychotherapy research holds promising potential for furthering our understanding of therapy processes and outcomes.

Limitations and Future Research

The generalizability of the results is limited by the relatively small sample size of therapists and clients in this study compared to larger-scale studies conducted in the past (Okiishi et al., 2006). Moreover, the information was generated within a relatively rigidly protocolized environment, which constrains the applicability of the findings to real-world therapeutic contexts. In addition to other attributes, randomized controlled trial (RCT) studies involve stringent treatment protocols, precise criteria for participant selection,

and therapists with specialized training (de Bruin et al., 2014, 2015, 2016, and 2017). As a result, caution should be exercised when extending the findings to a larger population of therapists and clients. While these limitations may impact the broader applicability of the findings, they do not diminish the validity of the results for answering the specific research questions of this study.

The methodological choices were constrained using ChatGPT for labelling the topics. While ChatGPT provided insights into the content of therapists' feedback, it is a general language model and not specifically designed for the domain of Cognitive Behavioural Therapy for Insomnia (CBT-I). As a result, there may be a level of uncertainty and potential inaccuracies in the topic labelling process. Future research could explore the use of domain-specific language models or train language models on data specific to CBT-I to enhance the accuracy of topic labelling and further improve the understanding of therapists' feedback.

Another limitation is related to the sentiment analysis conducted using the LiLaH lexicon in Orange. While the analysis provided overall sentiment scores and labels, it did not offer a detailed breakdown of sentiments at the word level, limiting the granularity of sentiment insights. To gain a more comprehensive understanding of the sentiments expressed in therapists' feedback, future research could utilize sentiment analysis tools that provide more detailed insights at the word level.

Further research is needed to explore specific factors that contribute to differences between therapists' written feedback and their potential effectiveness in improving treatment outcomes for adolescents. Understanding these factors could inform training programs for therapists and enhance the quality of feedback provided to adolescent clients. Additionally, future research should focus on investigating the potential benefits of incorporating automated sentiment analysis and topic modelling into the feedback process for therapists. Utilizing AI-supported feedback could streamline the process and offer therapists valuable insights into their practices, ultimately enhancing the effectiveness of CBT-I interventions for adolescents with insomnia. It is also advisable to conduct comparisons between protocol-based feedback and free-form feedback in CBT-I to determine which approach is more effective in achieving treatment goals.

Furthermore, future research could delve into exploring the effects of incorporating trust-related feedback into CBT-I interventions for adolescents with insomnia and examine how it influences treatment response and the therapeutic alliance. Investigating the dynamics of fear and trust in therapy feedback will allow us to gain a deeper understanding of how these factors contribute to the overall effectiveness of CBT-I for adolescents with insomnia, leading to improved treatment strategies in this population. By addressing these areas of inquiry, future studies can advance our knowledge of therapist practices in CBT-I and pave the way for more personalized and efficient therapeutic interventions in this context.

Conclusion

In conclusion, this study utilized text mining techniques to analyse written feedback from sleep therapists in online treatment for adolescent sleep problems. The analysis identified three main topics related to sleep therapy discussions: sleep duration and quality, sleep habits and patterns, and sleep tracking and monitoring. Furthermore, sentiment analysis found that therapists' feedback predominantly addressed clients' fears, resulting in fear being the predominant emotional tone expressed. Differences were observed among therapists in the topics and sentiments expressed in their feedback, indicating individual therapeutic approaches and emphases. While the study provided valuable insights into therapist practices, some potential limitations, such as sample size and topic labelling, were acknowledged. Further research is needed to explore factors contributing to differences in therapists' written feedback and its effectiveness in improving treatment outcomes for adolescents with insomnia. Utilizing AI-supported feedback through automated sentiment analysis and topic modelling could offer valuable insights to enhance CBT-I interventions while exploring trust-related feedback's impact on treatment response and the therapeutic alliance could further improve personalized therapeutic strategies in this context. This research highlights the importance of text mining techniques, such as LDA and LiLaH, in analysing therapists' written feedback in online CBT-I for adolescents with insomnia. The findings underscore the potential for improving therapist-client relationships and treatment outcomes by understanding underlying concepts within the therapeutic context.

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Appendix

Labelling topics in ChatGPT according to keywords from LDA

How could you label these topics?

Table 3

Topic Topic keywords

- | | |
|---|---|
| 1 | Uur, bed, goed, we, min, week, gemiddeld, kun, hebt, wakker |
| 2 | Week, uur, slap, hebt, bed, wakker, goed, bedtijden, minute, tijd |
| 3 | Week, hebt, uur, goed, slaap bedtijden, wakker, we, houden |



Based on the provided keywords, the topics could be labeled as follows:



1. Sleep duration and quality: keywords include "hour," "bed," "good," "minute," "week," "average," "wake up," "able to," suggesting a focus on the amount and quality of sleep that the individual is getting.
2. Sleep habits and patterns: keywords include "week," "hour," "sleep," "bed," "wake up," "good," "bedtimes," "minute," "time," suggesting a focus on the individual's sleep habits and patterns, such as the time they go to bed and wake up.
3. Sleep tracking and monitoring: keywords include "week," "hour," "sleep," "bedtimes," "good," "wake up," "keep," "we," suggesting a focus on monitoring and tracking sleep habits and patterns in order to make adjustments for better sleep.