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The asymmetries of the biopsychosocial model of depression in lay discourses - Topic modelling online depression forums

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ABSTRACT

Background: One of the most comprehensive approaches to depression is the biopsychosocial model. From this wider perspective, social sciences have criticized the reductionist biomedical discourse, which has been dominating expert discourses for a long time. As these discourses determine the horizon of attributions and interventions, their lay interpretation plays a central role in the coping with depression.

Methods: In order to map these patterns, online depression forums are analyzed with natural language processing methods, where computational tools are complemented with a qualitative approach. Latent Dirichlet Allocation topic model of depression-related posts from the most popular English-speaking online health discussion forums (N = ~70 000) reveals the monolog (attributions and self-disclosures) and interactive (consultations and quasi-therapeutic interactions) patterns.

Results: Following the evaluation of various models 18 topics were differentiated: *attributions* referring to health, family, partnership and work issues; *self-disclosures* referring to contemplations, introducing the experience of suffering and well-being, along with diaries of everyday activities and hardships; *consultations* about psychotherapies, classifications, drugs and the experience; and *quasi-therapeutic interactions* relying on unconditional positive regards, recovery helpers experience or spirituality. These topics were evaluated from the perspective of the biopsychosocial model: the weight of each dimension was measured along with the discursive function.

Conclusions: Biomedical discourse is underrepresented in lay discussions, while psychological discourse plays an overall dominant role. Even if actors are initially aware of the social mechanisms contributing to depression, they neglect these factors when it comes to considering the countermeasures.

1. Introduction

Depression is considered to be one of the most common mental disorders, also a leading cause of disability worldwide (WHO, 2020). Despite the ongoing debates (Garcia-Toro & Aguirre, 2007; Lehman, David & Grube, 2017), it may be argued that one of the most comprehensive approaches to depression is the biopsychosocial model (Bolton & Gillett, 2019; Engel, 1980). However, the awareness of these various causes does not automatically imply the same level of attention paid to biological, psychological, and social explanations. The dominant discourse of depression is the biomedical (Rose & Abi-Rached, 2013), which is also expressed in the dominant forms of intervention: most Western health care systems rely primarily on pharmaceutical treatment (e.g. OECD, 2017; Pratt et al., 2017); complemented with psychotherapy (e.g. Delgadillo et al., 2018; Epping et al., 2017).

Of course, that does not mean the social factor is completely missing from the expert discourses. Many psychological models include the social element as an indicator of depression (Dambi et al., 2018). Also, several therapies focus on close social networks (Cottrell, 2003; Gupta et al., 2003). Large scale surveys explore several structural factors related to depression, such as lower socio-economic status (Hoebel et al., 2017; Lorant et al., 2003; Patel et al., 2018); being a women (Abate, 2013); being a member of ethnic or racial minorities (Bailey et al., 2019; Simpson et al., 2007); cultural transformations (Horowitz &Wakefield, 2007). However, these conclusions hardly represent a mainstream approach: even if they are acknowledged on theoretical level, they seldom find a way to the level of interventions. In this sense, the social component of depression remains in the background of therapeutic discourses (Fuchs, 2014).

Due to the asymmetry between the expert biopsychosocial consensus

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and the mostly biomedical and psychological therapies, the sufferers' discursive framing of depression becomes a crucial one. The importance of 'illness narratives' is well-known (Frank, 2013; Kleinmann 1988). Especially in case of mental disorders the 'recovery narratives' are essential for constructing a renewed, coherent identity (Llewellyn-Beardsley et al., 2019). In this process peer support is indispensable: it is the relevant others, who provide platform for identity-construction interactions (Pfeiffer et al., 2011). These evidences highlight the general theoretical stakes of our research: by analyzing lay depression narratives, an attempt is made to map the support potential and limitations of the ongoing peer discussions.

From the perspective of the discourse theories of mental disorders, each dimension of the biopsychosocial model has specific connotations. If depression is predominantly interpreted according to a biological framing, then the patients understand themselves primarily as bodily entities relying on medical expertise (Rose, 1999). If a psychological framework becomes dominant, then depression is interpreted as an internal dysfunctionality (e.g. developmental, traumatic origins), whose therapeutic treatment aims at reestablishing agency by working on the past and present self (Cuijpers et al., 2019). However, if it is understood – at least partly – as a 'social suffering' (Sik, 2019), then interventions targeting the micro and macro social world also become relevant. Our research aims at exploring the lay implementation of these discursive variants: the application of biological, psychological, or social discourses highlights the trajectories of illness narratives and peer support. The mapping of potential asymmetries is given a special attention, as they reveal the biases and blind spots of these processes.

From a methodological perspective, such enterprise raises specific challenges. Due to the sensitive nature of related narratives, firstly a systematically analyzable dataset had to be defined: anonymous online depression forums were chosen, as they provide an equally large and detailed discursive universe. Secondly, an appropriate methodological apparatus had to be established capable of mapping lay depression discourses in a comprehensive manner: quantitative (NLP) and qualitative (deep reading) methods were combined to provide a hermeneutically valid and statistically sound analysis.

Recently several similar attempts of mapping online depression discourses with text mining methods appeared (Feldhege et al., 2020; Lachmar, 2017; Li et al., 2018; Németh et al., 2020; Pan et al., 2018; Reavley & Pilkington, 2014). While these researches contributed to understanding the online representation of depression in many ways, neither of them provided a comprehensive analysis. They either relied on one-sided methods or focused on specific platforms or forums. In the present paper, an attempt is made to overcome these limitations. Our research aims at expanding the horizon of both the amount of collected data and the applied analytical tools. We collected ~70 000 depression-related posts from most popular English-speaking online health discussion forums. Because of the large amount of data, we decided to use automatic knowledge acquisition from the corpus within the framework of natural language processing (NLP). We applied Latent Dirichlet Allocation (LDA) topic models that can provide an insight into the underlying latent structure of the corpus. Also, these quantitative analyses were complemented with qualitative elements: the final meanings of each topic were partly elaborated by a hermeneutic analysis of the posts. Two research questions were analyzed:

RQ1 What are the thematic clusters and discursive patterns appearing in the biggest English speaking online depression forums?

RQ2 Which dimensions of the biopsychosocial model play a dominant role in these lay discussions; and what are the specific discursive functions of the biomedical, psychological and social narratives?

2. Material and methods

2.1. Data

Although the users of online depression forums constitute a heterogeneous population, previous research have mapped several attributes: they are mostly used by people characterized by social and geographical isolation, also in need of practical information and advice (Smith-Merry et al., 2019). Although the majority of the users is currently or formerly suffered from depressed mood (Powell et al., 2003), some users are not involved personally, rather curious seekers of information (Nimrod, 2013). These attributes indicate the generalizability and the limitations of our study: it does not represent people living with clinical depression, rather the discursive processes facilitated by people directly or indirectly affected by depression.

For gathering the online forum posts, we used SentiOne, a web-based social listening and text analytics platform. We chose the most popular English-speaking online health forums (see Fig. 1), which were selected via Google search using the search terms "depression forum" and "depression online." Beside the practical reasons, this search strategy was further justified by the stakes of our research: as lay discourses were targeted, it seemed ideal to simulate the search processes of an ideal-typical lay actor seeking online answers to depression related concerns. As Google search defines not only the largest, but also the most accessible sites, its results are also considered to be the most widely used ones as well. Searching was restricted to those forums which were active in the last three years and were public and accessible without registration, in order to follow data protection and ethical regulations.

We aimed at collecting only posts explicitly discussing depression; for this purpose, (1) we selected threads which contained the word "depression" or "depressed" in their title or at least in one of their posts, then (2) we selected posts whose link, topic, or content contained a depression-related term, like "unipolar depression," "mood disorder," or "depressant." The data set, collected by SentiOne in compliance with GDPR regulations, contained 79 889 articles posted between February 15, 2016 and February 15, 2019 covering only publicly available posts, which were shared willingly by their authors. After removing duplicate and too short (less than 20 words) posts, our final corpus contained 67 857 posts. The posts were written by ~20.000 users identified by their nickname. The corpus in its raw form needs further preprocessing (a term coming from the data science community) to be useable for analytics. We used Python's NLTK package (Bird et al., 2009) for this purpose. Similarly to most text mining approaches, our analysis relied on a word-based representation of texts (e.g., Aggarwal & Zhai, 2012), assuming that texts are 'bags of words', while ignoring word order and syntactic relations etc. Also, the simplifying language model itself makes it highly important to validate the results, in our case, to qualitatively assess the coherence of the resulting topics.

We employed lemmatization to standardize different forms of the same word, discarded punctuation and capitalization, deleted URLs, e-mail addresses, repost part of the posts and very common words ('stop words'). We treated most relevant two-word collocations as single words, like "frontal lobe" or "epsom salt" (the latter is believed to relieve anxiety). We also treated the name of the most common mental disorders (e.g. "major depression" or "chronic fatigue syndrome") and proper nouns as single terms. The proper nouns successfully detected in our corpus were Chris Cornell, Stephen Fry (famous persons coming out with their depression) or John Grohol (a well-known online mental health expert).

After all, distribution of words within texts formed the numeric input data for the quantitative analysis, that is, the corpus was transformed into a numerical database. At some points of the analysis, we turned back to certain texts and analyzed them in a qualitative way. We can say that we followed an intra-method mixing (Johnson & Turner, 2003), as we used a single method of data collection to obtain a mixture of qualitative and quantitative data.

2.2. Analytical strategy: topic models

Natural language processing (NLP) concerns the development of algorithm-based analytical tools, with which large-scale text analysis

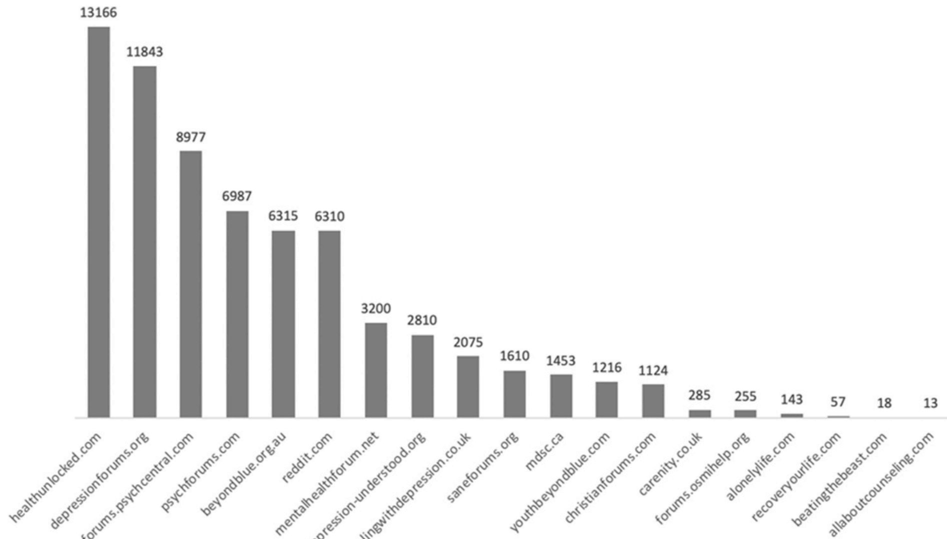

Fig. 1. Distribution of posts by domains.

becomes possible. Topic modelling in the context of NLP may be considered as a method of uncovering hidden topics in the corpus. Intuitively, the model assumes the existence of a finite set of topics, where a topic is statistically defined as a multinomial distribution over the terms of the given corpus. The model allows posts to relate to more than one topic. Latent Dirichlet Allocation (LDA, see Blei et al., 2003) is the first and widely used example of topic models. It assumes a Dirichlet distribution to determine per document topic distributions, this distribution is typically set to minimize the number of topics any particular post in the corpus is related to. Latent topics generate posts following their probability distribution over terms. Similarly to cluster analysis, the number of topics is an input parameter of the model.

We used LDA via the MALLET program (Mc Callum, 2002), which is available in Python using the "gensim" toolkit (Rehurek, Sojka, 2010). The algorithm was configured with an optimization interval of 10, but otherwise we used the default parameters. We ran topic models by varying numbers of topics from 5 to 20, trying to get not too broad but still not over-clustered topics. The algorithm's implementation relies on stochastic elements in its initialization, which can lead to somewhat different results (Belford et al., 2018). We tested this (rarely considered) instability by running each model with five different random number initializations.

There is no standardized procedure to determine the optimal number of topics. We combined quantitative and qualitative approaches for this task. First, we assessed interpretability of the models by calculating a coherence score for each of our models. Such scores try to quantify the semantic similarity between most relevant words in the topic. We chose the C_v measure that was proven to outperform all other coherence scores, where performance was measured by correlation with human ratings (Röder et al., 2015). Fig. 2 presents the coherence score for each model. Different initializations (denoted by different colors on the figure) led to models with quite different coherence. We choose models with 7, 13, 14, 18 and 19 topics that performed the best among the five initializations (denoted by five red circles on the figure) and that also

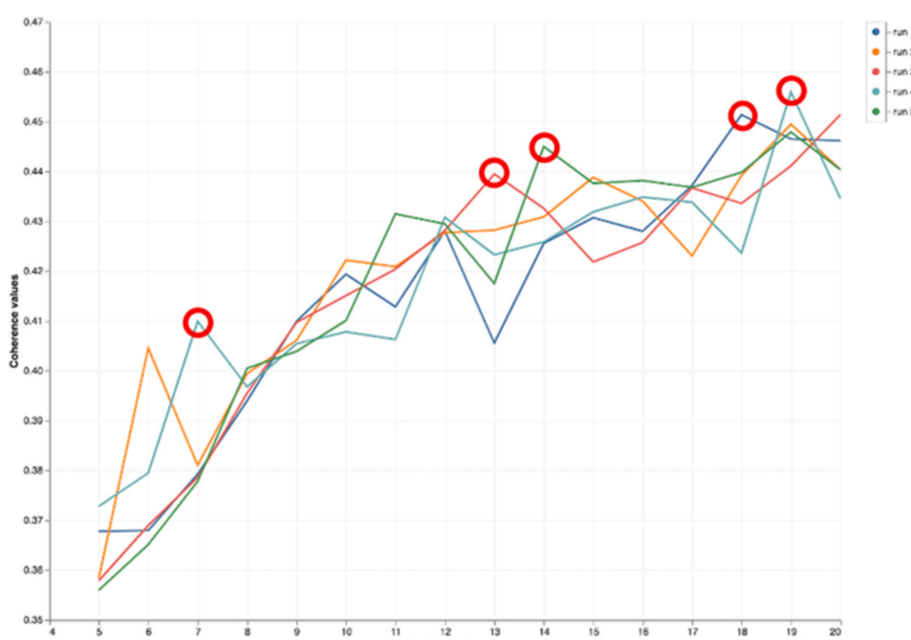

Fig. 2. Coherence score of models with different initializations/different number of topics, and the five models chosen.

marked the end of a rapid growth of coherence. As our aim was to qualitatively evaluate the chosen models, we selected models that represent a broader range of topic numbers, from 7 to 19, while keeping the number of selected models to be manageable to avoid over-detailing. The selected models are indicated later as T7, T13, T14, T18 and T19.

Having the five most coherent models, we qualitatively ranked them based on their interpretability. As it will be introduced in detail in the Discussion, the topic number of 18 proved to be the best for meaningful interpretation.

2.3. Supporting interpretation with visualization

To support the interpretation, we applied the interactive visualization tool LDAvis. We used the Python package pyLDAvis of Ben Mabey (2020), a Python port of the original R implementation of Sievert and Shirley (2014). Fig. 3 presents a global view of the topics (an interactive version of the figure can be found in Supplementary Material). The map on the left panel answers the questions regarding the prevalence of each topic and the relation between the topics. The areas of the circles are proportional to their relative prevalence in the corpus. Prevalence is measured by percentage of corpus words pertaining to the given topic.

The centers of the topics are laid out in two dimensions (see the left panel in Fig. 3), where original inter-topic distances are computed by Jensen-Shannon divergence and multidimensional scaling is used to get their two-dimensional representation. When interpreting such a map, there is ambiguity in the labeling of axes (Garson, 2013). A subjective approach is to take very distant objects and try to find an interpretation for the dimensions. It is important to note that the two-dimensional map inevitably simplifies the picture and its interpretation should be completed with a qualitative evaluation to get a more valid insight.

The right panel of Fig. 3 shows a horizontal bar chart whose bars represent the individual terms that are the most informative for understanding the topic model. The indicator of informativeness is saliency (Chuang et al., 2012), that measures how much information a term conveys about the topics. Saliency of a word is given as the multiplication of its relative frequency and distinctiveness. Even if a word occurs very frequently in the corpus, if it can be found in each topic (low distinctiveness), its occurrence in a post does not help us to determine which topic the post belongs to. The figure presents the 30 most salient terms ranked by saliency on the right panel, the bars represent their overall frequency. We will discuss later what roles these terms in our model have.

If hovering over a specific term on the right panel (see the interactive figure in Supplementary Material), the term's conditional distribution over topics is revealed by altering the areas of the topic circles. The new areas are proportional to the term-specific frequencies. This reveals, for example, that the term "feel" occurs most frequently in topic 13, which (among other information) helped us to identify this topic as a topic of *expressive speech acts* (see the Results). Similarly, the term "medication" occurs almost exclusively in topics 1 and 8 (see Fig. 4), which confirms that these topics were identified as showing patterns of *Making sense of psychotherapies* and *Making sense of drugs*.

Another important interactive visual component helps to answer the question what the meaning of each topic is. Selecting a topic on the left reveals its most relevant terms on the right (try the interactive visualization in the Supplementary Material). Fig. 5 shows the most relevant terms for topic 4 of T18. The terms are ranked by relevance. These terms helped us during the interpretation phase to identify this topic as *Partnership related attribution*, as the most relevant terms include the most important actors of the constellation: "friend, girl, women, boyfriend, partner" and also the potential conflict points, such as "cheat, porn, hurt". Relevance of a term (Sievert & Shirley, 2014) is the sum of its topic-specific frequency and a penalty term that is an increasing function of the term's overall frequency. Apparently, terms that often occur in the given topic but are very common in the whole corpus are less relevant for the topic. The sum is a weighted sum, using weights of λ and (1-λ) (λ is interactively adjusted between 0 and 1). The larger the λ, the less penalty is introduced. If λ equals 1, there is no penalty used, and relevance is simply defined as topic-specific frequency. We set λ to be 0.6, which we found to give well interpretable results, and which was also found to be optimal by Sievert and Shirley (2014).

Fig. 5 also presents topic-specific frequencies (red bars) and overall topic frequencies (blue bars). These pieces of information provide deeper understanding of the relevant terms' roles. For example, if the length of the blue and red bars is approximately equal, then the term exclusively characterizes the topic. Among most relevant terms in Fig. 5 are "time" and "girl". "Time" is a relatively common term, but topic 4 generates only about 1/7 of its occurrences, while "girl" is relatively rare and occurs almost exclusively in this topic. This conclusion is further confirmed if we hover over the two terms and reveal their topic-specific

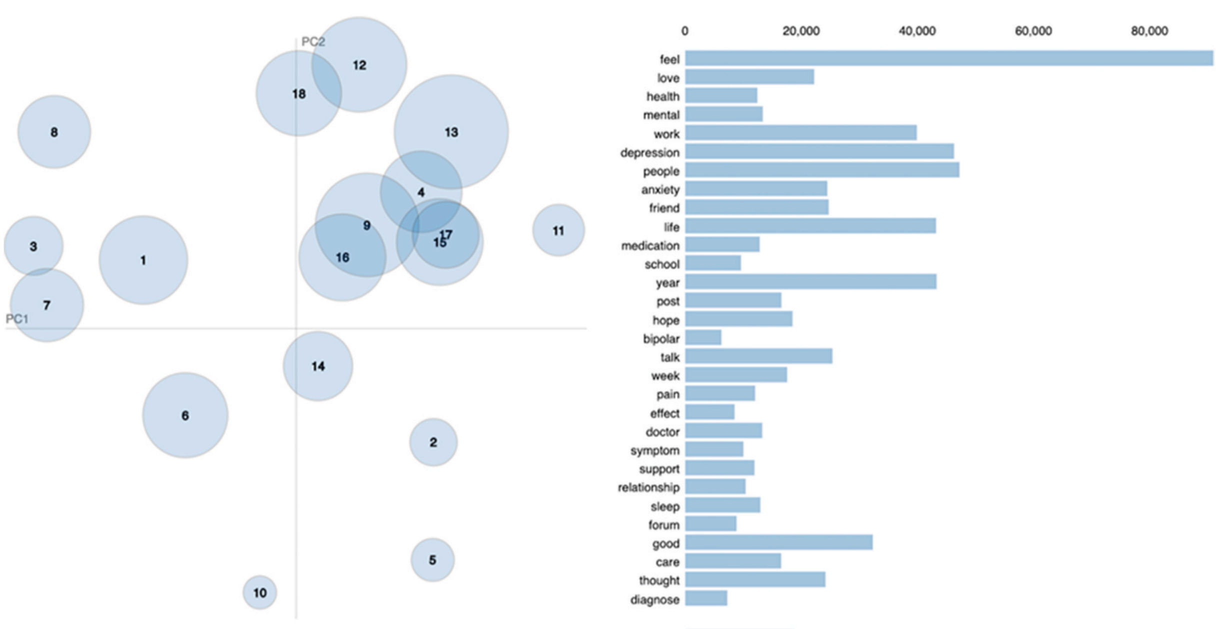

Fig. 3. Distance map of topics of T18 with the most salient terms.

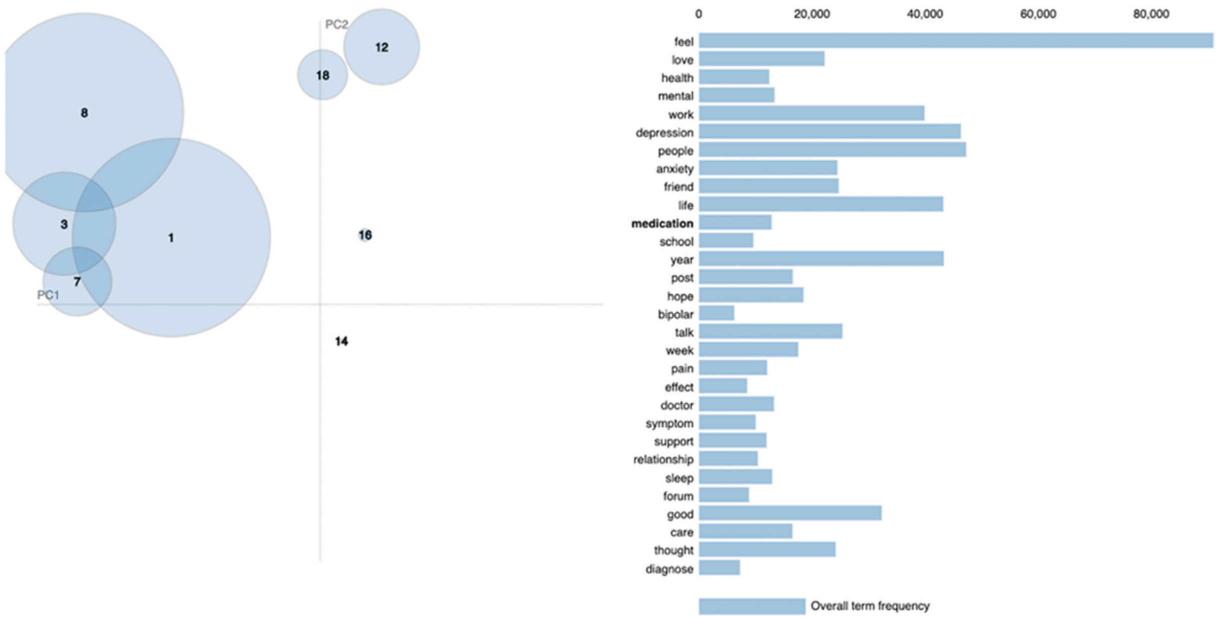

Fig. 4. Topic-specific frequencies of the term "medication" in T18.

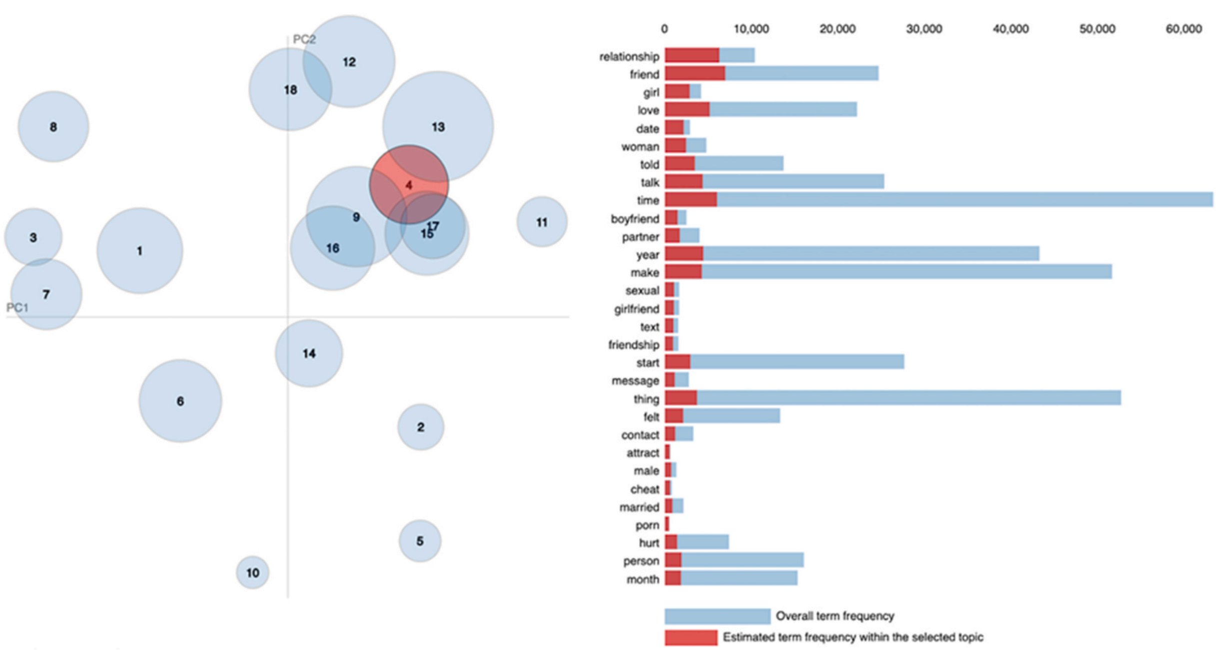

Fig. 5. Most relevant terms for topic 4 of T18 (relevance is calculated with $\lambda = 0.6$).

frequencies. "Girl" is specific to this topic, but "time" is also frequent in other topics, particularly those that are *monologues*, which thematize various aspects of the world and the self (see Discussion section).

2.4. Interpreting topics: combining quantitative and qualitative approach

While the statistical analysis enables the processing of large-scale textual data, when it comes to interpretation, it is rarely sufficient on its own. As our research questions aim at complex discursive patterns, a deeper understanding of the sense and the communicative functionality of the forum posts was required. Texts express structures of meaning, transcending the sum of the words: in order to give sense to the statistically identified patterns, a hermeneutic analysis was also called upon for supporting the interpretation. We inspected the 30 most relevant words (see later definition of relevance) and 10 most relevant posts (along with their context) in each topic with the method of 'deep reading' (Lee, 2017). Thus, in the qualitative study, we selected 180 posts, almost all of which were written by different authors. 'Most relevant' posts were defined as those having a contribution of minimum 90%, that is, these posts were almost exclusively about the given topic. The aim of these textual analysis was to interpret not only the content of the posts, but also their communicative purpose. This conceptual perspective is particularly important as forum posts are considered to be virtual 'speech acts': they are not only expressing something about the world or the self (that is the locutionary aspect); but also do something by expressing it (that is the illocutionary aspect); and also attempt to affect the other by doing something (that is the perlocutionary aspect – Austin, 1962).

Even though attempts of automatizing the interpretation of the performative aspects of online posts are not completely unknown (e.g. Carretero et al., 2015; Rus et al., 2012), we did not choose to proceed this way, since every automatized element of the interpretative process implies the loss of complexity of meanings. As depression forum posts are complex speech acts, constituted of varying locutionary, illocutionary and perlocutionary components, keeping as much from their complexity as possible was crucial. This way, the performative elements of the posts could have been interpreted more appropriately, therefore a richer understanding became possible, which would have been impossible while relying solely on automatized language processing.

Using mixed method approach is not unique in the text mining literature. Ignatow and Mihalcea (2017, pp. 67–68) take the view that social science text mining researches are usually performed as a pragmatic combination of quantitative and interpretative elements. One of the reasons for combining approaches is the fact that, as in our case, the interpretation of the output makes sense out of the whole modelling process, and complex NLP models are difficult to interpret without going back to the original texts. Bauer et al. (2014) go even further and claim that the qualitative/quantitative distinction is superficial and is motivated by the misconception that examining meanings is completely different from examining words. Users of topic models also often refer explicitly to mixing methods, see eg. Jacobs and Tschötschel (2019) or Chakrabarti and Frye (2017).

3. Results

As discussed above, we conducted a comprehensive analysis before selecting the 18-topic model (T18). As illustrated in Table 1, this analysis included systematic comparisons of topic contents pertaining to models T7, T13, T14, T18 and T19. The first dividing line was not drawn according to semantic differences (that is the substantive content of the post, a 'locutionary' dimension of the speech act), but according to performative ones (that is the communicative function of the posts, illocutionary and perlocutionary dimension of the speech act). Those posts were interpreted as *monologues*, which thematized various aspects of the world and the self without aiming at involving the others as partners in a mutual process of interpretation; those posts were interpreted as *interactions*, which were not oriented to the mere description of the world or the self, but to the exchanges with the others. Within these categories two-two subtypes were differentiated: monologues included more objective *attributions* (dominated by locutionary content) and

Table 1
Evolution of the topics while increasing their number.

		Number of topics: 7	Number of topics: 13	Number of topics: 14	Number of topics: 18	Number of topics: 19
Monologues	**Attributions**	Health-related attribution	Health-related attribution	Health-related attribution	Health-related attribution	Health-related attribution
			Partnership-related attribution	Partnership-related attribution	Partnership-related attribution	Partnership-related attribution
			Family-related attribution	Family-related attribution	Family-related attribution	Family-related attribution
			Work-related attribution	Work-related attribution	Work-related attribution	Work-related attribution
	Self-disclosures	Suffering-monologues	Suffering-monologues	Suffering-monologues	Suffering-monologues	Suffering-monologues
		Everyday diary			Everyday diary	Everyday diary
			Well-being monologue	Well-being monologue	Well-being monologue	Well-being monologue
					Cultural consumption reports	Cultural consumption reports
					Struggle diary	Struggle diary
					Contemplative self analysis	Contemplative self analysis
Interactions	**Consultations**	Making sense of drugs	Making sense of drugs	Making sense of drugs	Making sense of drugs	Making sense of drugs
		Making sense of the experience	Making sense of the experience	Making sense of the experience	Making sense of the experience	Making sense of the experience
			Making sense of psy-discourses	Making sense of psy-discourses	Making sense of psy-discourses	Making sense of psy-discourses
				Making sense of life-style intervention		Making sense of life-style intervention
					Making sense of psychotherapies	
						Making sense of biomedical discourse
	Quasi-therapeutic engagements	Spiritual support	Spiritual support	Spiritual support	Spiritual support	Spiritual support
		Recovery helpers counselling	Recovery helpers counselling	Recovery helpers counselling	Recovery helpers counselling	Recovery helpers counselling
			Unconditional recognition	Unconditional recognition	Unconditional recognition	
						Coaching
Misc	**Media representation of …**		… mental disorders		… mental disorders	… mental disorders
	Mixture of …			… school and work related attributions		
						..suffering monologues and recovery helpers counselling
						… suffering monologues and making sense of psy-discourse
						… suffering monologues and biomedical discourses, plus experiences

Table 2
The final 18 topics with their prevalence, most relevant terms and a short citation. ID is their identity number on Fig. 3.

Label	ID	Prevalence	10 most relevant terms
Health-related attribution	7	5%	pain blood thyroid symptom doctor level body treatment chronic diagnose
"*Depression is a clinical symptom of hypothyroidism. I will give you a list and you can tick off yours and present to your GP. Doctors haven't been educated in the function of thyroid hormones it would appear to me, in the UK in particular.*"			
Partnership-related attribution	4	6.2%	relationship love date talk sexual contact attract cheat hurt porn
"The *narcissist had reactivated his phone number, paraded his other woman in the main text messenger we communicated, he was so upset about it and had a nervous breakdown,i called and texted very often, so his only answer was i will have to block you.*"			
Family-related attribution	15	7%	mother child parent family abuse home life move divorce leave
"*There is no option to call the police for physical abuse anymore. It was a sad story anyway. I was sent to neurology and my brother was sent to a psychologist almost at the same time.*"			
Work-related attribution	14	4.4%	school work money study graduate career company apply time financial
"*I also have had chronic depression for over 25 years, and feel it is getting worse due to this job. When do you know that your job isn't worth the pressure? And how to leave?*"			
Suffering-monologues	13	12.1%	people, depressed, thing, hate, person, hurt, world, problem, lonely, shit
"ugh why am i a lazy sack of shit that cant do anything. Its not that life is hard its just my fucking fault and i shouldnt be depressed but im just such a fucking cunt i cant handle anything."			
Well-being monologues	11	2.5%	love, beautiful, hope, heart, care, light, warm, darling, honey, soul
" I was just outside and viewed the stars … they are particularly bright here tonight. We don't have street lights at my place either, so they are quite brilliant. Charli and I have just come back in from a wander outside, and it's a gorgeous evening out there."			
Cultural consumption reports	5	1.7%	music, play, watch, game, channel, book, film, YouTube, radio, show
"watching anything from the comedy team monty python the dead parrot sketch is my favorite, but anything will do also sitting in front of a cartoon and reliving your childhood as you watch the characters on screen be silly and have fun"			
Struggle diary	12	8.3%	week, month, year, time, hour, drink, stop, alcohol, quit, sleep
"Oh I usually sleep decently once each two weeks. I don't get enough sleep even on weekends. And even though I'm getting better it's like I'm permanently tired."			
Everyday diary	17	4.1%	food, walk, exercise, today, coffee, meal, shower, hour, minute, morning
"Not sure what I'll do the rest of the day. Probably take it easy and try to prepare more food for later. Made myself a tomato salad for dinner. I also cleaned the litter box and emptied the trash and cleaned off my kitchen counter. Today my main goal is to get a shower. That might get me motivated to do other things."			
Contemplative self-analysis	18	6.7%	anxiety, thought, head, fear, mind, dream, memory, voice, panic, stress
"I tend to feel lightheaded all day, upset stomach, EXHAUSTED (…). I am a huge hypochondriac so all of these symptoms worry me, even though all my check ups have been fine."			
Making sense of psychotherapies	1	7.2%	therapist, doctor, treatment, support, psychiatrist, psychologist, professional, talk, care, counsel
"I have been seeing a generalist psychologist to work on my depression and anxiety for about 2 months *now. I have gone to 3 sessions with her so far but I don't find it very helpful though. I guess my issues are: 1) my engagement problem that the counselling is unhelpful. I lean pretty much on her and I don't do much practice outside the sessions etc this can be an issue! 2) the psych i am seeing isn't a good fit for me. Yet I am trying to find another GP to fix my engagement problem. so the second issue I suspect is that my psych is generalist not clinical one. Should I find a clinical psych?"*			
Making sense of drugs	8	4.9%	drug, dose, medication, antidepressant, sleep, withdrawal, Zoloft, Prozac, Lexapro, weight
"Trintellix has worked miracles for me. I have tried over 20+ depression medications and this is the first to do anything. I'm not "cured", but have seen a noticeable improvement in mood as well as anxiety. I am currently on 15 mg. *I started at* 5 mg *for a good 2–3 weeks, then* 10 mg *for 3 weeks, now I am at* 15 mg*"*			
Making sense of the experience	6	6.7%	people, personality, emotional, experience, individual, sense, trauma, empathy, human, identity
"Although just personal opinion, I think focusing on flaws, seems to be more closely related to depression. Though saying that, many issues overlap, so I wouldn't dismiss OCD. I also think focusing on flaws perhaps influences some aspects of anxiety, as a further consequence. I also think that how old you are (life experience) is also intertwined into this"			
Making sense of psy-discourses	3	3.2%	bipolar, episode, mood, mania, psychosis, ADHD, hypomania, delusion, swing, hallucination
"bipolar II with psychotic features most often means that you can have psychotic episodes with your depressed or hypomanic/manic episodes. The reason it usually only happens during depressive episodes in bipolar II patients is because it's very rare for the lower levels of mania to be able to cause psychosis."			
Spiritual support	2	2.1%	Jesus, bible, Christ, pray, Lord, Allah, pastor, salvation, psalm, Satan
"What is your problem? Are you in denial that there will be a Great Tribulation, which is referred to as Judgment Day, the Day of the Lord. […] But nevertheless, the Judgment here is wrath, condemnation, destruction expressed in many scriptures throughout the Bible."			
Recovery helpers counselling	9	10%	change, find, learn, positive, step, hope, focus, happiness, future, accept
"We all know that depression can make it terribly difficult to function at even the most basic level in life, but that is not what all this is about. It is about the fact that exercise can help on many different levels, and that it can be a great step to try and find ways to slowly incorporate this into your own life, step by step"			
Unconditional recognition	16	7%	hope, support, share, talk, read, glad, chat, great, understand, join
"I'm so sorry to hear about your struggles. I know it's not easy to go through depression. It's a very complex issue that deserves personal and in-depth attention. It's good you're getting help. Please know that you can always come here to share, and I'm sure you'll find help and support."			
Media representation of mental disorders	10	1%	health, center, mental, service, hall, meeting, information, workshop, national, 2018
"A young pharmacist killed herself while on holiday with her boyfriend after battling with depression, an inquest has heard. Victoria Smith was discovered by her boyfriend Matt Arkwright, 31, after she had hanged herself on a stone jetty in Tenerife during a romantic holiday the couple took."			

emotionally charged *self-disclosures* (dominated by illocutionary intent); interactions included more pragmatic *consultations* (dominated by locutionary content) and *quasi-therapeutic* engagements (dominated by perlocutionary attempts).

Evolution of the topics can be clearly followed in Table 1. Most of the topics manifest firmly in these models, while others can be traced back to a former, broader theme that split into more sub-themes. Although T7 does not include any uninterpretable topics, it misses many key dimensions of the online discourses. T14 and T19 provide detailed classifications, however both of them include uninterpretable, mixed topics along the comprehensible ones. Based on interpretability, T13 and T18 are the best models, as both are free from incoherent topics. Being more detailed T18 is chosen as the final model: it is not burdened with inconsistencies, while providing a differentiated list. The coherent picture of topics evolution confirms the robustness of the final, T18 model.

Table 2 presents the topics of the "best" model, T18. Their thematic label, prevalence, most relevant terms, and a short citation from one of their representative posts are given. The 10 most relevant terms were selected from the 30 most relevant terms of the topic (see the visualization in the supplement) based on their interpretative power; they are ranked according to their relevance.

To link this table with Fig. 3, we gave the topics' identity number as well. When trying to find a direct interpretation for the dimensions of the map on Fig. 3, we took very distant topics along the two axes. Topics 12, 18, 13 (monologues – self-disclosures) are on the top of the y-axis, while topics 2, 6 (interactions) are at the bottom, thus we may infer a *locutionary dimension (performative function)*. However, the picture is not clear, see the position of topic 8, 10 and 5. Considering the x-axis, topics 1, 8, 7, 3 are on the left end and topics 11, 13, 17, 15, 4, 2 on the right end, thus we may infer a *locutionary dimension (substantive content)*, which primarily distinguishes between biomedical/psychological attributions and social/private life aspects.

4. Discussion

From a methodological perspective, our research demonstrated how NLP can effectively enrich our existing knowledge, if being connected to substantive theoretical questions and if the computational methods are combined with qualitative understandings. It can be also concluded that in large-scale quantitative research like ours, data visualization not only illustrates the results but is an inherent part of the study. It supports processing and interpretation both during analysis and in publication. Furthermore, as opposed to static figures, interactive visualization tools encourage the users' engagement by providing a platform for answering research questions. The interactive visualization tool in the Supplementary Material provides new discoveries even for the reader.

4.1. RQ1

The answer to our first research question (RQ1) is summarized by Table 2. Within the category of attributions five different topics were differentiated. *Health-related attribution* describes several physical hardships in an objective narrative style, while explaining depression as an illness. In case of *partnership-* and *family-related attribution* the central words express those hardships of everyday private life, which could become entrance points for interpersonal suffering: as the closest relationships are also the most important references in the shaping of the self, the disturbances of interaffectivity and intersubjectivity could lead to an unbearable existence (Fuchs, 2013). Despite the obvious emotional burden, these narratives maintain a remote perspective, their authors try to reconstruct the factors contributing to their suffering. In case of *work-related attribution,* the key terms refer to the hardships of the workplace as a potentially unbearable social environment (Battams et al., 2014). What sets attributions apart from other types of topics is on the one hand the lack of self-referential expressions (they address various aspects of the world); the lack of emotionally charged adjectives (they apply an objective semantic code) and the lack of intersubjective references (they do not expect deliberation).

Unlike attributions, various forms of self-disclosures are defined by their expressive function. *Well-being monologues* seem to serve no other purpose than to channel positive energies to the discussions: the author's main purpose is to gather as many positive events as possible, without any further reference, thus neutralizing negative recurring thoughts (Fitzpatrick & Stalikas, 2008). The counterpoints of these posts are the *suffering-monologues* defined by emotionally charged (mostly negative) words. They usually lack coherent argumentation, rather resemble a desperate call for help. Constituting the biggest topic, these posts express a central function of depression forums: the opportunity of ventilating negative automatic thoughts (Michikyan, 2020; Pietromonaco & Markus, 1985). Expressive speech acts do not seek actual response, they are rather demonstrations of agony or the actual or attempted overcoming of it. In this sense they are traces of intuitively applied cognitive self-therapies: while the expression of well-being directly denies negative thoughts; the expression of suffering provides opportunity for reflection and self-distancing from them (Spinhoven et al., 2018).

Besides these emotionally charged self-disclosures, there are several variants of more dispassionate, practical self-referential posts. *Contemplative self-analysis* refers to the inner life: it is constituted of narratives exploring distressing events in a self-reflective manner. Unlike the untargeted, non-argumentative suffering-monologues, contemplative self-analysis aims at resolving the mysteries of the damaged self by analyzing experiences in a detached, neutral way (Lou et al., 2019).

Two types of reports of the personal life were also detected: the *everyday diary* expresses a detailed documentation of the banal everyday life; the *struggle diary* introduces the grappling with depression. The first type consists of raw descriptions of daily routines serving the primary purpose of systematic time management (Wang & Wang, 2018). Struggle diary aims at documenting the daily struggles of the self in a more reflected manner. A third type of topic was also distinguished, *cultural consumption reports* introducing the cultural consumption habits. Despite their lack of interactivity, self-disclosures serve an important functionality: they enable experimenting in a secure environment, while also providing platforms for various attempts of self-therapy (Naslund et al., 2016).

The main difference between monologues and interactions is that the latter does not consist of mere statements or self-reports, but rather communicative speech acts aiming at mutual understanding. Accordingly, they bear the mark of a discussion or dialogue, which could either be argumentative or emphatic. The first group of interactions aim at discussing various aspects of depression with peers, who are going through similar experiences, thus face similar challenges: they are mutual attempts of making sense of the depressive condition including its phenomenological and discursive contingencies. The pattern of *making sense of the experience* is defined by key words referring to the generalized other and the phenomenological patterns. These discussions try to make sense of the mental hardships by contrasting the depressed condition with various constructions of normalcy (Kangas, 2001).

The patterns of *making sense of drugs*, *-psy-discourses* and *- psychotherapies* belong to the smaller topics. These threads help to reinterpret expert knowledge, thus granting personal agency and a better-informed decision about the praxes of taking medications or therapy. Despite the biomedical paradigm views patients as automatons following the expert directives, the actual practice of consuming medications is always embedded in a social context, implying personal decisions, which are elaborated in these topics. The topic focusing on psy-discourses fulfils similar purpose: in this case however not the drugs, but rather the classifications and interventions of psychology and psychiatry are at the center. Within this topic the participants try to make sense of the category attributed to them, therefore reclaim an identity, which is taken away from them due to the reifying biomedical gaze (Schreiber & Hartrick, 2002).

The second group of interactions differ from these various interpretations due to their alternative pragmatic functionality. Quasi-therapeutic engagements do not focus either on the content of the posts, or their intention; rather they are centered on the presumed impact on the other. R*ecovery helpers counselling* is related to seemingly long-time users of the forum talking from the position of someone who has already experienced and overcame the hardships of depressions (McCosker, 2018; Smith et al., 2015). Their goal is similar to the strategy of cognitive therapy: the moments of reflection do not simply provide comfort for the sufferer; rather they enable the distancing from the negative recurring thoughts (Seabrook et al., 2016).

A smaller, but similarly functioning topic is *unconditional recognition*. The related speech acts outline a double role: on the one hand, the contribution to a secure intersubjective atmosphere re-establishes trust; on the other hand, they provide support by including and integrating the newcomers to the forum community. The content of these posts has secondary importance compared to the inclusive and reassuring consequences: unconditional recognition is mainly about empathy and care, not providing advice or information. Within their own limited framework these speech acts, but they serve a function similar to the 'positive regard' in therapeutic practice (Rogers, 1956), they attempt to supplement the accepting social feedback, which are missing from many participants' lives. In this sense they serve as secular 'healing rituals' (Sik, 2020).

Spiritual support outlines an alternative discursive framework unrelated to either psychological or biomedical discourses, which promotes a spiritual lifestyle as a way out from depression. While this topic seems to be distant from the mainstream discussion, it could be the indicator of the presence of a biopsychosocial-spiritual model in lay discussions (Hatala, 2013; Saad et al., 2017). Besides the monologues and interactions, a few miscellaneous topics were also detected. However, they do not contribute substantially to the understanding of lay depression discourses.

Our research confirms and refines several findings from previous analyses: depression narratives are embedded in the broader complex of the life story (Hajela, 2012; Issakainen & Hänninen, 2015; Kangas, 2001; Ridge & Ziebland, 2012); social distortions play an important, but often latent role in reflective attributions (Pan, 2018); peer support constitutes an important element of online depression forums (Benzon, 2008; Galegher et al., 1998; Kotliar, 2015), both as a form of pragmatic advice and quasi-therapeutic interactions. Also, it broadens the horizon of topic models focusing on less extensive samples and strictly NLP models (Feldhege et al., 2020): beside cognitive strategies, treatments, feelings, dark thoughts, relationships and everyday life a complex substantive and performative structure of topics may be revealed.

4.2. RQ2

Our model also answers our second research question (RQ2). When interpreting the models with different numbers of topics (Table 1), the first dividing line was drawn according to performative differences. The posts were interpreted as *monologue*s, which thematized various aspects of the world and the self, and as *interactions*, which were oriented to the exchanges with the others. Within these categories further subtypes were differentiated: monologues included more objective *attributions* and emotionally charged *self-disclosures* (both dominated by locutionary content); interactions included more pragmatic *consultations* (dominated by locutionary content) and *quasi-therapeutic* engagements (dominated by perlocutionary content). The weight of the bio, psycho and social elements can be measured appropriately according to these dimensions.

Regarding the final model (T18), the two major dividing lines between topics were drawn according to their substantive content and communicative functions. This picture based on our thorough interpretation is consistent with the layout of topics across the two dimensions in Fig. 3, which demonstrates the robustness of our results.

The various performative functionalities of T18 outlined a balanced picture. Within the category of attributions, beside a biomedical topic (health-related) mostly social topics appeared (partner-, family-, work-related). Within the category of self-disclosures, beside two social topics (cultural consumption, everyday diary) mostly psychological ones were identified (suffering and well-being monologues, struggle diaries, self-contemplation). Within the category of consultations, beside a biomedical topic (drugs) mostly psychological ones were detected (making sense of psychotherapies, the experience and psy-discourses). Within the category of peer support beside a social topic (spiritual), mostly psychological ones were present (recovery helpers, unconditional positive regard).

From a substantive perspective a more asymmetrical picture appears. Biomedical (topic 7, 8), psychological (topic 1, 3, 6, 9, 11, 12, 13, 16, 18) and social (topic 1, 2, 5, 10, 14, 15, 17) discursive elements are represented with different weight and functionality. The majority (62%) of online forum discussions is related to psychological discourse, which serves as a dominant framework of most self-disclosing monologues, consultations, and quasi-therapeutic interactions. The majority of users turn to online depression forums for various psy-related reasons: venting about their distress; asking for advice about their psychologically framed suffering; seeking or giving emotional support. Only a minority of the discussions (10%) is embedded in a biomedical framework. These include health related attributions and drug related advice. These questions are not considered to belong to lay competences: only a few users expect adequate advice or explanation from the peers. The biomedical and psychological discourses seem to play contrasting roles, as the latter is applied as the primary language of elaborating depression narratives.

The topics related to social discourses (27%) play an ambivalent role: while these almost exclusively appear in monologues, they are predominating the attributions. This means that the more objective reflections - constituting a significant part of the corpus - mostly refer to the dysfunctions of private and institutional social relationships. However, the social elements almost completely disappear from both the consultative and supporting interactions. This asymmetry has serious consequences: while on the level of explaining depression, most actors mention ‘social suffering’, on the level of envisaged professional countermeasures and peer support, mostly psychological interventions appear targeting the individual.

Our analysis also has its limitations. Our target population is defined as people directly or indirectly affected by depression. Those who actively seek support through an online forum may not be representative of the entire target population. Additionally, as internet use is related to socioeconomic status, those with higher educational level may be over-represented in our study. Finally, due to data protection and ethical regulations, our searching was restricted to those forums which were public and accessible without registration. Password-protected support groups (see e.g. support. therapytribe.com) may be felt to be safer places to share experiences. However, from a different perspective, a study by Gulliver et al. (2015) showed that participants believed that the forums should be accessible to view content without registration because “people don’t want to join forums unless they’ve seen what’s in them first.” Presumably lower-threshold forums have greater reach, but less likely include those struggling with most serious problems.

We collected only posts including specific keywords, a decision justified by methodological reasoning. This criterion ensures that only posts which explicitly discuss depression are selected, however, the procedure may lead to the over-representation of conversations which consider depression as a pathological mood disorder, while under-representing cultural or social references.

We analyzed posts as individual expressions, while they are parts of conversations with dynamic and interactive patterns. To overcome this limitation, our future plan is to investigate networks of posts from the perspective of the topics detected in this study.

As there are no standardized procedures for determining the optimal number of topics, we conducted robustness tests and combined quantitative and qualitative approaches before selecting a 18-topic model. We do not state that 18 is the “right” number of topics, but this model contains all the important themes that emerged in the other models and does not contain any incoherent topic. Overall, it produces useful insights without being over-clustered.

5. Conclusions

All in all it seems that the majority of the ongoing discussions relies on the biopsychosocial model in an asymmetrical way: the psychological framings are at the center of attention; the biomedical ones appear only to a limited extent; the social attributions appear in a limited role. While these discrepancies were identified in the special setting of online forums, they might have a general relevance. Addressing the social element of suffering might be useful not only for practitioners when engaging their clients, but also the social policies aiming at preventing depression on a general level. These findings may help to refine online mental health forums. According to our experiences online depression forums hold many potentials: beside providing information to those, who have otherwise difficulties of seeking advice; they also play a much needed intermediator role by translating expert knowledge to lay language, which is particularly important in the process of establishing acceptable ‘illness narratives’; finally, they provide peer support, which has the potential of establishing missing intersubjectivities. On the other hand, online forums are burdened with a special challenge: while the traces of these potentials are detectable, they seem to function in a contingent manner. In order to actually profit from the immense potential of online depression forums, algorithmic mechanisms would be needed, which could direct the users of differing problems to appropriate segments of the platform. This conclusion highlights the health policy stakes of mapping the asymmetries and blind spots of online depression forums: with the help of a refined discursive map, the inherent contingency of forum discussion may be reduced.

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Ethics approval and consent to participate

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Availability of data and materials

Data used in this study is collected by SentiOne social listening platform and are not publicly available due to confidentiality reasons but the preprocessed data are available from the corresponding author on reasonable request.

CRediT authorship contribution statement

Renáta Németh: Methodology, Writing – original draft, Writing – review & editing, Supervision. **Domonkos Sik:** Conceptualization, Writing – original draft, Writing – review & editing. **Eszter Katona:** Formal analysis, Methodology, Software, Visualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ssmph.2021.100785. Web-based interactive visualization of the model with 18 topics

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