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Emotional labor in webcare and beyond: A linguistic framework and case study

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ABSTRACT

This article presents a novel framework for examining how emotional labor is performed linguistically. Bringing together Arlie Hochschild's pioneering sociological work and insights from the linguistic literature on emotion, the framework aims to capture the discursive mechanisms through which workers express, background and manage emotions in fulfilling their professional roles. We demonstrate the framework through a case study of a corpus of Twitter interactions involving passengers and airline customer service agents during the first wave of the Covid-19 pandemic. Following recent calls for triangulation in corpus linguistics, we explore the corpus using three complementary methods: lexical, move and dialogic analysis. From a theoretical perspective, this study contributes to improving our understanding of the pervasive phenomenon of emotional labor. From an applied perspective, it offers a new approach for assessing communication practices in various professional contexts.

1. Introduction

The term *emotional labor*, originally coined by sociologist Arlie Hochschild, refers to the kind of psychological work employees perform when they express and conceal their emotions and manage those of others to meet the requirements of the job (Hochschild, 1983: 7). For example, caregivers should demonstrate genuine care and concern for patients, while collection agents should be tough and unsympathetic with delinquent customers (Kruml and Geddes, 2000: 9). The concept of emotional labor has been hugely influential across a wide range of disciplines including sociology, psychology and organizational studies. So far, however, it has received limited attention in linguistics. With the exception of research in the area of English Language Teaching (e.g. Benesch, 2017), previous work either gives only a cursory treatment of this phenomenon or discusses potentially relevant aspects without explicitly referring to it. For example, in her research on call centers, Cameron (2000) finds that agents are instructed to smile, address customers by their first name, greet them 'warmly' and use personalized formulas like 'how are you doing?'. While the author does link these features to emotional labor, her analysis does not provide a comprehensive, systematic account of this phenomenon. Moreover, due to limited access to conversational data, Cameron (2000) relies on indirect sources such as employee training materials and interviews.

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As a result, we lack direct observation of how emotional labor is performed in actual conversations between agents and customers. Other work has investigated how emotions are expressed in various types of institutional discourse — without, however, referring to the concept of emotional labor. Hood and Forey (2008), for example, examine how levels of emotion rise and fall in call center interactions. Along similar lines, research within the paradigm of Conversation Analysis emphasizes the sequential nature of emotional displays and draws attention to the functions and constraints they fulfill in different institutional contexts, including medical consultations (e.g. Ruusuvuori, 2005) and helpline calls (e.g. Hepburn and Potter, 2007).

Thus, while previous research points to various aspects that are related to emotional labor, we still lack a coherent linguistic account of this phenomenon, a clear map of the features it involves, and appropriate methods to analyze it. This study addresses this gap by proposing a novel framework for examining how emotional labor is performed linguistically. We demonstrate the application of the framework through a case study analysis of a corpus of interactions between passengers and airline customer service agents on Twitter during the first wave of the Covid-19 pandemic. Following recent calls for triangulation in corpus linguistics (e.g. Baker and Egbert, 2016), the corpus will be explored from three complementary perspectives: lexical analysis, move analysis and dialogic analysis. The integration of these methodological tools will enable us to provide a more comprehensive and robust picture of the pragmatics of emotional labor.

The case study focuses on an emerging form of computer-mediated customer service discourse known as *webcare* (van Noort and Willemsen, 2012). Webcare takes place across a range of online platforms that facilitate direct communication between companies and their customers, including product and service review websites (e.g. TripAdvisor), online marketplaces (e.g. Amazon), and social media (e.g. Twitter). In our case study, we focus on webcare interactions occurring on the social media platform Twitter. While previous work has not approached webcare from the perspective of emotional labor, it nonetheless offers useful insights into the kinds of linguistic resources used by webcare agents to express emotions. Lutzky (2021), for example, examines the use of apologies to communicate remorse and empathy to customers. Fuoli et al. (2021) show that *affectivity* is a major stylistic component of webcare discourse, with webcare agents' tweets commonly incorporating devices such as affective adjectives (e.g. *delighted*, *excited*) or emphatic features such as exclamation marks and amplifiers (*absolutely*, *deeply*). Other studies use *move analysis* (e.g. Biber and Upton, 2007) to examine webcare communications and while they do not focus primarily on the expression of emotions, they reveal important affective aspects of these texts. For instance, Cenni and Goethals (2020) analyze the rhetorical moves used by webcare agents in replies to negative reviews on TripAdvisor from the perspective of *rapport management* (Spencer-Oatey, 2008). Among the eight moves they identify, at least two can be seen as performing an affective function: 'thank' and 'apologize/express regret'. Similarly, Van Herck et al. (2020) examine the legitimation strategies used by companies in responses to complaints via email and social media and note that the moves 'gratitude', 'apology' and 'empathy' are used to evoke *pathos*.

In this study, we bring together insights from linguistic research on emotion and webcare into a unified framework that can be used to systematically describe and explain how emotional labor is performed discursively. This framework is not meant to substitute but rather to complement well-established pragmatic theories of politeness and rapport management. It aims to offer a different and novel lens through which speakers' language choices can be viewed, both in webcare and in other contexts where emotional labor is at play. From a theoretical perspective, the model enhances our understanding of the pervasive phenomenon of emotional labor. From an applied perspective, it can be used as a tool for assessing current communication practices in various professional contexts and developing guidelines for practitioners.

2. A new framework for analyzing emotional labor in discourse

This section presents the framework we have developed for analyzing how emotional labor is performed linguistically, with a focus on webcare. Before describing the framework, we briefly summarize the general theoretical principles underpinning it. We begin by reviewing the core tenets of Hochschild's theory of emotional labor and foundational ideas from the linguistic literature on emotion. Next, we discuss the components of the model and explain how it can be operationalized.

2.1. Core principles of Hochschild's theory of emotional labor

Hochschild's theory of emotional labor is influenced by Goffman's (1959) dramaturgical perspective on social interaction, which views people as 'actors' performing different roles in different situations and adapting their behavior to manage other people's impressions. In line with this idea, Hochschild (1983) suggests that our behavior is influenced and constrained by tacit social conventions regarding appropriate emotional display, which she calls *feeling rules*. Feeling rules apply to a variety of everyday social interactions and become evident when we perceive a "pinch" between what we *do* feel and what we *should* feel (Hochschild, 1983: 57). Feeling unhappy at one's own wedding or indifferent at a funeral are examples of this kind of disconnect, which in turn reveals the underlying social norms governing our feelings. In customer service and other jobs involving emotional labor, feeling rules are "spelled out publicly" in formal company guidelines and training materials (Hochschild, 1983: 119).

According to Hochschild (1983), there are two main ways in which individuals manage their emotions to bring them in line with relevant feeling rules: *surface acting* and *deep acting*. With surface acting, a person feigns emotions that are considered appropriate or desirable in a given context. With deep acting, the person seeks to alter their inner feelings in order to make them consistent with their public emotional display. For example, one of the flight attendants interviewed by Hochschild (1983: 55) reported trying to picture an angry passenger as a little child to help block feelings of anger and resentment.

Emotional labor is not only about managing one's own emotions, but also about handling other people's. Ultimately, the purpose of emotional labor is to produce a desirable state of mind in others. Part of the job of a salesperson, for instance, is making sure that customers feel good about themselves and satisfied with their purchase, whereas criminal interrogators may try to make suspects feel bad in order to elicit a confession (Steinberg and Figart, 1999). Managing other people's emotions and regulating one's own are deeply interconnected facets of emotional labor. For instance, showing kindness and empathy to an angry customer requires one to suppress any negative feelings that the customer's words or demeanor might trigger.

2.2. Language and emotion

The linguistic literature on emotions is vast and the terminology used varies across scholarly traditions (Alba-Juez and Mackenzie, 2019: 14–15). Terms used to refer to the relationship between language and emotion include *emotion*, *affect*, *subjectivity*, *emotionality* and *involvement*. There is overlap between the study of language and emotion and the study of *attitude* (evaluation, stance, appraisal) and *intensification* (see e.g. Alba-Juez and Mackenzie, 2019: 5–6). In this study, we adopt *emotion* as an umbrella term encompassing all the ways in which language users display feelings, moods, dispositions and attitudes in discourse.[1] In our approach, the use of evaluative words (e.g. *great*, *excellent*) is regarded as one way (among many) of conventionally expressing emotion through language. Emphatic features such as amplifiers, superlatives, exclamation marks, etc. are also included as resources for expressing emotion (emotional intensity/involvement). More generally, our approach to emotion includes both linguistic expressions denoting emotions, referred to as *emotion talk*, as well as linguistic expressions acting as conventionalized indices of emotions, known as *emotional talk* (Bednarek, 2008). According to this distinction, emotion labels (e.g. *hate*, *love*) fall into the former category, while other resources such as evaluative lexis, comparatives, superlatives, amplifiers, exclamation marks, emoticons, swearing, emotive interjections, etc. fit the latter.

We understand emotions not just as individual but also as social phenomena (Ruusuvuori, 2013: 332). In line with this view, we treat expressions of emotions in discourse as forms of *emotional display*, that is, as strategic acts of self-presentation geared towards fulfilling relevant interactional and social goals (Caffi and Janney, 1994; Weatherall and Robles, 2021). This view is coherent with the dramaturgical perspective on communication that informs the concept of emotional labor. Emotional displays in discourse are shaped and constrained by both explicit and implicit behavioral norms at play in different social situations (Weatherall and Robles, 2021). In the case of webcare, for instance, agents' discourse is influenced, among other things, by company-internal guidelines, the goals and requirements of the professional role they serve, and by social conventions governing communication in online social media environments.

Finally, another important general premise is that emotions are not just subjective but also inter-subjective constructs. They are dialogically negotiated and co-constructed by interactants as they engage with, respond to and build on each other's stances (e.g. Hood and Forey, 2008; Du Bois, 2007; Pomerantz, 1994; Couper-Kuhlen, 2012). This dialogic work is at the heart of emotional labor. In order to manage customers' emotions, agents may for instance align with their affective stance as a way of showing understanding and empathy.

2.3. Description of the framework

Having explained the theoretical underpinnings of our framework, we will now turn to a description of its components and their linguistic realization. Fig. 1 gives a graphical representation of the fundamental building blocks of the model. Doing emotional labor in discourse involves two main interconnected tasks: (i) performing emotions and (ii) managing emotions. Emotional performance involves both expressing emotions linguistically (through emotion[al] talk) as well as backgrounding them (by adopting a communicative style marked by lack of overt emotional display). Emotional management involves handling the interlocutor's emotions as well as regulating one's own. The latter aspect is enclosed in a dashed box to indicate that it can only be examined indirectly via linguistic analysis. Below we discuss each of these aspects in more detail and how they can be operationalized and explored via linguistic analysis.

[1] In other approaches, emotion, or *affect* is a more narrowly defined category which concerns the expression of attitude via reference to/expression of emotion – e.g. a sub-category of the appraisal system of attitude (Martin and White, 2005), a sub-category of subjectivity (Finegan, 1995: 4), a sub-category of stance (Biber and Finegan, 1989; Englebretson, 2007: 17) or included in the mental state parameter of evaluation (Bednarek, 2006). Alba-Juez and Mackenzie (2019: 17–18) differentiate aspects of utterances that express evaluation (e.g. evaluative adjectives) and emotion (e.g. intonation, pitch, implicature), but note that emotion interacts with evaluation.

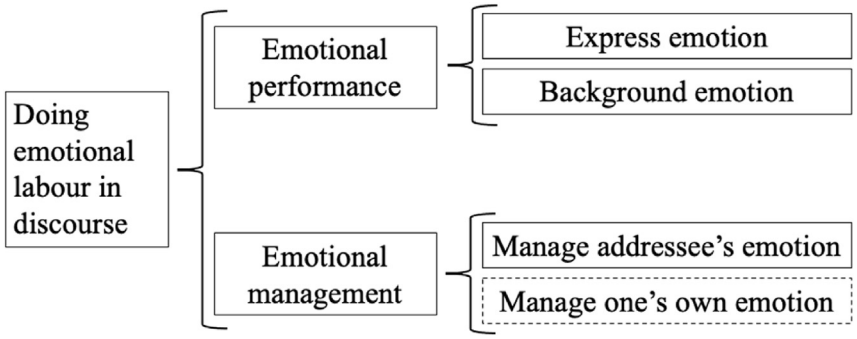

Fig. 1. A framework for the analysis of emotional labor in discourse.

The first of the four sub-components of the framework, i.e. 'express emotion', accounts for the ways in which individuals display their emotions linguistically. We propose that this aspect of emotional performance can be analyzed in two complementary ways by looking at (i) the (para-)linguistic markers of emotion used and (ii) the rhetorical moves performed. The former type of analysis entails identifying linguistic features that carry emotive meanings, i.e. emotion talk and emotional talk. A wide range of resources have been associated with emotion, including lexical and grammatical features (e.g. evaluative lexis, the emotion lexicon, metaphors of emotion, connotative meanings, diminutive affixes, intensifiers, emphatics, exclamation, swearing/expletives, interjections, vocatives, insubordination), prosodic signals (e.g. pitch, tempo, loudness, voice quality), typographical features (e.g. eccentric spelling, capital letters, emoticons) and paralinguistic and nonverbal features (e.g. facial expressions, vocal cues, gestures, body posture). Details about the features we considered in our case study are given in Section 3.1.

The analysis of emotive linguistic features is complemented with move analysis (for an overview, see Biber et al., 2007: Chapter 2). The purpose of move analysis is to describe patterns of discourse organization that are typical of a given genre (Upton and Cohen, 2009). This is achieved by segmenting texts into their constituent functional elements, referred to as 'moves', grouping these into distinct categories and inspecting their sequential arrangement in the discourse. Move analysis can aid the study of emotional performance in two main ways. First, it enables us to go beyond individual linguistic markers and look at how emotion stretches over larger text spans. Second, move analysis captures the ritualistic and institutionalized aspects of emotional labor by revealing the recurring pragmatic acts and phraseology used to display emotions in a given context.

As discussed above, doing emotional labor is not only about expressing emotions but also about backgrounding them, where appropriate, in line with the goals and requirements of a given professional role. For example, an aggressive complaint from a customer might trigger anger or frustration in the customer care agent tasked to handle it, but expressing such emotions would in most cases clash with institutional norms and company guidelines. Emotional backgrounding is thus found in utterances that lack overt emotional expression in an interactional context where emotions are at stake, such as when dealing with customer complaints. Evidence of emotional backgrounding can be obtained through lexical analysis by measuring the relative density of explicit lexical markers of emotion in the data. Where explicit emotive words are rare (in contexts where emotional reactions would be expected), we can hypothesize that emotions are being backgrounded. Findings from the lexical analysis can be triangulated and complemented via move analysis. Move analysis can be used to describe the totality of the pragmatic acts performed in a given set of interactions and can therefore help us pinpoint stretches of text that serve a referential or conative function as opposed to an emotive function. In other words, with move analysis we can identify pragmatic acts that are not directly involved in expressing or managing other people's emotions. By comparing the relative frequency of emotive and non-emotive moves, we can gauge the degree to which emotions are backgrounded in a corpus of interactions and thus validate the results of the lexical analysis. Finally, further evidence of emotional backgrounding can be gathered via dialogic analysis, which looks beyond messages produced by a single participant to examine turn exchanges between interactants. Specifically, dialogic analysis aims to determine how given emotions expressed by the initiator (e.g. a complaining customer) are addressed by the responder (e.g. a customer service agent). This type of analysis introduces a useful additional perspective by enabling us to study how different kinds of emotions are handled by responders. For example, we could test whether more intense emotional expressions (e.g. anger vs mild discontent) tend to prompt responders to foreground or background emotions in their replies. In corpus linguistic case studies such as ours, we propose that this type of analysis could be performed through a novel use of *parallel concordance* software (originally developed for multilingual corpora), as it allows retrieval of instances of emotive language and how they are responded to across multiple interactions (as explained in Section 3.1). In other studies, different types of dialogic analysis could be used instead.

The second major task involved in performing emotional labor concerns the management of the addressee's and the speaker's own emotions. To analyze the former aspect linguistically, we can again use a combination of lexical, move and dialogic analysis. Lexical analysis can be used to pinpoint emotive words involved in discursive attempts to manage the interlocutor's emotions. A customer service agent might, for instance, use emotion labels (e.g. *confusion*, *frustration*) to acknowledge and try to mitigate the addressee's negative emotions. Similarly, move analysis can be used to identify stretches of text whose communicative function is directly related to emotional management. Calling for patience or showing empathy are examples of communicative acts geared towards lowering the emotional intensity of the interaction. Finally, dialogic

analysis can reveal patterns in the way responders handle different kinds of emotions across multiple interactions and thus offers a more holistic, 'birds-eye' view of the discursive mechanisms of emotional management.

The final component of the model concerns the speaker's management of their own emotions. Inner emotional states, however, are not directly observable and, as a result, this aspect is less amenable to linguistic analysis. Nonetheless, traces of emotional management could be tentatively identified by inspecting dialogic patterns for (un)expected responses. For example, research has shown that verbal aggression can have a range of negative emotional outcomes for people who experience it (e.g. Karni-Vizer and Walter, 2020; Madlock and Dillow, 2012; Walsht and Clarke, 2003). In view of this, if we were to observe that customer service agents consistently respond to instances of verbal abuse by expressing positive emotions or by communicating empathy, we could tentatively infer that they engaged in emotional management to control and suppress the negative feelings triggered by the customers' messages. However, any conclusions based on such observations will inevitably be speculative and should be triangulated via other research methods such as qualitative interviews along the lines of Widdershoven et al. (2021).

3. Case study

In this section, we apply the framework described above to the analysis of a corpus of webcare interactions between airlines' webcare agents and their passengers during the initial phase of the Covid-19 pandemic. The main purpose of this case study is to demonstrate the application of the framework outlined above. Accordingly, the analysis is selective and focuses on aspects that most clearly illustrate how the model can help shed light on the discursive workings of emotional labor. As discussed above, we triangulate three different methods – lexical analysis, move analysis and dialogic analysis – and give the results for each in separate sub-sections. Combining these three methods enables us to capture the workings of emotional labor at different levels of granularity – from individual words (lexical analysis), to larger discourse chunks (move analysis), to conversational interactions between participants (dialogic analysis) – and thereby understand the complexity of this multifaceted phenomenon better than if we were to focus on one aspect only. Before presenting our findings, we describe the corpus and methodological choices we made.

3.1. Data and methods

The corpus we compiled for this case study is made up of 1300 complaint-response interactions, which were collected from the Twitter profile of 13 major airlines between March and July 2020 using the *R* package *rtweet* (Kearney, 2019). We decided to focus exclusively on complaints because in this kind of interaction emotions are clearly at stake, thus offering an ideal testbed for the analysis of emotional labor. From the ranking of the world's 25 largest airlines published by the International Air Transport Association (IATA, 2019), we selected those that had at least 500 interactions with passengers in English over the target period. To ensure balance, we only included one airline per country, namely the one with the highest average number of daily interactions. The list of airlines included in the corpus is given in Table 1. From the totality of downloadable exchanges, we randomly sampled 100 complaint-response pairs per company.[2] Interactions revolving around generic questions, positive feedback or complaints about issues unrelated to Covid-19 (e.g. lost luggage) were manually discarded. The total corpus size is 88,036 words. The conversations in our corpus were collected from public Twitter profiles and were processed in accordance with Twitter's terms and conditions. To protect users' privacy, all corpus examples shown in the analysis have been anonymized. The data will not be redistributed to third parties. The project was reviewed by the Humanities and Social Sciences Ethical Review Committee of the University of Birmingham and received full ethical approval.

Table 1
Airlines included in the corpus.

Airline	Country
Air Canada	Canada
Air France	France
All Nippon	Japan
American Airlines	USA
British Airways	United Kingdom
Cathay Pacific	Hong Kong (China)
KLM	Netherlands
Latam	Chile
Lufthansa	Germany
Qantas	Australia
Qatar Airways	Qatar
Ryanair	Ireland
Singapore Airlines	Singapore

[2] We used the R function sample() to draw random rows from the data frame containing the Twitter conversations. For each company, we initially drew 100 random rows per company, manually checked them to remove irrelevant interactions (e.g. not involving complaints) and repeated this process until 100 suitable interactions had been obtained.

The lexical analysis was conducted using SketchEngine (Kilgarriff et al., 2014) and focused on webcare agents' responses to passengers. Table 2 shows the categories of emotive linguistic devices we considered. These categories were informed by the existing literature on language and emotion (for general overviews, see e.g. Caffi and Janney, 1994, Bednarek, 2008, Wilce, 2009, Mackenzie and Alba-Juez, 2019, Weatherall and Robles, 2021) and integrated with findings from Fuoli et al.'s (2021) analysis of affectivity features in webcare discourse. Of the latter, we only included those resources that are mentioned in the linguistic research on emotion/affect – such as superlatives, amplifiers, exclamation marks. Since our focus is on webcare interactions on Twitter, we only included linguistic resources that are relevant to this communicative context. For example, prosodic signals and features to do with the embodied performance of emotion were excluded, while typographical features such as exclamation marks, emoticons and emojis were included. In line with research on emotion in webcare (see Section 1), we incorporated expressions of apologies and gratitude. Instances of emotive linguistic features were identified and quantified by manually annotating the wordlist generated by SketchEngine, which comprised 3470 unique tokens. To test the reliability of the coding procedure, an inter-coder agreement test was performed on a sample of 10% of the wordlist. The results indicated almost perfect agreement between two independent coders ($kappa = 0.86$). Where a potentially polysemous lexical item was found, the frequency returned by SketchEngine was corrected based on manual coding of concordance lines via SketchEngine's concordance annotation tool. For example, the word *so* can function as both an intensifying adverb (e.g. *so important to us*) and as a subordinating conjunction (e.g. *so we can assist you further*). Since SketchEngine is not equipped to retrieve emojis, we used the *R* package *emo*[3] to do so, while emoticons were searched for using regular expressions. Quantitative analysis was complemented with qualitative concordance analysis of selected items.

Table 2
Linguistic resources for expressing emotion included in the lexical analysis.

	Category	Conceptualization	Examples
(potential) emotion talk	Reference to feelings	The verb *feel* in all its forms	*feel, feels, felt*
	Emotion labels	Words that explicitly denote an emotion (including desire)	*glad, happy, keen, frustrated, frustrating want, hope, like, love, patience*
(potential) emotional talk	Evaluative lexis	Words that are explicitly evaluative but do not denote an emotion	*good, great, right, suspicious inconvenience, kindly, trouble, unfortunately*
	Gratitude expressions	Expressions related to gratitude (including acceptance of gratitude)	*appreciate, ta, thank, thanks, thx, cheers, no worries*
	Apology expressions	Expressions conventionally related to remorse	*apologise, apologies, regret, sorry*
	Comparatives and superlatives	Emotion labels and evaluative lexis in comparative/superlative form; use of *more* in various structures (not just in comparative adjective phrases)	*faster, best, more*
	Amplifiers	Degree adverbs that increase the intensity of the meaning of the word they modify	*really, so, very, extremely*
	Swearing expressions	Swear words and expressions (including but not limited to use as interjection)	*Wtf* [what the fuck]
	Emotive interjections	Emotive (rather than cognitive) interjections (that are not also swear words/ expressions)	*wow*
	Exclamation mark	One or more instances of an exclamation mark	*!*
	Emoticons and emojis	Emoticons and emojis associated with positive and negative emotion.	😀 🙂 😌 😕 😭 #GOT

The move analysis was carried out following the procedure outlined in Biber et al. (2007: 34ff) and, like the lexical analysis, focused on webcare agents' responses to passengers. The first step consisted in developing the coding protocol by identifying move types and developing definitions for them via collaborative pilot coding of a random sample of tweets from the corpus. Once the first version of the coding protocol was ready, we conducted an inter-rater reliability check to confirm that the moves were clearly defined and operationalized. The check was performed on a random sub-sample comprising 10% of the corpus. Given that coded units are not pre-determined (e.g. words or sentences), we used *F-score* as a measure of inter-coder agreement (Fuoli and Hommerberg, 2015). The comparison yielded an F-score of 0.89, indicating substantial agreement between annotators (Fuoli and Bednarek). All discrepancies were resolved through discussion and the coding protocol was updated accordingly. After the inter-rater reliability check was complete, Fuoli annotated the rest of the corpus. The annotation was performed using the UAM corpus tool (O'Donnell, 2008). The full coding protocol is available in the Supplementary Materials.

Finally, the dialogic analysis was carried out using the parallel concordance tool in SketchEngine and involved examining both passengers' complaints and webcare agents' responses to them. We repurposed this tool for the analysis of dialogic patterns by configuring it in such a way that customers' tweets were treated as the 'original' text and webcare agents' responses as the 'translated' text. This enabled us to retrieve instances of various kinds of emotive language and inspect how they are responded to across multiple interactions, as shown in Section 3.2.3.

[3] This package can be downloaded from GitHub: https://github.com/hadley/emo.

3.2. Results

3.2.1. Lexical analysis

As discussed above, lexical analysis can provide insights into how emotions are expressed, backgrounded and managed. With regards to emotional expression, our analysis shows that 4.66% of the words in the corpus served an explicit emotive function. This finding suggests that overt emotional expression was relatively uncommon in our corpus which, in turn, can be taken as tentative evidence of emotional backgrounding.

Table 3 gives a breakdown of the distribution of types of emotive language alongside the items coded in each category in order of frequency. These quantitative results provide useful information on the kinds of emotive resources used and can help us identify patterns that may not be apparent through manual inspection of individual interactions. We can observe, for instance, that evaluative lexis is the most frequent type of emotive language in the corpus. Many of the evaluative items used are negative, such as *inconvenience*, *unfortunately* and *difficult*. To elucidate the communicative function these words perform, we can inspect their usage via qualitative concordance analysis. Concordance analysis suggests that negative evaluative language is predominantly used by webcare agents to acknowledge the passenger's problem and show empathy. This is often achieved using conventional formulas drawn from the stock repertoire of customer service discourse. The word *inconvenience*, for instance, is always used as part of formulaic expressions of apology, as exemplified in Fig. 2.

Table 3
Types and frequency of emotive language used in the corpus.

Category	Frequency (occurrences per thousand words)	Words used
Reference to feelings	0.49	*feel, felt*
Emotion labels	9.08	*patience, like, hope, wish, concern, want, appreciate, confusion, concerns, gladly, frustration, care, appreciated, happy, disappointment, concerned, hoping, afraid, exhausted, frustrating, hopefully, satisfied, comfort, confidence, surprised, discontent, discomfort, upset, upsetting, wanting*
Evaluative lexis	11.92	*kindly, inconvenience, unfortunately, sincerely, enhanced, right, good, safe, kind, optimized, well, special, difficult, humbly, diligently, value, issues, sensitive, difficulties, unprecedented, prefer, misused, flexibility, appropriate, simply, committed, healthy, priority, timely, challenges, difficulty, preferred, troubles, exceptional, trouble, patient, hard, closely, successfully, correct, improve, safely, odd, flexible, commitment, setback, successful, effective, blaming, bizarre, opportunity, challenging, proactive, great, accurate, clear, high-risk, rudeness, comfortable, serious, advantages, polite, problem, problems, correctly, inconvenient, seriously, spamming, kudos, drastic, loyalty*
Gratitude expressions	9.42	*thank, thanks, thankful*
Apology expressions	6.11	*sorry, apologize, regret, apologise, apologies, apology*
Comparatives and superlatives	4.98	*more, better, best, sincerest, deepest, most, stronger, simpler*
Amplifiers	2.29	*so, very, highly, quite, strongly, truly, utmost, indeed, fully, really, extremely, sheer, terribly, totally*
Swearing expressions	n.a.	–
Emotive interjections	n.a.	–
Exclamation mark	2.32	
Emoticons and emojis	0.08	😉

would like to sincerely apologize for the	inconvenience	this has caused you. @[name] Hello there, @
! Our sincerest apologies for this	inconvenience	. As of the moment, the only way to process
we could. Again, we are very sorry for the	inconvenience	this has caused you. Please accept our
helps. @[name] Sorry for the	inconvenience	, @[name]. Due to the large
We sincerely apologize for the	inconvenience	, @[name]. Due to the huge volume of
[1/2] We sincerely apologize for the	inconvenience	, @[name]!. For a faster transaction,
[name] [1/2] We apologize for the	inconvenience	, @[name]. Please bear with us as
Thank you. We sincerely apologize for the	inconvenience	, @[name]. Please take note
! Our sincerest apologies for this	inconvenience	. We are humbly asking for your patience in
requests we are receiving. Sorry for the	inconvenience	. @[name] Hi, sorry for the late reply

Fig. 2. Concordance of a random sample of occurrences of *inconvenience*.

The frequent use of negative evaluative language for the purpose of showing understanding and empathy highlights the close connection between performing and managing emotions in the discursive enactment of emotional labor. By aligning with the passenger's negative emotions, the webcare agent is simultaneously attempting to contain them. The formulaic nature of agents' language indicates that emotional expression in webcare discourse is to a large extent routinized (Fig. 2 illustrates one of multiple instances of this in the corpus). The use of formulaic emotive language may be tentatively interpreted as evidence of discursive 'surface acting'. When dealing with huge numbers of complaints on a daily basis, it is hard to imagine webcare agents being able to truly empathize with each and every individual they engage with. Conveying empathy has become a ritualistic form of emotional expression that is given and expected by default.

A significant number of negative words can also be observed in the category of emotion labels, which is the third most frequent type of emotive language in the corpus. In total, negative words (e.g. *concern*, *confusion*, *frustration*) account for 20% of all word occurrences in this category. In the vast majority of cases, negative emotions are not expressed by the webcare agent. Instead, they are attributed to the passenger as a way of acknowledging and validating their feelings, as illustrated in Example (1).

(1) We **understand your frustration** and would like to sincerely apologize for the inconvenience.

There are also instances where the emotion label is used to try to pre-empt negative emotions. The word *confusion*, for instance, is predominantly used for this purpose, as shown in Example (2).

(2) **To avoid confusion** please continue communicating with us via DM only.

These findings thus indicate that a substantial proportion of the emotion labels found in our corpus are primarily involved in emotional management, rather than emotional expression.

The results also show a number of positively valenced words across different categories of emotive language. The most frequent positive evaluative word in the corpus is *kindly*. Inspection of concordance lines reveals that this word tends to occur in the context of requests directed by webcare agents to passengers, as illustrated in Fig. 3. In this context, *kindly* performs an emotional management function in the sense that by toning down the request it can help preempt negative feelings arising from it (e.g. frustration or disappointment). Concordance analysis emphasizes again the highly formulaic nature of webcare discourse on Twitter and the linguistic routinization of emotional labor.

been affected by a flight irregularity.	Kindly	send us your booking reference or ticket
to your inbox for more details. Also, we	kindly	ask that you continue contacting us via DM
that we have replied to your DM. We	kindly	ask that you refer to your inbox and keep
: [url]. We also	kindly	ask for your patience and understanding
to the situation. – – For more details,	kindly	refer to our Special Measures for
@[name] Hello [name], could you	kindly	share your booking code and ticket number
We'd like to check this for you. Can you	kindly	share your booking code via Direct
as soon as possible. /[name] @[name] We	kindly	ask for your understanding that due to the
@[name] We have sent you a DM.	Kindly	check. Thank you @[name] Please
check and proceed. @[name] Hi [name].	Kindly	DM us with your booking reference,

Fig. 3. Concordance of a random sample of occurrences of *kindly*.

Among the most frequent positive emotion labels we find a group of words that convey emotive meanings related to wishes and desires: *like* (always used as part of the construction 'I/we would like + verb'), *hope*, *wish* and *want*. The Emoter is predominantly either the webcare agent themselves or the company as a whole via the first person plural pronoun *we*. Concordance analysis suggests that these lexical resources serve to display a desire to resolve the passenger's problems, as illustrated in Example (3).

(3) **We want** to look into it - can you please send us your booking reference in DM?

Another set of resources that is involved in emotional expression is apology, which is the fourth most frequent type of emotive language in the corpus. Our results thus confirm previous findings showing that apologies are a very common feature of webcare discourse. In line with Page (2014), we find that *sorry* is the most frequent word used to convey apologies. In 19.35% of cases, apologies were boosted via either an amplifier (e.g. *so sorry*) or an evaluative word (e.g. *our sincerest apologies*). The use of amplifiers serves to boost the emotional investment in the apology. From the point of view of emotional labor, we can interpret this as a discursive strategy aimed to present the apology as authentic rather than feigned and perfunctory.

In sum, lexical analysis enables us to (i) identify micro-level linguistic devices that are used for expressing and managing emotions, (ii) quantitatively assess the prominence of overt emotional displays as well as the relative importance of different kinds of emotive resources, and (iii) qualitatively investigate the functions emotive linguistic devices serve in the discourse. This kind of analysis, however, is narrowly focused on individual, explicit emotive words and is therefore ill-equipped to detect emotive acts spanning multiple words as well as more implicit acts of emotional management, such as promises or explanations, which might be delivered without the use of explicit emotive language. We can compensate for these limitations by conducting a move analysis, which we turn to next.

3.2.2. Move analysis

Move analysis can shed light on various different aspects of the discursive performance of emotional labor. First of all, it can be used to dissect messages into their basic pragmatic components and map these onto the various strategies of emotional labor included in our model. Our analysis of webcare agents' complaint responses uncovered 18 unique moves. These are listed in Table 4 (in order of frequency), together with the strategy of emotional labor they most directly relate to ('primary' strategy), their frequency expressed as a percentage of tweets in which they appeared, and a corpus example. The category labelled 'other' includes stretches of text that did not fit any of the categories. Detailed move descriptions and additional examples are provided in the coding protocol given as Supplementary Materials.

Table 4
Rhetorical moves identified in the corpus.

Move	Primary emotional labor strategy[a]	Example from the corpus	Frequency
Salutation	n.a.	Hello [name]	60.3
Closing	n.a.	Regards.	45.6
Request additional information	Background emotions	Please DM us your booking reference and the name of the passenger.	43.0
Pledge further action	Manage addressee's emotions	We will look into it.	41.2
Express gratitude	Express emotions	Thank you for contacting us.	32.7
Explanation	Manage addressee's emotions	Due to the ongoing situation, it may take longer processing the refund requests, than the usual time.	25.5
Apology	Express emotions	We apologise for any inconvenience this may cause.	22.2
Divert to private messaging	Background emotions	We have replied to your DM. Kindly continue the conversation there.	15.4
Direct to other customer service	Background emotions	I can only recommend you to phone our Service Center to check on your refund [url].	13.5
Corrective action	Manage addressee's emotions	Please rest assured that we have increased capacities and optimized procedures so that you may receive your refund as quickly as possible.	10.7
Signal availability	Manage addressee's emotions	We await your message.	10.6
Direct to other webpage	Background emotions	Please visit [url] for more info.	10.1
Call for patience	Manage addressee's emotions	We ask for your patience as this may take longer than usual.	9.5
Show concern	Manage addressee's emotions	We understand your frustration.	6.0
Admit inability to help	Manage addressee's emotions	Unfortunately, I'm not able to provide you with a time frame.	5.3
Data protection warning	Background emotions	We'll also need you to confirm your full name and contact details. We may need to ask you a few more questions for data protection.	4.4
Other			4.3
Bolstering	Express emotions	We really do our best to avoid delays and to minimize them, whenever it's possible.	2.3
Privacy warning	Background emotions	You may also wish to remove your tweet as it contains your booking reference which is sensitive info.	1.9

[a] Note that some of these moves may perform multiple functions. The 'apology' move, for example, is not only used to express emotion (remorse, empathy) but also to manage customers' negative emotions, such as frustration or anger. The labels included in this table refer to the emotional labor strategies that we interpret to be the most salient ('primary') in relation to each move.

Several of the moves we identified can be viewed as performing an emotional backgrounding function. These moves focus on practical aspects at stake in the interaction and on providing solutions to the problem voiced by the passenger. With 'divert to private messaging', for instance, webcare agents seek to shift the conversation away from the company's public twitter profile onto direct messaging in order to provide personalized assistance more efficiently. This move also aims to protect the passenger's privacy, as personal data shared on airlines' Twitter profile would be visible to all platform users. The moves 'direct to other customer service' and 'direct to other webpage' give explicit instructions to passengers, while simultaneously discharging responsibility for solving their problem onto third parties. In sum, a number of moves found in our corpus are inherently transactional, directive and goal-oriented. In these moves, emotion is backgrounded in favor of practical guidance and advice.

In addition to indicating moves that may be directly involved in performing emotional labor, the move analysis can help us get a more complete picture of the phraseology used, and assess the extent to which emotional labor strategies are linguistically routinized in a set of interactions. Using the UAM tool, we can automatically retrieve all the text spans coded in each move category and examine patterns in the wording used. Table 5, for example, shows the five most frequent types of phrases used to express gratitude in the corpus, which together account for 85.9% of all instances of thanking. The narrow range of expressions used, combined with the comparatively high frequency of the form *thank you*, provide strong evidence of the routinization of gratitude in our corpus, as also observed by Cenni and Goethals (2020) in responses to negative hotel reviews.

Table 5
Five most frequent phrases used for expressing gratitude in the corpus.

Gratitude phrase	Percentage frequency
thank you	56.5
thank you for reaching out to us	14.1
thanks	8.7
thank you for your understanding	4.8
thank you for reaching out	1.8

This kind of phraseological analysis can also reveal aspects of emotional labor in moves that do not at first glance seem to be directly relevant to it. For instance, the 'salutation' and 'closing' moves may be seen to perform a merely phatic function. Their role in the performance of emotional labor, however, becomes evident once we look more closely at their phraseology. In over 60% of instances, salutation formulas are followed by either the passenger's name or their Twitter alias. This can be viewed as a *synthetic personalization* strategy (Fairclough, 1989) aimed at making passengers feel as though they are addressed as individuals rather than *en masse*. Synthetic personalization, according to Cameron (2000: 76), is one of the most common discursive strategies through which emotional labor is accomplished. Further, 5% of the occurrences of the 'salutation' move included an exclamation mark. Exclamation marks are used to display an enthusiastic and keen attitude, even when faced with negative feedback, as shown in Example (4).

(4) After two hours on hold with the number listed for Argentina on your website, they tell me they don't deal with flights, only "marketing" (??). That number is clearly marked as "Flight/Bookings/Reservations" on your website but they claim they don't deal with flights?
Hi [name]! Can we ask what number did you contact?

Another aspect we can uncover via move analysis is the sequential patterning of pragmatic acts (Groom and Grieve, 2019). We can establish where in the message a certain move tends to occur and which other moves it usually co-occurs with. For example, in our corpus, the 'request additional information' move is followed in 75% of cases by the 'pledge further action' move, as illustrated in Example (5).

(5) Hi, can you DM us your reference number, passenger names, route, dates and email used for the booking [request additional information]. I can then add you to the refund queue [pledge further action]. Thanks, [name]

When juxtaposed to 'request for additional information', the 'pledge further action' move can be interpreted as a way of justifying the request and reassuring the passenger that a satisfactory solution to their problem will eventually be found. In this sense, this move sequence performs an emotional management function, because it can help pre-empt frustration on the passenger's part due to the lack of an immediate solution and the imposition created by the request.

Finally, we can leverage the quantitative data from the move analysis to gauge the relative importance of different communicative strategies of emotional labor and in this way complement and triangulate the findings of the lexical analysis. The results support the idea that emotional backgrounding is a dominant strategy of emotional labor in our corpus. This is evidenced in the fact that 6 out of 18 moves we identified can be linked to emotional backgrounding, with 'request additional information' being the third most frequent move in the corpus. Emotional management is also a relatively prominent strategy, with 'pledge further action' and 'explanation' among the most frequently used moves. Emotional expression is comparatively less frequent and to a large extent routinized, as shown above. Thus, the results of the move analysis are in line with the patterns observed in the lexical analysis in terms of the relative importance of different discursive strategies of emotional labor.

As the examples above have shown, move analysis usefully complements lexical analysis by enabling us to (i) account for the totality of pragmatic acts performed and map them onto emotional labor strategies, (ii) examine the phraseology of the moves and assess the degree of routinization of emotional labor, (iii) examine the interplay of pragmatic acts in the performance of emotional labor via inspection of move sequences, and (iv) quantitatively gauge the relative prominence of different emotional labor strategies. Both the lexical and the move analysis, however, focus exclusively on the responder's discourse (the webcare agents'). What we still lack is an understanding of the role of the initiator's messages and how these influence the discursive strategies of emotional labor employed. Dialogic analysis, demonstrated in the next section, can help us gain useful insights into this important aspect of emotional labor.

3.2.3. Dialogic analysis

Dialogic analysis leverages the repurposed parallel concordance tool to explore how individuals performing emotional labor — such as webcare agents — manage their interlocutors' and their own emotions, in response to others – in this case, dissatisfied airline passengers. Thus, while the previous steps of the analysis focused exclusively on the agents' discourse, here we are looking at both agents and passengers with the aim of exploring patterns of dialogic interaction between them. This kind of analysis can be used to examine responses to any kind of emotion, both positive and negative. By way of example, let us consider how passengers' anger is handled by webcare agents in our corpus.

The first step in the analysis consists in identifying potential markers of anger in the passengers' tweets. These will be used as 'seed terms' for retrieving relevant parallel concordances for qualitative examination. There are various ways in which this task can be approached. One way is to inspect all adjectives used in the passengers' sub-corpus and identify negative evaluative items as potential linguistic markers of anger. We focus on adjectives as opposed to inspecting the complete word list because adjectives are more likely to carry evaluative meanings compared to other parts of speech. Using SketchEngine's wordlist function, we created a list of all the adjectives found in the passenger sub-corpus. We then manually inspected the list and identified all negative adjectives. Table 6 lists the 10 most frequent negative adjectives used by passengers in our corpus.

Table 6
10 most frequent negative adjectives in passengers' tweets.

Item	Frequency	Frequency per thousand words
bad	18	0.33
ridiculous	16	0.29
terrible	10	0.18
difficult	8	0.15
hard	7	0.13
horrible	7	0.13
disgusting	7	0.13
poor	6	0.11
unbelievable	6	0.11
awful	6	0.11

Next, we use SketchEngine's parallel concordance tool to search for these adjectives and examine how webcare agents respond to the tweets that contain them. From the perspective of emotional labor, an interesting question is whether webcare agents react differently depending on the intensity of the anger expressed by passengers. By way of illustration, let us consider the adjectives *ridiculous* and *disgusting*. While both these adjectives clearly convey a negative sentiment, *disgusting* is more negative and confrontational, potentially indexing a higher degree of anger. Fig. 4 shows the parallel concordance for a sample of ten instances of *ridiculous*.

1	@[airline] with Covid-19 cases rising again. I want to ask you to do the right thing and not sit the middle seats on your flights. I was beyond nervous last time I flew, it was sort of ridiculous . Do the right thing please, I have an upcoming flight.	@[name] Hi, [name]. We're looking forward to seeing you again. Check out all that we're doing under Your Travel Experience. [url]
2	What a ridiculous move made for profit. @[airline] put all your top execs on these crammed flights as personnel. [url]	@[name] We've implemented many layers of protection including enhanced cleaning and requiring face coverings. [url]
3	@[airline] @[airline] This is ridiculous already... My flight has been switched from [airline] >> [airline] to leave days later, missing best friends wedding! no one is answering/ being helpful!	@[name] Hello @[name], we regret we were unable to reply to you faster. Do let us know if our assistance is still required, please provide us with your booking reference via DM or renew your request. We remain available.
4	Bonjour @[airline], I'm still waiting for a refund from February 16, an answer to a claim from March that was closed without being resolved, the answer to a claim from April 1, and the answer you promised me via Twitter that hasn't come yet. This is getting ridiculous .	@[name] Hello @[name], thank you for reaching out to us. Please DM us your booking reference and the name of the passenger so we can assist you accordingly. We await your reply via DM.
5	Hey @[airline] forcing me to wait 2.5 hours to rebook my flight over the phone when I could've done the same thing myself online in 5 mins is actually ridiculous give us a coupon code, something I could've flown back and forth to my destination in that time #worksmarternotharder	@[name] Hello, We're really sorry to learn about the amount of time you had to wait when you contacted our Call Center. We realize your time is important, and we apologize for our slow response. We invite you to send us a DM for further assistance. /[name]
6	@[airline] so you cancel my flight and re-route me to an airport that is not close and won't refund me?? Absolutely ridiculous !! Another terrible AC experience	@[name] Hello [name], we suggest to reach our colleagues at the Contact Centre for further assistance with re booking a connecting flight with a partner airline. They may be reached at [number] or [url] . Regards /[name]
7	@[airline] @[airline] Stop playing with people & rip'em off their money. I'm demanding my money back and I will get it.Stop making people wait on hold for hours then hung up on them,you're being ridiculous ! My flight [number] on [date] has been cancelled. I demand a refund	@[name] Hello [name], we regret to learn of this. Pls DM us your booking reference, so we could take a look and better advise. /[name]
8	@[airline] The only way to use my voucher is by calling you, but all of your #CustomerService call centres are unavailable. You have Morphe d from one of my favourite #airlines to the worst. Ridiculous ! [url]	@[name] Hi, [name]. I'm sorry you can't use your voucher to rebook online. It's something we're looking at, but we can't say when it will be possible. However, we can help you, but you will need to follow us and send us your details via DM. [name] [url]
9	@[airline] Hi, since yesterday I'm trying to claim my refund by phone call, yesterday wasn't possible because wasn't working for some reason and today I can even go to the menu options to speak with someone. I already tried 20 times on the phone today, this is ridiculous	@[name] Hello, bear in mind you can request the refund here [url]. Do not hesitate to write us back in case you need our help. Regards.
10	@[airline] You put out this same message back in March when everyone started attempting to get back home. I see similar comments to the ones in March- no one answering. I know we're still waiting for proper information for refunds. Ridiculous .	@[name] Hello [name], in order to assist you, please let us know through DM your reservation code or ticket number, and the passengers' full name. We'll be waiting for your response. Regards.

Fig. 4. Parallel concordance for ten instances of *ridiculous*.

If we look at the webcare agents' response tweets, we find that 4 out of 10 include an apology (lines 3, 5, 7 and 8). This sample therefore contains a higher proportion of apologies compared with the corpus as a whole, where they were found in 22.2% of the agents' tweets (see Table 4). The intensifier in line 5 (*We're really sorry*), the repetition of *we* in line 3 and the use

of a first person singular pronoun in line 8 project heightened personal and emotional investment in the apology. We also observe a higher than average number of 'signal availability' moves, with 40% of this sample containing this move (lines 3, 4, 9 and 10) compared with 10.6% in the whole corpus. Thus, overall, webcare agents' responses can be described as markedly accommodating and as expressing concern and a keen willingness to help.

When we look at responses to complaints containing the more intensively negative adjective *disgusting*, shown in Fig. 5, a different pattern seems to emerge. While the frequency of apologies (lines 2, 4 and 6) is comparable to the case of *ridiculous*, the wording is more formulaic and impersonal, as indicated by the frequent use of nominalizations (*delayed response*, *apologies*, *inconvenience*), the lack of intensifiers and first person singular pronouns. Moreover, two tweets contain the 'call for patience' move (lines 3 and 6), which in this context can be interpreted as a discursive anger management strategy. Overall, the tone appears to be more detached and less accommodating compared with responses to tweets containing *ridiculous*.

1	Something must be done with airlines who won't issue full refunds due to COVID 19 @[airline] Absolutely disgusting . Taking advantage and capitalizing on people. "Their website states care of customers is highest priority" well that's a joke !	@[name] Refunds are processed if the flight cancels while holding a confirmed reservation. Change waivers are available to help reschedule.
2	@[airline] why have I not gotten a response? It is disgusting to see that you are only responding to customer with a lot of followers. How is it fair that my team booking is considered one credit and not spilt up by passenger? Also why are some people getting refunds?	@[name] Hello, we regret the delayed response, we are experiencing a high message volume at the moment. If you still require assistance, please DM us your booking reference along with the details of your request. /[name]
3	@[airline] @[airline] @[airline] All have been a nightmare during this pandemic. Customers have spent thousands of pounds and these companies take the money immediately but take up to 8 weeks for a refund????? Disgusting	@[name] Hello. We have actioned your refund request from our end. Please check your bank account within 14 working days. We appreciate your patience and understanding. [url]
4	@[airline] You have forgotten all the British still stuck in [place] that have flown with you also no notice of flights cancelled our flight was [date] still not heard from anyone from [airline] and nobody answering phone calls absolutely disgusting service	@[name] Hello. apologies for the inconvenience caused. We request you to get in touch with us in regards of your cancelled flight via [url] Aditionally, you may send your feedback online at, [url] for our customer care review and action. Thank you.
5	@[airline] you are taking advantage of the situations by inflating the price your economy to first tickets to London! How disgusting . I hope everyone from the U.K. will stop using you when situation gets back to normal😠	@[name] Hi [name]. Allow us to highlight that the prices are currently higher due to the number of seats left and it can be changed anytime. Let us know if you need any further assistance. Thank you!
6	@[airline] are an absolute disgrace. Unlawfully holding onto our refund money of £600 telling us we have to wait until the COVID situation is resolved. Absolutely disgusting . You have no right to hold on to money which isn't yours. Contact me immediately please.	@[name] Hi, given the current situation, the deadline for receiving it may be longer. It could take several more weeks, we apologise for the delay. Thanks for your patience.
7	@[airline] @[name] @[airline] Stop pretending you do not know what is happening. It is your new policy. You cancelled the flights and now blackmailing this poor soul for more money to bring her home. Disgusting .	@[name] Hi there, we've responded to you at [url]. Thank you.

Fig. 5. Parallel concordance for all instances of *disgusting* in the corpus.

The comparison above seems to suggest that webcare agents respond to higher levels of passenger anger by backgrounding emotions and employing a more formulaic and impersonal communicative style. We can probe this hypothesis further by analyzing additional examples of interactions involving highly negative passenger tweets. One way to identify additional interactions would be to search for further negative evaluative adjectives (e.g. *pathetic*, *disgraceful*, *dishonest* and *criminal*) or for swearing expressions or negative emotive interjections (see Table 3). However, an alternative strategy that we illustrate here for retrieving passenger tweets expressing high levels of anger is to search for instances of repeated punctuation such as strings of exclamation and question marks. These paralinguistic devices typically serve to boost the emotions expressed in a text. In the context of a complaint tweet, they can signal a high degree of anger. Fig. 6 shows a random sample of interactions where the passenger tweet contains a string of two or more exclamation marks.

1	Sorry @[airline] I WARNED YOU NOT TO DO THIS. NOW WE HAVE TO CANCEL YOU! They have put greed above the health and safety of us and their employees. Shut them down !!! RETWEET. [url]	@[name] We've put into effect multiple layers of protection including enhanced cleaning and requiring face coverings: [url]
2	@[airline] Where is my refund?!! I have been promised a refund for my cancelled trip to Europe since May! On June 1st I was told I could expect my refund in two weeks! Tomorrow is July 1st and no refund !! I have filed a complaint with both the Better Business Burea and DOT!	@[name] Hello @[name], we would like to inform you that we have replied to your DM, please refer to your inbox for more details. Also, we kindly ask that you continue contacting us via DM to avoid confusion. Thank you.
3	@[airline] still waiting on my flight refund 3 months on. Been told on numerous occasions that it will be with me soon still nothing. Waste of time, will not be using them again !!!	@[name] Hello @[name], thank you for reaching out to us. Please DM us your booking reference and the name of the passenger so we can assist you accordingly. We await your reply via DM.
4	[AIRLINE] STEALING MY MONEY!!!!!! REFUND MY MONEY ASAP. I NEED YOUR HELP PEOPLE TO BRING TO THIS TO JUSTICE!!!! YOU CANCELLED THE FLIGHT AND YOU NEED TO REFUND THE MONEY AND NOT GIVING A YEAR VOUCHER !!!! @[airline]	@[name] Hello @[name], thank you for reaching out to us. Please DM us your booking reference and the name of the passenger so we can assist you accordingly. We await your reply.
5	@[airline] You've sent the same email twice with cancelled flight info @[airline] from [place] to [place]. My cancelled flight from [place] to [place] scheduled today with @[airline] has not been acknowledged!!! I have emailed, messaged dropped calls! Help me !! I'm not going away!!!	@[name] Hello, Thank you for reaching out to us. Could you please provide us your booking reference in a direct message, so we may better assist? Regards / [name]
6	@[airline] ok so [airline] changed my flight, my boarding airport and my landing airport without any advice !! I never see that ! What is that airline ???! just full refund of my round trip or I sue you ! No consideration for the customer !! #[airline] #COVID19	@[name] Hello, thank you for reaching out. We are currently undergoing many schedule changes due to the impacts caused by COVID-19. We invite you to DM us your booking reference so we may better advise about your next steps. Regards /[name]
7	@[airline] Hi you cancelled my trip to [place] in February, it has been more than 6 weeks, and I'm still waiting for my refund, please !!!!	@[name] Hi [name], mind sending us DM with the passenger full name, email address and 13-digit eTicket number so we can have a look? [url]
8	@[airline] 8 days have passed after succesfully submission. But still i have not received promotion kod mail Healthcare professionals who have not received promotion code mail (altough succesfully submission) are waiting your support. Please you don't ignore us !! .. please #[airline]	@[name] Hello, we have replied to you via a DM. Please check. Thank you.
9	@[airline] the promo code for Healthcare Workers is not working for anyone and customer services are clueless about it !!	@[name] Please check your DM we have replied.
10	@[airline] @[name] @[name] When will I get my refund? I replied to an email for a refund but have now had an email for a voucher !!!!!! I HAVE ASKED FOR A REFUND.	@[name] @[name] @[name] Hi. Please, write to us in a Private DM. [name] [url]

Fig. 6. Parallel concordance for ten instances involving repeated exclamation marks.

Overall, the passenger tweets in this sample appear to express a high degree of anger. This is signaled, among other things, by paralinguistic cues such as repeated punctuation and capitalization, explicit blaming (e.g. *[airline] stealing my money*), acts of verbal aggression (e.g. *shut them down*!!!) and negative evaluative language (*waste of time*, *clueless*). The webcare agents' answers seem to confirm the pattern observed in relation to *disgusting*. We find evidence of marked emotional backgrounding in the agents' responses. There are no apologies in this sample, the language is highly formulaic, especially in relation to expressions of gratitude, and the tweets predominantly contain rhetorical moves performing an emotional backgrounding function, such as request for additional information and divert to private messaging. In fact, all but one of the agents' tweets direct the passenger away from the company's public profile onto private messaging. In addition to serving an anger management function, this strategy could also serve to protect the airline's reputation from the damage such negative tweets may cause in the eye of onlookers.

In sum, these examples seem to suggest that webcare agents use different emotional management strategies depending on the degree of negativity and anger expressed by passengers. Moderate levels of anger tend to be addressed with positive emotional displays and a generally accommodating attitude. Conversely, when confronted with high levels of anger and aggressiveness, agents tend to respond by backgrounding emotions and by adopting a less accommodating and more pragmatic type of discourse. Clearly, given the very limited amount of data analyzed here, these suggestions should be taken as tentative hypotheses.

What the dialogic analysis also shows is that emotional labor is manifested not only in aspects of the content of the message (i.e. references to specific emotions, the moves used), but also in *how* the message is formulated, that is, the kind of communicative style adopted by responders. For example, intensifiers and nominalizations, seen in the examples above, can respectively function as markers of an affective and a detached communicative style (Fuoli et al., 2021). In turn, these two styles appear to match up with the 'express' and 'background' strategies of emotional labor. Other linguistic aspects discussed above relate to the personal *versus* impersonal dimension of style. For instance, the use of first person pronouns (seen in the examples above) is one of the most common tactics used in webcare to humanize the company and personalize the message (van Noort et al., 2015). Along similar lines, Cameron (2000) reported the use of the customer's name and direct second person address as some of the most commonly prescribed synthetic personalization tactics in call center discourse. From the perspective of our model, we can interpret message personalization as an emotional management strategy aimed to make the receiver *feel* valued and 'special', and to pre-empt negative feelings.

The examples discussed in this section provide a clear illustration of the potential of undertaking dialogic analysis in corpus linguistics via the parallel concordance tool. The patterns of emotional management observed here can only be revealed by inspecting and comparing units of *interaction* rather than a single speaker's contribution. Dialogic analysis thus usefully complements lexical and move analysis. Together, these three methods help us gain a more comprehensive picture of the discursive mechanisms of emotional labor.

4. Conclusion

This article has introduced a novel linguistic framework for analyzing how emotional labor is performed in discourse. Building on insights from Arlie Hochschild's pioneering work and from the linguistic literature on emotion, the framework aims to capture the discursive mechanisms through which workers express, background and manage emotions in fulfilling their professional roles. By presenting this framework, we aim to contribute to a better understanding of the linguistic and pragmatic underpinnings of emotional labor, which have so far remained underexplored, and offer a tool that can be used to analyze and systematically deconstruct the emotional dynamics at play in different institutional and professional contexts. This study has also introduced methodological innovations by showcasing a new technique for dialogic analysis in corpus linguistics based on the repurposed parallel concordance tool and by demonstrating an original formula for triangulating lexical, move and dialogic analysis. This is important because corpus linguistic studies often do not include examination of discourse structure or conversational interaction, focusing on patterns *across* texts rather than patterns *within* texts ('intra-textual' analysis, see Caple et al., 2020: 27–28). We have demonstrated the application of the framework with a case study of a corpus of Twitter interactions between airline webcare agents and passengers during the first wave of the Covid-19 pandemic. The results of this analysis, albeit not exhaustive, contribute to the growing literature on webcare by providing a comprehensive picture of the emotive linguistic resources used by webcare agents and of the pragmatic functions they serve. More generally, the case study demonstrates the usefulness of Twitter as a source of data for emotional labor, which can help us overcome access issues that have so far hampered research into institutional and professional discourses (Hood and Forey, 2008: 390).

The framework presented here should be considered as an initial proposal and may, as such, be enhanced in future work. Since we have developed the framework around the specific characteristics of webcare interactions via Twitter, when used to describe other communicative contexts it would have to be adapted to account for their unique properties. For example, when applied to spoken conversational data, prosodic and paralinguistic signals should be included in the analysis. It is also important to note that, while the framework is implemented here using a combination of corpus linguistic tools and move analysis, its application is not restricted to these methods. Future studies may fruitfully incorporate qualitative approaches such as speech act analysis and Conversation Analysis. Another important future direction is to combine linguistic analysis of interactions with analysis of company guidelines and training materials, surveys and interviews with professionals to gain a more complete and robust picture of the motivations behind their linguistic choices and a better understanding of their

conscious emotional management strategies. Finally, since emotional labor interacts with societal power structures and phenomena such as sexism and racism, there is a wide range of potential communicative contexts (beyond webcare and other professional/institutional contexts) in which the linguistic analysis of emotional labor has the potential to provide new insights. To conclude, we hope to have achieved three major aims with this article: to raise awareness of the concept of emotional labor in pragmatics and applied linguistics; to promote a *linguistic* approach to this concept; and to introduce a new analytical framework that can be used in its analysis.

Declaration of competing interest

The authors do not have any conflict of interest to disclose.

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Appendix A. Supplementary data

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