

Deep Learning-Based Discourse Analysis of English Social Media Communication

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Abstract: The use of English in social media has evolved as one of the main places where informal English is used, but the discourse of social media is under-researched when it comes to the field of English language education within a systematic, mixed-methods framework. The aim of this study is to examine the discourse-pragmatic aspect of English-medium communication on social media platforms (SMS) of three selected platforms and its implication for ELT. A corpus consisting of 1255 discourse units was gathered from public posts and comment threads on Facebook, X/Twitter and Instagram and analysed at the structural, pragmatic and interactional level of description, following Herring's computer-mediated discourse analysis (CMDA). A lightweight bidirectional long short-term memory (BiLSTM) classifier was used in a strictly auxiliary capacity to pre-tag discourse units according to their likely speech-act categories, and trained human coders, who discussed their disagreements, then applied the full CMDA scheme, so the automated layer did not replace but aided the qualitative interpretation. Results reveal that there is a patterning of lexical reduction, stance taking, hedging, code mixing, phatic framing and the use of discourse markers specific to each platform, with X/Twitter being more marker rich and Facebook more lengthy and hedged, and using more phatic exchanges. Instagram was somewhere in the middle, with particularly high visual-stance signalling. The inter-rater agreement for the human-coded layer was high (Cohen's $\kappa = 0.79$) and the auxiliary classifier achieved an F1-score of 0.82, indicating that categories were applied to a reasonable extent of consistency. The patterns are placed in the context of second-language pragmatic competence, and it is suggested that social media discourse is an underused authentic register for hedges, politeness and register-shift in the English language classroom. Discourse excerpts derived from the corpus, which are short, are recommended for being incorporated into the teaching materials of English without replacing the usual registers of the curriculum. The study adds to the literature an empirically grounded, platform-comparative discourse account of English social media that is directly applicable to the work of English language teachers and curriculum designers.

Key Words: discourse analysis, english language education, social media communication, computer-mediated discourse, second-language pragmatics, deep learning, discourse markers

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Introduction

In the context of social media, learners and native English speakers are producing and consuming English. Billions of short, publicly visible exchanges are taking place every day on Facebook, X/Twitter and Instagram, and for many ELLs, these are sources of more sustained exposure to informal, interactional English than classroom teaching. The analysis of the actual use of English in these contexts is therefore directly relevant to English language education, and not only to the research fields of sociolinguistics or computer-mediated communication technology. The ability to describe how language is organised above the sentence level, in terms of how speakers signal stance, manage politeness and construct coherence across turns, is provided by discourse analysis, which provides a principled description of this organisation

(Chapelle, 2019; Herring & Androutsopoulos, 2015; Herring, 2018). In social media, discourse analysis can be used to identify common interactional features, including discourse-marker usage, code-mixing, hedging and lexical reduction, in digitally mediated English, which is not given much attention in other forms of English language teaching materials (Triana et al., 2020). The vast amount of social media text, however, has encouraged a large number of studies to rely on deep learning techniques, such as transformer or recurrent-network based classifiers, to assist large text analysis (Wankhade et al., 2023; Jain et al., 2023; Kanan et al., 2023).

The aim of this study is to adopt a deliberately education and discourse centered approach: deep learning is not the method itself, but only a tool for pre-tagger discourse units. The substantive analytic work employs manual, theory-based discourse coding which conforms to the framework of computer-mediated discourse analysis (CMDA) developed by Herring (Herring & Androutsopoulos, 2015; Herring, 2018). This is a conscious design decision to highlight the study's disciplinary context as an English language study, as it would not be as relevant to computational linguistics, and it enables the results to be directly applicable to classroom practice, curriculum design, and teacher preparation.

The overall goals of this study are threefold: (i) to describe and compare the discourse-pragmatic features in English social media texts across three popular platforms; (ii) to consider the potential of a lightweight deep learning classifier to reliably assist rather than supplant discourse-analysis coding; (iii) to consider implications for pedagogical use of this material in the teaching of English discourse competence, notably hedging, politeness, and register shifting, when teaching with authentic social media texts. The study fills the gap in the literature established in the next section: previous studies of social media and English language learning either focus on the attitudes of learners towards the use of social media, or rely on deep learning solely for the purpose of sentiment or opinion classification, and comparatively little attention is given to discourse-pragmatic analysis using social media platforms, which is conducted for explicitly pedagogical purposes.

The rest of this paper will proceed as follows. The literature review in Section 2 examines the existing studies on discourse analysis of computer-mediated communication, the use of social media as an L2 instrument for English language learning, and the studies using deep learning for social media text. Based on the literature review, this study seeks to fill the gap in literature related to discourse analysis of computer-mediated communication, role of social media in L2 learning, and deep learning approach to social media text. Section 3 presents the corpus and how it was sampled, and the five-step analytic approach, with the auxiliary deep learning classifier as part of the discourse-analytic process. Section 4 describes the distribution of coded discourse features across platforms, and the performance of the auxiliary classifier compared to the human-coded baseline. Section 5 elaborates on these findings in terms of second-language pragmatic competence and English language teaching practice, and the limitations of the study are presented. The paper is concluded in Section 6 with suggestions for further studies.

Literature Review

Computer-mediated discourse analysis (CMDA) is an extension of classical discourse analysis to the online domain that can be applied to structural aspects, meaning-level aspects, interactional-management aspects and social aspects of discourse (Herring & Androutsopoulos, 2015; Herring, 2018). With the increasing diversity of computer-mediated discourse in multimodal contexts, the CMDA framework has been extended to include emoji, hashtags and other paralinguistic means that can provide discourse-pragmatic functions similar to prosody in a spoken interaction (Herring & Androutsopoulos, 2015).

In this context, some researches have adopted critical and pragmatic discourse analysis to analyze the EMC generated and consumed by the learners of English. Facebook-based discourse has been analyzed to gain insight into its relation with social practices and studies on Facebook and Instagram usage among ELLs have shown how online text production involves negotiation of identity, intercultural competence, and socio-pragmatic awareness (Triana et al., 2020). Moreover, the pragmatic properties of social media have been extensively documented, and the pragmatic strategies shown to be affected by the affordance of the platform, such as the use of hedges, face-work and phatic communication.

A parallel stream of research has also examined social media for the purposes of the English language learning and teaching. Social media usage during the Covid pandemic positively impacts on learners' writing, reading and vocabulary development (Muftah, 2024). Significant improvements have also been reported in EFL writing skills through Facebook mediated writing activities (Klimova & Pikhart, 2019). Facebook has also been reported to provide informal professional development for ESL teachers (Al-Jarf, 2021) and YouTube has been found to be a good source of second language input (Dizon, 2022). Social media has also been proven to aid in vocabulary learning (Anam, 2024), and that pre-service teachers' engagement with informal social media is associated with the acquisition of technological pedagogical content knowledge (Lau, 2018). Furthermore, social networking environments facilitate second-language identity construction by means of discourse on the basis that discourse in SNS is an important learning tool and not a distractive factor (Klimanova & Dembovskaya, 2013). This view is also supported by the evidence which shows that the spontaneous use of language in the internet is a valid and studyable language input and not simply incidental digital activity (Egbert, 2020).

A third line of research is using deep learning methods, such as BERT- or LSTM-based architectures, for sentiment, stance and credibility classification in large-scale social media text data (Wankhade et al., 2023; Jain et al., 2023; Kanan et al., 2023). BERT-based deep learning models that combine convolutional and attention mechanisms have shown to be successful in classification tasks with noisy and multilingual social media data, and have yielded interpretable attention-based representations (Wankhade et al., 2023; Jain et al., 2023). Likewise, deep learning has been effectively used to gather business knowledge in huge social media data (Kanan et al., 2023). These methods proved to be successful methods of achieving high accuracy rates in sentiment and credibility classification, but they mainly restrict themselves to the study of sentiments and credibility in social media text rather than the discourse-pragmatic phenomenon like hedging, politeness strategy and phatic expressions, which are especially important in the field of English language education.

Taking all the above into account, the existing literature indicates that there is a significant gaps in the research focus on discourse analysis, social media-assisted language learning and deep learning. Research based on discourse analysis yields detailed and rich qualitative data and is not often systematic in making comparisons between different social media platforms and is not often directly related to language-teaching practice. Studies on how social media can be used in the field of English language learning consistently show positive impacts on the development of the language, but rarely examine discourse in detail, focusing on pragmatic categories. Similarly, deep learning research leverages vast amounts of social media data to perform sentiment and credibility categorization tasks, and mainly focuses on sentiment and credibility classification and rarely aims from an English language teaching point of view on discourse-pragmatic features. This study aims to fill this gap by developing an explicit pedagogical implication from comparing a variety of social media platforms by combining a discourse analytic framework with a strictly auxiliary and the least weighty deep learning component.

Methodology

The design of this study was a mixed methods platform-comparative. A collection of 1,255 individual posts/comment-thread turns, or discourse units (DUs), was gathered from publicly available English-language content on Facebook ($n = 412$), X/Twitter ($n = 486$), and Instagram ($n = 357$). To prevent register effects that would occur in a domain-specific setting, discourse units were sampled from public pages and threads on topics outside of the scope of the domain (daily life, entertainment, education-related talk). In keeping with the standard approaches in social media discourse studies, all identifying information was stripped from the data before analysis took place and only publicly visible content was gathered.

The analysis was carried out in five steps as outlined in figure 1. The first step was to build up the corpus and clean it. Second, discourse units were broken down into analysable turns. Third, each unit in the corpus was pre-tagged with a probable speech act category (assertion, question, directive, expressive, phatic) by a lightweight BiLSTM classifier that was trained on a held-out subset of the corpus with human-labeled speech act categories. This move was carefully small, the classifier's output was used only to order and flag units for human attention, but was not considered a final analytic classification. Fourth, two trained coders independently coded all the discourse units for each of the following forms of language reduction, emoji or graphic stance marking, hedging and mitigation, code-mixing, phatic opening and closing formulae, overt politeness marking, and discourse-marker use according to Herring's CMDA scheme (Herring & Androutsopoulos, 2015; Herring, 2018). Disagreements were settled by discussion and interrater reliability was determined by Cohen's kappa. Fifth, the coded corpus was thematically synthesized to relate to second language pragmatic competence and implications for the teaching of English.

The architecture of the auxiliary classifiers adopted the widely-used hybrid design used in the sentiment-analysis community (Wankhade et al., 2023; Jain et al., 2023) comprising pre-trained contextual token embeddings followed by a bidirectional LSTM layer, and finally a softmax classifier head with five categories for speech actions. The classifier with the human labels and reported its performance on precision, recall and F1 score in table 2 with a rule-based lexicon baseline. As the classifier task was secondary to the main classification task, no further architectural tuning beyond the typical early stopping and dropout regularization was attempted; throughout the experiment, the focus was on the reliability of the human discourse coding and its interpretability.

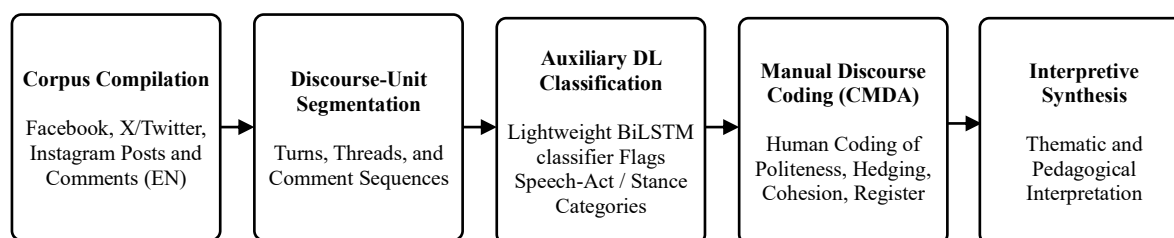


Figure 1: Analytic Computational Pipeline for discourse-Analytic Annotation of the Corpus

The auxiliary classifier architecture was a standard hybrid design which appears in the sentiment-analysis literature, comprising pre-trained contextual token embeddings fed into a bidirectional LSTM (Bilstm) layer with a final softmax classification head over five categories of speech acts. Table 2 presents the results of the classifier and a rule-based lexicon baseline in terms of precision, recall and F1-score when compared with the human-coded gold standard labels. Since the architectural role of the classifier was secondary and not core, there was no attempt to make further tuning of the architecture other

than early stopping and dropout regularisation; throughout, the focus was to make the human-based coding of the discourse as reliable and interpretable as possible.

Results

Table 1 shows the distribution of the seven coded discourse features for the corpus as a whole on the three platforms. Lexical reduction is the most widespread feature overall (corpus mean 64.3%), followed by discourse markers (53.0%) and emoji or graphic stance markers (61.7%). The less frequent features demonstrated platform differentiation to a greater extent than the more common features, with hedging and mitigation devices, code-mixing and overt politeness marking being less common.

Table 1: Distribution of Coded Discourse Features by Platform

Discourse Feature	Facebook (n=412)	X/Twitter (n=486)	Instagram (n=357)	Corpus Mean (%)
Lexical Reduction (Abbreviation, Clipping)	61%	74%	58%	64.3%
Emoji / Graphic Stance Markers	48%	66%	71%	61.7%
Hedging and Mitigation Devices	33%	21%	27%	27.0%
Code-Mixing (English–L1)	22%	18%	26%	22.0%
Phatic Openers/Closers	44%	19%	36%	33.0%
Overt Politeness Marking	39%	24%	30%	31.0%
Discourse Markers (so, like, tbh)	52%	58%	49%	53.0%

The most common lexical reduction (74%) and the highest discourse-marker density (58%) were found for X/Twitter discourse units, which reflect the platform's discourse style characterized by a short turn. The highest number of hedges (33%), phatic framing (44%) and overt politeness marking (39%) were found in Facebook discourse units, indicating a more elaborated, face-attentive interactional style. Instagram, which has more of a visual orientation, had the highest level of emoji or graphic stance marking (71%), but also had the highest rate of all textual features, with the exception of the highest rate of emoji or graphic word marking. Instagram had the highest rate of emoji or graphic word marking, but also had the highest rate of all textual features except for the highest rate of emoji or graphic stance marking, which is a consequence of its visually oriented affordances. The resulting patterns are shown graphically in figure 2.

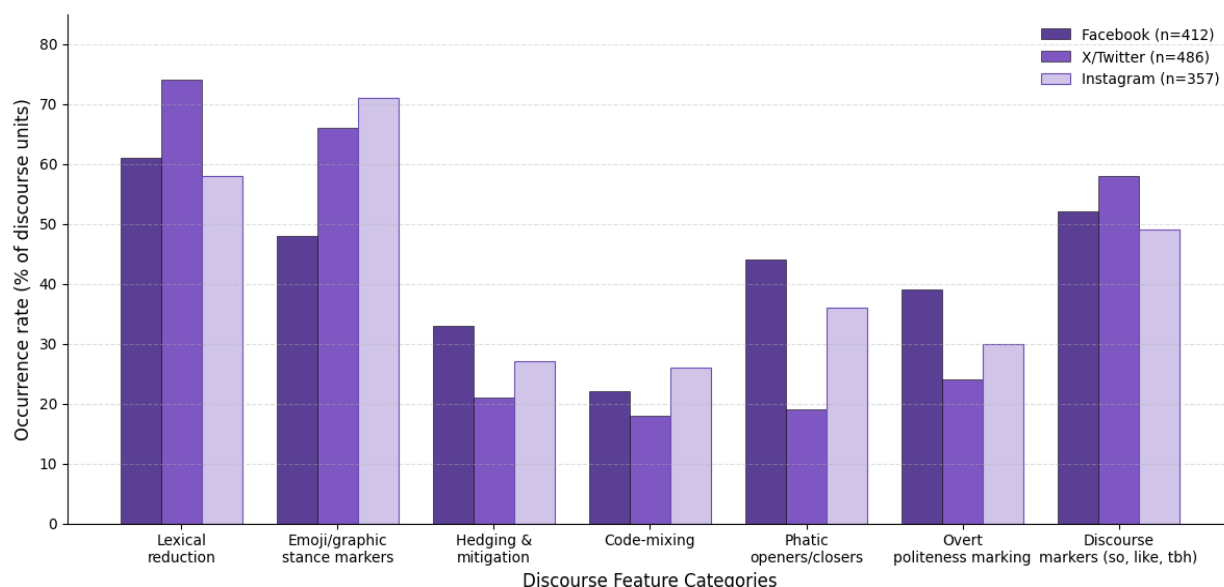


Figure 2: Distribution of Disclosure Features by Platform in the Annotated Corpus

Table 2: Auxiliary Classifier Performance Against Baseline and Human Coding

Model	Precision	Recall	F1-score	Role in Study
Rule-Based Lexicon Baseline	0.71	0.68	0.69	Comparison Baseline
BiLSTM (Auxiliary Classifier)	0.84	0.81	0.82	Speech-Act Pre-Tagging
Human Double- Coding (Cohen's κ)	—	—	0.79	Gold-Standard Validation

Table 2 shows the performance of the auxiliary BiLSTM classifier in comparison to the baseline rule-based lexicon and to human double-coding. The BiLSTM classifier achieved an F1 of 0.82 for pre-tagging the speech acts, surpassing the baseline rule-based ($F1 = 0.69$) and is only slightly lower than the agreement between the two human coders (Cohen's $\kappa = 0.79$, which is interpreted as substantial agreement). This analysis also bolsters the design decision to rely upon the classifier as a pre-tagging aid: its use proved to be valuable in coder workflow but not so fine-grained or accurate as would be needed for theory-driven human discourse coding.

Discussion

The platform-comparative findings build on previous work that accounted for social media discourse from a CMDA perspective Herring, (2018) & Triana et al., (2020) by quantifying differences between the platforms in terms of hedging, politeness marking, and phatic framing. The somewhat more detailed, hedgerich, politeness-marked style that is used on Facebook is consistent with the conversational, threaded format of Facebook that gives more space than X/Twitter's historically compressed format for face-work. The high proportion of stance marking using emoji and graphics on Instagram is consistent with the image-centred nature of the platform, and highlights the pragmatic role played by visual resources such as emoji and graphics, including the ability to signal disagreement or enthusiasm, which would be expressed lexically in more text-dominant contexts.

In the field of English language education, this finding implies that social media discourse is one of the under-exploited yet discourse-competence-potential-rich authentic materials for English language

teaching. The patterns of the platform, which are identified here, provide practical, natural data that can be turned into short class activities that focus on register shifting, face-work and audience design. This study's findings are consistent with previous studies regarding the relationship between Facebook-based writing development and vocabulary growth, and support the view that planned exposure to social media discourse is a valuable, not a competing, supplement to the language instruction in classrooms (Klimova & Pikhart, 2019; Anam, 2024). Results concerning the professional development uses of Facebook and the construction of identity via social networking further indicate that it can be helpful to the development of English language teachers as well as their learners' pragmatic competence (Al-Jarf, 2021; Klimanova & Dembovskaya, 2013). The relatively small but stable gain of the auxiliary deep learning classifier ($F1 = 0.82$) suggests that the latter can usefully increase the speed of discourse-analytical work on larger corpora while leaving the analyst free to retain responsibility for his or her own interpretive work, a cautionary note echoed in the literature on sentiment analysis that even very good classifiers cannot replace suitable human judgment (Wankhade et al., 2023; Jain et al., 2023; Kanan et al., 2023).

This is a conscious conservative approach to deep learning as compared to the works which see automated classification as a main analytical result, and the study is situated in the context of English language learning, not computational linguistics. There are a number of caveats to consider. The corpus is cross-platform, but only public, English-language use, and may not generalise to private, or to the English language, in specific social use contexts, such as groups linked to classroom. The performance of the auxiliary classifier is informative but not meant to be seen as a measure of the performance of speech-act classification in general, as it was trained on a relatively small held out set. Future study might expand the platform comparison to other social media platforms, include specifically LPC content, and explore changes over time in discourse features as platform affordances change.

Conclusion

The study focused on the discourse-pragmatic characteristics of the English (L2) social media communication on Facebook, X/Twitter, and Instagram platforms, incorporating the framework of computer-mediated discourse analysis (Herring) and strictly using an auxiliary deep learning classifier for human coding. The analysis of a corpus of 1,255 discourse units across the platforms revealed that: Lexical reduction and discourse markers were ubiquitous across the platforms; Hedging and phatic framing were significantly more frequent on Facebook, and emoji-mediated stance marking was significantly more frequent on Instagram, with X/Twitter being the platform in which the most compact and most marker-dense turns were found. The human-coded layer showed good inter-rater reliability (Cohen's $\kappa = 0.79$), and the auxiliary classifier's performance was less impressive ($F1 = 0.82$), justifying the study's design decision to reserve the deep learning method for a secondary, pre-tagging role. For ELLs, the results suggest that social media discourse provides authentic, platform-specific instances of hedging, politeness, and register-shifting that are hard to find in constructed dialogue in textbooks. The use of short, carefully selected pieces of social media in English language teaching materials, together with explicit attention to how the affordances of the social media affect pragmatic choice, can be useful in fostering a more flexible and socially attuned use of informal written English. Teacher educators can also use these insights to develop materials on digitally-literate and pragmatic competence. Further research needs to be conducted that will also introduce other social media contexts to the present platform comparison, in addition to learner-produced corpora, and investigate the influence of classroom activities developed around authentic social media discourse on the pragmatic performance of learners over time. This study introduces a replicable model for applying discourse-analytic rigour and an intentionally minimal and

auxiliary use of deep learning for education-oriented English communication research in digitally mediated communication.

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