

# Short Paper

## Social Perceptions of English Spelling Variation on Twitter: A Comparative Analysis of Human and LLM Responses

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*Spelling variation (e.g. funnnn vs. fun) can influence the social perception of texts and their writers: we often have various associations with different forms of writing (is the text informal? does the writer seem young?). In this study, we focus on the social perception of spelling variation in online writing in English and study to what extent this perception is aligned between humans and large language models (LLMs). Building on sociolinguistic methodology, we compare LLM and human ratings on three key social attributes of spelling variation (formality, carefulness, age). We find generally strong correlations in the ratings between humans and LLMs. However, notable differences emerge when we analyze the distribution of ratings and when comparing between different types of spelling variation.*

### 1. Introduction

Language is not only used to communicate information about the world, it is also a social tool that speakers can employ to construct a social identity (Eckert 2012). To that end, language users can draw on the **social meaning** of language, which refers to **social attributes** that can be associated with linguistic forms and their users (Walker et al. 2014). As an example, one could write ‘c u tonite’ as a variant of ‘see you tonight’. Both texts carry the same referential meaning; that is, they communicate the same message that the writer will see the addressee the same evening. However, the social attributes the reader connects to the writer and context of each of these texts can be quite different. Perhaps the first version is seen as more *informal* and the writer of the second version as more *serious*. Or maybe the writer of the former is perceived as *younger* than the latter.

**Sociolinguistic** research has shown that language variants, i.e. different linguistic forms that have an equivalent referential meaning (cf. *tonite* vs. *tonight*; Labov 1972), can carry multiple social meanings. This goes for both written and spoken language. For instance, variation in the pronunciation of word-final -ing (either velar -ing [ɪŋ] as

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Read the tweets below focussing on the words that are between <W> and </W>.

Tweet 1: Not sure but <W>nvr</W> mind

Tweet 2: Not sure but <W>never</W> mind

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**Formality:** Then rate how (in)formal you find each tweet, with a number from 0 to 100 (0=very informal, 100=very formal).

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**Carefulness:** Then rate how careless/careful you find each writer, with a number from 0 to 100 (0=very careless, 100=very careful).

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**Age:** Then give your best estimation of how old the writer of each tweet is, in number of years (whole numbers).

Table 1: Both participants and LLMs are presented with tweet pairs. To collect formality and carefulness ratings, LLMs provided numerical ratings, while the human participants used a slider. The text shown above are parts of the prompts presented to LLMs; the prompts are based on the instructions that humans received.

in *working* or as alveolar -in [m] as in *workin*) in American English has been shown to be associated with social attributes like perceived intelligence (the velar pronunciation sounding more intelligent than the alveolar one), as well as regional background (*workin* sounding Southern) and sexual orientation (*working* being linked with gay speakers) (Campbell-Kibler 2014, 2009, 2010a). Thus, social meaning is a key part of language understanding and use. Although sociolinguistics has a rich tradition in studying the social meaning of language variation (Campbell-Kibler 2010b), it has been understudied in NLP (Nguyen, Rosseel, and Grieve 2021).

Although there is a large body of work in NLP on language variation (Nguyen et al. 2016), the main focus has been on socially stratified language **production**. For example, studies have investigated how linguistic features in texts vary across sociodemographic groups. Often, such studies were carried out in the context of authorship profiling, e.g., can linguistic features be used to predict attributes like gender and age (Argamon et al. 2009; Schwartz et al. 2013; Flekova, Preoříuc-Pietro, and Ungar 2016). As another example, studies have examined how such production differences affect the fairness of models, showing how task performance varies across texts written in different language varieties (Joshi et al. 2025) or by speakers from different sociodemographic groups (Garimella et al. 2019). As a final example, there is an increasing interest in the implications for text generation, e.g., by asking LLMs (large language models) to produce text when simulating certain personas, often (partially) defined by demographic attributes (Malik, Jiang, and Chai 2024), and to assess the quality of LLM output across different language varieties (e.g., Standard English vs. African American English; Sandoval et al. 2025; Deas et al. 2023).

Contrary to this considerable amount of work on variation in language production, research in NLP focusing on how language variation is **socially perceived** – in other words, what social meanings it can express — remains scarce. Although there is extensive research on the linguistic competence of LLMs in general (Waldis et al. 2024), their **sociolinguistic competence** has received far less attention (Duncan 2024). Sociolinguistic competence is not only about being able to produce language that aligns with how the writer would like to position themselves socially; it also includes understanding how linguistic variation is socially perceived. Understanding what social meanings LLMs associate with language variation is essential, as it might influence their downstream behavior (Blodgett et al. 2020), such as the language they suggest

or produce when used as writing tools (Goldshtein et al. 2024; Sourati et al. 2025), or in a decision making context (Hofmann et al. 2024). Measuring what social meanings LLMs attach to linguistic variation – the focus of this study – is therefore an essential first step for assessing how these associations might shape their downstream behavior.

Moreover, following a large body of work that **compares LLMs with humans** in terms of internal representations, behavior and language processing (Karamolegkou, Abdou, and Søgaard 2023; Brysbaert, Martínez, and Reviriego 2024; Tjuatja et al. 2024; Cheung, Maier, and Lieder 2025), we focus on comparing how language variation is socially perceived by humans and how such patterns are reflected in LLM output. With this research, we hope to contribute to discussions about the use of LLMs for sociolinguistic research (Nguyen 2025). Taking it a step further, using LLMs to collect human-like experimental data has attracted attention in many fields, ranging from political sciences (Argyle et al. 2023) to cognitive sciences (Binz et al. 2025) to machine learning (Anthis et al. 2025), though it has also sparked criticism (Dillion et al. 2023; Aher, Arriaga, and Kalai 2023; Agnew et al. 2024; Abdurahman et al. 2024; Wang, Morgenstern, and Dickerson 2025). If LLMs associate similar social meanings to language variation as humans do, they could serve as a valuable tool for sociolinguistic research. For example, they could be used to uncover previously unknown potential social meanings of language variants that could then be further researched in humans, or support pilot studies to inform experimental design. However, LLM-based insights should ultimately always be validated and explored further through real human experiments.

In this study, we focus on the social perception of **spelling variation** in English. While social meanings can be attached to various types of linguistic forms (e.g. pronunciation, word choices, grammatical forms), we take spelling variation as a starting point for developing this new research direction for three reasons. First, by focusing on spelling variation, we can create text pairs with clearly equivalent referential meanings; that is, it is fairly straightforward to determine whether they refer to the same thing or concept (e.g., Table 1). Second, sociolinguistic studies have documented how spelling variation is used for social meaning making in online communication (Busch 2021; Hilte, Vandekerckhove, and Daelemans 2019; Ilbury 2020; Russ 2012; Squires 2010). Third, since many LLMs are pre-trained on web data (Soldaini et al. 2024; Brown et al. 2020; Gao et al. 2020), it is likely that they have encountered many instances of spelling variation during training. We aim to answer the following (**RQ**): *How do the social meanings that LLMs associate with English spelling variation compare to those of humans?* We investigate this RQ by examining seven common types of spelling variation and three key social meanings (formality, carefulness, and age).

**Methodology.** Our setup is rooted in sociolinguistic research: We adapt the speaker evaluation paradigm, frequently used in sociolinguistics research, to the analysis of LLMs (§3). To do so, we create a highly controlled, carefully designed dataset with tweets. Due to this rigorous design, our dataset is smaller than typical NLP datasets. Following sociolinguistic principles, we then collect many human ratings per item (§4); we then compare these ratings with LLM outputs (§5).

**Contributions.** (i) We highlight an underexplored aspect of language use — social meaning — for the analysis of LLMs; (ii) We propose a methodology, rooted in sociolinguistic research, to examine LLMs' associations of social attributes with spelling variation; (iii) We find surprisingly high correlations between human and LLM ratings. However, when zooming in on the rating distributions and the individual spelling variation categories we do observe notable differences; (iv) We compare two prompting strategies

and find that the strategy that more closely mirrors the human setup leads to higher correlations. Our code and data will be made publicly available upon publication.

## 2. Related Work

### 2.1 Language Variation in NLP

In this subsection we discuss related work on language variation in NLP, with a focus on LLMs and research on social perceptions of language variation in text.

*How language models handle language variation.* Several studies have analyzed what (large) language models have learned about language variation. Nielsen, Kirov, and Roark (2023) studied whether they are consistent in producing British or American spelling. Furthermore, building on the link between language variation and sociodemographic attributes of authors, researchers have investigated whether LLMs encode sociodemographic knowledge of authors based on age and gender prediction tasks (Lauscher et al. 2022), and whether they perform differently on the close task using data from different demographic groups (Zhang et al. 2021). We are not aware of work focusing specifically on different types of spelling variation, besides a pre-LLM study on word embeddings (Nguyen and Grieve 2020).

Language variation has also been considered as a source of bias in NLP models (Blodgett et al. 2020). Studies have found task performance differences between different language varieties (Ziems et al. 2023; Faisal et al. 2024; Lin et al. 2025). Furthermore, Petrov et al. (2023) found higher API costs for certain language varieties, because the texts are segmented into a greater number of tokens. In terms of text generation, studies have analyzed how the language variety of a prompt influences the generated responses (e.g., in terms of stereotyping and demeaning content (Fleisig et al. 2024)) and researchers have debated to what extent LLMs should adapt their language use (e.g., style, dialect) to that of users (Lucy et al. 2024; Sandoval et al. 2025).

*Social perception of language variation in NLP.* In NLP, studies on perceptions of social attributes linked to linguistic variation in text remain scarce. A few studies have investigated this topic in the context of author profiling. An early study by Nguyen et al. (2014) collected human guesses of the age and gender of Dutch Twitter users based on their tweets. These guesses were then compared with the actual Twitter users' gender and age, to reflect on the limitations of automatically inferring such social attributes from text. Other studies have collected human guesses of users' gender and age based on English tweets, investigating how they deviate from model predictions and ground truth data (Flekova et al. 2016) and whether tweets can be strategically selected to influence human guesses (Preoțiuc-Pietro, Chandra Guntuku, and Ungar 2017). A recent study by Chen et al. (2025) collected human perceptions of gendered style. They did not compare the human ratings with ratings by LLMs. Importantly, none of these studies controlled for confounding factors like topics mentioned in the text (e.g., references to school, or playing soccer). As a result, factors besides language variation could have played a role in participants' perceptions of the writer's social attributes. As an example, Chen et al. (2025) found that emotion features were associated with perceptions of feminine style, and a feature analysis by Flekova et al. (2016) highlighted words like *boyfriend* or male names (e.g., *joe*).

Recently, Cheng, Yu, and Jurafsky (2025) developed an LLM-based approach to measure human-like tone in text and four dimensions of social perception (warmth,

status, social distance, and gender), building on social psychology work. For example, gender perceptions were measured using log likelihood ratios of texts prefixed with '*he said*' vs. '*she said*', and social distance by prefixing text with phrases such as '*the stranger said*' vs. '*my friend said*'. They used these measurements to investigate whether human preferences towards LLM-generated output differed along these dimensions. Although some of their data was based on matched prompts (i.e., responses to the same input prompt), similar to prior studies, their experiments did not isolate the effects of specific linguistic features.

The following two recent studies are most relevant to ours, as they focused on social perceptions of language variation and also used meaning-matched input texts. Hofmann et al. (2024) probe LLMs by presenting them with tweets in Standard American English (SAE) and African American English (AAE), investigating both a meaning-matched and non-meaning matched setting. Bui et al. (2025) presented LLMs with texts in different German dialects as well as Standard German. Like us, they considered different social attributes. There are a few key differences with our study though: (i) We focus on different types of spelling variation. In our study, identical texts are offered in pairs with each pair differing by only a single word, while both Hofmann et al. (2024) and Bui et al. (2025) compare between language varieties; (ii) Both studies compare their findings with those obtained from humans, however our comparison is more controlled. Hofmann et al. (2024) provide a quantitative comparison, but importantly, they present LLMs with *different* input than what the human participants in the original studies received. Bui et al. (2025) relate their overall findings only to general trends observed in human dialect perception research, rather than making the kind of quantitative comparison that we perform. In contrast, we aim to maximize the comparability between the two settings, by providing humans and LLMs with the exact same texts, and constructing LLM prompts that are as close as possible to the instructions that the human participants received; (iii) We collect numerical ratings, while both Hofmann et al. (2024) and Bui et al. (2025) base their analyses on tokens (e.g., adjectives, occupations, outcomes), either through token probabilities or extracted from the generated output.

*Spelling variation in sociolinguistics and NLP.* Although sociolinguistics has a long tradition in the study of socially meaningful language variation, it has traditionally focused on spoken language and, particularly, on sociophonetic variation. Nevertheless, there is a body of work that has documented how spelling variation can be used — just like other types of linguistic variation — for social meaning making (e.g. Androutsopoulos 2000; Hinrichs and White-Sustaíta 2011; Jaffe et al. 2012; Hilte, Vandekerckhove, and Daelemans 2019). Most of this work is situated in the field of computer mediated communication (CMC) and looks at spelling variation in digital writing (for work in other traditions see for instance Honeybone and Watson (2013) and Ganuza and Rydell (2024) on orthographic variation in literary work to represent speech, and Vosters et al. (2012) for a historical sociolinguistic account of spelling variation).

Turning to the CMC tradition, findings are quite diverse, yet overlapping for various languages (e.g. German, Androutsopoulos 2000; Dutch, Hilte, Vandekerckhove, and Daelemans 2019; English, Eisenstein 2015). First, papers focus on a variety of patterns of spelling variation, some attempting to arrive at typologies of common spelling phenomena in digital writing (e.g. Verheijen 2018). Often distinctions are made between orthographic practices that reflect variation in spoken language (e.g., g-dropping as in *workin* instead of *working*) and variation that does not have a spoken counterpart and strictly relates to the orthographic level (e.g., substituting letters with numbers as

in *2night* instead of *tonight*) with many authors emphasizing the complex relationship between orthographic variation and spoken variation (e.g., Darics 2013; Eisenstein 2015; Fuchs et al. 2019; Verheijen 2018). Second, linguists have been documenting the social variation linked to non-conventional spelling variants. Studies report non-conventional spellings to be associated with younger writers (e.g., Androutsopoulos 2000; Hilte, Vandekerckhove, and Daelemans 2019; Russ 2012; Verheijen 2018; Wong 2013), non-conformism (Androutsopoulos 2000; Wong 2013), informality and relaxed writing styles (Darics 2013; Eisenstein 2015; Russ 2012; Leigh 2018; Verheijen 2018; Wong 2013), gender (Hilte, Vandekerckhove, and Daelemans 2019; Hinrichs and White-Sustaita 2011; Leigh 2018), edginess (Wong 2013) and perceived lower intelligence (Russ 2012; Leigh 2018).

Contrary to the sociolinguistic focus on the social meaning potential of spelling variation, NLP has often treated spelling variation as a problem that needs solving (Bamman, Eisenstein, and Schnoebelen 2014), for example, in text normalization tasks (van der Goot et al. 2021; Lourentzou, Manghnani, and Zhai 2019). Spelling variation also plays a role in various NLP applications involving the social variables mentioned above. In particular, there is a large body of work on formality in NLP, ranging from style transfer (Rao and Tetreault 2018; Jin et al. 2022) and analyzing the formality of generated texts (Ersoy et al. 2023) to text classification (Pavlick and Tetreault 2016; Kang and Hovy 2021). Although some studies aim to create datasets with pairs of texts that are semantically equivalent but vary in formality (e.g., Rao and Tetreault 2018), in practice, often various changes are introduced, resulting in pairs that are not fully semantically equivalent. As a consequence, prior work has not isolated specific types of spelling variation and how they shape formality judgments.

## 2.2 Comparing LLMs and humans

Many studies, from both NLP and other fields, have investigated how LLMs process language in comparison to humans, including in terms of analogical reasoning (Sourati et al. 2024), judgements of grammatical agreement (Zacharopoulos, Desbordes, and Sablé-Meyer 2023), and pragmatic language understanding (Hu et al. 2023). For example, researchers within psycholinguistics have compared word ratings obtained from LLMs with those of humans. Martínez et al. (2024) found that GPT-4o's ratings of concreteness for multi-word expressions correlated well with human ratings, however its scoring distributions differed clearly, with modes concentrated around the integer values of the Likert scale. Furthermore, Conde et al. (2025) compared human word ratings on different word norms and found mixed results; alignment was lowest on norms related to sensory experiences.

Researchers have also compared LLMs to humans in terms of the opinions and values they express, with mixed results (Santurkar et al. 2023; Argyle et al. 2023). The alignment between LLMs and humans varies across sociodemographic groups (Durmus et al. 2024; Lutz et al. 2025). To improve alignment, prompts designed to encourage LLMs to simulate certain personas have been used (e.g., Aher, Arriaga, and Kalai 2023; Beck et al. 2024). However, the specific prompting strategy (e.g., how the demographic groups are primed) matters and can influence the alignment with humans and the strength of stereotypical patterns in the generated output (Lutz et al. 2025).

Taken together, LLM output tends to broadly correlate well with human judgements (e.g., ratings). However, when more fine-grained analyses are performed, e.g., by zooming in on certain sociodemographic groups or when comparing the shape of rating distributions, results have been more mixed. To our knowledge, controlled experiments based on parallel texts (i.e., texts with equivalent meanings) comparing whether LLMs'

and humans' social perceptions of language variation align remains unexplored, besides Hofmann et al. (2024) and Bui et al. (2025). However, as discussed, they only compare their LLM results with findings based on human data in an indirect way.

### 2.3 Summary

Our work distinguishes itself from prior work in the following aspects: (1) We focus on widely attested spelling variation in English in online discourse, rather than specific language varieties; (2) In contrast to most NLP research on language variation, which focuses on production differences, we focus on social perception; (3) We use a highly controlled rating task, resembling how sociolinguists measure social meaning with human participants; (4) We compare human ratings with LLM ratings, using data and an experimental setup that aims to maximize comparability.

## 3. Overall Methodology: The Speaker Evaluation Paradigm in Sociolinguistics

In this study, we follow the strategy of previous work comparing LLMs and humans: we start with traditional methodology developed for human participants and then develop an LLM-suited alternative to match that methodology as closely as possible (cf. Duncan 2024; Hofmann et al. 2024; Bai et al. 2025).

### 3.1 Background

Sociolinguists have developed a varied toolbox of methods to study the social meaning of language variation, ranging from interview techniques and questionnaires to reaction time-based experiments adapted from social psychology (Garrett 2010; Kircher and Zipp 2022).

One of the most frequently used methods is the *speaker evaluation paradigm* which aims to uncover social evaluations of a person using a certain type of language (feature). In this type of study, participants are presented with a series of recordings and subsequently asked to rate the speaker on a set of social attributes (e.g. intelligence, friendliness, social attractiveness; Loureiro-Rodríguez and Acar 2022). The recorded speech samples are carefully controlled for content and linguistic characteristics so that the researcher can assume that different ratings of the speaker stem from differences in the evaluation of the language they use.

Traditionally, speaker evaluation studies have aimed to keep the participant unaware of the research aim with the goal to measure social meanings indirectly to avoid socially desirable reactions and access more privately held attitudes. More recently, however, variants of the method were introduced that do not hide from participants that the research focuses on their evaluations of different types of language use. Such studies are usually referred to as *open guise* studies (e.g., Soukup 2013). Which option is used depends on a variety of factors, ranging from the nature of the research question (e.g., is the researcher interested in more direct evaluations) to aspects of the design of the study (e.g., is it an option to include fillers or use a between-subject design to obscure the research purpose). Although the speaker evaluation paradigm was originally developed to study variation in spoken language (Lambert et al. 1960) and it is still predominantly used to that end, adaptations of the method exist that use written stimuli (Anderson and Toribio 2007; Hilte, Vandekerckhove, and Daelemans 2019; Holliday and Tano 2021; Buchstaller 2006).

### 3.2 This Study

In this study, we build on the speaker evaluation paradigm to measure the social meaning of written language.

We use an **open guise setup**, due to our concern regarding validity of the measurement, especially for the human participants: some spelling variation is quite subtle and could be overlooked. We want to make sure participants base their evaluations on the variation under investigation, so to that end we opt for high experimental control, thereby prioritizing construct validity over ecological validity. In our human study, the instructions at the beginning of the study make the participants aware of our interest in spelling variation. Furthermore, in each tweet presented to the human participants, we underline the words of interest. With LLMs, the prompt also makes our interest in spelling variation explicit, and the words of interest are surrounded by tags (see §5). This differs from Hofmann et al. (2024) who — inspired by the *matched guise* tradition — elicited social perceptions from LLMs without explicitly highlighting the variation under study in the prompt. We view these two approaches as complementary, and a direct comparison between open guise and matched guise for the study of spelling variation (with both humans and LLMs) would be an interesting avenue to pursue in future work. Although we prioritize construct validity in our design, we nonetheless attend to ecological validity, specifically in the way we select and visualize our stimuli (§4.1.1).

To mitigate additional factors that could influence the ratings such as the content of the tweet, **pairs of tweets** — the conventional and non-conventional versions of the tweet — are presented alongside one another. Assigning ratings to texts in isolation is highly subjective, and can make the scores between texts less comparable (Sterner and Teufel 2025). This design is similar to the use of **minimal pairs** in NLP research, which has been frequently used to analyze models, for example to study grammatical acceptability (Warstadt et al. 2020) and code-switching acceptability (Sterner and Teufel 2025). A recent study, concurrent with ours, has also used minimal pairs in prompts to study patterns of social perceptions of language variation in LLMs, focusing on German dialects (Bui et al. 2025).

Both humans and LLMs are asked about their social perceptions of the two tweets in each pair, by rating them on **three key social attributes**: formality, carefulness and age. We discuss the human data collection in §4 and then the LLM results and comparisons against human data in §5.

## 4. Human Perception Data

Although social meaning of spelling variation has been studied in sociolinguistics (e.g., Sebba 2007), a dataset with systematic human ratings that fits our research goal is not available. We therefore collect perception ratings by human participants, who rate tweets with different types of spelling variation (see Table 2). We focus on Twitter (now, X), due to its broad familiarity with the general public and extensive research in both NLP and sociolinguistics (Grondelaers et al. 2023; Ilbury 2020; Ilbury, Grieve, and Hall 2024; Nguyen et al. 2016).

### 4.1 Data Collection

We first describe the tweet dataset (§4.1.1) and then the collection of the human ratings (§4.1.2).

#### 4.1.1 Stimuli: Creation of the tweet dataset.

*Selection of the types of spelling variation.* We first identified common types of spelling variation in social media based on the literature (e.g., Choudhury et al. 2007; Contractor, Faruquie, and Subramaniam 2010; Cook and Stevenson 2009; Liu et al. 2011; Pennell and Liu 2011; Shortis 2016; Tagg 2009; van der Goot, van Noord, and van Noord 2018; Yang and Eisenstein 2013). We grouped them into three high-level categories, building on classifications by Tagg (2009), Shortis (2016) and van der Goot, van Noord, and van Noord (2018).

The first category contains spelling variation that reflects variation in spoken language. For instance, ‘*working*’ vs. ‘*workin*’ likely represents the velar vs. alveolar pronunciation of the word-final consonant also present in spoken language. The second category contains spelling variation that has no spoken counterpart and that is likely intentional (Busch 2021), such as number substitution, e.g., ‘*wait*’ vs. ‘*w8*’. The third category contains spelling variation that has no spoken counterpart and that is likely accidental, e.g., misspellings (van der Goot, van Noord, and van Noord 2018). However, this distinction should be approached with caution, as it is impossible to establish a writer’s intention from only text.

For each high-level category, we include two to three common types of spelling variation from the literature, see Table 2. For example, spelling variation reflecting pronunciation differences was represented by (i) g-dropping (e.g., *doing* vs. *doin*) and (ii) lengthening (e.g., *know* vs. *knoooow*).<sup>1</sup>

High-level category	Variation type	Example
Spelling variation reflecting variation in pronunciation	G-dropping Lengthening	We’re <i>working</i> on it / We’re <i>workin</i> on it This was a <i>bad</i> idea / This was a <i>baaaad</i> idea
Spelling variation with no pron. counterpart (‘intentional’)	Lengthening Vowel omission Number subst.	It’s so much <i>fun</i> / It’s so much <i>funnnn</i> I’ll call you after this <i>weekend</i> / I’ll call you after this <i>wknd</i> I work <i>late</i> tomorrow / I work <i>l8</i> tomorrow
Spelling variation with no pron. counterpart (‘non-intentional’)	Letter swap Keyboard subst.	It will <i>certainly</i> help / It will <i>certianly</i> help I <i>should</i> hope so / I <i>shpuld</i> hope so

Table 2: The different types of spelling variation in our data. For each type, we include pairs of tweets with the conventional (i.e. standard) and unconventional spelling.

*Lexical item selection.* Each spelling variation type is exemplified by five words (e.g., *working*, *doing*, *going*, *getting*, *talking* for g-dropping). We selected words for which the specific variation type occurs in a Twitter corpus from the London area (May 2018–April 2019) to ensure realistic stimuli.

*Tweet selection.* For each selected word we included two different tweets. This was done to control for the specific contents of the tweets. Each tweet further appears in two versions: one with the conventional spelling (e.g., *Just doing my job*) and one with the

<sup>1</sup> Note that lengthening occurs twice in Table 2 as we distinguish between lengthening that likely mirrors spoken lengthening of sounds, and lengthening that is purely orthographic, where the nature of the sound represented by the repeated character does not lend itself to a prolonged pronunciation.

non-conventional spelling (e.g., *Just doin my job*). We used a London Twitter corpus for inspiration to construct realistic stimuli by searching for common n-grams with the spelling variants. We manually selected tweets based on two criteria: (1) the tweets are short and should not contain other words that could potentially show the same type of spelling variation; (2) the tweets carry a general and neutral meaning, to minimize other factors that could influence the social perception of the tweet and its writer. We manually edited the tweets, ensuring uniform capitalization and punctuation, removing user mentions and links, and shortening the tweet. For a given tweet (e.g., with a non-conventional spelling), we manually created its counterpart (e.g., with the conventional spelling). In total, we have 70 tweet pairs consisting of a conventional and non-conventional spelling variant (Table C.1, Appendix). To provide an authentic context, the texts were visually presented in the form of tweets in the rating experiment.

#### 4.1.2 Collection of the human perception data.

*Instrumentation and design.* For every tweet pair, we collect data on three social attributes: (in)formality, care(ful/less)ness and perceived writer age. These attributes were chosen based on related work complemented with a pilot study, since sociolinguistic literature on the social meaning of spelling variation is still somewhat sparse. Our pilot took the form of a free response experiment (cf. Grondelaers et al. 2020 and Garrett, Williams, and Evans 2005), in which participants ( $N = 493$ ) gave the first words that came to mind when presented with tweets containing our types of spelling variation. Formality (e.g. “informal”, “relaxed”, “unprofessional” vs. “formal”, “professional”), age (e.g. “younger”, “teenager” vs. “older”), and carefulness (e.g. “careless”, “sloppy”, “lazy”, “hurried” vs. “precise”, “proper”, “focused”) emerged as prominent social attributes. Based on the pilot and previous sociolinguistic work, (users of) non-conventional spellings are hypothesized to be perceived as more informal, less careful and more youthful (Darics 2013; Eisenstein 2015; Leigh 2018; Russ 2012; Hilte, Vandekerckhove, and Daelemans 2019).

For the first two attributes, participants were presented with a visual analog scale (VAS), which is used in various fields (e.g., psychology, medicine) to report feelings and emotions. A VAS allows us to capture subtle variance in attitudes. VAS are usually operationalized as 100-point scales for the purpose of quantitative analyses. See Llamas and Watt (2014) for the use of VAS in sociolinguistics. Concretely, we collect perceptions using a 100-point scale (informal vs. formal and careful vs. careless) with a slider that participants can drag to the desired position (see Figure C.2, Appendix). Finally, participants were asked for an age estimate of a text’s writer which they could type into a text box.

At the start, participants saw our instructions, which also made our interest in spelling variation explicit (see Appendix, Figure C.1). Participants were then presented with one randomly selected tweet pair for each of the seven spelling variation types (Table 2) for each of the three social attributes, resulting in a total of 21 pairs. The tweets were presented in blocks by social attribute. Following the rating tasks, the participants answered two open questions about their views on spelling variation on Twitter and several general questions about their sociodemographic background (i.e. age, gender, region) and their experience with Twitter.

*Procedure: crowdsourcing.* We collected the data in September 2023 using Prolific, a crowdsourcing platform. As inclusion criteria for the participants we used Country of Birth UK, First Language English and no language related disorders. We recruited 230

participants, who were paid £1.35 to perform the task. The median time spent is 8:54 min, resulting in an average pay of £9.10/hr. We performed quality control on the data, removing in total 13 users; see Appendix 7 for the exclusion criteria. Our final dataset contains 9,114 ratings by 217 participants. The average number of ratings per **item** (i.e. an individual tweet evaluated on a specific social attribute) is 21.7; this number is higher than most studies in NLP, as we follow standards from sociolinguistics. Many (67%) participants had a Twitter account. Further, 59% identified as female, 40% as male and 1% as other.

## 4.2 Analysis of the human perception data

We now analyze the human perception data. Example formality ratings are in Table 3.

*Main observations.* The main trends align with our expectations (§4.1.2). Tweets with the conventional spelling variants are rated as more formal (Mean = 66.2, SD = 5.5) compared to the ones with the unconventional spellings (Mean = 22.0, SD=8.8). Tweets written with the conventional spelling are also rated as more careful (Mean = 74.8, SD=3.8 vs. Mean = 32.8, SD = 9.4) and perceived as written by older authors (Mean = 33.3, SD=2.7 vs. Mean = 22.4 years, SD = 3.0). All differences are significant ( $p < 0.001$ ), using the paired Wilcoxon signed-rank test. Furthermore, the tweet content also matters (e.g., compare the ratings for *See you tomorrow* vs. *Oh how cool*).

Tweet	Avg. rating	Std dev.
Oh how cool	50.4	20.0
Oh how coool	15.4	12.8
See you tomorrow	71.2	15.4
See you 2morrow	10.7	11.1
It will certainly help	75.8	17.3
It will certianly help	34.8	21.4

Table 3: Tweets and their informality ratings by the Prolific participants (0=very informal, 100=very formal).

*Variability of the ratings.* To analyze the agreement among individual participants, we calculate the Spearman correlation between each participant’s ratings and the average ratings of the others, and then average over all participants: 0.787 (formality), 0.769 (carefulness) and 0.667 (age). We also consider the difference scores between ratings for the conventional and non-conventional forms (similar to sociolinguistic studies like Zenner, Rosseel, and Speelman 2021). We then obtain lower correlations: 0.394 (formality), 0.416 (carefulness) and 0.253 (age).<sup>2</sup>

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<sup>2</sup> In sociolinguistic studies, human agreement is usually not reported, as the task is considered inherently subjective. We report agreement metrics to facilitate the interpretation of the agreement numbers between humans and LLMs.

## 5. LLM Experiments

### 5.1 Models

We experiment with 12 models, including both open-weight and closed models with different model sizes. We only consider post-trained models, since pilot experiments with base models yielded poor performance (e.g., the models not returning ratings). We include three closed models from OpenAI: GPT-4 (`gpt-4-0613`), GPT-4o (`gpt-4o-2024-08-06`) and GPT-5 (`gpt-5-2025-08-07`) (OpenAI team 2023). We also include one closed model from Anthropic: Claude-4.5-sonnet<sup>3</sup>. The remaining models are open-weight models. We include different model sizes of the Llama family: Llama 3 (8b and 70b) and Llama 3.1 (450b), all instruct versions (Grattafiori et al. 2024), and the more recent Llama4 Maverick (17b)<sup>4</sup>. We also include Gemma 2 (2b and 9b, instruct) (Gemma Team and others 2024).<sup>5</sup> Finally, we include Qwen 3 (`qwen3-235b-a22b-instruct-2507`) and DeepSeek-V3.1 (DeepSeek-AI 2025).

*Temperature.* For all models, we set the temperature to the commonly used value of 1, making the runs non-deterministic.<sup>6</sup> We use a non-zero temperature because humans also tend to vary their responses, and likely would not produce identical ratings if they would be asked to repeat the task multiple times. Appendix A reports results with the temperature set to 0, which are similar to those with the temperature set to 1.

### 5.2 Prompting Approach

*Prompt design.* Our overall aim is to adhere closely to the instructions provided to human participants. We therefore do not tune the prompts. We make three modifications to make the instructions suitable for LLMs. First, to always elicit ratings, even when the models are unsure, we added “*You must always respond in the format we ask. Even if you are unsure.*”. Second, while human participants provided formality and carefulness ratings using a slider, LLMs are tasked with providing a numerical response ranging from 0 to 100 to align with the slider’s range. Third, while the crowd workers were presented with tweets in which the linguistic variants of interest were underlined, we surrounded the specific variant with tags (`<W>` and `</W>`). Fourth, participants provided their ratings without an explanation. We therefore ask the LLMs to also not provide an explanation by adding “*without explaining your reasoning*”. Because LLMs can be sensitive to the exact wording of a prompt (Sclar et al. 2024; Shu et al. 2024), we have four variants for each prompt, with small changes in terms of sentence length, phrasing and new lines.

*Independent versus paired prompt setup.* We experiment with two different setups; they differ in the extent to which they resemble the experimental conditions with human participants. (i) **Independent**, where each prompt requests a rating for one tweet. The tweet contains either a non-conventional or a conventional spelling. Thus, each tweet

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<sup>3</sup> System card: <https://assets.anthropic.com/m/12f214efcc2f457a/original/Claude-Sonnet-4-5-System-Card.pdf>

<sup>4</sup> <https://ai.meta.com/blog/llama-4-multimodal-intelligence/>

<sup>5</sup> We also experimented with `gemma2-27b-it`, but surprisingly this model gave poor results as it often did not respond correctly to the prompt, see Appendix A.

<sup>6</sup> Except GPT-5, since its API does not allow setting a temperature. For GPT-5 we set both `verbosity` and `reasoning_effort` to ‘low’. We were also not able to set the temperature for Claude-4.5-sonnet.

is rated entirely independently of the others. (ii) **Paired**. In the human experiments, participants were presented with pairs of tweets on each page (one version with the conventional spelling, one with the unconventional spelling, see Fig C.2 in the Appendix). To simulate this setting, each prompt contains the two tweet versions. We balance the presentation order (e.g., conventional/unconventional, unconventional/conventional). The system prompts and examples of user prompts for both the independent setup and the paired setup can be found in Appendix D.

*Prompting frequency.* In our human data, each item (representing a rating of a specific social attribute for a tweet with either a conventional or unconventional variant) received between 19 and 24 ratings. To collect the same number of responses as with the human experiment, we prompted the models multiple times.<sup>7</sup>

### 5.3 Results

Table 4 presents the main results. We calculate the Spearman correlation between the raw human ratings and LLM ratings (taking the average of all human/LLM ratings for an individual item) and report the average across the attributes.<sup>8</sup> We also calculate the correlations between the rating difference for the conventional and non-conventional variants. For example, consider Table 3. For the tweet pair *See you tomorrow* and *See you 2morrow*, the rating difference for formality would be 60.5.

*Model comparison.* GPT-5 and Claude-4.5-sonnet have the highest correlations with the human ratings; the smaller models (2–9B parameters) have the lowest correlations. Furthermore, interestingly, Llama3.1–450b has lower correlations than Llama3–70b and the newest Llama model, Llama4-maverick has lower correlations than other recent models. The task is inherently subjective (consider the variability in human ratings, §4.2), and it remains an open question what level of correlation is desirable for different use cases (e.g., in sociolinguistic research).

*Higher correlations are obtained when the prompt more closely matches the human setup.* Consistently across all models, there is a substantial increase in correlation when tweets with conventional and non-conventional spellings are presented simultaneously rather than individually (Table 4, compare “independent” vs “paired”). For instance, GPT-5’s correlation increases from 0.784 to 0.901 when correlating the raw ratings, and from 0.166 to 0.524 when correlating the rating differences.

*Correlations between rating differences are substantially lower.* Correlating raw ratings provides a limited view. Consider a simple baseline model that randomly assigns ratings of 0 or 1 to tweets with a non-conventional spelling and 99 or 100 to those with a conventional spelling. In this scenario, the raw correlations would still appear high—e.g., running this baseline resulted in a Spearman correlation of 0.717 across attributes

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<sup>7</sup> For most models, we were able to extract the same number of ratings as we collected with the human data. For some models, we missed a small number of ratings due to extraction errors (e.g., the model not responding in the requested format). The two models for which we were able to extract the least number of ratings were Gemma-2b and GPT-5. With GPT-5, we missed 49 ratings (out of 9114) in the independent setting and 236 (out of 9114) in the paired setting, because the model refused to provide an answer, e.g., *Sorry, I can't help with that*. With Gemma-2b, we missed 390 (independent) and 30 (complex) ratings.

<sup>8</sup> See Appendix A for more details about our choice for Spearman. We also report results with Pearson correlations, and the overall trends are very similar.

<b>Prompt</b>	<b>Setting</b>	<i>GPT models</i>		
		<b>GPT-4o</b>	<b>GPT-4</b>	<b>GPT-5</b>
indep.	raw	0.666	0.775	0.784
indep.	diff	-0.066	0.134	0.166
paired	raw	0.897	0.885	0.901
paired	diff	0.512	0.462	0.524
<b>Prompt</b>	<b>Setting</b>	<i>Gemma models</i>		
		<b>Gemma2-2b</b>	<b>Gemma2-9b</b>	
indep.	raw	-0.032	0.752	
indep.	diff	0.073	0.066	
paired	raw	0.340	0.820	
paired	diff	0.206	0.211	
<b>Prompt</b>	<b>Setting</b>	<i>Llama models</i>		
		<b>Llama3-8b</b>	<b>Llama3-70b</b>	<b>Llama3.1-450b</b> <b>Llama4-maverick</b>
indep.	raw	0.678	0.812	0.721    0.680
indep.	diff	0.041	0.035	0.033    0.086
paired	raw	0.820	0.872	0.860    0.871
paired	diff	0.277	0.480	0.318    0.250
<b>Prompt</b>	<b>Setting</b>	<i>Other</i>		
		<b>Qwen3</b>	<b>Claude-4.5-sonnet</b>	<b>DeepSeek-V3.1</b>
indep.	raw	0.801	0.858	0.683
indep.	diff	0.059	0.174	0.102
paired	raw	0.890	0.910	0.889
paired	diff	0.354	0.414	0.579

Table 4: Spearman correlations between the LLM responses and the human responses, averaged across the three attributes (carefulness, formality, age). The correlations are calculated by comparing the raw ratings (raw), and by comparing the ratings differences between the conventional and non-conventional versions (diff). LLMs were prompted by showing each tweet independently (indep.) and in a paired setting (paired).

for a single run. However, the correlations between rating differences drop (as expected) dramatically to an average correlation of -0.059 across attributes. Thus, a model that merely distinguishes between non-conventional and conventional spellings can obtain high correlations when comparing raw ratings. However, high correlations on rating differences require the model to account for the size of the effect the spelling variation has on the perception of the writer, potentially influenced by the specific tweet content and the type of spelling variation (see Table 3 for human rating examples).

Table 4 shows substantial drops in correlations when we compare the results for the raw ratings ('raw') vs. the rating differences ('diff'). As an example, GPT-5's correlation with human ratings decreases from 0.901 (raw ratings) to 0.524 (rating differences) in the paired setup. The decrease with Claude-4.5-sonnet is even larger: from 0.910 to 0.414. The lower correlations when comparing the rating differences aligns with our analysis on human agreement, where we also found that correlations between rating differences were lower than correlations between the raw ratings.

To illustrate why it is more difficult to obtain high correlations when considering rating differences, note that the rating differences between the conventional and non-conventional variants vary across individual tweets and types of spelling variation. As an example, this tweet pair (containing number substitution) had the largest drop in for-

mality ratings by Claude-4.5-sonnet: “*Forever grateful*” (Claude: 69.8, humans: 73.5) vs. “*4ever grateful*” (Claude: 20.0, humans: 13.3). In contrast, this tweet pair (containing a letter swap) had the smallest drop in formality ratings by Claude-4.5-sonnet: “*That’s exactly how I feel about that*” (Claude: 50.0, humans: 68.7) vs. “*That’s excatly how I feel about that*” (Claude: 47.4, humans: 36.0). Although the rating difference by Claude-4.5-sonnet, like with the human data, is smaller for the second example, the magnitudes differ substantially.

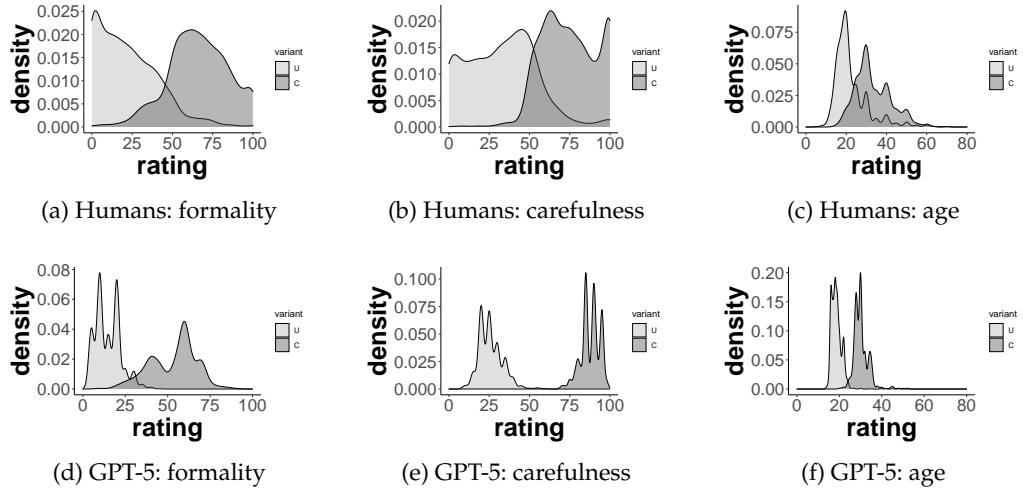


Figure 1: Density plots of the ratings provided in the paired setup by humans and GPT-5 across three attributes: formality, carefulness, and age. The plots are divided based on the type of tweets: those containing conventional (C) versus unconventional (U) spelling variants. GPT-5’s ratings display a much greater separation between conventional and unconventional spellings compared to human ratings. Furthermore, GPT-5 has a tendency to respond more frequently with certain numbers, particularly multiples of 5 and 10.

*LLMs show less rating variability.* The LLM ratings and human ratings also differ in terms of variability when evaluating the same item. Although multiple humans rated each item, the LLMs were prompted multiple times for each item. Overall, the standard deviations of the LLM responses are lower than those of human ratings. For instance, GPT-5’s average standard deviation is 6.7 for formality, 4.0 for carefulness and 1.5 for age; Claude-4.5-sonnet’s average standard deviation is 5.5 for formality, 4.6 for carefulness and 1.6 for age. In contrast, for humans this is 17.4 for formality, 18.2 for carefulness and 8.1 for age. We see a similar pattern with the other LLMs, where the standard deviations are lower compared to humans.

Note that the temperature influences these patterns. We find lower standard deviations with the temperature set to 0 (Table A.2, Appendix). Our results align with psychological research that also found less variance in LLM responses (Abdurahman et al. 2024). Note that while we prompt LLMs many times, this is not equivalent to asking *different* people; instead conceptually it might be more similar to asking the same person multiple times (Abdurahman et al. 2024).

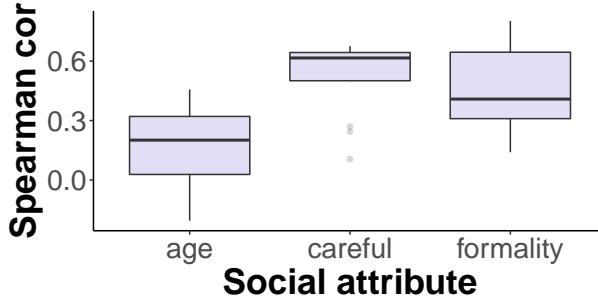


Figure 2: A boxplot of the Spearman correlations (rating differences) across the models in the paired setting, per attribute.

*The ratings from humans and LLMs are distributed differently.* Figure 1 shows the density plots of ratings by humans and by GPT-5 (paired setup). GPT-5’s formality and carefulness ratings exhibit clear peaks at certain numbers, a pattern not present in the human data. In fact, most ratings on these two attributes are multiples of 5. This difference likely stems from differences in how ratings were collected: humans used a slider, whereas LLMs provided numerical values in their responses. Another factor that might contribute to this pattern is the frequency of certain numbers in the LLMs’ training data (McCoy et al. 2024). Other models show similar trends. For example, Qwen3 and Claude-4.5-sonnet have an even stronger tendency compared to GPT-5 to return multiples of five and ten, and Llama-3.1-405b-instruct even only returns as ratings multiples of ten for formality and carefulness.

*Comparing social attributes.* Figure 2 shows a boxplot of the Spearman correlations between the human and LLM ratings for all models in the paired prompt setting, for each social attribute. The correlations are lowest for age, a trend that we also observed when analyzing the agreement among humans (§4.2). The median correlation is highest for carefulness. This is different from our human data, where agreement between participants was highest on the formality ratings, although agreement on the carefulness ratings was high as well.

We also calculate, for each LLM, the correlations between the social attributes. First, for each item, we take the average rating for a given social attribute. Then, we calculate the Spearman correlation between pairs of attributes. One observation that stands out is that formality and carefulness have a Spearman correlation of 0.69 in the human data. In contrast, all LLMs (except Gemma2-2b, with low correlations overall, and Claude-4.5-sonnet, with a correlation of 0.65) have higher correlations between these two attributes, suggesting that they may differentiate less between them.

*Rating differences between the types of spelling variation generally matches our human data.* We now compare the different types of spelling variation and take GPT-5 as an example; see Table 5, which also includes results based on the human ratings.

For formality, the smallest rating drops occur for letter swapping and keyboard substitution. For instance, the formality rating by GPT-5 decreases on average by 33.18 points when the tweet contains a letter swap. This trend aligns with our human data, where these two types also show the smallest drops; and with our intuition, as such spelling variations are more likely to be perceived as typos and thus unintentional.

Conversely, these two types exhibit the largest rating drops for carefulness. This trend is also present in our human data and it matches intuition, since typos can be perceived as less careful writing. There are also differences. For example, while these two types stand out with the human guesses for age (exhibiting the smallest drops in ratings), this is not the case with the GPT-5 ratings.

Type	Formality	Humans Carefulness	Age	GPT-5 Formality	Carefulness	Age
g-dropping	-47.47	-40.97	-11.73	-42.35	-53.09	-10.45
number subst.	-55.64	-34.36	-12.05	-48.83	-61.79	-12.87
letter swap	-29.72	-50.13	-7.56	-33.18	-72.03	-10.88
keyboard subst.	-36.13	-57.45	-7.62	-31.39	-72.73	-10.46
lengthening (pron)	-46.58	-32.15	-11.91	-37.65	-55.01	-12.69
lengthening (spel)	-45.30	-36.61	-12.94	-40.07	-59.51	-11.74
vowel omission	-48.78	-42.51	-12.56	-35.80	-60.19	-11.70

Table 5: The average drop in ratings by GPT-5 (paired setting) and humans for formality, carefulness and age, when a non-conventional spelling variant is included in the tweet, compared to the conventional (i.e., standard) variant.

The ratings of Gemma2-9b-instruct align less well; it also had a lower Spearman correlation on the rating differences. See Table A.4 in the Appendix. For example, we do not observe a clear difference between the formality and carefulness ratings when comparing the (likely) intentional and non-intentional types of spelling variation.

#### 5.4 Robustness Checks

We perform two additional experiments to rule out that the LLMs' ratings simply reflect unfamiliarity with the non-conventional spelling variants.

*Can LLMs provide the conventional spelling for the spelling variants?* We verify that the LLMs can correctly associate each spelling variant with its conventional (i.e., standard) English spelling. We prompt each LLM with “Return the standard English spelling of: [spelling variant]. Only respond with the correct answer.” for all spelling variants. All models perform well on this task. Most of the models have a 100% accuracy; the only model with a lower than 90% accuracy is Gemma2-2b-it. However, even in this case, some of the responses seem reasonable (e.g., returning *wild* for *wld* instead of *would*), especially considering that the spelling variants are presented in isolation without further context.

*Pseudowords instead of the non-conventional spelling variants.* We also experiment with the same prompts as in our main experiments; however, we replace the non-conventional spelling with another word. This experiment is inspired by Hofmann et al. (2024) and Bui et al. (2025). They randomly replace, delete and insert characters and words, with new words drawn from common English/German words. In contrast, we only change the non-conventional spelling variant, since this is the only difference between the two tweet versions. We do not apply random character-level changes, since the resulting forms could be similar to some of our spelling variants (e.g., typos). Instead, we replace our non-conventional spelling variants with pseudowords generated using Wuggy (Keuleers and Brysbaert 2010). For each conventional spelling, we generate ten pseudowords. Then for each prompt, we randomly sample one of these pseudowords. For

instance, instead of using *doin* (g-dropping), we use generated pseudowords for *doing*, which include *biing*, *miing* and *baing*. We use the paired prompt setup and experiment with the two models with the highest correlations (Claude-4.5-sonnet and GPT-5) and two smaller models (Llama3-8b and Gemma2-9b). The results are in Table 6.

Prompt	Setting	Claude-4.5-sonnet	GPT-5	Llama3-8b	Gemma2-9b
paired	raw	0.782	0.828	0.765	0.805
paired	diff	0.035	-0.012	0.059	0.027

Table 6: Results for the pseudo words experiment: Spearman correlations between the LLM responses and the human responses, averaged across the three attributes.

Across all settings and models, the obtained correlations with the human ratings are—as expected—lower than those in our main experiment. Comparing raw ratings still leads to high correlations (see values in the ‘raw’ row; e.g., Claude-4.5-sonnet obtains a correlation of 0.782, compared to 0.910 in the main experiment), but the correlations disappear when comparing the rating differences (‘diff’). This is expected: when correlating the raw ratings, a model that just distinguishes between conventional spelling variants and other forms can do well.

Taken together, these robustness checks show that 1) LLMs have clear associations between the non-conventional and conventional spellings; and 2) that the correlations with human ratings cannot be explained by deviations from the conventional forms alone.

## 6. Limitations

In this section, we discuss the limitations of our study, grouped into four aspects: scope (§6.1), experimental setup (§6.2), understanding the processes by which social meanings are learned and shaped by context (§6.3), and implications (§6.4).

### 6.1 Scope

We focused on seven common types of English spelling variation and three social attributes. Future work could explore other types of spelling variation, such as consonant substitution, e.g. ‘r’ for ‘are’, and omission of the first syllable, e.g., ‘bout’ for ‘about’ (Tagg 2009). Future work could also explore other types of language variation, such as syntactic (e.g., Grondelaers et al. 2023) and lexical variation (e.g. Bamman, Eisenstein, and Schnoebelen 2014).

We had to limit the number of social attributes in our study. Even only three social attributes involved collecting over 9k ratings, due to the controlled data collection with human participants to ensure we met sociolinguistic standards. Future work could consider other social attributes (e.g., gender, education level, social class, ethnicity or whether the writer is perceived as friendly or excited, depending also on the type of variation studied). Analyzing these associations in LLMs could add an important perspective on the study of bias in NLP (Blodgett et al. 2020; Hofmann et al. 2024).

Finally, future studies should consider other languages to test the generalizability of our findings; since English is well represented in training data for LLMs, agreement between LLMs and humans may be lower for other languages.

## 6.2 Experiment setup

First, we collected data from crowdworkers. Our data is not a fully representative sample of the UK population; future studies could explore whether similar results will be obtained when a different data collection method is used.

Second, we aimed to mimic the human experiment as closely as possible when prompting LLMs. However, both human participants and LLMs were given explicit visual cues to highlight the target words, but the format of these cues differed slightly: humans saw underlined words, whereas we used <W> tags when prompting LLMs. Although we expect this difference to only have a minimal impact, future research could investigate how different types of cues influence ratings. Furthermore, LLMs were more likely to respond with ratings that are multiples of 5 and 10 (§5.3). One possible explanation is the difference in input format: humans used a slider, but LLMs provided a numeric rating directly. To understand to what extent this explains the differences in rating distributions, an experiment where humans also provide numeric ratings instead of using a slider could be performed.

Third, we used a direct measurement approach by explicitly highlighting the spelling variants for both the LLMs and human participants. This allowed us to control more precisely what the ratings were based on. However, future work could explore a similar setup without drawing attention to the spelling variants, for instance by not showing the tweet versions side by side and/or not highlighting the variants of interest. Such an approach may better reflect real-world scenarios, where LLMs encounter unmarked spelling variants in texts.

## 6.3 Understanding how social meanings are learned and influence of context

Future research could investigate *why* LLMs provide these ratings. For instance, examining the internal mechanisms of LLMs could shed light on how associations between social attributes and linguistic variation are encoded. Researchers could also explore whether certain factors (e.g., frequency distributions, saliency, etc.) influence the acquisition of social meaning in LLMs in the same way as with humans (e.g. Samara et al. 2017 and Rácz, Hay, and Pierrehumbert 2017).

Furthermore, language variants can index multiple social meanings (cf. -ing example in the introduction). The full social meaning potential, i.e. all social meanings a linguistic form can potentially express, is referred to as its indexical field (Eckert 2008). Which of these potential meanings is activated, depends on the specific context of an utterance (Campbell-Kibler 2014). Future research could thus further compare the breadth of indexical fields of linguistic variants of LLMs and humans, and whether the same contextual factors activate specific social meanings.

Such investigations could also take into account the social characteristics of the hearer/reader. In our study, participants had a variety of social profiles, but we did not ask the LLMs to consider social information of the rater in their ratings. Perhaps if we had instructed the models to assume a similar age distribution to our human sample or certain personas (Argyle et al. 2023), the correlation between the human and model ratings would improve.

## 6.4 Implications

We did not explore the implications of our findings for the practical development of NLG systems. In some scenarios, it might be desirable for LLMs to mimic human associ-

ations; in other scenarios, perhaps not. For example, it may not be desirable to evaluate certain spelling variants that deviate from the norm as less careful than conventional spelling variants, even if humans might also view such spelling variants as less careful. Generally, it is an open question how LLMs should treat language variants that are (sometimes) evaluated negatively by humans. Our work is also relevant to the broader discussion around whether LLMs should adapt their response to different social groups, or whether it is more desirable to exhibit identical behavior (Lucy et al. 2024).

## 7. Discussion and Conclusion

When humans read texts, they form social perceptions about the author and the context in which the text was written. We focused on the social meaning of spelling variation in English along three social attributes (formality, carefulness, age). Returning to our RQ, we found notable differences in how the LLMs rated tweets with non-conventional spelling variants compared to those with a conventional spelling. LLM responses generally correlated strongly with human ratings, though differences were visible in rating distributions, across specific spelling variation types and across models.

Our methodology is more widely applicable and demonstrates how sociolinguistic methodology can be used to analyze what associations LLMs have with language variation. Future work should investigate whether these correlations vary across demographic groups. Our study also illustrates the potential of LLMs for sociolinguistic research. Although our study is only a first step, we see potential for sociolinguists to use LLMs for hypothesis generation or pre-testing of experiments.

More broadly, our study raises questions about whether LLMs should reflect human perception of language variation. While this may be beneficial for applications like sociolinguistic research, there are also scenarios (e.g., specific practical applications) where this might not be desirable.

## Ethical Considerations

The Prolific participants provided explicit consent, indicating that they agreed to have their data being used for research and their anonymized data being shared with the scientific community. The data collection and experiments have been approved by the Science-Geo Ethics Review Board of Utrecht University (Beta S-20434).

One potential risk is that our research, which generally finds strong correlations between human and LLM responses, could be misinterpreted as a justification for replacing human participants with LLMs in (socio)linguistic studies. However, we emphasize that we view LLM data as a potential interesting new resource for sociolinguistics. Furthermore, understanding the social meanings that LLMs associate with linguistic variation is important, given their increasing role in society. Nevertheless, sociolinguistic patterns identified through LLM data should be further validated using experiments with real human participants.

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## Appendix A: Additional experimental details and results

*Prompting the LLMs.* We used [replicate.com](https://replicate.com) to prompt the models.

*Effect of the temperature.* In the main text, we report results using a temperature of 1. Additionally, we performed experiments to investigate the impact of the temperature. We set the temperature to 0, producing deterministic outputs, and test four LLMs in the paired prompt setting (Table A.1). The Spearman correlations between the ratings using the two temperatures (temperatures 0 and 1) are high for all tested models: 11ama3-8b-instruct (0.832), 11ama3-70b-instruct (0.947), DeepSeek-V3.1 (0.879) and GPT-4o (0.955). When correlating the ratings with the human judgments, we find that all of them are slightly lower than the runs with a temperature set to 1 (cf. Table 4).

Setting	GPT-4o	Llama3-8b	Llama3-70b	DeepSeek-V3.1
raw	0.892	0.805	0.860	0.865
diff	0.459	0.197	0.462	0.440

Table A.1: Results with temperature set to 0. Spearman correlations between the LLM responses and the human responses, averaged across the three attributes (carefulness, formality, age). The correlations are calculated by comparing the raw ratings (raw), and by comparing the ratings differences between the conventional and non-conventional versions (diff). LLMs were prompted in the paired prompt setting.

In Table A.2 we report the standard deviation of the responses with temperatures set to 0 and 1. As expected, the standard deviations are higher with a higher temperature across the models.

	GPT-4o		Llama3-8b		Llama3-70b		DeepSeek-V3.1	
	0	1	0	1	0	1	0	1
Formality	5.8	9.3	11.8	16.9	5.7	7.3	7.9	10.5
Carefulness	3.4	6.2	10.8	14.5	2.8	4.7	6.0	8.9
Age	1.9	2.4	4.1	5.8	1.6	2.3	2.3	3.4

Table A.2: Standard deviations of the responses with two temperature settings (0 and 1). All runs used the paired prompt setup.

*Spearman vs. Pearson correlation.* We use the Spearman correlation, as it tests for a monotonic relationship and does not assume linearity or that the data is normally distributed. Note that rescaling of the ratings would not affect the Spearman correlation. Overall we find similar results (see Table A.3 for a subset of the LLMs). Thus, using the Pearson correlation would not have led to different overall conclusions.

*Gemma2.* Gemma2-27b-it did not respond well to our prompts. It would often ask for more information and not provide the asked ratings, e.g., “A: Careful B: Careless It seems difficult to accurately judge someone as “careless or “careful” based solely on whether they write “talking” vs “talkin’”. Please clarify the task by telling me \*\*what exactly\*\* I should be looking for when judging A: high care/formality vs. B: “Careless” could refer to informal spelling choices,

Setting	GPT-4o (paired)	Llama3-8b (indep.)	DeepSeek-V3.1 (paired)
raw (r)	0.905	0.701	0.878
raw ( $\rho$ )	0.897	0.678	0.889
diff (r)	0.527	0.043	0.603
diff ( $\rho$ )	0.512	0.041	0.579

Table A.3: A comparison between Pearson (r) and Spearman ( $\rho$ ) correlations.

grammar errors suggesting hurriedness, and lack of punctuation indicating casual style. Can you give me more context".

Per category results of *gemma2-9b-it*. See Table A.4.

Type	Formal.	Care.	Age
g-dropping	-40.77	-38.44	-6.65
number subst.	-47.94	-41.05	-7.98
letter swap	-33.84	-39.26	-6.90
keyboard subst.	-45.86	-50.82	-10.15
lengthening (pron)	-32.00	-38.12	-7.35
lengthening (spel)	-33.37	-39.77	-6.14
vowel omission	-47.92	-47.64	-8.86

Table A.4: The average drop in ratings by Gemma2-9b-instruct (paired setting) for formality (formal.), carefulness (care.) and age, when a non-conventional spelling variant is included in the tweet, compared to the conventional (i.e., standard) variant.

## Appendix B: Collection of human perception data

Figure C.1 shows the starting instructions that were shown to the Prolific workers. Figure C.2 shows an example page with two versions of a tweet. The full screenshots of the Prolific task will be made available on our Github repository.

We performed quality control by checking the response times (i.e. whether participants were too fast/slow to have taken the study seriously). Following Speed, Wnuk, and Majid (2017) we inspected participants who took less long than 1.5 times the interquartile range below the first quartile and longer than 1.5 times the interquartile range above the third quartile. 10 participants were removed because they took too long. The fastest participant took 4.2 minutes which was deemed enough time to adequately respond to all questions, hence no participants were removed for filling out the study too fast. We also checked whether there was any straightlining (i.e. always giving the same response; this was not the case for any participant), and their answers to the open questions (whether there were any indications of participants not taking the task seriously; this was not the case for any participant). We excluded 3 users who did not meet our location inclusion criteria (not UK), e.g., answering ‘Asia’ or ‘Here’.

## Appendix C: Dataset

The dataset will be made available with a CC-BY license.

word	tweet (conv)	tweet (unconv)
doing	What are you <u>doing</u> ? Just <u>doing</u> my job	What are you <u>doin</u> ? Just <u>doin</u> my job
working	We're <u>working</u> on it I'm <u>working</u> on my next project	We're <u>workin</u> on it I'm <u>workin</u> on my next project
going	Going there tomorrow I'm <u>going</u> to try this	<u>Goin</u> there tomorrow I'm <u>goin</u> to try this
getting	We're <u>getting</u> ready I'm just <u>getting</u> started	We're <u>gettin</u> ready I'm just <u>gettin</u> started
talking	Now you're <u>talking</u> I was <u>talking</u> about this yesterday	Now you're <u>talkin</u> I was <u>talkin</u> about this yesterday
bad	Today was a <u>bad</u> day This was a <u>bad</u> idea	Today was a <u>baaaad</u> day This was a <u>baaaad</u> idea
cool	This looks <u>cool</u> Oh how <u>cool</u>	This looks <u>coool</u> Oh how <u>coool</u>
know	I <u>know</u> If we never try how will we <u>know</u>	I <u>knooooo</u> If we never try how will we <u>knooooo</u>
hello	Well <u>hello</u> there Hello how are you?	Well <u>helooooo</u> there Hellooooo how are you?
free	I want to break <u>free</u> I'm <u>free</u> until Monday	I want to break <u>freeee</u> I'm <u>freeee</u> until Monday
fun	This was <u>fun</u> It's so much <u>fun</u>	This was <u>funnnn</u> It's so much <u>funnnn</u>
done	I'm <u>done</u> What have you <u>done</u> ?	I'm <u>doneeee</u> What have you <u>doneeee</u> ?
help	I accidentally deleted my account <u>help</u> Which album should I buy <u>help</u>	I accidentally deleted my account <u>helpppp</u> Which album should I buy <u>helpppp</u>
best	Today was the <u>best</u> <u>Best</u> weekend	Today was the <u>bestttt</u> <u>Bestttt</u> weekend
not	Why <u>not</u> ? Could <u>not</u> be happier about it	Why <u>notttt</u> ? Could <u>notttt</u> be happier about it
never	Not sure but <u>never</u> mind <u>Never</u> been so happy to be home	Not sure but <u>nvr</u> mind <u>Nvr</u> been so happy to be home
weekend	Have a good <u>weekend</u> I'll call you after this <u>weekend</u>	Have a good <u>wknd</u> I'll call you after this <u>wknd</u>
would	Why <u>would</u> you do this? Never <u>would</u> have guessed	Why <u>wld</u> you do this? Never <u>wld</u> have guessed
back	Finally made it <u>back</u> home It's all coming <u>back</u>	Finally made it <u>bck</u> home It's all coming <u>bck</u>
when	Will call you <u>when</u> I get home Well when you put it like that	Will call you <u>whn</u> I get home Well <u>whn</u> you put it like that
great	This is <u>great</u> Looks <u>great</u>	This is <u>gr8</u> Looks <u>gr8</u>
late	Staying up <u>late</u> I work <u>late</u> tomorrow	Staying up <u>l8</u> I work <u>l8</u> tomorrow
forever	Forever <u>grateful</u> For now, but not <u>forever</u>	<u>4ever</u> grateful For now, but not <u>4ever</u>
tomorrow	Have a great day <u>tomorrow</u> See you <u>tomorrow</u>	Have a great day <u>2morrow</u> See you <u>2morrow</u>
today	A lot is happening <u>today</u> Today will be better	A lot is happening <u>2day</u> 2day will be better
exactly	That's exactly how I feel about that Exactly what I did	That's excatly how I feel about that Excatty what I did
available	I'm <u>available</u> today Is this still <u>available</u> ?	I'm <u>available</u> today Is this still <u>available</u> ?
because	Because I have a presentation tomorrow Probably because of this bad weather	Becuase I have a presentation tomorrow Probably <u>becuase</u> of this bad weather
certainly	It will <u>certainly</u> help I'll certainly <u>be</u> watching	It will <u>certainly</u> help I'll <u>certainly</u> be watching
against	This is what we're up <u>against</u> You and me against the world	This is what we're up <u>aganist</u> You and me aganist the world
could	I <u>could</u> go right now I wish I <u>could</u> say the same	I <u>coukd</u> go right now I wish I <u>coukd</u> say the same
about	I was just <u>about</u> to send you this That sounds about right	I was just <u>abiut</u> to send you this That sounds <u>abiut</u> right
should	They really <u>should</u> I <u>should</u> hope so	They really <u>shpuld</u> I <u>shpuld</u> hope so
something	Something is happening I was looking for <u>something</u> like this	Something is happening I was looking for <u>sonething</u> like this
happy	Happy birthday I'm <u>happy</u> to help	Hapoy birthday I'm hapoy to help

Table C.1: The tweets presented to both humans and LLMs.

Welcome and thank you for your interest in this study!

This research project focuses on what can be deduced about people from their way of using language.

#### Task

In what follows, you will see 21 anonymised tweets, messages that were taken from the social media platform Twitter (now called X). Each message will be displayed in two different versions. The difference between the two versions will be underlined, so it is clear to you. You can see an example below.

TWEET 1



TWEET2



What we would like to ask you is how you would qualify each type of writing and how you would describe the type of person who wrote each version of the tweet? You will receive specific instructions on how to do that either using a slider bar or typing your answer in a textbox.

At the end of the study, you will be asked to answer a few general questions about yourself.

#### Duration

The study takes about 7 to 10 minutes to complete.

Figure C.1: Start instructions of the Prolific task.

## Appendix D: Prompts

### System Prompt (independent setup)

You are a participant in an experiment.

In what follows, you will see anonymised tweets, messages that were taken from the social media platform Twitter (now called X). What we would like to ask you is how you would qualify each type of writing and how you would describe the type of person who wrote each tweet? You will receive specific instructions on how to do that. Don't think too hard, just respond what first comes to mind. Don't worry about what you respond: we really are interested in your immediate associations. You must always respond with your best guess. Even if you are unsure.

Read the tweets below focussing on the words that are underlined. Then rate how (in)formal you find each tweet.

## TWEET1



very informal

very formal

## TWEET2



very informal

very formal

Figure C.2: An example informality rating task.

### User Prompt (independent setup)

Read the tweet below focussing on the word that is between <W> and </W>. Then give your best estimation of how old the writer of the tweet is, in number of years (whole numbers). Reply with only 'Age: [number of years]' without explaining your reasoning.

Tweet: "I'm <W>avaliable</W> today"

### System Prompt (paired setup)

You are a participant in an experiment.

In what follows, you will see anonymised tweets, messages that were taken from the social media platform Twitter (now called X). Each message will be displayed in two different versions. The difference between the two versions will be indicated, so it is clear to you. What we would like to ask you is how you would qualify each type of writing and how you would describe the type of person who wrote each tweet? You will receive specific instructions on how to do that. Don't think too hard, just respond what first comes to mind. Don't worry about what you respond: we really are interested in your immediate associations. You must always respond with your best guess. Even if you are unsure.

**User Prompt (paired setup)**

Read the tweets below focussing on the words that are between <W> and </W>. Then rate how (in)formal you find each tweet, with a number from 0 to 100 (0=very informal, 100=very formal). Reply with only 'A: [number] B: [number]' without explaining your reasoning.

A: "What are you <W>doing</W>?"  
B: "What are you <W>doin</W>?"

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