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AGEISM IN AI: CORPUS-BASED ANALYSIS OF AI-GENERATED ESSAYS

Age-related language plays an increasingly important role in shaping societal assumptions about older people and may contribute either to the reinforcement or mitigation of ageist beliefs. The detrimental effects of ageist biases on wellbeing and social equity underscore the need for systematic examination from a linguistic perspective. Ageist biases have been explored in various contexts, such as social, intuitional and cultural. However, the linguistic realization of ageism has received less academic attention to date. The present study addresses this gap by investigating the lexical portrayal of age and later life in the corpus of nine AI-generated essays created by three large language models (ChatGPT (based on OpenAI's GPT-5.2 model), Claude Sonnet 5 (developed by Anthropic), and Gemini 3 (developed by Google DeepMind)).

The analysis integrates quantitative and qualitative approaches. The former applies *AntConc*, a corpus analysis toolkit, to study the presence and frequency of age-related terms (*blue-hair*, *codger*, *dinosaur*, *fossil*, *geezer*, *old fart*, *old hag*, *old-timer*, *senile*, *wise*, *old and age*) in the nine AI-generated texts, while the latter employs S. Hunston's evaluative and non-evaluative distinction to examine the evaluative meaning of age-linked terms and their contribution to ageism in the essays under examination.

The findings suggest that the target openly ageist and non-ageist terms are absent from the corpus. The only present age-focused term is *age*. It appears 27 times and depicts later life and retirement either neutrally or negatively. The research results also indicate that although the AI-generated texts do not possess explicitly ageist language items, they tend to generate implicit ageism in the representation of chronological age.

Keywords: ageism, age representation, age-related stereotypes, AI language, corpus-based analysis.

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Жасанды интеллекттегі эйджизм: ЖИ құрастырған эсселерді корпустық талдау арқылы зерттеу

Жасқа қатысты тілдік қолданыстар қарт адамдар туралы қоғамдық түсініктерді қалыптастыруда маңызды рөл атқара бастады, сонымен қатар эйджистік нанымдардың күшеюіне немесе әлсіреуіне ықпал етуі мүмкін. Эйджистік біржақты көзқарастардың әл-ауқат пен әлеуметтік теңдікке тигізетін зиянды әсері бұл құбылысты лингвистикалық тұрғыдан жүйелі түрде зерттеу қажеттілігін көрсетеді. Эйджизм әлеуметтік, институционалдық және мәдени сияқты әртүрлі контекстерде зерттеліп келеді. Алайда, эйджизмнің тілдік тұрғыдан жүзеге асырылуына бүгінгі күнге дейін академиялық зерттеулерде салыстырмалы түрде аз көңіл бөлінген. Осы зерттеу аталған олқылықтың орнын толтыру мақсатында үш ірі тілдік модель (ChatGPT (OpenAI компаниясының GPT-5.2 моделіне негізделген), Claude Sonnet 5 (Anthropic компаниясы әзірлеген) және Gemini 3 (Google DeepMind әзірлеген) жасанды интеллект арқылы генерацияланған тоғыз эсседен тұратын корпуста жас пен егде кезеңнің лексикалық тұрғыдан бейнеленуі зерттелді.

Зерттеу сандық және сапалық тәсілдерді ұштастырады. ЖИ арқылы генерацияланған мәтіндегі сандық және корпустық талдау негізінде *AntConc* бағдарламасын қолданылуымен тоғыз лексикалық бірліктің (*blue-hair*, *codger*, *dinosaur*, *fossil*, *geezer*, *old fart*, *old hag*, *old-timer*, *senile*, *wise*, *old* және *age*) қолданылуы мен жиілігі анықталды. Сапалық талдау С. Хунстонның бағалауыштық және бағалауыштық емес қолданыстарды ажырату тұжырымдамасына сүйене отырып, жасқа қатысты лексикалық бірліктердің бағалауыш мағынасын және олардың зерттеліп

Зерттеу нәтижелері ашық түрде эйджистік және эйджистік емес деп белгіленген нысаналы лексикалық бірліктердің корпуста кездеспейтінін көрсетеді. Корпуста кездескен жалғыз жасқа қатысты негізгі лексикалық бірлік – *age*. Ол 27 рет қолданылып, егде жасты және зейнетке шығуды бейтарап немесе жағымсыз тұрғыдан сипаттайды. Зерттеу нәтижелері, сондай-ақ, жасанды интеллект арқылы генерацияланған мәтіндерде айқын эйджистік лексикалық бірліктер болмағанымен, олардың хронологиялық жасты бейнелеу тәсілінде имплицитті эйджизмді қалыптастыруға бейімділік бар екені айқындалды.

Түйін сөздер: эйджизм, жас бейнелеуі, жасқа қатысты стереотиптер, ЖИ тілі, корпуста негізделген талдау.

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Эйджизм в ИИ: корпусный анализ эссе, сгенерированных ИИ

Язык, связанный с возрастом, приобретает всё большее значение в формировании общественных представлений о пожилых людях и одновременно способен способствовать усилению или смягчению эйджистских убеждений. Негативное воздействие эйджистских предубеждений на благополучие и социальное равенство подчёркивает необходимость систематического изучения данного явления с лингвистической точки зрения. Эйджизм исследовался в различных контекстах, включая социальный, институциональный и культурный. Однако языковой реализации эйджизма до настоящего времени уделялось сравнительно мало внимания в академических исследованиях. Настоящее исследование направлено на восполнение данного пробела посредством изучения лексической репрезентации возраста и позднего периода жизни в корпусе из девяти эссе, сгенерированных искусственным интеллектом с использованием трёх больших языковых моделей (ChatGPT (на основе модели GPT-5.2 компании OpenAI), Claude Sonnet 5 (разработанной компанией Anthropic) и Gemini 3 (разработанной Google DeepMind)).

В исследовании сочетаются количественный и качественный подходы. Количественный анализ предполагает использование инструмента корпусного анализа *AntConc* для выявления наличия и частотности возрастных лексем (*blue-hair*, *codger*, *dinosaur*, *fossil*, *geezer*, *old fart*, *old hag*, *old-timer*, *senile*, *wise*, *old* и *age*) в девяти текстах, сгенерированных искусственным интеллектом. Качественный анализ, в свою очередь, основывается на разграничении оценочных и неочечных употреблений, предложенном С. Ханстон, с целью выявления оценочного значения возрастномаркированных единиц и определения их вклада в формирование эйджизма в анализируемых эссе.

Результаты исследования показывают, что целевые лексические единицы с открыто выраженной эйджистской и неэйджистской семантикой отсутствуют в корпусе. Единственной присутствующей единицей, непосредственно связанной с возрастной тематикой, является *age*. Она встречается 27 раз и репрезентирует поздний период жизни и выход на пенсию в нейтральном или негативном ключе. Результаты также свидетельствуют о том, что, несмотря на отсутствие в текстах, сгенерированных искусственным интеллектом, явно эйджистских языковых единиц, они демонстрируют тенденцию к формированию имплицитного эйджизма посредством репрезентации хронологического возраста.

Ключевые слова: эйджизм, возрастное представление, возрастные стереотипы, язык ИИ, корпусный анализ.

Introduction

Recent philological studies have begun to focus on ageism alongside other social issues of gender and race. International scholarship has examined ageism from multiple perspectives. Notably, in *Ageism: Stereotyping and Prejudice against Older Persons* (Nelson, 2002), the author attempted to explore ageism from various facets, such as linguistic and social, including developmental and implicit ageism. While above-mentioned T. Nelson's work con-

siders ageism mainly as a broad form of stereotyping, later studies address the importance of gendered dimensions of aging. In this regard, *Discourses of Aging in Fiction and Feminism: The invisible woman* (King, 2013) provides a sophisticated analysis of female ageing in fiction and feminist discourse, emphasizing how ageism functions through narrative patterns long before the refinement of digital technologies. Additionally, ageism has been studied with respect to media discourse and representation, targeting stigmatization mechanisms of older adults

(Camacho-Markina & Santos-Diez, 2025, p. 2). A further strand of research has addressed ageism in platform-based culture and educational settings, considering the usage of memes as a tool for communicating age-related meanings (Ayalon et al., 2025, p. 2602).

These studies mentioned above reveal that ageism is not a solely social perception, but rather a linguistically encoded and transmitted phenomenon. The question of who and what constructs discourse grows in importance as language patterns form and mirror cultural views of age. In modern contexts, both human speakers, writers and digital technologies produce language. Within this group, artificial intelligence systems possess an important role as text generators in various fields, such as academic, institutional and daily. Computational models rely on large corpora of human-authored texts, which unavoidably display already existing language norms, values, and stereotypes, to create AI-produced language. Consequently, this phenomenon may lead to the reproduction, transformation and sometimes amplification of age-related meanings and evaluative patterns existing in human discourse in AI-generated outputs. This transition requires treating AI not only as a technical tool, but also as a main contributor in the age-related language. Although artificial intelligence has become increasingly prominent in language research, earlier investigations have mostly focused on specific functions and domains. For example, AI-facilitated language learning has been studied in business English classrooms, stressing its capacity to facilitate and accelerate vocabulary acquisition, communication skills and education results (You & You, 2026, p. 34). Likewise, emotional examinations juxtaposing human and computational perspectives have revealed AI's potential to identify affective states and assess textual tone (Moreno-Ortiz & García-Gámez, 2026, p. 22). Despite the fact that these studies recognize the importance and assistance of AI in language learning and emotional understanding, they do not primarily focus on the content of the language from the perspective of social biases. Notably, the linguistic representation of age and ageism in AI-generated texts remain largely insufficiently examined. This demonstrates a gap in the literature, as AI-produced discourse may recreate, support, or implicitly represent ageist attitudes existing in its training data. Therefore, inspecting ageism in AI-generated language is relevant and essential, connecting computational linguistics and sociolinguistics.

The present study aims to explore how AI-generated texts use age-marked vocabulary, investigating the semantic structures and linguistic tendencies. The research also seeks to identify how computational models may reflect or reinforce age-related language norms. Accordingly, this study investigates the following research questions:

1. What is the frequency of the age-related lexical items (*blue-hair, codger, dinosaur, fossil, geezer, old fart, old hag, old-timer, senile, wise, old and age*) in the corpus?
2. What lexical item carries evaluative meaning toward older individuals?
3. What is the contribution of the identified evaluative instances of the age-related lexical units to ageist assumptions?

The relevance of the study stems from adopting S. Hunston's evaluative framework, originally designed for human-authored discourse, to AI-generated language, which provides preliminary evidence of whether large language models reflect or challenge ageist language patterns in an era of growing AI-assisted academic and public communication.

The results of the study shed light on how language models reproduce or mitigate ageist linguistic biases. In addition, the research expands the empirical basis for age-related discourse from the perspective of computational linguistics and critical age studies.

The scientific novelty of the study is reflected in its focus on AI-generated text as the object of ageism-related linguistic examination. Unlike other studies that examine a single model in isolation, this research employs a comparative approach involving three different AI systems, such as ChatGPT, Claude Sonnet 5 and Gemini 3.

The research findings may be applied in the development of bias-evaluation frameworks for large language models, in the creation of AI educational materials for both educators and students, and in the formation of guidelines for AI-generated content.

Materials and methods

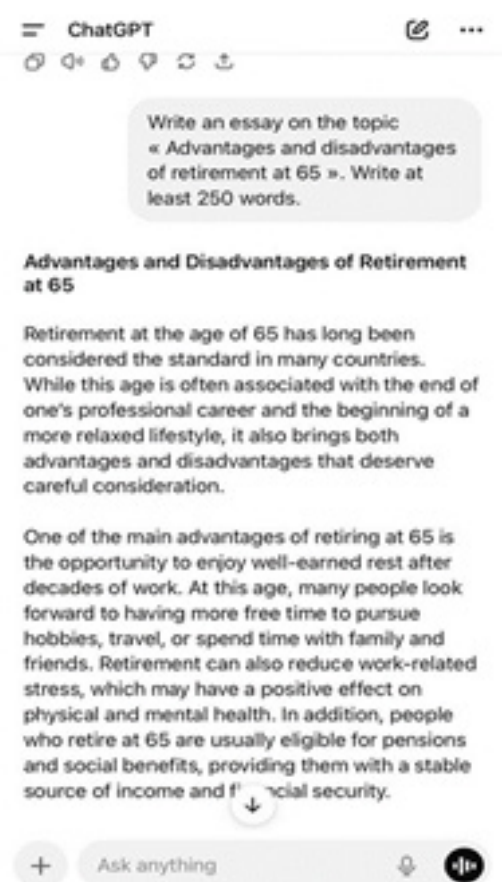
The data analyzed in this study consist of nine AI-generated argumentative essays produced as a result of a pre-defined prompt. The target essay discusses the topic "*Advantages and disadvantages of retirement at age 65*". The essay topic was chosen due to its precise age-related representation and relevance to age discussions. In addition, the chosen topic contributes to the detection of age-marked lexical items and judgmental discourse connected

with retirement and later life. The first three essays were produced employing The ChatGPT language model (GPT-5.2). Another three essays were generated by Claude Sonnet 5 (developed by Anthropic). A final three essays were produced by Gemini 3 (developed by Google DeepMind). This study selected these three large language models (LLMs) as they are widely used, accessible to general users, and developed independently. In addition, the cross-model comparison is capable of identifying both similarities and differences in the representation of age.

These three LLMs generated the texts in response to the specified prompt illustrated in Figure 1. Although the models were instructed to generate essays with a minimum length of 250 words, the generated texts considerably exceeded the established length, ranging from 307 to 407 words. In total, the corpus of nine AI-generated essays consisted of 3045 tokens.

Figure 1

Prompt used to generate the AI essays and an example of a ChatGPT-generated response



Note. The same prompt was used for ChatGPT (GPT-5.2), Claude Sonnet 5 and Gemini 3

However, the target corpus remains manageable for comprehensive qualitative and quantitative linguistic examination. The application of the corpus limited to nine controlled texts ensures comparability and enhances methodological transparency. The essays therefore can function as suitable and standard samples for studying age-correlated language in AI-mediated discourse. The research involved the following steps:

Firstly, the linguistic examination is conducted with the assistance of *AntConc*. *AntConc* is a corpus analysis toolkit created by Laurence Anthony. According to L. Anthony, *AntConc* is one of the most widely used free and versatile offline corpus analysis tools for Windows (Laurence, 2022, p. 107).

This study employed *AntConc*'s Word function, to investigate the presence and frequency of the target age-related lexical items in the corpus. In greater detail, nine of the target lexical items (*blue-hair*, *codger*, *dinosaur*, *fossil*, *geezer*, *old fart*, *old hag*, *old-timer*, *senile*) are ageist and one non-ageist lexical unit (*wise*), as documented in the volume *Ageism: Stereotyping and Prejudice against Older Persons* (Nelson, 2002, pp. 38, 59). Additionally, drawing on B. Bytheway's analysis of the vocabulary of age, the study examined the presence and distribution of common age-related lexical items, such as *old* and *age* (Bytheway, 2011, p. 76) in the corpus.

J. Sinclair argues that concordance-based evidence about the language is usually better than any other method (Sinclair, 1991, p. 42). In addition, S. Hunston (Hunston, 2011, p. 15) observes that the evaluative meaning of a lexical item cannot be usually determined from the node word alone. Instead, it may be obtained from its surrounding linguistic context. In line with J. Sinclair and S. Hunston's guidelines above, at the following stage *AntConc*'s KWIC function was used to retrieve the concordance lines of the node word *age*. This enabled each instance to be assessed for evaluative and non-evaluative function in accordance with S. Hunston's distinction (Hunston, 2011, p. 15).

The final stage employed *AntConc*'s File View tool to examine individual concordance hits within their full paragraph-level context. This process determined the linguistic contribution of the evaluative instances of the node word *age* to ageism.

The combination of corpus-based quantitative measures and qualitative analysis enables a systematic evaluation of language patterns and their pragmatic significance. This integrated approach secures a thorough exploration of the appearance and prag-

matic meaning of age-related language in machine-generated texts.

All nine essays were generated using the same prompt: “Write an argumentative essay of at least 250 words on the advantages and disadvantages of retirement at age 65.” The texts were generated in a new chat session for each model, without additional clarifying prompts or post-editing.

Literature review

Ageism has been studied from various perspectives so far. From the perspective of sociolinguistics, C.V. Monsees examined stereotypes about age and older people. According to her, perceptions and judgements about other people are usually formed rapidly and unconsciously. Therefore, stereotypes largely remain difficult to recognize. Moreover, stereotypes tend to amplify certain traits related to some group members and link the unfavourable features to ageing (Monsees, 2002, p. 36). A. Phelan observes that ageism manifests in both formal systems and informal interactions, affecting not only groups but individuals as well (Phelan, 2018, p. 551). T.A. van Dijk suggests that social identities, such as age, gender, and ethnicity, affect language patterns by shaping speaker’s perceptions of themselves and those they interact with (van Dijk, 2009, p. 7). B. Bytheway (2005, p. 338) highlights that ageism stands apart from racism and sexism in that it does not involve one group targeting another, but instead functions as a universal belief system that applies normative pressures across all age groups. D. Cameron focused on the term *senior citizen* in their academic studies. She observed the unstable nature of euphemistic terms and illustrated this tendency by the replacement of *old-age pensioners* with *senior citizens* and *old* with *elderly* (1995, p. 146).

Turning to the discursive construction of ageism, A. Phelan uses Foucauldian discourse analyses and discursive psychology to trace the construction of the older people’s identities at the broader societal and individual levels (Phelan, 2018, p. 549). In addition, she focuses on the possibility of non-ageist discourse, questioning whether age can be removed as a defining factor in the portrayal of individuals. Although A. Phelan argues that people can be represented without age-based categories, she acknowledges the challenges in achieving age-independent discourse (Phelan, 2018, p. 561).

Ageism has likewise been examined in literary studies. M. Goldman and S. Powell analyzed memo-

ry and aging in Alice Munro’s *The Bear Came Over the Mountain* and its film adaptation *Away from Her*, directed by Sarah Polley (Goldman & Powell, 2015, p. 82). J.E. Joseph notes that fictional characters tend to appear more “real” than actual people due to their fully contained and easily understood identities. Perhaps, the reason people today long for a coherent self-identity is because, unlike the well-defined characters in novels and films, they perceive themselves as unclear and only partially understood (Joseph, 2004, p. 4). These perspectives, when combined, reveal the broad reach of ageism and the crucial part that language plays in maintaining such stereotypes. J. M. Montepare and L. A. Zebrowitz suggest that children’s literature is capable of contributing to the perceptions of aging, especially when it is presented by trusted adults in close, familiar settings (Montepare & Zebrowitz, 2004, p. 108). While the exact influence of children’s books on age-related perceptions is still under investigated, existing research highlights that literature can effectively spread ageist ideas, both openly and subtly.

Media scholars have also investigated the interplay between ageist and sexist stereotypes. J. Chonody et al. (2025, p. 85) examined films starring older figures and found the presence of biases based on both age and gender. S. Westwood (2019, p. 3) deepens this discussion underscoring how dominant narratives are shaped by research that often lacks diversity and social inequality. Regarding social media discourse, B.R. Levy et al. found a high prevalence of negative age stereotypes occurring in 83 of 84 Facebook examined groups (Levy et al., 2014, p. 173).

As the participation of AI in the production and mediation of language is increasing, it has introduced a new field in which age-related language can be examined. The existing research has studied ageism in AI conducting a scoping review drawing on findings from the existing literature (Chu et al., 2023) and interviews (Neves et al., 2023). However, the research on ageism has not applied a corpus-based analysis to AI-generated texts yet. The present study seeks to narrow this gap by examining AI-produced essays through corpus analysis to identify and study representations of ageism in them.

Results and discussion

As Table 1 presents below, ten age-related terms, nine categorized as *ageist* (Greenberg et al., 2002, p. 38) (Levy & Banaji, 2002, p. 59) and one as *non-ageist* (Levy & Banaji, 2002, p. 59) were exam-

ined with the assistance of *AntConc*, a corpus-based analysis tool. The findings reveal that none of the target age-related words is present in the target essays. This phenomenon may demonstrate AI's overt refraining from generating bias based language, particularly age-focused biases, to maintain linguistic inclusivity.

Table 1

Occurrence of Todd Nelson's Ageist and Non-Ageist Lexical items in the Essays (N=9)

No.	Target lexical item	Word category	Frequency in the essays
1	blue-hair	ageist	0
2	codger	ageist	0
3	dinosaur	ageist	0
4	fossil	ageist	0
5	geezer	ageist	0
6	old fart	ageist	0
7	old hag	ageist	0
8	old-timer	ageist	0
9	senile	ageist	0
10	wise	non-ageist	0

Note. Compiled by the authors

Another interesting point is that common age-defining lexical item, *old*, is also absent from the essays under investigation. However, the corpus-analysis software detects that presence of the lexical item *age* in the essays. It occurred 27 times throughout the corpus, displayed in Table 2, and each instance is analyzed and interpreted below relying on S. Hunston's binary distinction between evaluative and non-evaluative language as shown in Table 4.

Table 2

Occurrence of old and age in the essays (N=9)

No.	Target lexical item	Frequency in the essay
1	old	0
2	age	27

Note. Compiled by the authors

Table 3 presents the frequency of the term *age* across the nine essays with raw token totals. The normalized frequencies per 1000 words were in-

cluded to ensure comparison despite text length differences. The 3,045-token pooled corpus identified 27 occurrences of *age*, representing a normalized frequency of 8.87 instances per 1000 words. The analysis reveals a higher incidence of age in Gemini-generated essays, representing 10.79 per 1000 words, $f=12$, $N=1,112$. It is followed by ChatGPT essays, with 7.88, $f=8$, $N=1015$. Claude showed the lowest normalized frequency at 7.63 occurrences per 1000 words ($f=7$, $N=918$).

The frequency analysis demonstrated that ChatGPT Essay 1 and Gemini Essay 2 used *age* equally often ($f=5$). However, ChatGPT Essay 1 showed the highest density (15.29 per 1000 words), as opposed to the longer Gemini Essay 2 with 12.29 per 1000 words, when text length was taken into consideration. Normalized frequency data suggest that Gemini-generated essays have a slightly higher use of *age* in comparison with those generated by ChatGPT and Claude. The difference between ChatGPT and Claude was negligible, with frequencies of 7.88 versus 7.68 per 1000 words, respectively. ChatGPT Essay 1 demonstrates the limitations of raw frequency as a comparative measure. To clarify, although ChatGPT Essay 1 contained the same frequency of *age* as Gemini Essay 2, its shorter length generated a markedly greater concentration of the target term *age*. This observation underscores the importance of normalizing frequency counts to ensure methodological validity, as recommended in corpus stylistic analysis.

Table 3

Frequency distribution of the word "age" in the essays

No.	Text	Words (N)	Frequency (f)	Frequency per 1000 words
1.	ChatGPT Essay 1	327	5	15.29
2.	ChatGPT Essay 2	347	2	5.76
3.	ChatGPT Essay 3	341	1	2.93
4.	Claude Essay 1	303	3	9.90
5.	Claude Essay 2	312	2	6.41
6.	Claude Essay 3	303	2	6.60
7.	Gemini Essay 1	326	4	12.27
8.	Gemini Essay 2	407	5	12.29
9.	Gemini Essay 3	379	3	7.92
Total		3045	27	8.87

Note. ChatGPT = GPT-5.2; Claude = Claude Sonnet 5; Gemini = Gemini 3

The application of S. Hunston's evaluative and non-evaluative distinction to the 27 instances of age, detected its 6 (22%) evaluative occurrences in the corpus. This limited presence of evaluative uses (22, 2%) suggests that *age* functioned largely as a neutral factual marker in the sampled essays. This pattern may also reflect the informational discourse context prompted by the retirement-oriented essay task. The remaining 21 (77, 8%) instances of *age* served as neutral references without attitudinal loading (Table 4). Five of the six instances framed *age* as an important temporal boundary or endpoint

imagery, with the usage of the expressions, such as “*monumental milestone*”, “*standard threshold separating decades*” and “*standard finish line for a career*”. This finding reveals an implicit form of ageism, which communicates age-related assumptions through seemingly neutral linguistic choices rather than openly disparaging expressions. Only one occurrence linked ageing directly to physical deterioration “*health problems become more common with age*”. However, none of the six evaluative instances of the term *age* contained overtly pejorative language.

Table 4

Concordance lines for “age” Coded by Evaluative Status (Hunston, 2011)

No.	Concordance lines	Source	Evaluative Status
1.	Advantages and Disadvantages of Retirement at 65 Retirement at the traditional <i>age</i> of 65 represents a monumental milestone in modern society. For...	Gemini Essay 1	Evaluative
2.	...an important stage of life, and many people consider the <i>age</i> of 65 to be an appropriate time to stop working...	ChatGPT Essay 3	Evaluative
3.	...represents a monumental milestone in modern society. For generations, this <i>age</i> has served as the standard threshold separating decades of ...	Gemini Essay 1	Evaluative
4.	...on retirees, particularly as health problems become more common with <i>age</i> . Another disadvantage is that mandatory or expected retirement at 65 ...	ChatGPT Essay 1	Evaluative
5.	...milestones in modern society. For generations, society has treated this <i>age</i> as the standard finish line for a career, transitioning...	Gemini Essay 3	Evaluative
6.	In many countries, 65 has traditionally been considered a suitable retirement <i>age</i> . However, retiring at this age has both advantages and...	ChatGPT Essay 1	Evaluative

Note. Compiled by the authors

Conclusion

This study has examined the linguistic representation of ageism in AI-generated texts, conducting a corpus-based quantitative analysis with the assistance of *AntConc* to identify the presence and frequency of age-related terms in the LLM outputs under investigation. The qualitative interpretation of the corpus analysis observations was informed by S. Hunston's evaluative framework. The examination of evaluative features and lexical patterning traced recurrent forms of ageist language and established the linguistic processes supporting their realization. The research responded to the emerging need to investigate how large language models reflect, perpetuate or resist age-related stereotypes in their generated content. The analysis reveals four findings:

Large language models mainly generate neutral texts, with no explicitly negative age-related lexical

items identified. Notably, Claude's essays contained no evaluative uses of the term *age*.

Although the task addressed partly the advantages of retirement, none of the nine essays applied the term *wise* for positive representations of older age.

Similarly, no occurrence of the lemma *old* was detected for the negative portrayal of retirement.

The absence of overtly ageist lexical items did not exclude the presence of implicit ageism, in which age is depicted as a rigid categorical boundary linked to decline rather than a continuous and individually variable process.

Although the analysis has focused on the corpus comprised only nine essays, the findings present the relevance of critical interrogation of artificial intelligence as a mediator and enhancer of social age biases.

Future research could extend this study to larger corpora, namely AI-generated short stories, longer

narrative texts and field-specific genres. Consequently, the range of analysis would enable scholars to investigate whether age-related stereotypes persist, amplify or modify throughout various text formats and interactional settings. These studies would result in a deeper understanding of the interconnection between ageism, discourse practices, and developing content-generating tools.

Conflict of Interest

The authors declare that there is no conflict of interest.

Author Contributions

D.A. Karagoishiyeva developed the scientific concept of the article, designed the corpus-based methodology, collected the research materials and wrote the main text. Zh.K. Oraztayeva participated in verifying the results of the analysis, supplementing the theoretical section and editing the final version of the article. A.A. Karshigayeva contributed to the literature review, interpretation of the findings and preparation of the manuscript for publication. All authors approved the final version of the article and are responsible for the accuracy of the research results.

References

- Nelson, T. D. (Ed.). (2002). *Ageism: Stereotyping and prejudice against older persons*. MIT Press.
- King, J. (2013). *Discourses of ageing in fiction and feminism: The invisible woman*. Palgrave Macmillan.
- Camacho-Markina, I., & Santos-Diez, M.-T. (2025). The social construction of age: Media stigmatization of older adults: A systematic review. *Journalism and Media*, 6(3), 150.
- Ayalon, L., Suberry, A., Okun, S., Awad, R., & Gazawi, R. (2025). Learning from memes about ageism among Israeli Arab tweens. *Ageing and Society*, 45(12), 2602–2624.
- You, X., & You, X. (2026). AI-mediated genre learning in the business English class. *English for Specific Purposes*, 82, 34–48.
- Moreno-Ortiz, A., & García-Gámez, M. (2026). Emotion in context: Human and AI perspectives on the affective landscape of *Severance*. *Corpus Pragmatics*, 10(1), 15.
- Laurence, A. (2022). What can corpus software do? In A. O’Keeffe & M. J. McCarthy (Eds.), *The Routledge handbook of corpus linguistics* (pp. 103–125). Routledge.
- Bytheway, B. (2011). *Unmasking age: The significance of age for social research*. Policy Press.
- Sinclair, J. M. (1991). *Corpus, concordance, collocation*. Oxford University Press.
- Hunston, S. (2011). *Corpus approaches to evaluation: Phraseology and evaluative language*. Routledge. <https://doi.org/10.4324/9780203841686>
- Monsees, C. V. (2002). Ageism. In D. J. Ekerdt, R. Applebaum, K. C. A. Holden, S. G. Post, K. Rockwood, R. Schulz, R. L. Sprott, & P. Uhlenberg (Eds.), *Encyclopedia of aging* (pp. 36–39). Macmillan Reference USA.
- Phelan, A. (2018). Researching ageism through discourse. In L. Ayalon & C. Tesch-Römer (Eds.), *Contemporary perspectives on ageism* (Vol. 19, pp. 549–564). Springer International Publishing.
- van Dijk, T. A. (2009). *Society and discourse: How social contexts influence text and talk*. Cambridge University Press.
- Bytheway, B. (2005). Ageism. In M. L. Johnson, V. L. Bengtson, P. G. Coleman, & T. B. L. Kirkwood (Eds.), *The Cambridge handbook of age and ageing* (pp. 338–345). Cambridge University Press.
- Cameron, D. (1995). *Verbal hygiene*. Routledge.
- Goldman, M., & Powell, S. (2015). Alzheimer’s, ambiguity, and irony. *Canadian Literature*, 225, 82–99.
- Joseph, J. E. (2004). *Language and identity: National, ethnic, religious*. Palgrave Macmillan.
- Montepare, J. M., & Zebrowitz, L. A. (2004). *A social-developmental view of ageism* (T. D. Nelson, Ed.; 1st MIT Press paperback ed.). MIT Press.
- Chonody, J., Perez, C., Fillmore, Q., & McGuinness, M. (2025). Ageism and sexism in films with older people as the lead. *International Journal of Ageing and Later Life*, 18(1), 59–88.
- Westwood, S. (Ed.). (2019). *Ageing, diversity and equality: Social justice perspectives*. Routledge, Taylor & Francis Group.
- Levy, B. R., Chung, P. H., Bedford, T., & Navrazhina, K. (2014). Facebook as a site for negative age stereotypes. *The Gerontologist*, 54(2), 172–176. <https://doi.org/10.1093/geront/gns194>
- Chu, C. H., Donato-Woodger, S., Khan, S. S., Nyrup, R., Leslie, K., Lyn, A., Shi, T., Bianchi, A., Rahimi, S. A., & Grenier, A. (2023). Age-related bias and artificial intelligence: A scoping review. *Humanities and Social Sciences Communications*, 10(1), 510. <https://doi.org/10.1057/s41599-023-01999-y>
- Neves, B. B., Petersen, A., Vered, M., Carter, A., & Otori, M. (2023). Artificial intelligence in long-term care: Technological promise, aging anxieties, and sociotechnical ageism. *Journal of Applied Gerontology*, 42(6), 1274–1282. <https://doi.org/10.1177/07334648231157370>
- Greenberg, J., Schimel, J., & Martens, A. (2002). Ageism: Denying the face of the future. In T. D. Nelson (Ed.), *Ageism: Stereotyping and prejudice against older persons* (pp. 27–48). MIT Press.
- Levy, B. R., & Banaji, M. R. (2002). Implicit ageism. In T. D. Nelson (Ed.), *Ageism: Stereotyping and prejudice against older persons* (pp. 49–75). MIT Press.

References

- Ayalon, L., Suberry, A., Okun, S., Awad, R., & Gazawi, R. (2025). Learning from memes about ageism among Israeli Arab tweens. *Ageing and Society*, 45(12), 2602–2624.
- Bytheway, B. (2005). Ageism. In M. L. Johnson, V. L. Bengtson, P. G. Coleman, & T. B. L. Kirkwood (Eds.), *The Cambridge handbook of age and ageing* (pp. 338–345). Cambridge University Press.
- Bytheway, B. (2011). *Unmasking age: The significance of age for social research*. Policy Press.
- Camacho-Markina, I., & Santos-Diez, M.-T. (2025). The social construction of age: Media stigmatization of older adults: A systematic review. *Journalism and Media*, 6(3), 150.
- Cameron, D. (1995). *Verbal hygiene*. Routledge.
- Chonody, J., Perez, C., Fillmore, Q., & McGuinness, M. (2025). Ageism and sexism in films with older people as the lead. *International Journal of Ageing and Later Life*, 18(1), 59–88.
- Chu, C. H., Donato-Woodger, S., Khan, S. S., Nyrup, R., Leslie, K., Lyn, A., Shi, T., Bianchi, A., Rahimi, S. A., & Grenier, A. (2023). Age-related bias and artificial intelligence: A scoping review. *Humanities and Social Sciences Communications*, 10(1), 510. <https://doi.org/10.1057/s41599-023-01999-y>
- Goldman, M., & Powell, S. (2015). Alzheimer's, ambiguity, and irony. *Canadian Literature*, 225, 82–99.
- Greenberg, J., Schimel, J., & Martens, A. (2002). Ageism: Denying the face of the future. In T. D. Nelson (Ed.), *Ageism: Stereotyping and prejudice against older persons* (pp. 27–48). MIT Press.
- Hunston, S. (2011). *Corpus approaches to evaluation: Phraseology and evaluative language*. Routledge. <https://doi.org/10.4324/9780203841686>
- Joseph, J. E. (2004). *Language and identity: National, ethnic, religious*. Palgrave Macmillan.
- King, J. (2013). *Discourses of ageing in fiction and feminism: The invisible woman*. Palgrave Macmillan.
- Laurence, A. (2022). What can corpus software do? In A. O'Keeffe & M. J. McCarthy (Eds.), *The Routledge handbook of corpus linguistics* (pp. 103–125). Routledge.
- Levy, B. R., & Banaji, M. R. (2002). Implicit ageism. In T. D. Nelson (Ed.), *Ageism: Stereotyping and prejudice against older persons* (pp. 49–75). MIT Press.
- Levy, B. R., Chung, P. H., Bedford, T., & Navrazhina, K. (2014). Facebook as a site for negative age stereotypes. *The Gerontologist*, 54(2), 172–176. <https://doi.org/10.1093/geront/gns194>
- Monsees, C. V. (2002). Ageism. In D. J. Ekerdt, R. Applebaum, K. C. A. Holden, S. G. Post, K. Rockwood, R. Schulz, R. L. Sprott, & P. Uhlenberg (Eds.), *Encyclopedia of aging* (pp. 36–39). Macmillan Reference USA.
- Montepare, J. M., & Zebrowitz, L. A. (2004). *A social-developmental view of ageism* (T. D. Nelson, Ed.; 1st MIT Press paperback ed.). MIT Press.
- Moreno-Ortiz, A., & García-Gámez, M. (2026). Emotion in context: Human and AI perspectives on the affective landscape of *Severance*. *Corpus Pragmatics*, 10(1), 15.
- Nelson, T. D. (Ed.). (2002). *Ageism: Stereotyping and prejudice against older persons*. MIT Press.
- Neves, B. B., Petersen, A., Vered, M., Carter, A., & Omori, M. (2023). Artificial intelligence in long-term care: Technological promise, aging anxieties, and sociotechnical ageism. *Journal of Applied Gerontology*, 42(6), 1274–1282. <https://doi.org/10.1177/07334648231157370>
- Phelan, A. (2018). Researching ageism through discourse. In L. Ayalon & C. Tesch-Römer (Eds.), *Contemporary perspectives on ageism* (Vol. 19, pp. 549–564). Springer International Publishing.
- Sinclair, J. M. (1991). *Corpus, concordance, collocation*. Oxford University Press.
- van Dijk, T. A. (2009). *Society and discourse: How social contexts influence text and talk*. Cambridge University Press.
- Westwood, S. (Ed.). (2019). *Ageing, diversity and equality: Social justice perspectives*. Routledge, Taylor & Francis Group.
- You, X., & You, X. (2026). AI-mediated genre learning in the business English class. *English for Specific Purposes*, 82, 34–48.

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