Title

The Managerialization of Personal Life From 1950 to the Present

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Abstract

Recent advances in computational linguistics have enabled significant progress in measuring large-scale cultural shifts, as reflected in people's language use over time. We extend and apply these methods to massive historical corpora from across domains – including newspapers, films, novels, congressional speeches, case law proceedings, and interviews with ordinary Americans – and show that, since the mid-20th century, Americans have steadily shifted toward framing themselves and their relationships as projects requiring monitoring and optimization, like how a firm manages inventory or productivity. Across datasets, the 1980s mark a key turning point, consistent with accounts of this period as witnessing the expansion of markets, neoliberal ideology, and the meticulously managed firm. We document sociodemographic variation in the uptake of managerialized language, finding that women were among its earliest adopters; yet, by the turn of the 21st century, this language became institutionalized, with younger, White, affluent, and college-educated individuals leading its entrenchment. We refer to this shift as the managerialization of personal life.

Teaser

Large-scale computational analyses of language data reveal that Americans increasingly view themselves and their relationships as objects of managerial control.

MAIN TEXT

Introduction

Modern life is increasingly viewed through a market lens. Time is money. Science is a marketplace of ideas. Dating is a value-maximizing transaction. This market-oriented language gained particular prominence since the 1980s (*1*, *2*), with the rise of Anglo-Saxon neoliberal ideology and its elevation of free markets as, in Ronald Reagan's words, "the one true path to peace and human happiness" (*3*). Market society is often understood as a socio-cultural arrangement emphasizing competition, commodification, and individual freedom (*4*). Yet, the market is not unambiguously liberating. Its rise was also accompanied by the growth and ascendance of the meticulously managed modern firm, with its reliance on regulation and control (*5*–*7*). To remain competitive in such a market-driven world, individuals need to manage themselves and their relationships like firms manage productivity – strategically, efficiently, and with an eye toward continuous improvement (*8*, *9*). Indeed, some observers contend these large-scale economic shifts ushered in a cultural transformation, wherein individuals increasingly came to view themselves as objects requiring control and optimization. The self becomes a project; relationships become defined by their goals and strategies; emotions become skills to be cultivated and regulated; and the body becomes an asset requiring constant attention and refinement (*10-12*). We refer to this cultural process as the *managerialization of personal life*.

While anecdotal evidence for this shift abounds, its systematic and quantitative documentation remains scarce. Some scholars have linked the rise of managerialization to the ascendancy of neoliberal politics in the United States and the United Kingdom since the early 1980s, and to their gradual spread across the industrialized world (*4*). These accounts suggest this sociopolitical transformation helped legitimize the extension of managerial logic from the economic realm into the personal sphere. In particular, they point to three areas of personal life traditionally outside the reach of managerial control: the body (e.g., health and pain), subjectivity (e.g., emotions and beliefs), and social relationships (e.g., family and friends). However, much of the evidence supporting these claims relies on qualitative historical analyses, which focus on the rhetoric of psychologists (*11*, *12*), politicians (*2*), and management experts (*9*). It remains unclear whether managerial language spread to lay discourse and, if so, when and by whom.

Here, we develop novel algorithmic methods for quantifying the expansion of managerial language into three non-business domains: the body, subjectivity, and social relationships. Our approach traces both explicit and implicit managerialized language. We define and measure explicit managerialization as the rise of overt coinages (e.g., "anger management") where a managerial label is formally applied to a personal domain. Our measure of implicit managerialization rests on the intuition that to construe something as being managed implies that it is a quantity that can be optimized and that requires strategic control. We therefore define implicit managerialization the use of management-adjacent logic, such as "optimizing," "controlling," or "strategizing", without the direct use of management terminology. For example, individuals may not use the phrase "friend management," yet they may increasingly discuss friendships as assets to be optimized or goals to be achieved. To do so, we use BERT-based fill-mask prediction of whether non-business concepts are framed as managed entities (see Methods and *SI* Tables S9–S10 for examples).

We apply these methods to a novel compilation of massive historical datasets of text spanning the 1950s to the present, comprising mainstream news, popular fiction, movie scripts, congressional speeches, and case law proceedings, as well as a representative sample of ordinary Americans interviewed about their "everyday lives." To understand the social circumstances that facilitated the diffusion of managerialization, we trace the sociodemographic profiles of the authors and speakers driving its adoption. Whereas recent work suggests that rationality has declined in recent decades (*13*), our analyses show the opposite: the steady rise of management language – implying monitoring, regulation, and optimization – applied to the self and to social relationships with others. Since the 1980s, this managerial language has emerged as a pervasive cultural vehicle through which rationalized control has become increasingly conventionalized beyond the purview of the modern organization.

Results

The Explicit Rise of Managerialization

We find that there has been a sharp rise in the population-level usage of new, explicit extensions of management language from 1950 to 2020. This historical rise is consistent across multiple datasets, as illustrated by Figure 1a. Among all sentences that contain the word *manage* and its variations, the proportion of sentences where management is applied to personal domains has steadily increased over the past decades. Specifically, we observe an approximately fivefold increase in personal management in the Congressional Speech and Case Law datasets, a twofold increase in the Movie and Fiction datasets, and a tenfold increase in the New York Times dataset (*SI* Figure S1). Strikingly, as indicated by the aggregate trend in Figure 1a, the expansion of explicit uses of management construals takes off shortly after 1980. Consistent with our expectations, this increase aligns with the rise of neoliberal politics in the U.S. and U.K., marked by the electoral victories of Ronald Reagan in 1980 and Margaret Thatcher in 1979.

Figure 2a breaks down these historical trends by the three personal domains, which are the focus of our analyses: the body, subjectivity, and social relationships. For comparison, the figure plots trends in the use of two additional impersonal objects---time and money---that are conventionally understood as objects of management, when discussed in non-business contexts. Two patterns are readily apparent. First, while explicit managerial language related to the self has increased markedly since 1980 across all datasets, its application to time and money has remained largely stagnant over the same period. The rise of explicit managerialization is thus primarily driven by the extension of managerial logic into domains of the self. Second, explicit managerial references to social relationships have not increased as sharply as those related to the body or subjectivity. This suggests that social relationships may retain a degree of cultural sanctity, making them more resistant to explicit construals as things that should be managed.

To validate these findings and account for fluctuations in the baseline popularity of various personal domains, we compared changes in the usage rate of management-related verbs to common verbs unrelated to management (*SI* section *Verb Replacement Analysis*). As shown in Figures S6 and S7, verbs denoting control and planning, such as *manage*, *monitor*, and *track*, have seen substantial increases in their relative use when applied to personal domains. Some exhibit a tenfold rise between 1950 and 2020, with many usages first appearing in the 1980s and 1990s. In contrast, verbs like *express*, *suffer*, *stir*, and *relieve*, which denote a passive or experiential engagement with personal domains, exhibit zero or negative growth rates before and after 1980 (*SI* Figure S8).

The Implicit Rise of Managerialization

The explicit shifts captured above are the surface expressions of deeper, large-scale shifts in meaning space that indicate the growth of managerial logic beyond its traditional domains. Next, we examine the expansion of managerial thinking through implicit shifts in semantic associations.

Figure 1b displays the rise of implicit associations with management across datasets. In all datasets, we observe a steady expansion of implicit managerial language across personal domains over the last several decades. The aggregate trend once again highlights 1980 as a key turning point, but the inflection is not as pronounced as the historical shift in explicit extensions in managerial language during the same period. In this case, the increase in implicit management language traces to the 1970s, potentially because such implicit shifts precede and set the stage for more explicit linguistic coinages that conventionalize large-scale changes in word co-occurrences (*14–17*).

The same pattern holds when we disaggregate these historical trends into the three domains of personal life: body, subjectivity, and social relationships. Figure 2b reveals a secular increase in implicit managerialization across all datasets and domains. Importantly, and in contrast to explicit extensions of managerial language, the implicit construal of social relationships in managerial terms shows a consistent increase across all datasets. While speakers remain hesitant to explicitly describe their social ties as objects of management, they have nonetheless gradually come to implicitly frame these ties through a managerial lens. This dynamic is illustrated by the case of parenting (see SI section *The Managerialization of Parenting*). While the term "children management" was never widely adopted, verbs associated with permissive nurturing (e.g., *allow*, *accept*) have declined, while those associated with interventionist control (e.g., *track*, *monitor*) have surged. Consequently, even in the absence of explicit labels, the discourse of parenting has become implicitly managerialized.

Although there is some variation in trajectories across the datasets, the trends are strongly correlated between the three domains within each dataset, suggesting that no single domain experienced systematically stronger or earlier growth in managerialization. Moreover, variation in these patterns is consistent with the contexts in which they occur. It is not surprising, for example, that subjectivity is more frequently discussed in fiction and movies than in congressional or legal hearings. Overall, these findings support the view that the expansion of managerialization has unfolded in a broad, domain-general fashion across social contexts, rather than originating in specific domains and gradually diffusing into others.

The Agents of Managerialization

The results above document a persistent rise in managerialization since the 1980s. Here, we examine which social actors were at the forefront of this cultural change. One might expect that members of the upper-middle and managerial classes, more deeply immersed in managerial ideology through their professional roles, would be especially inclined to adopt a managerial lens in their personal lives. At the same time, women, who disproportionately shoulder emotional labor in the workplace, may be particularly likely to extend this mode of thinking into the private sphere (*18*).

To test these hypotheses, we retrieved demographic information, including gender, age, education, and occupation, for authors across the three datasets where such matching was feasible: Congress, fiction, and movies. We then estimated the relationship between these sociodemographic attributes and managerial language using OLS regression models, interacting each attribute with time to capture shifting dynamics over decades (see Methods).

Figure 3a-e presents the marginal effects estimated by regression models across all demographic variables for explicit (top row) and implicit (bottom row) extensions of managerial language. The results reveal two overarching trends. First, women are early advocates of managerialization, both explicitly and implicitly. The gender gap is especially pronounced before 1980. Second, we see a strong institutionalization effect post-1980, where individuals receiving business education or who are exposed to managerial occupations are more likely to use management language in the personal sphere. Given that this sample of congresspeople and writers is overwhelmingly composed of highly educated individuals, it is unsurprising that college education shows only a moderate effect. Moreover, the stronger tendency among younger cohorts to express managerialization likely reflects increased exposure to managerial thinking through the education system and other dominant institutions over time.

Contemporary Managerialization among Ordinary Americans

The historical datasets analyzed thus far capture the perspectives of intellectual, political, and administrative elites, and may not reflect the views of ordinary Americans. To address this limitation, we turn to data from the American Voices Project (AVP) (*19*), a nationally representative and contemporary sample of interviews with Americans. Because these interviews follow a structured protocol that limits the range of topics discussed, observed sociodemographic patterns are less likely to reflect differences in topic salience across social groups. We analyzed 157,395 sentences from AVP interviews describing the body, subjectivity, and social relationships, and, using ordinary least squares, estimated differences in implicit managerialization by sociodemographics (*SI* Table S7). Marginal effects estimated from these models are illustrated in Figure 3f-k.

The results exhibit clear socioeconomic divergences in contemporary Americans' espousal of managerial logic. White, high-income, and educated respondents are more likely to construe their bodies, emotions, and relationships through a managerial prism than their lower-status counterparts. The effects of college education are especially pronounced: those with a bachelor's degree have almost twice higher an implicit managerialization score, compared to those with high-school education or less. The differences are equally stark by age, as younger cohorts, especially those born after 1980, are more likely to express managerialization than those coming of age before neoliberalism took hold. Consistent with the historical trends among elites reported in Figure 3a, there are no differences in managerialization by gender. By the time the AVP interviews were conducted in 2020, the process of managerialization appears to have been largely institutionalized, with women no longer leading its propagation. Finally, Democrats exhibit a slightly higher proclivity for managerialization, an effect that is statistically fragile (*SI* Table S8).

Discussion

Across a wide range of datasets and contexts, our analyses document a persistent extension of the meaning of *management* in everyday discourse to encompass the personal sphere. Americans increasingly see their bodies, emotions, and social relationships as projects that, like warehouse inventory or employee productivity, need to be regulated, controlled, and optimized. In doing so, these framings preclude alternative construals that emphasize spontaneity and authenticity in personal life.

While the origins of this cultural shift trace back to the mid-20th century, it only took root in the 1980s with the rise of neoliberalism as a dominant socioeconomic and ideological framework (*5*, *20*). Although our observational data cannot directly speak to the mechanisms that facilitated this large-scale diffusion, its consistent timing across datasets suggests a connection with neoliberal ideology. Commonly understood as a cultural logic that promotes market rationality, neoliberalism casts people as commodities (*2*, *4*). To be competitive on the market, people need to regulate themselves in the same way that businesses manage their operations. Our analyses suggest that as neoliberal tropes about human capital and responsibility were popularized by pundits and politicians---and as the modern firm reached new heights of scale and cultural dominance---the managerialization of personal life became broadly legitimized.

Sociodemographic decompositions of these historical trends further reveal that, among the cultural elites producing congressional speeches, fiction, and film, managerialization was most readily adopted by young, educated people, and especially women.
Two long-term sociohistorical trends help illuminate this striking gender pattern. First, scholarship has documented how the rise of modern psychology as a scientific field encouraged individuals---in particular, women---to view their emotions as sites of control (*10*, *12*, *22*). Second, the expansion of the service economy since the 1980s placed disproportionate emotional demands on women in female-stereotyped occupations, such as waitresses and airline hostesses, where emotional labor became a key component of professional identity (*18*, *23*). These developments help explain why women, who have long borne the brunt of emotional labor and who have been historically invested in therapeutic culture (*24*), appear in our data as early agents of managerialization. Still, it was only in the early 1980s that this managerial logic fully escaped the confines of the workplace and the therapist's clinic to inhabit everyday language. As the analyses of the AVP dataset illustrate, today managerialization is most commonly espoused by high-status Americans, and the initial gender gap in its use has disappeared.

The semantic extension of *management* offers a new perspective on recent claims that rationality is waning, while emotionality and subjectivity are on the rise (*13*, *25*, *26*). Our findings suggest that, rather than receding, rationality is encroaching on the subjective and relational dimensions of personal life. Although the frequency of discourse about subjectivity, relative to language expressing rationality, may have also intensified since the 1970s (*13*), our findings indicate that people are increasingly framing subjectivity through a managerial lens either implicitly or explicitly, thereby treating it as an object of calculative optimization. These findings also appear to reinforce the notion that practical rationality and emotion are no longer seen as mutually exclusive spheres of life, and are instead becoming intertwined (*27*). While a burgeoning industry of self-help and life coaches monetizes the cultural imperative of self-realization (*22*, *28*), emotional expression in the workplace is becoming normatively accepted, even encouraged (*29*).

An important limitation of our study is that, in focusing on large-scale trends in language use across millions of people over several decades, we sacrifice the ability to directly link linguistic shifts with individual decision-making and behavior. A known challenge in the use of linguistic analysis in the service of historical psychology (*30*) is that innumerable aspects of daily life are constantly changing over the course of decades, making it difficult to isolate the effects of particular linguistic shifts on people's cognition and consequent behavior. To address this, we employed a range of strategies, including comparative analyses and the use of object fixed effects, to ensure that the trends we document are not methodological artifacts or reflections of sociodemographic variance in topic salience. Still, we cannot definitively conclude, for example, that when a speaker frames a relationship in managerial terms, they approach it as something requiring oversight and intervention, rather than a space for spontaneous connection.

There are, nevertheless, strong reasons to believe such a conclusion is warranted. Research demonstrating the causal impact of linguistic framings on judgment, decision-making, and behavior abounds (*31–33*). Specifically, recent work shows that the use of managerial and economic logic helps explain the gendered division of labor in the household (*34*), as well as judges' rulings and sentencing behaviors (*35*). Moreover, qualitative evidence strongly suggests the trends we identify do not merely reflect superficial changes in linguistic convention. Middle-class parents' frequent use of managerial language, for instance, mirrors their interventionist parenting style, which emphasizes monitoring and optimizing their children's development (*36*). Similarly, there is growing evidence that high-status individuals strategically manage non-professional social relationships in ways that serve instrumental purposes, including advancing career prospects (*37*), navigating emotional needs (*38*), and curating moral identities (*39*). The proliferation of measurement, ranking, and social comparisons through digital platforms and wearable technologies reinforces such processes by quantifying the self for the purposes of optimization (*40*). Ultimately, the growing managerialization of personal life is culturally significant, regardless of whether it is a byproduct or a driver of these broader societal shifts. We conjecture it is likely a combination of both.

Materials and Methods

Research Design

Our overall analysis framework is demonstrated in Figure 4. We compiled several corpora to reflect public discourse, including news, fiction, movie scripts, congressional speeches, and case laws (*SI* section *Data Collection*). These corpora collectively cover the period from 1950 to 2020. The year 1950 marks the post-World War II era when business schools began to proliferate, and the managerial class rose to prominence (*6*, *7*), thus serving as an appropriate starting point for our analysis.

Large historical text corpora have two limitations: they are produced primarily by cultural elites, and they often lack sociodemographic information about the authors. To address these limitations, we utilized an additional corpus: the American Voices Project (AVP) dataset (*19*, *41*). This nationally representative dataset consists of open-ended interviews with 1,600 American adults conducted between 2019 and 2020, covering stories of their "everyday lives," including life history, daily routines, family, work, healthcare, stress, and economic decisions. The richness of open-ended interviews, coupled with extensive sociodemographic characteristics, allows us to map the permeation of managerialization into contemporary discourse, and its sociodemographic determinants.

Measuring Explicit Managerialization

In all datasets, we identify sentences containing management-related words (i.e., *manage* and its morphological variants) and use natural-language processing techniques to determine whether they refer to the management of personal or business-related matters (see *SI* section *Explicit Measure*). To ensure the word *manage* conveys meanings related to control and planning, we apply a Word Sense Disambiguation (WSD) filter (*SI* Figure S2). We then classify the filtered sentences using a supervised classifier based on the Bidirectional Encoder Representations from Transformers (BERT) model. For each sentence, the BERT classifier produces two labels: one primary label, determining if the context is business-related or personal, and a secondary label, detailing the specific domain to which management is applied, with a focus on the body, subjectivity, and relationships. Both the WSD filter and the BERT model were trained on examples annotated by GPT-4.

Our explicit approach assumes "*manage"* carries business-oriented connotations, an assumption supported by etymological analysis. Although the word traces its roots to the Latin *manus* (hand) and later Italian *maneggiare* (horse handling) (*42*), its modern meaning---associated with business control and supervision---became dominant during the Industrial Revolution. Since the 20th century, the term *manage* has been associated with supervising and directing business operations, involving key activities such as planning, organizing, commanding, delegating, coordinating, and controlling. Our analysis of the term's trajectory in semantic space shows that its business-oriented meaning has remained stable throughout the 20th century, with less semantic change than other comparably common words (*SI* Figure S4). As our study focuses on the period after the 1950s, we consider the baseline conventional meaning of *manage* (the source domain) to be sufficiently stable for our purposes.

Measuring Implicit Managerialization

We develop an implicit managerial language score to measure how strongly a sentence frames non-business domains (i.e., bodies, subjective states, relationships) in using managerial logic. Building on recent methodological advances (*43*, *44*), we use a fine-tuned BERT model to predict the likelihood that a masked non-business word (such as *feelings*), given the context in which it is used, could have been a typical element of management (such as *budget*).

To reduce noise, we consider a broad array of management-related words, group them into predefined categories (*manager*, *employee*, *asset*, *business*, *product*, *operations*), and calculate their average probabilities (see *SI* section *Implicit Measure*). We define this implicit score as the logarithm of the ratio between the aggregated probability of a management-related category and that of the original (non-business) masked word. Log ratios are symmetric and centered around zero, making them easier to interpret than raw probability ratios. Since multiple management categories are considered, we calculate the score for each category c and take the maximum as the sentence's overall implicit managerial language score:

$$Implicit\ Managerial\ Language\ Score = \max_{c}\left[log\left(\frac{P(\ predicted_{c})}{P(\ original)}\right)\right]$$

To better capture historical perceptions of implicit associations with management, we use MacBERTh (*45*), a BERT model trained exclusively on pre-1950s texts. This allows us to analyze how implicit managerial language emerged over time, avoiding biases introduced by modern linguistic conventions. For example, a phrase like "optimizing sleep" would have been a novel application of managerial terminology in the 1950s but is now conventionalized and less likely to be recognized as implicitly managerial. By using a model that predicts language as it was understood in the 1950s, we aim to study historical trends in managerial construal without the influence of later language developments.

Statistical Analysis

Following the sentence-level estimation of implicit and explicit managerialization, we linked authors in the historical datasets (congressional speeches, fiction, and movie scripts) using the Wikidata API (*SI* Figure S3). We excluded the news and caselaw corpora because they do not provide author identifiers necessary for demographic linkage. We successfully matched 100% of congressional members (N=3,287), 55% of screenwriters (N=65,666), and 59% of fiction writers (N=30,927) via the Wikidata API (*SI* section *Wikipedia Matching*).

We then examined the impact of authors' sociodemographic characteristics (age, gender, race, income, education, occupation, and ideology) on managerialization between the 1950s and the present. We pooled the historical datasets and estimated marginal effects using linear probability models (for explicit managerial language) and ordinary least squares (for implicit managerial language) (*SI* section *Sociodemographic Analyses*). All models controlled for dataset and document fixed effects. Implicit analyses additionally included masked object fixed effects to account for topic salience. The final sample comprised 523,545 sentences for explicit and 31,431,291 for implicit analysis, plus 157,395 sentences from the AVP dataset.

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Data and Materials Availability: Data, code, and materials needed to reproduce the results are available at: https://github.com/ziwnchen/MGMTMetaphor. For proprietary data obtained through university subscriptions, we provided the processed results in the GitHub repository, along with the source for accessing the dataset in the SI.

Figures and Tables

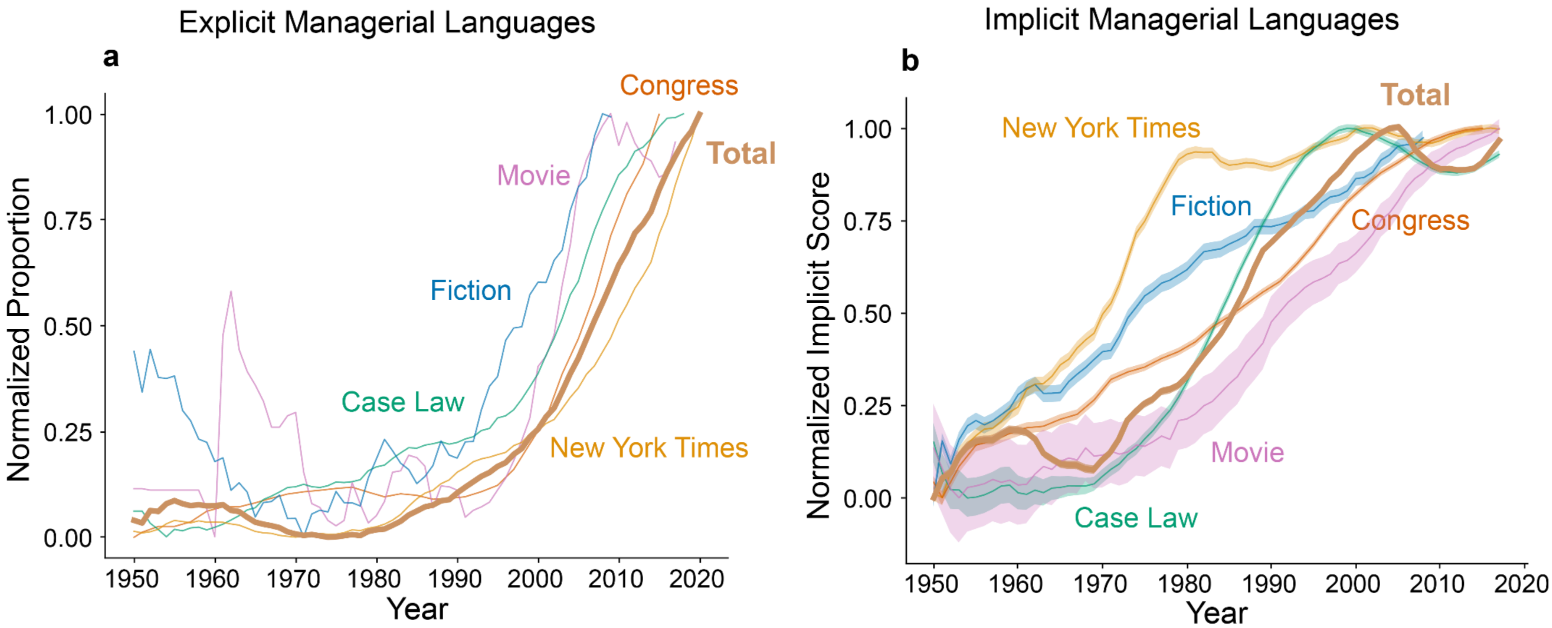

Fig. 1. Historical rise of explicit and implicit managerialization. Trends across five corpora (news, movie scripts, novels, congressional speeches, and case law) from 1950 to the present. (A) Proportion of explicit management sentences (occurrences targeting personal domains relative to all variations of the word "*manage*"). (B) Mean implicit managerial language score in personal domains (with 95% confidence intervals). Values are min-max normalized; lines represent 10-year moving averages.

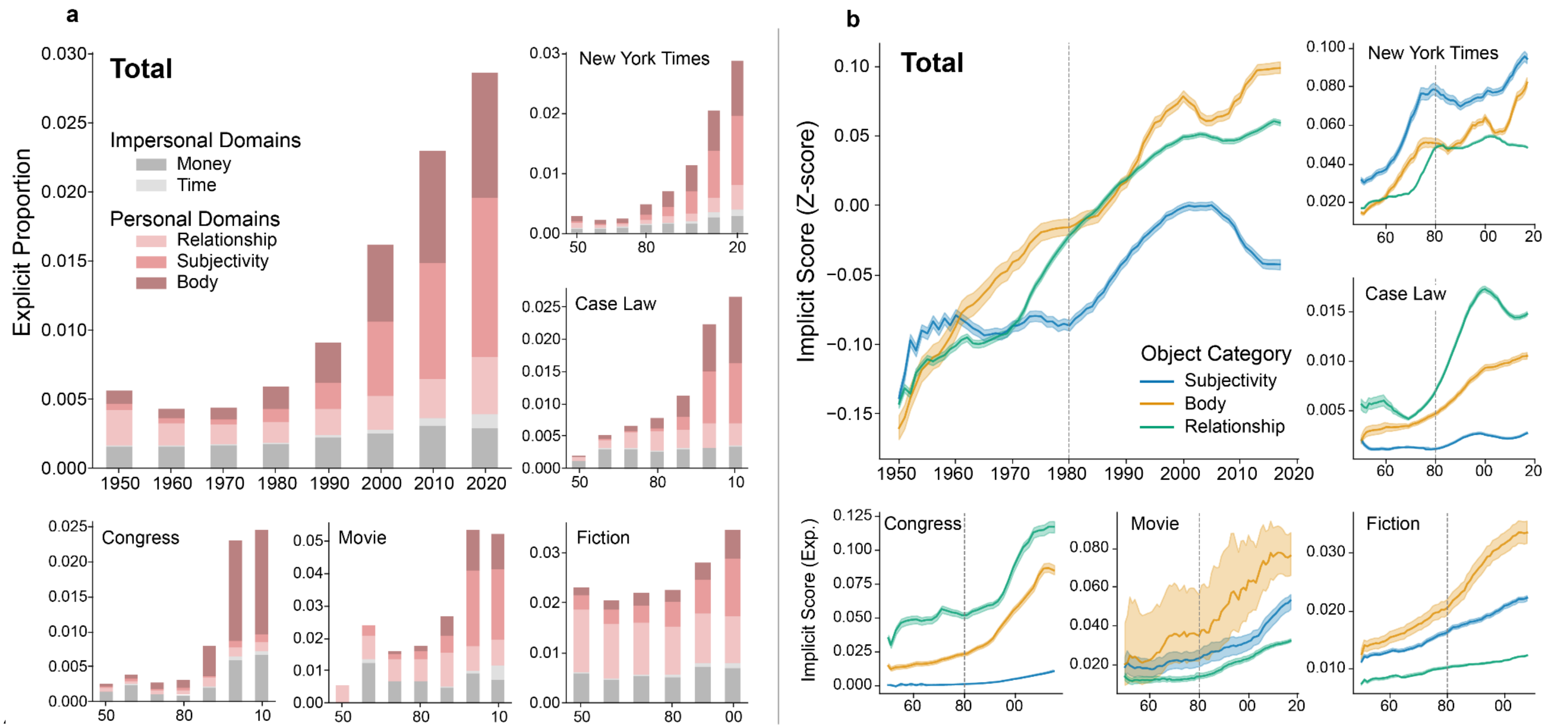

Fig. 2. Historical trends of managerialization by domain. (A) Proportion of explicit managerialization by domain and decade, including non-business "time" and "money" for comparison. Subplots show proportions by dataset; totals are aggregated across all sentences. (B) Mean implicit managerial language score (exponentiated) by domain and year. Lines indicate 10-year smoothed averages with 95% confidence intervals. Subplots show trends by dataset; totals are standardized and aggregated across all sentences.

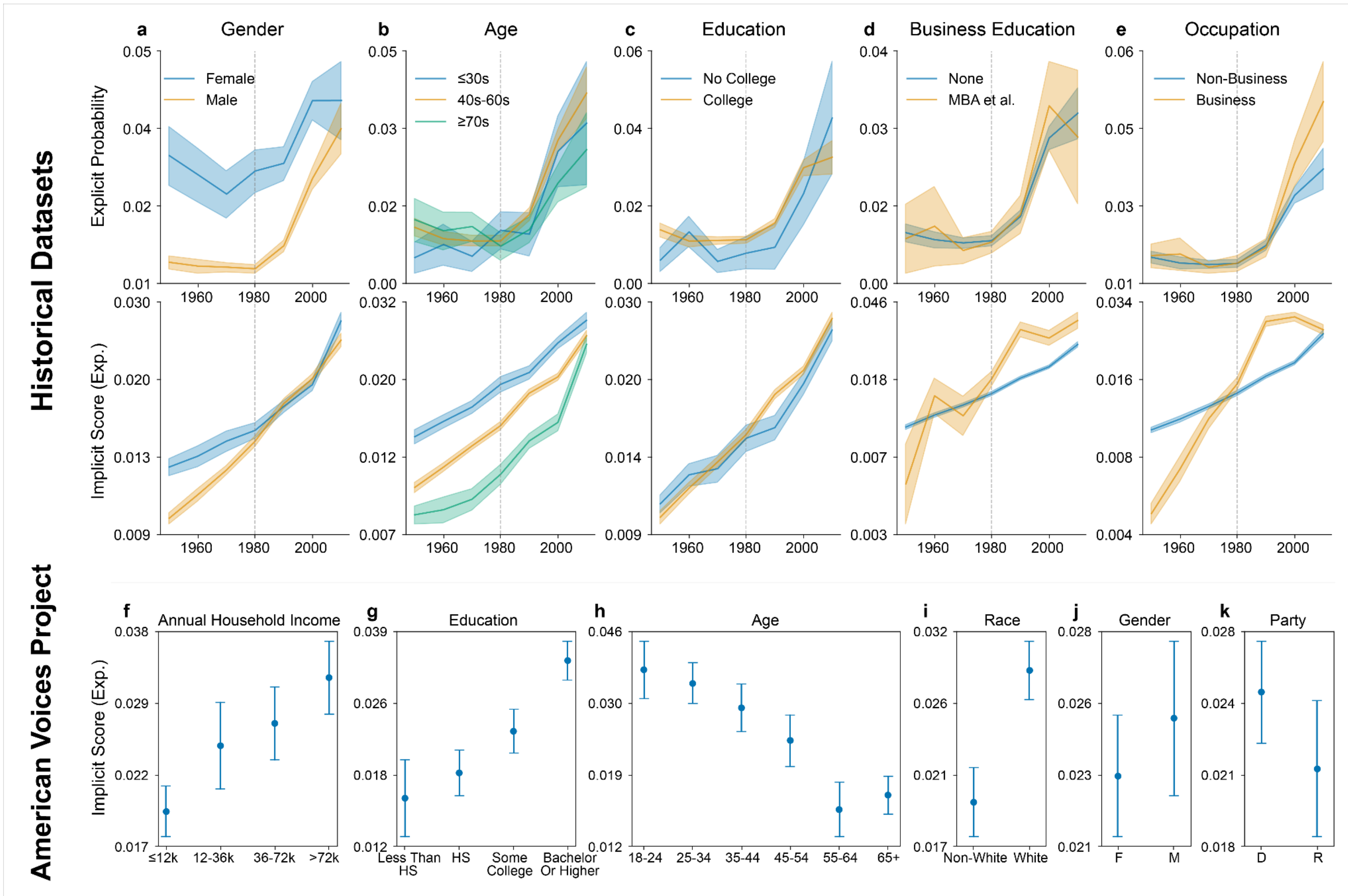

Fig. 3. Marginal prediction plots of managerialization by sociodemographics.

(A–E) Trends in explicit managerialization (top row) and implicit managerial language scores (middle row; exponentiated) by author sociodemographics, interacted with decade. Data are aggregated across congress, movie, and fiction datasets. Models include dataset FE, document FE, and object category FE (for implicit scores). Shaded areas indicate 95% confidence intervals. (F–K) Marginal predictions of implicit managerial language scores (exponentiated) for AVP interviews by interviewee characteristics. Models are estimated separately for each variable; error bars indicate 95% confidence intervals.

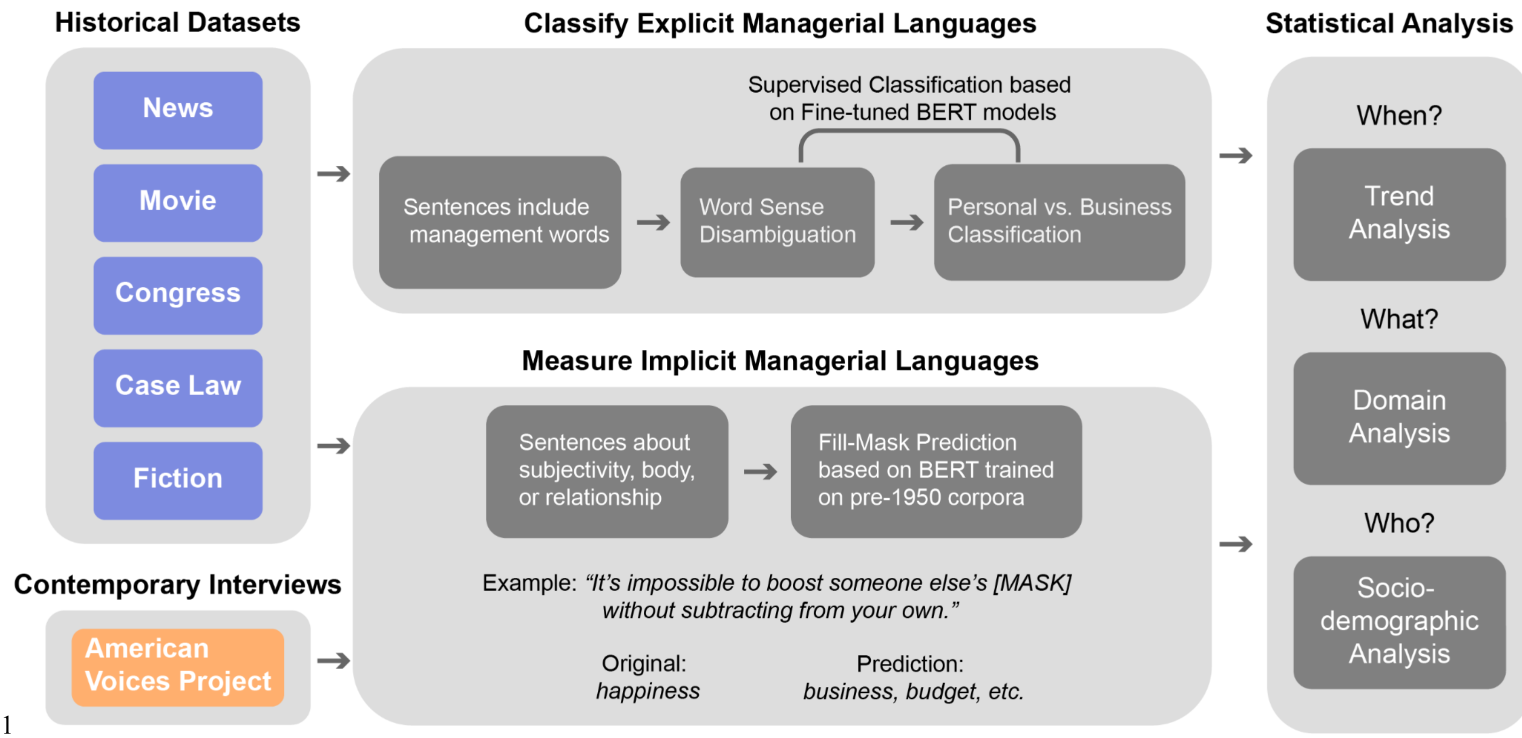

Fig. 4. Research pipeline. This methodological framework measures managerialization across historical text corpora (News, Movies, Congress, Case Law, Fiction) and contemporary interviews (AVP). The process distinguishes between explicit managerialization (supervised classification of direct management references) and implicit managerial language (BERT-based prediction of whether non-business concepts are framed as management entities). Historical datasets are analyzed using both measures, whereas contemporary interviews are limited to implicit measurement due to sample constraints. Finally, statistical models analyze these measures to uncover historical trends, domain-specific shifts, and sociodemographic patterns.

Supplementary Materials for

The Managerialization of Everyday Life From 1950 to the Present

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This PDF file includes:

Supplementary Text
Figs. S1 to S7
Tables S1 to S10
References (46 to 58)

Supplementary Text

Data Collection

New York Times

The New York Times (NYT) data used in this study were accessed through ProQuest's text analysis platform, [TDM Studio], via Stanford University's institutional subscription. Due to ProQuest's dataset size limitations, we were unable to work directly with the full corpus of NYT articles. Instead, we constructed two separate datasets, tailored for the explicit and implicit measurement tasks, respectively. Each dataset was created using distinct search queries.

Table S1 demonstrates the search queries used. The dataset for explicit measurement includes 3,059,319 NYT articles containing management-related terms. In contrast, the dataset for implicit measurement includes 9,975,346 articles containing terms associated with private life, based on a predefined list of keywords. Both datasets range from 1950 to 2019.

Fiction

The fiction data were obtained from the HathiTrust Research Center (HTRC), which provides access to the full-text corpus of the Google Books project. We accessed HTRC through Stanford University, one of the early partner institutions. The list of fiction works was sourced from the Post45 Data Collective, a project curated by literary scholar Ted Underwood. This collection includes metadata and HathiTrust IDs for fiction titles published between 1945 and 2013, held by the HathiTrust Digital Library. Underwood (*1*) has also compiled a related fiction list known as NovelTM previously used in large-scale text analyses. We chose to use the Post45 dataset, as it additionally includes Wikipedia IDs for authors, which were useful for our study.

A central challenge in working with scanned book corpora is accurately determining the publication date. The Post45 dataset provides two time-related variables: *inferreddate* (the earliest known publication date for a volume) and *latestcomp* (the latest possible date of composition). In some cases, *latestcomp* precedes *inferreddate* due to either (1) the existence of earlier editions or (2) posthumous publication. We chose to use *latestcomp* for two reasons: it aligns with prior historical text analysis using the HathiTrust dataset (*2*), and it more accurately reflects the period in which the fiction was likely written. Importantly, our results are robust to the choice of time variable—using *inferreddate* instead of *latestcomp* does not substantively alter the outcomes.

Since the Post45 list was originally curated using *inferreddate*, we further filtered the data to include only books with a *latestcomp* value between 1950 and 2010. We excluded works after 2010 due to the discontinuation of the Google Books project in 2009, which led to a sharp decline in available volumes after that point. After filtering, our final dataset included 63,493 books out of the original 75,954 listed.

CaseLaw

The case law documents were obtained from the Caselaw Access Project, an initiative by Harvard University that provides public access to U.S. court decisions. Because the raw text requires specialized parsing tools, we used a pre-parsed and tokenized version of the corpus provided by prior research on legal text (*3*). The dataset includes approximately 2,613,748 state-level case law documents from the 1960s to the 2010s and 1,475,208 federal-level documents from the 1950s to the 2010s.

Congressional Speech

We accessed congressional speech data from a dataset compiled by political scientists (*4*), which includes both the bound and daily editions of the U.S. Congressional Record spanning the 43rd to 114th Congresses (1873–2017). As our study focuses on historical developments post-1950, we restricted the sample to the 81st Congress (1949–1951) through the 114th Congress. For this period, the dataset contains approximately 6,469,769 speech segments.

Movie Subtitles

Movie dialogue was sourced from OpenSubtitles.org and organized by an organization called Open Parallel Corpora. The dataset was originally organized to support machine learning and machine translation tasks. However, the dataset has also been adopted in social science research (*5*). OpenSubtitles offers two primary versions: one compiled in 2016 and another in 2018. We used the 2018 version. From this dataset, we extracted subtitles for approximately 135,991 movies written between 1950 and 2017.

The American Voices Project

The American Voices Project (AVP) is a large-scale qualitative research initiative designed to capture everyday life experiences in the United States. Between 2019 and 2021, the project conducted over 1,500 in-depth interviews—either in-person or by phone—covering a wide range of topics, including daily routines, social relationships, economic hardship, employment, neighborhood conditions, healthcare, mental well-being, political beliefs, and identity.

The AVP sample primarily targets lower-income individuals, offering a valuable counterpoint to our historical corpora, which largely reflect the voices of societal elites. This contrast enables us to explore whether managerial and economic thinking has permeated the lower strata of the social hierarchy. It also offers us a contemporary, cross-sectional view of managerialization. Further details on the sampling strategy of AVP can be found on their website.

Data Preprocessing

Text Cleaning

Given the wide range of datasets used in this study, ensuring analytical consistency across corpora is critical. To that end, we developed a unified preprocessing pipeline to clean and structure all textual data.

We first cleaned the raw text using the following criteria:

- Whitespace and punctuation removal: All whitespaces and quotation marks were stripped from the text.
- Sentence length filtering: We removed sentences shorter than 10 words or longer than 100 words, based on thresholds used in prior research (*3*). Sentences with fewer than 10 words often lack sufficient contextual information, while those exceeding 100 words tend to be paragraph-like and may introduce excessive noise.
- Language filtering: We excluded sentences in which fewer than 50% of the words were recognized as English. This step was especially important for mitigating OCR errors in historical corpora, serving as a rough proxy for text quality.

To the best of our knowledge, these filtering criteria do not materially affect the substantive results. Following initial cleaning, we used two specialized preprocessing pipelines to generate the explicit and implicit measures, respectively.

Explicit Measure Preprocessing

For the explicit measure, we searched the cleaned text for all grammatical forms of the word *manage* (e.g., *"managing," "manage," "manager," "managerial," "management"*). Part-of-speech (POS) tagging was used to identify the grammatical function of each management-related word. If the term was identified as a noun (e.g., *"management"*), we extracted its grammatical modifier using dependency parsing. If it was a verb (e.g., *"manage"*), we extracted its direct object. These modifiers and objects were primarily used in robustness checks (see subsection *Verb Replacement*). They also help the selection of words related to private life for the implicit measure (see subsection *Implicit Measure Preprocessing)*.

Implicit Measure Preprocessing

To construct the implicit measure, we searched the cleaned text for sentences containing a predefined dictionary of words associated with private life. These words fall into three primary categories:

- Subjectivity: terms related to internal states or emotional expression
- Body: references to physical well-being or the body
- Relationship: words describing interpersonal relationships and social roles

We selected these categories based on both theoretical and empirical considerations. Theoretically, they reflect key dimensions of everyday life: navigate social interaction, control emotions, and tend their own bodies. Empirically, we prioritized words that frequently appeared as modifiers or direct objects of management-related terms in our earlier parsing for explicit measure, as these associations suggest relevance to how private life is framed in managerial contexts. The full dictionary of words for each category is presented in Table S1.

After filtering for sentences that contain the aforementioned private life–related words, we replaced each of these words with the [MASK] token. This masking procedure enables the BERT (Bidirectional Encoder Representations from Transformers) model to infer the most contextually appropriate word for that position, which is a key step in constructing the implicit measure. The implementation details of this measure are provided in the section *Implicit Measure*.

Explicit Measure

Word Sense Disambiguation (WSD) Filtering

The verb *manage* has two primary dictionary senses: (1) be in charge of (a company, establishment, or undertaking); administer; run; (2) succeed in surviving or in attaining one's aims, especially against heavy odds; cope.

In the context of measuring managerialization, we are concerned exclusively with the first definition. That is, instances where *manage* conveys meanings related to control, direction, or supervision.

To exclude sentences in which *manage* is used in the second sense, we applied a Word Sense Disambiguation (WSD) filter. Prior research (*6*, *7*) has shown that contextual embeddings produced by transformer-based language models can reliably distinguish between different senses of polysemous words. We confirmed this finding for *manage*. Figure S1 visualizes the contextual embeddings of 1,000 sentences using *manage* in the control/supervision sense and 1,000 sentences using it in the coping/surviving sense. The two senses form clearly separable clusters in the embedding space.

To automate this filtering, we trained a supervised WSD classifier using contextual embeddings from BERT. Sentences were input into the BERT model, and the contextual embeddings of *manage* were extracted and classified into a binary sense category using a logistic regression classifier. The classifier was trained on a balanced dataset of 2,000 sentences, 1,000 for each sense, sampled from the Corpus of Historical American English (COHA). Each sentence was labeled using GPT-4. The classifier achieved an F1 score of 0.95. We then applied the WSD filter to our corpus, retaining only those sentences in which *manage* was predicted to convey the sense of control or supervision with a confidence score greater than 95%.

Person Business Classification

Training Classifier. After identifying sentences that contain management-related words and applying the WSD filter to those where the word is used as a verb, we performed a supervised classification to construct the explicit measure. This classification task distinguishes between:

- Context type: whether the sentence reflects a personal or business context;
- Managed object category: whether the object being managed falls into one of the following nine categories: emotion, body, time, family, friendship, romantic relationship, household, financials, and business operations.

To train the classifier, we used GPT-4 to annotate examples from the Corpus of Historical American English (COHA). The annotation prompt is provided in Section *GPT Annotation*. After annotation, the training set consisted of 5,060 sentences labeled as personal management, 31,240 sentences labeled as business management, and 1,599 sentences labeled as neither.

In training the classifier, we employed a dual-head classification model. We extracted the contextual embeddings of the management-related word generated from the final layer of a BERT model. These embeddings were fed into two parallel logistic classifiers: A primary classifier to distinguish between personal and business contexts, and a subcategory classifier to assign each sentence to one of the nine management domains listed above.

The total loss function was computed as the sum of the losses from both classification tasks. This dual-head design was chosen for two reasons. First, the primary and subcategory classifications are inherently related. The subcategories typically serve as finer-grained distinctions built upon the broader personal/business divide. Second, joint training reduces the risk of error propagation, which can occur when classifiers are stacked sequentially.

GPT Annotation. Large-scale annotation using GPT models has become increasingly common in social science research, with multiple studies demonstrating that GPT achieves high and consistent annotation quality across a variety of tasks (*8*, *9*). Building on this precedent, we employed the GPT-4 model to annotate the examples used for training our supervised classifier.

We opted not to apply GPT classification directly to our full corpora due to copyright restrictions and infrastructure limitations—many of our datasets are hosted on servers without internet access. As an alternative, we used GPT-4 to generate a substantial set of annotated examples offline, which were then used to train our own supervised classification model.

In addition, previous work has shown that domain-specific supervised classifiers can sometimes outperform general-purpose language models like GPT when applied to targeted classification tasks (*10*). This further supports our decision to use GPT-annotated data to train a specialized model. Below is the prompt we used for annotation:

> *The following sentence contains a management-related word highlighted using [TGT]. This word can be any part of speech (noun, verb, adjective, etc.), such as "manage," "manager," "managing," etc. Please answer the following question based on the context of the sentence:*
>
> *Question 1: What is the context of the management-related word?:*
> - *Business and Professional: for example, work, job, industry etc.*
> - *Personal: for example, self, personal life, personal relationship etc.*
> - *Others: Any context not fitting into the above categories.*
>
> *Question 2: Categorize the object being managed into one of the following categories:*
> - *Emotion and subjective experiences: feelings like happiness, stress, expectations, etc.*
> - *Human body: physical aspects like health, fitness, etc.*
> - *Time: for example, scheduling, deadlines, etc.*
> - *Family: relationships with family members like parents, siblings, children, spouse, etc.*
> - *Friendship: relationships with friends*
> - *Romantic relationships: for example, love, dating, intimacy, etc*
> - *Household: for example, home, groceries, backyard, etc*
> - *Financials: for example, money, savings, wealth, etc*
> - *Business Operations: for example, sales, marketing, production, employee, etc*

- *Others: Any object not fitting into the above categories.*

Instructions:

- *Focus only on the management-related word highlighted using [TGT] in the sentence.*
- *Only identify instances that strictly fall under the identified categories. Label all other instances as "Others".*
- *If the highlighted word is intransitive (e.g., “manage .. to do”), assume the context and object being managed are "Others".*

Example:

- *Sentence: The manager cannot [TGT] manage [TGT] his children when they misbehave. Answer: Question 1: Personal; Question 2: Family*
- *Sentence: The [TGT] manager [TGT] cannot manage his children when they misbehave. Answer: Question 1: Business and Professional; Question 2: Business Operations*
- *Sentence: I [TGT] manage [TGT] to write him a letter. Answer: Question 1: Others; Question 2: Others*

Implicit Measure

Implicit Managerial Language Measurement

The intuition behind our implicit managerial language measure is conceptually straightforward: implicit framing occurs when non-business concepts are treated as if they were business entities within a specific context. For example, consider the sentence:

“I wish my [MASK] would stop bossing me around.”

The phrase "bossing me around" evokes a workplace or hierarchical authority context, suggesting plausible candidates for the masked word such as manager, employer, or supervisor. If the actual word is mom, the usage projects a managerial hierarchy onto a domestic relationship. By juxtaposing the domestic sphere (i.e., mom) with a workplace role, the sentence implicitly construes a family member as a workplace superior. This form of conceptual transfer signals implicit managerialization.

We formalize this intuition using a historical BERT model to predict the masked word in each sentence. This Fill-in-the-Mask (FillMask) approach has gained traction in recent social science research for measuring constructs such as prescience (*3*), stereotyping (*11*), dehumanization (*12*), and cultural change (*13*).

For each sentence containing a [MASK] token, we compute: the model-predicted probability of the original word (i.e., the word that was masked), and the average probability assigned to each group of business-related words, as defined in Section *Prediction Business Object List*. Because we consider multiple managerial categories, we calculate a managerial proximity score for each category *c* and define a sentence’s overall implicit managerial language score as the maximum among these category scores. This approach captures the strongest implicit association with management embedded in a given sentence.

$$Implicit\ Managerial\ Language\ Score = \max_{c}\left[\log\left(\frac{P(predicted_{c})}{P(original)}\right)\right]$$

In rare cases, we adjusted the predicted probability of a word by averaging it with that of a close literal synonym (e.g., *mom* and *mother*) to reduce prediction noise introduced by lexical variation. For instance, we expect *mother* and *mom* to refer to the same social role. However, if the model systematically assigns a higher probability to one word over the other due to random noise or differences in underlying vocabulary frequency, this averaging helps mitigate such artifacts. The following synonym pairs were considered for this adjustment: *emotion* and *feeling*, *happiness* and *joy*, *jealousy* and *envy*, *passion* and *zeal*, *child* and *kid*, *mom* and *mother*, *father* and *dad*, *disease* and *illness*.

Prediction Business Object List

Table S2 lists the business-related words used in the fill-mask prediction task. One limitation of BERT-family models is that they can only predict a single token in place of the [MASK] token. Because BERT models have a fixed vocabulary, any word not included in that vocabulary is tokenized into multiple subword units, making it impossible for the model to generate such words directly as predictions.

Upon analysis, we found that 64 out of the 246 prediction words listed below are tokenized into multiple subword units and thus cannot be predicted as complete words. Nonetheless, we retain the full list to reflect our initial selection, which aligns more closely with our theoretical considerations. In Table 3, words shown in italics indicate terms not present in the BERT vocabulary and therefore unrepresentable in direct model inference. Given that the majority of the italicized terms are plural forms, we believe this should not significantly impact the performance of the measurement. To the best of our knowledge, adding or removing plural forms of the words to be predicted does not significantly change the results of our measurement.

Prediction Original Object List

As discussed in the previous section, certain terms cannot be predicted using the fill-mask process because they are not part of the model's vocabulary. As part of our implicit measurement, we also need to estimate the probability of masked words related to private life, but some of these terms are not included in BERT's vocabulary. Consequently, we have revised our original list of target words to exclude those that the BERT model cannot predict. These excluded terms will not be used in the subsequent analysis. The updated list is presented in Table S3.

Wikipedia Matching

To examine the historical agents of managerialization, we extracted all available demographic information on authors across our datasets. This was possible for three of the datasets: Congress, fiction, and movies, where author identities were accessible. In contrast, author name information was unavailable for the New York Times and Case Law datasets.

For each dataset, we first matched individuals' names to identifiers specific to their respective institutions. For example, congressional members were matched using their Congress Bioguide ID, while movie scriptwriters were matched using their IMDb ID. We then queried these identifiers through the Wikidata API to retrieve demographic details, including gender, age, education, and occupation. For fiction writers, the dataset already included Wikidata IDs, allowing us to directly retrieve associated information.

We further calculated the author's age by subtracting the publication date of their work with their birth dates. We coded the author's education by looking at (1) whether they attended college or universities and (2) whether they attended business schools. We coded the author's occupation by looking at whether they worked in business-related careers. Table S4 provides details of the coding criteria.

Figure S2 outlines the full matching process, and Table S5 presents the corresponding matching rates for each step.

Sociodemographic Analyses

We analyzed historical and AVP data by author/interviewee sociodemographic attributes to identify early and contemporary adopters of managerialization. We ran separate sets of analyses on explicit and implicit managerialization measures. For historical corpora, we ran our analysis on a pooled dataset that contains data from all three corpora: Fiction, Movie, and Congressional Speech. For the contemporary corpus (i.e., American Voices project), we ran our analysis only estimating the implicit measure due to data scarcity for the explicit measure.

Sociodemographic Analysis of Explicit Managerialization

We estimated a linear probability model to perform sociodemographic analyses of explicit managerialization. The dependent variable (*IsPerson*) is a binary indicator at the sentence level, coded 1 if a sentence containing management-related language refers to personal (rather than business) management. The independent variables include the author's gender (*Gender*), age group (*AgeGroup*), college education background (*IfCollege*), business education background (*IfBusinessEd*), and business occupation status (*IfBusinessJob*). To examine temporal heterogeneity in each variable's effect, we interact each independent variable with the publication decade (*Decade*). All models include fixed effects for the dataset (*Dataset*), and standard errors are clustered at the document level to account for intra-document correlation. In what follows, *d* indexes documents (i.e., authors), and *s* indexes sentences. Note that *CollegeEd* and *BusinessEd* are not included in the same model simultaneously due to multicollinearity concerns.

Gender Effect

$$IsPerson_s = \beta_0 + \beta_1 \cdot Gender_d + \beta_2 \cdot Decade_d + \beta_3 \cdot (Gender \times Decade)_d + \beta_4 \cdot AgeGroup_d + \beta_5 \cdot IfCollege_d + \beta_6 \cdot IfBusinessJob_d + \beta_7 \cdot Dataset_d + \varepsilon_s$$

Age Effect

$$IsPerson_s = \beta_0 + \beta_1 \cdot AgeGroup_d + \beta_2 \cdot Decade_d + \beta_3 \cdot (AgeGroup \times Decade)_d + \beta_4 \cdot Gender_d + \beta_5 \cdot IfCollege_d + \beta_6 \cdot IfBusinessJob_d + \beta_7 \cdot Dataset_d + \varepsilon_s$$

College Education Effect

$$IsPerson_s = \beta_0 + \beta_1 \cdot IfCollege_d + \beta_2 \cdot Decade_d + \beta_3 \cdot (IfCollege \times Decade)_d + \beta_4 \cdot Gender_d + \beta_5 \cdot AgeGroup_d + \beta_6 \cdot IfBusinessJob_d + \beta_7 \cdot Dataset_d + \varepsilon_s$$

Business Education Effect

$$IsPerson_s = \beta_0 + \beta_1 \cdot IfBusinessEd_d + \beta_2 \cdot Decade_d + \beta_3 \cdot (IfBusinessEd \times Decade)_d + \beta_4 \cdot Gender_d + \beta_5 \cdot AgeGroup_d + \beta_6 \cdot IfBusinessJob_d + \beta_7 \cdot Dataset_d + \varepsilon_s$$

Business Occupation Effect

$$IsPerson_s = \beta_0 + \beta_1 \cdot IfBusinessJob_d + \beta_2 \cdot Decade_d + \beta_3 \cdot (IfBusinessJob \times Decade)_d + \beta_4 \cdot Gender_d + \beta_5 \cdot AgeGroup_d + \beta_6 \cdot IfCollege_d + \beta_7 \cdot Dataset_d + \varepsilon_s$$

Sociodemographic Analysis of Implicit Managerialization

We estimate OLS models to analyze how individual-level characteristics influence implicit managerialization. The dependent variable, *ImplicitScore*, is a continuous measure at the sentence level that reflects the degree to which a sentence implicitly frames non-business domains as management entities. Consistent with the analysis using explicit managerialization, the key independent variables include the author's gender (*Gender*), age group (*AgeGroup*), undergraduate education background (*IfCollege*), business education background (*IfBusinessEd*), and professional experience in a business-related occupation (*IfBusinessJob*). To assess temporal heterogeneity, each independent variable is interacted with the publication decade (*Decade*).

All models control for dataset fixed effects (*Dataset*) and target object category fixed effects (*ObjectCategory*)—with categories such as body, emotion, and relationship. The latter controls for sociodemographic variation in topic selection. In a separate robustness check, we include fixed effects at the specific target object level; the results remain substantively unchanged. Standard errors are clustered at the document level to account for intra-document correlation. In what follows, *d* indexes documents (i.e., authors), and *s* indexes sentences. Due to multicollinearity concerns, *CollegeEd* and *BusinessEd* are not included in the same specification.

Gender Effect

$$ImplicitScore_s = \beta_0 + \beta_1 \cdot Gender_d + \beta_2 \cdot Decade_d + \beta_3 \cdot (Gender \times Decade)_d + \beta_4 \cdot AgeGroup_d + \beta_5 \cdot IfCollege_d + \beta_6 \cdot IfBusinessJob_d + \beta_7 \cdot Dataset_d + \beta_8 \cdot ObjectCategory_s + \varepsilon_s$$

Age Effect

$$ImplicitScore_s = \beta_0 + \beta_1 \cdot AgeGroup_d + \beta_2 \cdot Decade_d + \beta_3 \cdot (AgeGroup \times Decade)_d + \beta_4 \cdot Gender_d + \beta_5 \cdot IfCollege_d + \beta_6 \cdot IfBusinessJob_d + \beta_7 \cdot Dataset_d + \beta_8 \cdot ObjectCategory_s + \varepsilon_s$$

College Education Effect

$$ImplicitScore_s = \beta_0 + \beta_1 \cdot IfCollege_d + \beta_2 \cdot Decade_d + \beta_3 \cdot (IfCollege \times Decade)_d + \beta_4 \cdot Gender_d + \beta_5 \cdot AgeGroup_d + \beta_6 \cdot IfBusinessJob_d + \beta_7 \cdot Dataset_d + \beta_8 \cdot ObjectCategory_s + \varepsilon_s$$

Business Education Effect

$$ImplicitScore_s = \beta_0 + \beta_1 \cdot IfBusinessEd_d + \beta_2 \cdot Decade_d + \beta_3 \cdot (IfBusinessEd \times Decade)_d + \beta_4 \cdot Gender_d + \beta_5 \cdot AgeGroup_d + \beta_6 \cdot IfBusinessJob_d + \beta_7 \cdot Dataset_d + \beta_8 \cdot ObjectCategory_s + \varepsilon_s$$

Business Occupation Effect

$$ImplicitScore_s = \beta_0 + \beta_1 \cdot IfBusinessJob_d + \beta_2 \cdot Decade_d + \beta_3 \cdot (IfBusinessJob \times Decade)_d + \beta_4 \cdot Gender_d + \beta_5 \cdot AgeGroup_d + \beta_6 \cdot IfCollege_d + \beta_7 \cdot Dataset_d + \beta_8 \cdot ObjectCategory_s + \varepsilon_s$$

Sociodemographic Analysis of the American Voices Project

To examine sociodemographic differences in the use of implicit managerial language in contemporary American discourse, we analyzed interviews from the American Voices Project (AVP). In the main text, we report estimates of marginal effects for each demographic variable separately, estimated from an OLS regression. The dependent variable in each model was the implicit managerial language score, and the independent variable was one of the following: gender, age, race, income, education, or political affiliation. Standard errors were clustered at the interview document level.

We opted for separate models (Table S6) rather than a full model with all covariates due to high collinearity between income and education. Including both in a single model would obscure their individual effects.

To supplement the main analysis, we also report results from OLS regressions that include multiple variables. These models use the same dependent variable—implicit managerial language score at the sentence level—and include subsets of the independent sociodemographic variables, as well as fixed effects for the personal object category (body, subjectivity, or relationship). The object category serves as a control to account for thematic variation that might influence the degree of managerial framing. Again, standard errors were clustered at the interview level, d indexes interview documents (i.e., authors), and s indexes sentences.

Table S7 presents results from three models: a full model including all variables, a model excluding income, and a model excluding education. The results are consistent with the main analysis: younger, White, higher-income, and college-educated individuals are significantly more likely to use implicit managerial language. Gender exhibits no significant effect. Notably, income and political affiliation are significant when education is excluded, likely due to multicollinearity between them and education.

Robustness Tests

Implicit and Explicit Measurement Examples

We provide examples from our implicit and explicit measurements for better intuitions. Table S8 presents example sentences from the COHA dataset classified by our dual-headed personal–business classifier. These examples illustrate the application of the explicit measure. As shown, the primary (personal vs. business) and secondary (subdomain) categories do not always correspond in a one-to-one manner. Overall, the results underscore the flexibility of the concept of management—a term historically rooted in business organizations—in extending to diverse domains of everyday human life.

Table S9 presents example sentences that achieved the highest scores in the implicit measurement. We include representative examples from each subgroup; that is, the group with the highest implicit managerial language score for a given sentence.

The Managerialization of Parenting

One domain of private life where we expect managerialization to manifest is parenting. Sociological literature has long documented the historical rise of an interventionist, “managerialized” parenting style. Rather than allowing children to grow naturally, these parents create highly organized schedules, invest significant resources, and engage in extensive negotiation with their children. Effectively, the child is treated as a “project” requiring constant development to ensure optimal outcomes. This form of intensive parenting is observed most frequently among the middle class (*14*) and has been linked to unequal educational outcomes that reproduce class-based inequality.

This transition from a permissive to a managerialized style largely occurred during the 1980s and 1990s. Following the permissive approach of the "Baby Boomers," Gen X and Millennial parents drastically increased the amount of time, money, and energy spent on child-rearing. This cultural shift is often attributed to changes in the economic environment, particularly the rise of a more competitive economy (*15*, *16*).

Because the managerialization of parenting is theoretically well-established, we use this domain to validate our method. Figure S3 demonstrates the managerialization of parenting based on our analysis of the New York Times dataset. We extracted all parenting actions, defined as verbs used by parents (*“mom”, “dad”, “mother”, “father”, “parent”*) toward children (*“son”, “daughter”, “kid”, “child”*). Figures S3a and S3b demonstrate that, across all parenting actions, the managerialized category has increased while the nurture category has declined. Furthermore, Figure S3c confirms that these categories align with our measure: managerialized actions exhibit significantly higher implicit managerial language scores — closer to the managerialization construal— than nurturing actions. This validation confirms our method's ability to detect the cultural shifts toward managerialization discussed in the main text.

Meaning of Management in Semantic Space

We examined the changing meaning of the word *management* using historical word embeddings, which include a word2vec embedding for every decade (*17*). Figure S4a illustrates how the semantic representation of *management* traveled in the semantic space from 1910 to 1990, indicating minimal changes in its core meaning over time. To quantify semantic changes in individual words, we calculated the cosine distance between the embedding vector of each word in 1900 and its counterpart in 1990. A smaller cosine distance indicates a lower semantic shift and thus higher stability over time. Figure S4b shows that the words *manage* and *management* experienced relatively minor changes in meaning across the 20th century. Among 10,000 randomly selected words, *management* and *manage* ranked in the top 6% and 16%, respectively, in terms of semantic stability.

To provide further intuition, we also analyzed the word *gay*, which is widely recognized to have undergone a significant semantic shift—from denoting joy and happiness to referring to sexual orientation. As expected, *gay* ranked in the bottom 13% of words in terms of stability, consistent with its known trajectory of meaning change.

Because the original embedding data covers only the 20th century, we are unable to trace word trajectories beyond the year 2000. However, we believe this limitation is acceptable, as our goal here is to demonstrate that the meanings of *manage* and *management* have remained relatively stable since the 1950s, aligning with their modern, business-oriented usage.

Verb Replacement Analysis

One concern regarding the results of the explicit analysis is whether they are driven by the changing frequency of the personal domain terms themselves. Specifically, if concepts such as *anger* or *pain* have simply gained more prominence in public discourse and are now discussed more frequently, this could also explain the increased use of expressions like *anger management* or *pain management*. In such a case, the trend would not reflect an expansion of managerial discourse into new domains, but rather an increase in references to *anger* or *pain* more generally.

To address this alternative explanation, we identified a set of top words that have been found to be associated with management expressions—either as modifiers or direct objects. These words include: subjectivity-related terms such as *stress, expectation, anxiety, emotion, and grief*; body-related terms such as *illness, disease, addiction, and health*; relationship-related terms concerning social roles such as *family, child, brother, sister, husband, and wife*; and relationship-related terms concerning social interactions, such as *conflict, communication, rivalry, disagreement, friendship, jealousy, coordination, compassion, conversation*, among others. Using this set of terms, we examined whether the verbs used to describe these words have changed over time, and, if so, whether this change reflects a shift toward a more managerial tone. We conducted our analysis on the New York Times dataset.

Our analysis demonstrated that, after controlling for the frequency of the domain-specific terms, the verbs associated with these domains have indeed undergone a significant shift toward a more managerial tone. For example, among all verbs used to describe *stress*, the use of the verb *manage* has increased notably, with the trend beginning around the 1980s.

Figures S5 show that similar trends were observed for a number of subjectivity-, body-, and relationship-related words. In each case, the use of management-related language began to rise around the 1980s and 1990s. This increasing use of managerial language in personal domains cannot be fully explained by a general rise in the frequency of the word *manage* in the English language, as the relative increase in these specific contexts is considerably larger. One exception we identified is the word *trust*, which does not show a notable increase in association with the verb *manage*. This is understandable given that *trust* is polysemous and can also refer to a legal or financial arrangement—*"an arrangement whereby a person (a trustee) holds property as its nominal owner for the benefit of one or more beneficiaries."*

Figures S6 explore verbs beyond *manage* that carry a similar connotation, such as *track* and *monitor*. These verbs also convey notions of control and supervision. Our findings indicate that, starting in the 1980s, these verbs have increasingly been applied to social relationships, including terms such as *friend, family, and colleague*.

Figure S7 shows the distribution of growth rates for verbs describing words related to subjectivity, the body, and relationships, as previously identified. The growth rate captures how the relative usage of each verb has changed over time by comparing its frequency before and after 1980. We chose 1980 as the cutoff point because our earlier trend analysis identified the 1980s as a pivotal moment in the rise of managerialization and the emergence of neoliberal thought. To ensure reliability, we excluded verbs that appeared fewer than 100 times in total. The growth rate is calculated as follows:

$$\text{Growth Rate} = \frac{P_{\text{after1980}} - P_{\text{before1980}}}{P_{\text{before1980}}}$$

Here, *P* represents the proportion of a given verb relative to the total frequency of all verbs used during a specific time period. In calculating these frequencies, we only considered instances where the verb was used to describe words related to subjectivity, the body, and relationships, as listed above. As shown in Figure 11, verbs associated with control and planning—such as *manage, monitor, oversee, and track*—exhibit the highest growth rates, increasing by approximately a factor of ten. In contrast, verbs like *express, suffer, stir, and relieve*, which reflect more passive engagement, show little to no growth and appear at the lower end of the distribution.

Overall, our verb replacement analysis supports the conclusion that managerialization is not merely a byproduct of increased frequency in either personal domain terms or management-related language. Rather, it represents a distinct expansion of managerial discourse into the personal domain. We also demonstrate that managerialization is not limited to the use of the word *manage*, but extends to other terms with similar connotations.

This, in turn, raises the question: Why does our main analysis focus solely on the word *manage*? The primary reason is signal clarity. Including additional focal verbs such as *monitor*, *track*, or even terms like *buy* or *sell* could dilute the core signal and obscure the conceptual boundaries of managerialization. For example, *monitor* or *track* may introduce meanings related to surveillance, which, while related, may fall outside the intended scope of our analysis.

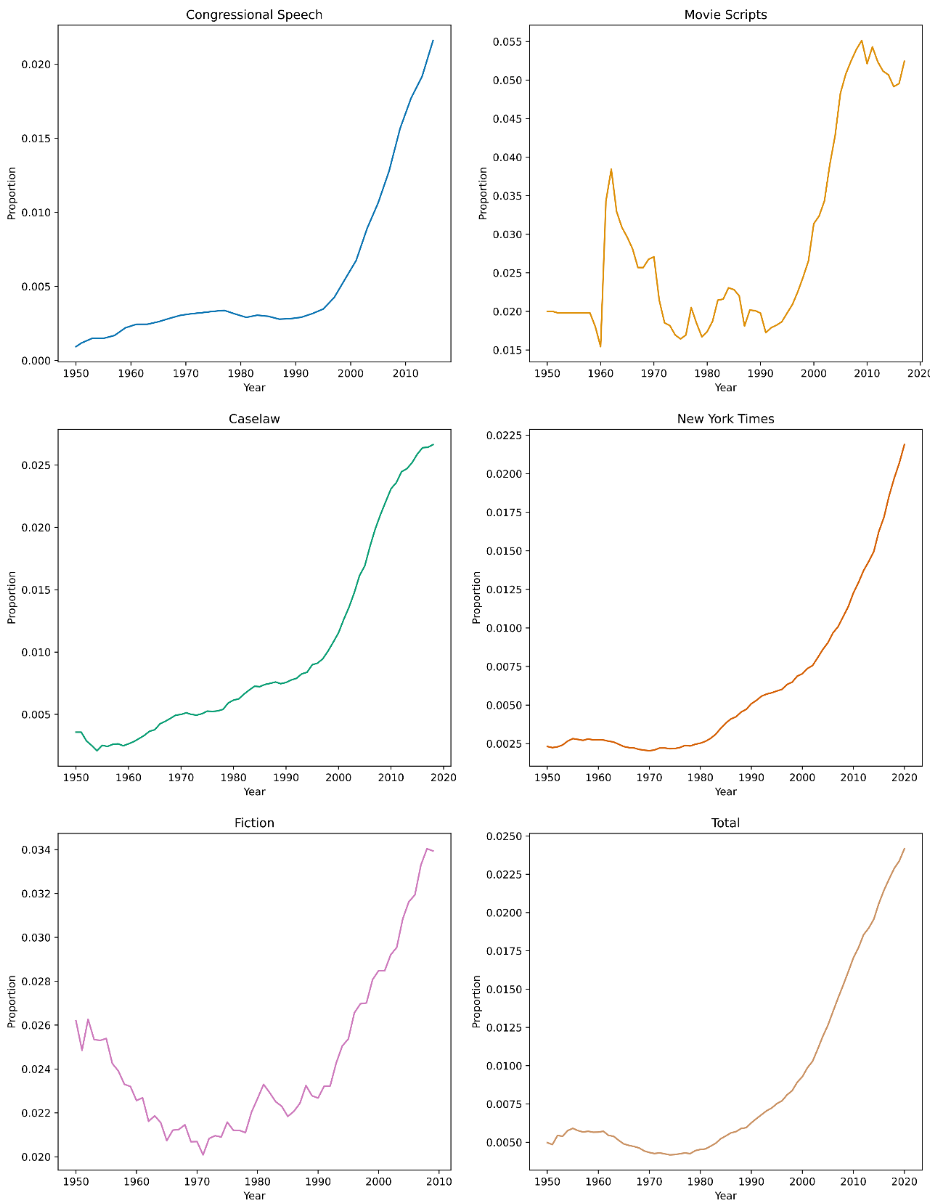

Figure S1.
Disaggregate plots of changes in the proportion of explicit management sentences in personal domains from 1950 to today across five large-scale textual datasets. Proportions represent the number of sentences referring to the management of personal domains relative to all sentences containing the words "manage" or "management". Lines represent 10-year moving averages.

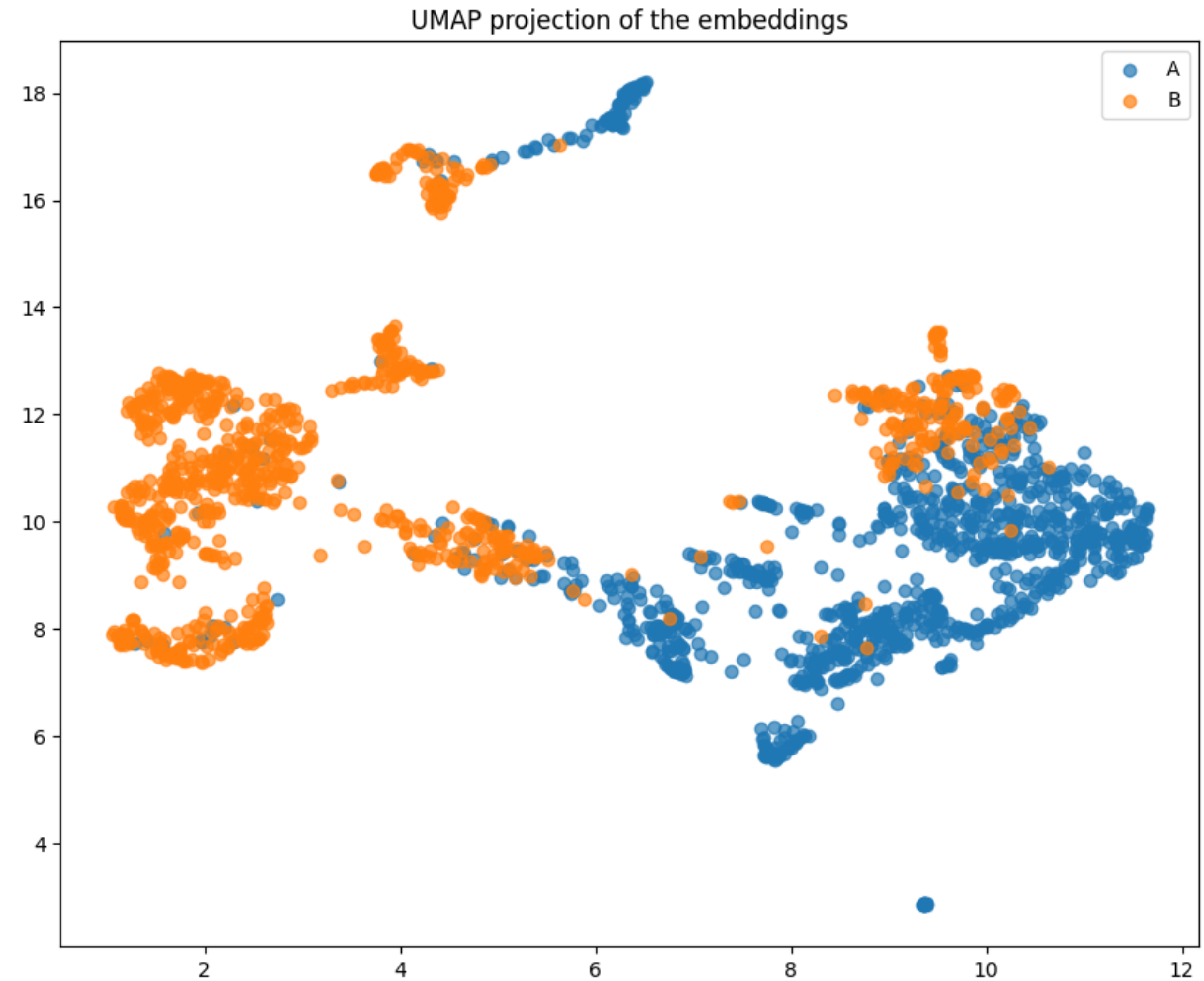

Figure S2.
The contextual embedding of the two different senses of the verb *“manage”* from the 2000 sentences used to train the Word Sense Disambiguation (WSD) filter. Label A corresponds to the sense *“to be in charge of (a company, establishment, or undertaking); administer; run”*. Label B corresponds to the sense *“to succeed in surviving or in attaining one's aims, especially against heavy odds; cope”*.

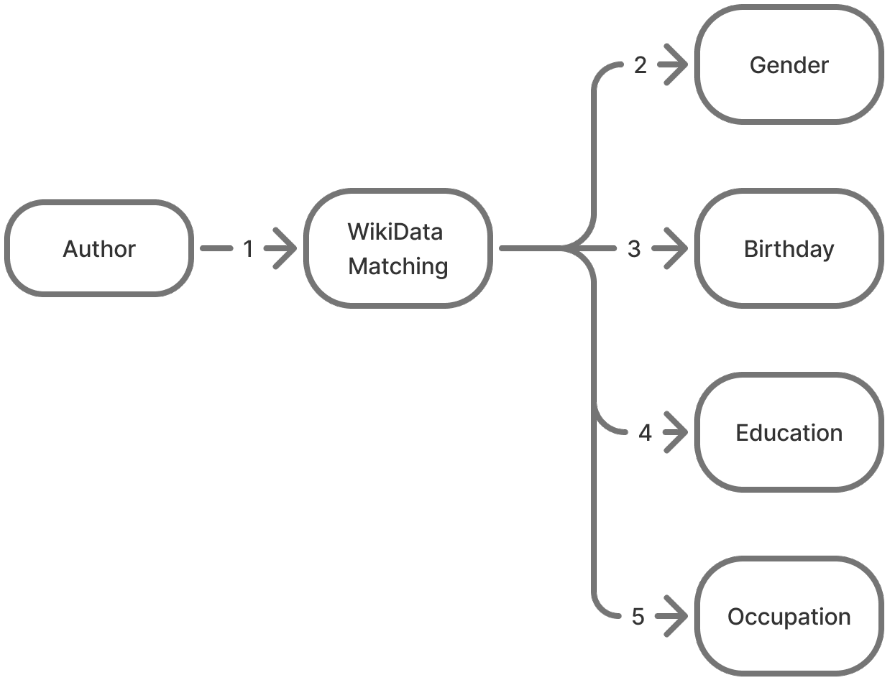

Figure S3.
The Wikipedia matching process to retrieve authors' demographic information.

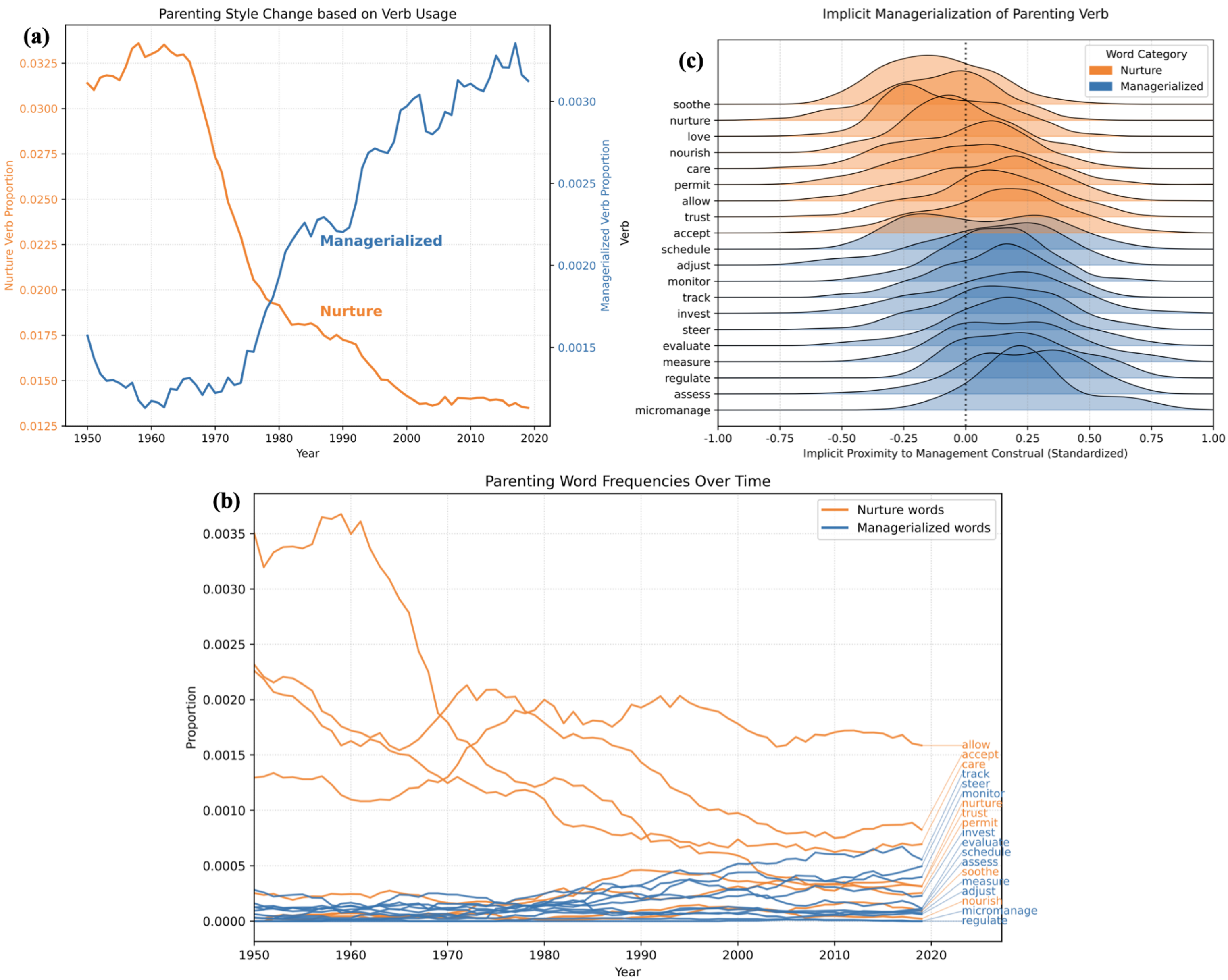

Figure S4. The Managerialization of Parenting. (a) verbs used by parents and/or towards children have seen an increase in managerialized category (*micromanage, assess, regulate, track, monitor, evaluate, schedule, develop, coach, steer, invest, adjust*), and a decline in nurture category (*love, soothe, care, nurture, nourish, allow, permit, accept, trust*) (b) Word-level trends corresponding to (a). The verb *love* is omitted due to its substantially larger magnitude of decline. (c) In sentences involving parents or children, these two verb groups (managerialized vs. nurture) differ in their average implicit managerial language scores: managerialized verbs exhibit higher scores, indicating closer proximity to management-oriented construals.

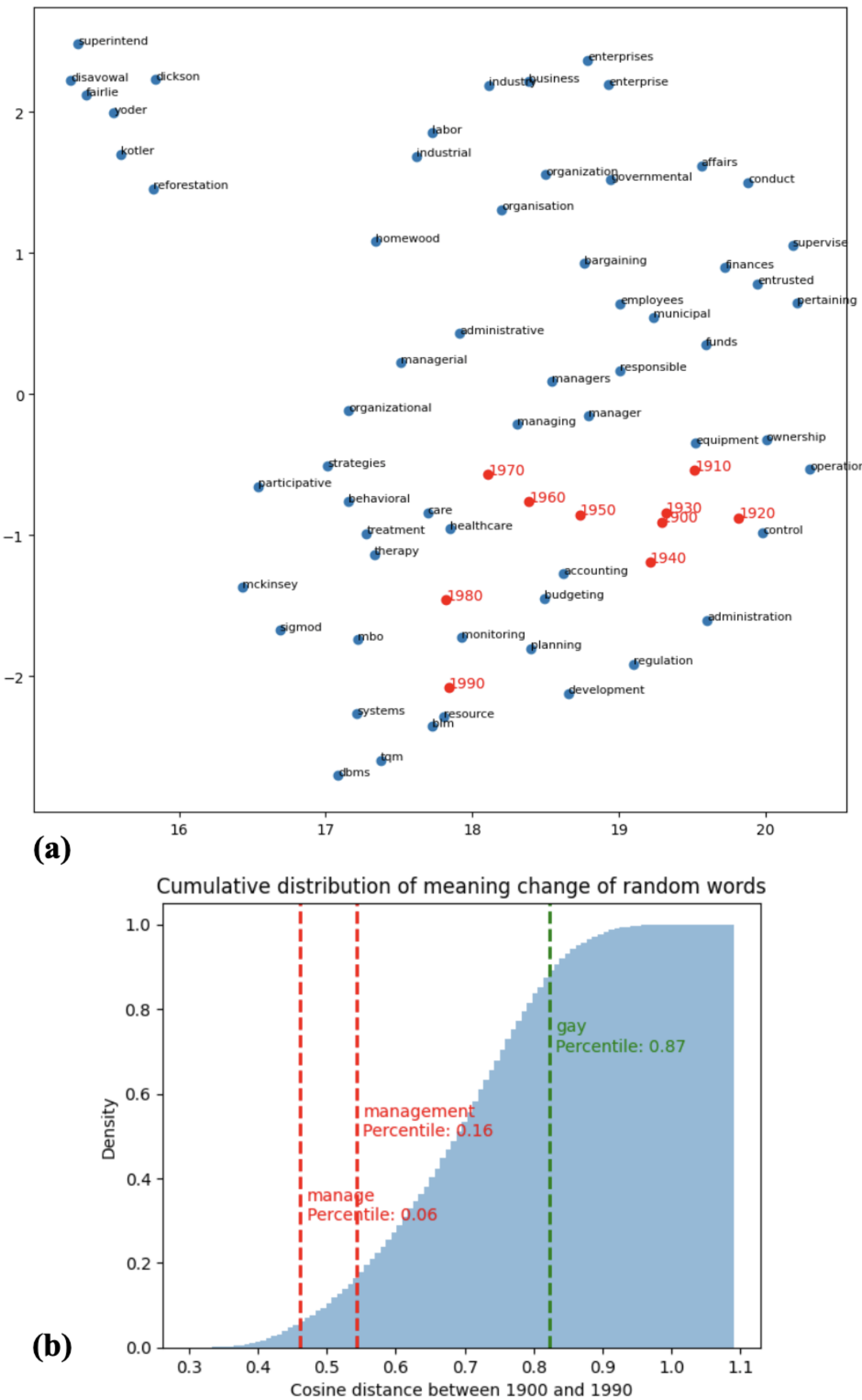

Figure S5. Stability of Management Meaning from 1950 to the present (a) Trajectory of the word *management* in semantic space over time. Each red dot represents the position of *management* in a given decade from 1910 to 1990. The semantic space is visualized using UMAP, with the two axes representing dimensions derived from dimensionality reduction. (b) Cumulative distribution of semantic changes for 10,000 randomly selected words, measured using cosine distance between word embeddings from 1900 and 1990. Vertical lines indicate the positions of *manage*, *management* and *gay* within the distribution. Their relative percentiles (i.e., degree of semantic stability) are also annotated in the plot.

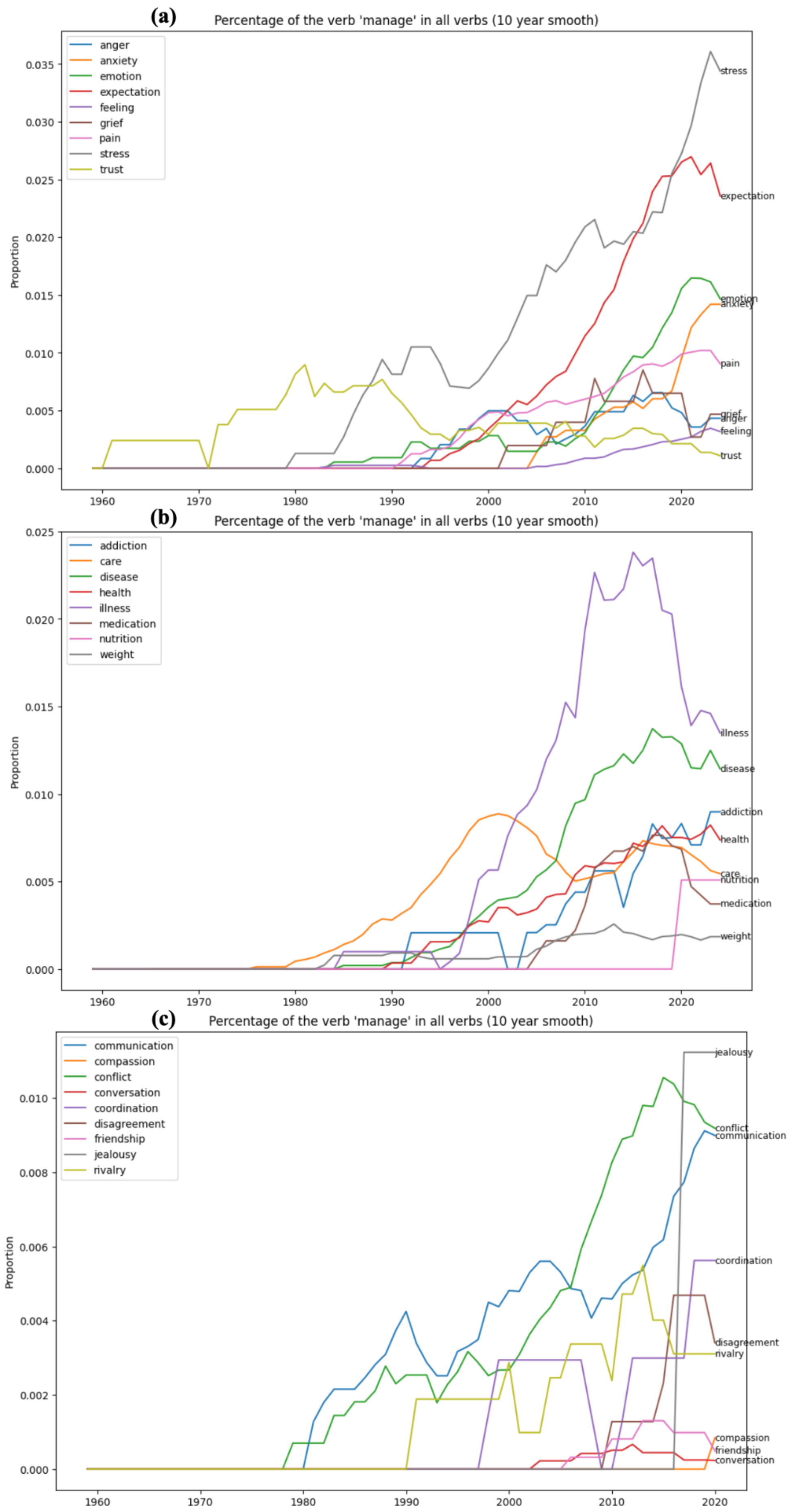
(a)
Percentage of the verb 'manage' in all verbs (10 year smooth)
anger
anxiety
emotion
expectation
feeling
grief
pain
stress
trust
Proportion
(b)
Percentage of the verb 'manage' in all verbs (10 year smooth)
addiction
care
disease
health
illness
medication
nutrition
weight
Proportion
(c)
Percentage of the verb 'manage' in all verbs (10 year smooth)
communication
compassion
conflict
conversation
coordination
disagreement
friendship
jealousy
rivalry
Proportion
Year

Figure S6. Increasing use of “manage” in emotion, body, and social relationships. Percentage of the verb “*manage*” in all verbs describing target features of the (a) emotion (*anger, anxiety, emotion, expectation, feeling, grief, pain, stress, and trust*), (b) body (a*ddiction, care, disease, health, illness, medication, nutrition, and weight*), and (c) relationship (*conflict, communication, rivalry, disagreement, friendship, jealousy, coordination, compassion, conversation*). Most of these words exhibit an increasing association with the verb '*manage*' over time. The percentage is calculated relative to all verbs used with each target word, thereby controlling for changes in the overall frequency of the words themselves. Lines represent 10-year moving averages.

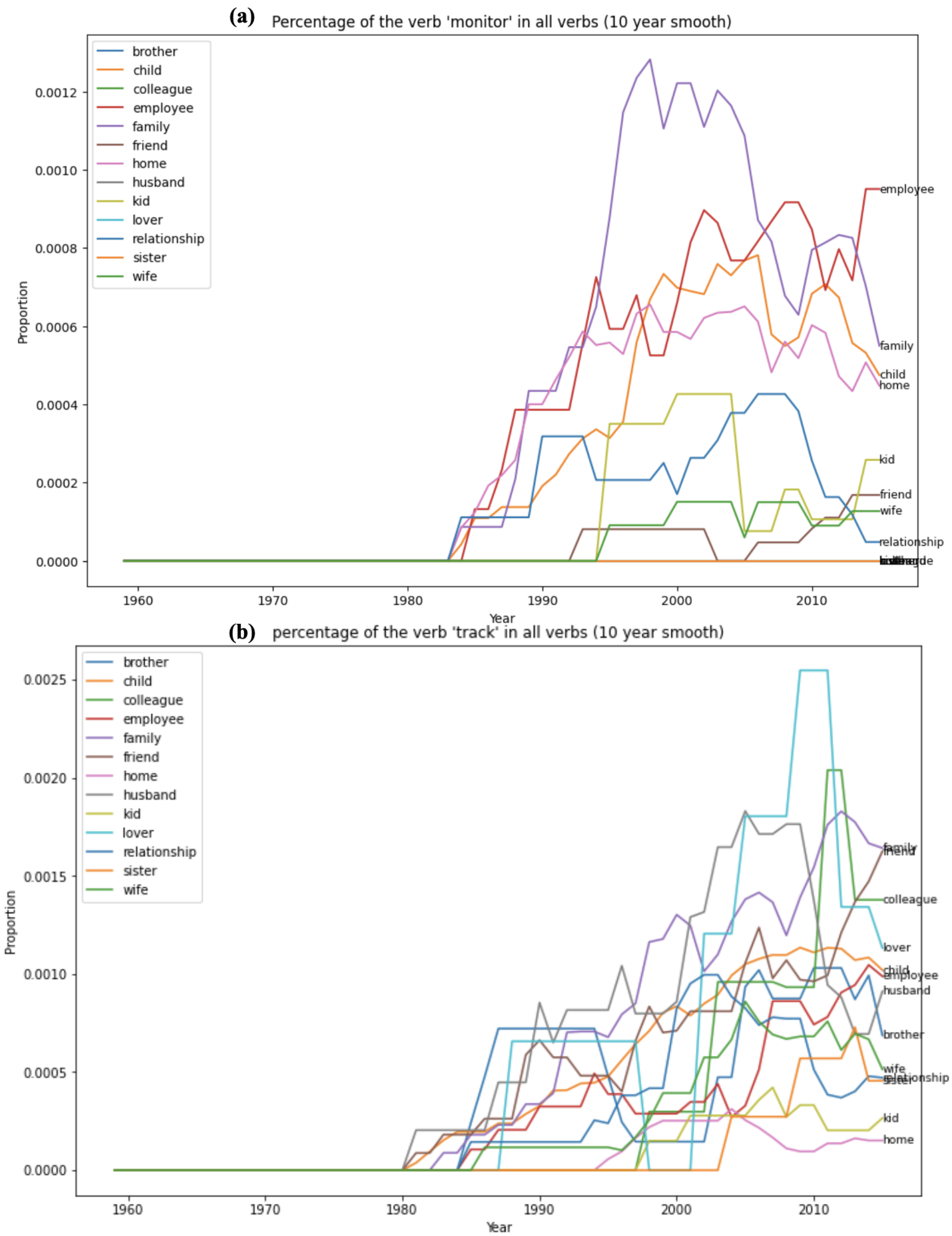

Figure S7. Percentage of the verb (a) "*monitor*" and (b) "*track"* in all verbs describing target features of relationships. Relationship-related words include *brother, child, colleague, employee, family, friend, home, husband, kid, lover, relationship, sister, wife.* Lines represent 10-year moving averages.

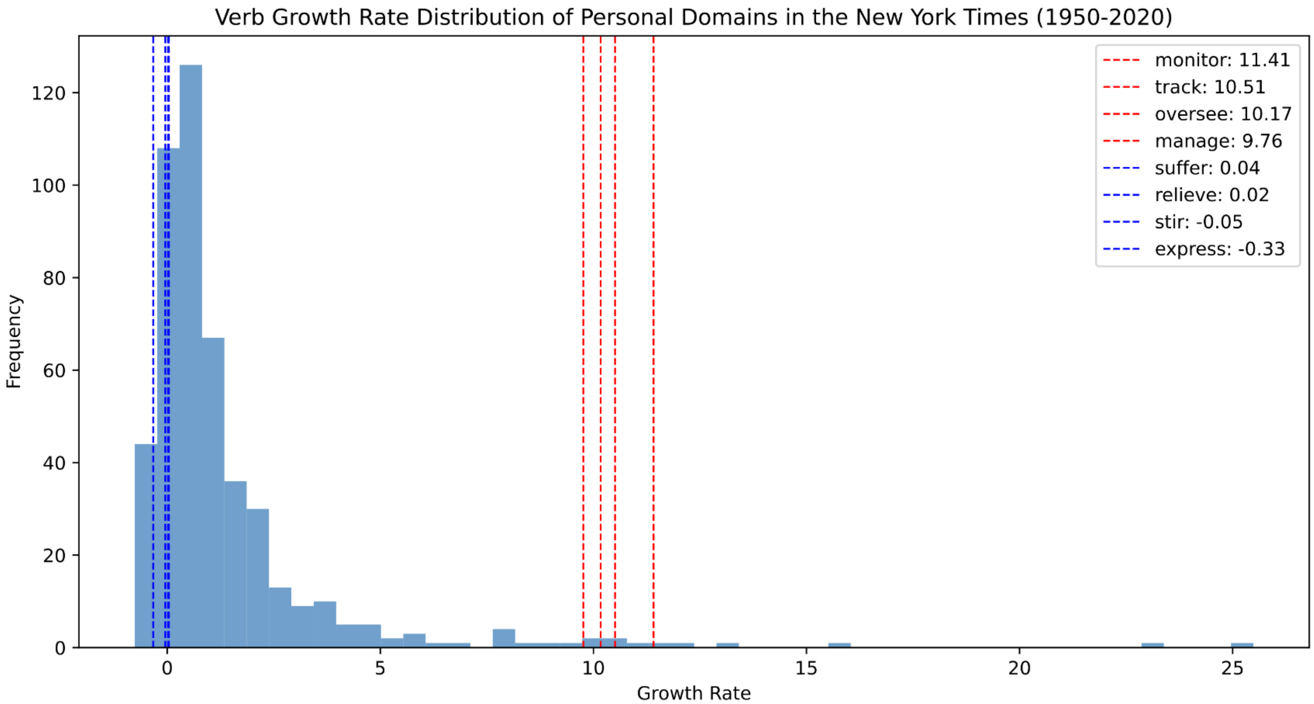

Figure S8. Distribution of growth rates of all verbs describing words associated with subjectivity, body, and relationship. Growth rates are calculated based on the change in relative verb frequency before and after 1980. Each vertical line represents the growth rate of an individual verb. Blue lines highlight passive verbs: *express, stir, relieve, and suffer* (from left to right). Red lines indicate management-related verbs: *manage, oversee, track, and monitor* (from left to right).

Purpose	Date Range	Search Query
Explicit Measure	1950-01-01 to 2019-12-31	manag[*10]
Implicit Measure	1950-01-01 to 2019-12-31	parent OR child OR kid OR sibling OR brother OR sister OR mother OR father OR mom OR dad OR uncle OR aunt OR husband OR wife OR wives OR spouse OR partner OR fiance OR fiancee OR lover OR friend OR son OR daughter OR nephew OR niece OR cousin OR neighbor OR jealousy OR envy OR compassion OR empathy OR affection OR appreciation OR desire OR hope OR relationship OR friendship OR support OR confidence OR enthusiasm OR sympathy OR respect OR admiration OR integrity OR loyalty OR devotion OR commitment OR solidarity OR intimacy OR weight OR health OR care OR disease OR illness OR diabetes OR medication OR nutrition OR addiction OR anger OR stress OR pain OR emotion OR expectation OR anxiety OR anxieties OR trust OR feeling OR grief OR happiness OR sadness OR fear OR disgust OR surprise OR shame OR guilt OR love OR joy OR passion OR zeal OR despair OR disappointment OR excitement

Table S1.

Search Queries used to create datasets for explicit and implicit measurement tasks from the New York Times corpus

Category	Words
Subjectivity	anger, stress, pain, emotion, expectation, anxiety, anxieties, trust, feeling, grief, happiness, sadness, fear, disgust, surprise, shame, guilt, love, joy, passion, zeal, despair, disappointment, excitement, jealousy, jealousies, envy, envies, compassion, empathy, empathies, affection, appreciation, desire, hope, confidence, enthusiasm, sympathy, sympathies, respect, admiration, integrity, integrities, loyalty, loyalties, devotion, commitment, solidarity, solidarities
Body	weight, health, disease, illness, medication, nutrition, addiction
Social Relationship	parent, child, kid, sibling, brother, sister, mother, father, mom, dad, uncle, aunt, husband, wife, wives, spouse, partner, fiance, fiancee, lover, friend, son, daughter, nephew, niece, cousin, neighbor, support, relationship, friendship, intimacy, intimacies

Table S2.
List of words related to private life used in the implicit measure

Category	Words
Asset	investment, *investments*, capital, *capitals*, budget, *budgets*, money, monies, finance, finances, fund, funds, estate, estates, property, properties, equity, *equities*, stock, stocks, profit, profits, margin, *margins*, deficit, *deficits*, inflation, *inflations*, revenue, revenues, income, incomes, salary, salaries, wage, wages, pay, pays, compensation, *compensations*, expense, expenses, cost, costs, price, prices, fee, fees, charge, charges, payment, payments, dividend, dividends, bill, bills, account, accounts, balance, balances, credit, credits, loan, loans, mortgage, *mortgages*, interest, interests, tax, taxes, taxation, *taxations*, liability, liabilities, *liquidity*, *liquidities*, *portfolio*, *portfolios*
Personnel	worker, workers, labor, labors, staff, staffs, *employee*, *employees*, personnel, *personnels*, subordinate, *subordinates*, intern, *interns*, client, clients, consumer, consumers, buyer, buyers, seller, *sellers*, patron, patrons, profession, professions, job, jobs, occupation, occupations, career, *careers*
Business	business, businesses, commerce, *commerces*, corporation, corporations, bank, banks, firm, firms, company, companies, industry, industries, market, markets, economy, economies, enterprise, enterprises, trade, trades, organization, *organizations*, project, projects, task, *tasks*, initiative, *initiatives*, campaign, *campaigns*, program, *programs*, *oligopoly*, *oligopolies*, monopoly, *monopolies*, *subsidiary*, *subsidiaries*, venture, *ventures*
Product	product, products, merchandise, *merchandises*, commodity, commodities, goods, good, service, services, offering, offerings, brand, *brands*, *franchise*, franchises, patent, patents
Manager	manager, managers, employer, employers, director, directors, executive, *executives*, chairman, chairmen, leader, leaders, controller, *controllers*, trustee, trustees, *boss*, *bosses*, *supervisor*, *supervisors*, *shareholder*, *shareholders*, stakeholder, stakeholders, *investor*, *investors*

Operation	contract, contracts, agreement, agreements, *protocol*, *protocols*, deal, deals, transaction, transactions, sale, sales, purchase, purchases, innovation, innovations, acquisition, *acquisitions*, negotiation, negotiations, operation, operations, production, productions, consumption, *consumptions*, calculation, calculations, estimation, *estimations*, *analysis*, *analyses*, outsource, *outsources*, management, *managements*, *partnership*, *partnerships*, supply, supplies, demand, demands, *strategy*, *strategies*, supervision, *supervisions*, control, *controls*, employment, employments

Table S3.
List of business words to be predicted by the BERT model in the [MASK] position. Italicized words represent terms missing from the BERT vocabulary.

Category	**Words**
Subjectivity	anger, stress, pain, emotion, expectation, anxiety, trust, feeling, grief, happiness, sadness, fear, *disgust*, surprise, shame, guilt, love, joy, passion, zeal, despair, disappointment, excitement, jealousy, envy, compassion, *empathy*, empathies, affection, appreciation, desire, hope, confidence, enthusiasm, sympathy, respect, admiration, integrity, loyalty, devotion, *commitment*, *solidarity*
Body	weight, health, disease, illness, *medication*, *nutrition*, *addiction*
Social Relationship	parent, child, kid, *sibling*, brother, sister, mother, father, mom, dad, uncle, aunt, husband, wife, spouse, partner, *fiance*, *fiancee*, lover, friend, son, daughter, nephew, niece, cousin, neighbor, support, relationship, friendship, *intimacy*

Table S4.
List of words of private life to be predicted for implicit measure. Italicized words represent terms missing from the BERT vocabulary.

Variable	**Coding Criteria**
Gender	As provided in Wikipedia.
Age	Publication date minus birth year as provided in Wikipedia (limited to values between 20 and 100).
IfCollege	If one of the following is true: ● The educational institution attended by the author includes the word *"college"* or *"university"*; ● The author holds one or more of the following degrees: *bachelor, master, doctor, PhD, BA, MA, BS, MS, MBA, JD, LLB, LLM, MD*.
IfBusinessEd	If one of the following is true: ● The educational institution attended by the author is in the list of business schools provided by Wikipedia; ● The author holds one or more of the following degrees: *BBA, MBA, EMBA*.
IfBusinessJob	The author's occupation includes any of the following keywords: *businessperson, business executive, entrepreneur, businessman, business, investor, executive, CEO, banker, manager, consultant, chief executive officer, finance, managing, investment*.

Table S5.
Coding criteria for social demographic variables retrieved from Wikipedia.

	Fiction	Congress	Movies
# Authors	30,927	3,287	65,666
# Matched at 1	18,153	3,287	36,160
# Matched at 2	17,901	3,287	35,110
# Matched at 3	17,654	3,287	29,754
# Matched at 4	9,871	3,170	14,598
# Matched at 5	17,251	3,287	35,985

Table S6.
Number of authors and matched entries across each step of Wikipedia matching.

	Gender	Race	Age	Income	Education	Party Affiliation
Intercept	-3.765^{***}	-3.932^{***}	-3.308^{***}	-3.953^{***}	-4.138^{***}	-3.692^{***}
	(0.042)	(0.049)	(0.089)	(0.049)	(0.105)	(0.054)
Gender						
Male	0.0785					
	(0.068)					
Race						
White		0.367^{***}				
		(0.064)				
Age Group						
25–34			−0.084			
			(0.110)			
35–44			-0.233^{*}			
			(0.116)			
45–54			-0.433^{***}			
			(0.120)			
55–64			-0.856^{***}			
			(0.124)			
65+			-0.767^{***}			
			(0.108)			
Annual Household Income						
$12k–$36k				0.249^{*}		
				(0.097)		
$36k–$72k				0.334^{***}		
				(0.086)		
Over $72k				0.507^{***}		
				(0.086)		
Education						
High school					0.135	
					(0.122)	
Some college					0.357^{**}	
					(0.121)	
Bachelor's or higher					0.733^{***}	
					(0.118)	
Party Affiliation						
Other						−0.050
						(0.073)
Republican						−0.161
						(0.090)
R^2	0.000	0.002	0.005	0.002	0.003	0.000
Adj. R^2	0.000	0.002	0.005	0.002	0.003	0.000
Num. obs.	157,395	157,395	157,395	157,395	157,395	157,395
RMSE	4.556	4.552	4.544	4.552	4.548	4.556

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table S7.
OLS Models with Separate Sociodemographic Variables from the AVP dataset

	Full Model	Income Only	Education Only
Intercept	-1.901^{***}	-1.829^{***}	-1.922^{***}
	(0.145)	(0.116)	(0.143)
Demographics			
Gender (Male)	-0.027	-0.009	-0.009
	(0.057)	(0.058)	(0.057)
Race (White)	0.305^{***}	0.376^{***}	0.311^{***}
	(0.058)	(0.059)	(0.058)
Age (25–34)	-0.144	-0.113	-0.116
	(0.099)	(0.100)	(0.098)
Age (35–44)	-0.308^{***}	-0.267^{***}	-0.258^{***}
	(0.107)	(0.109)	(0.104)
Age (45–54)	-0.465^{***}	-0.474^{***}	-0.414^{***}
	(0.113)	(0.112)	(0.111)
Age (55–64)	-0.888^{***}	-0.860^{***}	-0.866^{***}
	(0.112)	(0.112)	(0.110)
Age (65+)	-0.836^{***}	-0.772^{***}	-0.852^{***}
	(0.102)	(0.102)	(0.099)
Political Affiliation			
Other	-0.070	-0.102	-0.075
	(0.062)	(0.063)	(0.062)
Republican	-0.123	-0.174^{*}	-0.120
	(0.079)	(0.081)	(0.079)
Annual Household Income			
\$12k–\$36k	0.017	0.056	
	(0.085)	(0.085)	
\$36k–\$72k	0.080	0.166^{*}	
	(0.081)	(0.080)	
Over \$72k	0.160	0.312^{***}	
	(0.091)	(0.086)	
Education			
High School	-0.042		-0.015
	(0.104)		(0.103)
Some College	0.102		0.134
	(0.106)		(0.102)
Bachelor's or Higher	0.379^{***}		0.442^{***}
	(0.107)		(0.099)
Object Category			
Relationship	-1.920^{***}	-1.947^{***}	-1.918^{***}
	(0.070)	(0.070)	(0.071)
Subjectivity	0.663^{***}	0.654^{***}	0.663^{***}
	(0.091)	(0.091)	(0.091)
R^2	0.035	0.034	0.035
Adj. R^2	0.035	0.034	0.035
Observations	157395	157395	157395

Note: $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table S8.

OLS models with full sociodemographic variables from the AVP dataset

Primary Category	Secondary Category	Examples
Personal	Emotion and subjective experiences	With these stress **management** tools, this patient and others are better able to rely on their internal resources to decrease their distress.
	Human body	But with diets such as Atkins and the Zone reinforcing the idea that carbohydrates are the main stumbling block to weight **management**, low-carb bars are crowding the racks near the registers at supermarkets, pharmacies, and health-food stores
	Time	We're **managing** our free time like we manage our work time
	Family	Of course, **managing** Papa had been Lucy's job until she'd left for school
	Friendship	For Eileen had a knack for **management** and she so managed her friends that times while she entertained them once.
	Romantic relationship	You see, this art of courtship needs some **management**.
	Household	I never could **manage** even my own furnace and I'm not the least bit musical.
	Financials	Her salary was small, but by close **management,** she was able to meet the homestead payment once more.
Business	Time	About now, corporate time **management** experts would recommend that you keep a time log and record every fifteen minutes how you've been spending your time.
	Household	Where the houses were not owner-occupied, the **managing** agencies had them painted yellow and tan and dusty green
	Financials	To Aaron, it is improving the **management** of social security reserves.
	Business Operations	One is Roberta J. Arena, 48, an American who runs credit cards in North America and Europe and who is widely admired for her **managerial** skills

Table S9. Examples of explicit managerialization across domains. Each row presents an example in which the language of management is explicitly applied to a particular domain. Primary Category distinguishes between personal and business contexts, while Secondary Category specifies the domain being described (e.g., emotion, time, household, finance). The examples illustrate cases where management terminology is overtly used to frame non-business activities (e.g., “stress management,” “managing Papa”) as well as business-related practices. Primary–secondary category combinations that do not appear in the COHA data are omitted.

Example Sentence	Masked Word	Predicted Managerial Frame	Implicit Score
I have shown the data which show our [MASK] are not at the level we need for them to be if we are to remain competitive in the global marketplace.	**children**	**Asset**	17.59
It was a practice that had cost her some [MASK].	**friends**		10.14
Two hundred and fifty thousand farms [MASK] who work earlier and later than anyone else.	**mother**	**Personnel**	17.76
Often by taking low-paying jobs with few benefits because many employers will not hire military [MASK] whom they are afraid will move away soon.	**spouse**		16.08
A prosperous [MASK] should be encouraged both at home and abroad.	**happiness**	**Business**	12.65
The senators from Michigan do not have a monopoly on [MASK].	**disappointment**		12.15
Our amendment would address this desperation by promoting the development of [MASK] management.	**pain**	**Product**	12.86
Why boot her out just because her [MASK] aren't packed on ice yet?	**emotion**		13.36
You didn't know that the board and I, as representatives of the high school [MASK] ' league, discussed your case last night?	**parent**	**Manager**	11.6
Further, their [MASK] often are complicated by family or other personal relationships within the corporation.	**expectation**	**Operation**	14.06
Our statutes provide for an expedited process when other [MASK] have been terminated, or the state could have simply waited a couple more months to allow the requisite time to lapse.	**Children**		20.78

Table S10. Examples of implicit managerialization across domains. Each row shows a sentence in which a non-business concept (e.g., children, happiness) is implicitly framed using managerial logic, without the explicit use of management terminology. The masked word indicates the original non-business term in the sentence. The Predicted Managerial Frame identifies the managerial concept most strongly associated with that word by the model (e.g., treating children as assets). The Implicit Score reflects the strength of this association, with higher values indicating stronger alignment with managerial language patterns.