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Age-related shifts in temporal narrative content: A structural topic modeling analysis of a life-span corpus

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Abstract

Across the life span, people recall their past and envision their future, yet how the content of these narratives changes with age has rarely been examined at scale. We constructed a rare cross-sectional corpus of short essays in which participants ranging from elementary-school children to adults aged 60–80 years each wrote about a past event and an anticipated future event, and we modeled topic prevalence with a Structural Topic Model (STM) that incorporates age, gender, and temporal reference (past versus future) as covariates. The model yielded ten interpretable topics without manual coding. Five topics showed significant age × gender interactions in prevalence, and the focus of future narratives shifted with age from work and self-oriented life planning toward family, the next generation, and health. Future narratives were also consistently more abstract than past narratives. The approach provides a scalable framework for quantifying age-related change in temporal narrative without large-scale manual coding.

Introduction

Across the life span, people continually recall events from their past and imagine events in their future[1–7]. The content of these narratives—what a person chooses to talk about when asked about “the past” or “the future”—is likely to differ qualitatively with developmental stage. What an elementary-school child imagines when prompted with “the future” and what an older adult envisions are expected to differ at both the lexical and the conceptual levels: a child may describe a school excursion or becoming a sports star, whereas an older adult may describe a grandchild’s growth or maintaining health into later life. Characterizing how this content is reorganized across the life course—at scale and reproducibly—is the goal of the present study.

Several lines of work in psychology bear on this question. Socioemotional selectivity theory proposes that the perception of remaining time shapes motivation: when the future is perceived as open-ended, people prioritize knowledge-related and exploratory goals, but as the perceived future time horizon contracts with age, they increasingly favor emotionally meaningful goals and close, familiar relationships[8–13]. Applied to narrative content, the theory predicts that the future events older adults choose to describe should move away from open-ended exploration and self-expansion—such as careers and novel experiences—toward emotionally significant others and the management of a finite life. Construal level theory offers a complementary prediction about *how*, rather than *what*, people narrate[14–17]: the greater the psychological distance of an event—in time, space, social distance, or hypotheticality—the more abstractly it is mentally represented. Because anticipated future events are generally more psychologically distant than remembered past events, future narratives should be couched in more abstract language than past narratives. Research on cultural life scripts and the reminiscence bump points to a third, culturally shared layer: people draw on a semi-standardized, culturally shared timetable of important life events—schooling, marriage, childbirth, retirement—when

they recall or anticipate their lives, and systematic age- and gender-related structure has been reported across studies, including in Japanese samples[18–23].

Despite these rich theoretical predictions, the empirical base has been constrained by method. Many studies of autobiographical and future-oriented narrative have relied on manual coding, in which trained raters code texts according to predefined content categories. Hand coding is labor-intensive, scales poorly to the hundreds or thousands of texts needed to compare many age groups at once, and makes the resulting topic structure dependent on the analyst's category scheme, which can limit cross-study comparability and reproducibility. As a consequence, how the *distribution of topics* in free narratives shifts as a continuous function of age—and whether that shift differs by gender or by temporal reference (past versus future)—has rarely been modeled directly. Computational text analysis—treating text as data and inferring latent structure from patterns of word use—offers a scalable and reproducible alternative to hand coding[24–29].

Our study addresses that gap with two contributions. First, it draws on a rare resource: a cross-sectional corpus in which participants spanning from childhood to old age each contributed paired past and future essays under identical prompts. The corpus has previously supported two studies: a preliminary conference analysis using Latent Dirichlet Allocation (LDA) to explore the latent topic structure of past and future essays, and a linguistic analysis based on morphologically annotated text[30,31]. Such data are scarce: most narrative corpora are confined to a single age group or to a single temporal direction, so matched past/future narratives spanning childhood to old age are uncommon in a single dataset. The within-participant pairing further enables a controlled comparison of how the same person narrates past versus future.

Second, the study applies the Structural Topic Model (STM), a probabilistic topic model that, unlike conventional latent Dirichlet allocation, allows document-level covariates to enter the model directly: covariates can shape both how prevalent each topic is in a document (prevalence) and which words express a topic (content)[32,33]. This lets us estimate age, gender, and temporal-reference effects on topic usage within a single generative model, rather than treating estimated topic proportions as fixed outcomes in a separate post hoc analysis. In this domain, where narrative content has often been organized into predefined categories through manual coding, obtaining an explicit and reproducible set of data-driven topics together with quantified covariate effects provides a methodological advance.

Using this corpus and method, we pursue three aims.

1. Extract the latent topic structure of the essays in an unsupervised manner.
2. Test how each topic's prevalence changes with age and whether that change interacts with gender.
3. Compare the topic composition of past and future essays across age cohorts, and characterize how both the past and the future are narrated.

As a preview of the central finding, the focus of future-oriented narratives shifts with age from work and self-oriented life planning toward family, the next generation, and health, while future narratives are

consistently more abstract than past narratives.

Dataset

Corpus design

The corpus consists of short Japanese essays collected within a broader research initiative on the emergence of temporal consciousness[30]. Each participant completed two writing tasks under identical instructions: (1) describe the most enjoyable event you experienced in the *past* (hereafter the past essay), and (2) describe the most enjoyable event you anticipate experiencing in the *future* (hereafter the future essay). Participants were instructed to write at least half a page on a lined sheet, and the instructions were identical for adults and children. Restricting both prompts to the “most enjoyable” event was a deliberate design choice, ensuring comparable emotional valence across temporal references while keeping the task ethically unproblematic and readily understandable for participants of all ages.

Participants and procedure

Adult data were collected through a survey company. Prospective participants received an invitation letter, an informed-consent form, one response sheet, two lined sheets (one for the past essay and one for the future essay), and a return envelope, and returned all completed materials, including the signed consent form, by mail. All adult participants were residents of Tokyo or prefectures adjacent to Tokyo. Children’s data were collected through schools with the consent of the principals and the children's legal guardians. Two public elementary schools in the greater Tokyo area participated: fourth-grade pupils from one school and third- through sixth-grade pupils from the other completed the writing tasks, and both schools provided analyzable data. In total, 741 participants contributed paired essays across four age groups, with approximately balanced gender distributions within each group (Table 1). All participants were native speakers of Japanese. Gender was self-reported.

Table 1
Composition of the corpus by age group and gender.

	Elementary school	20–30s	40–50s	60–80s	Total
Participants at data collection (each contributed one past and one future essay)					
Female	127	83	89	90	389
Male	120	75	79	78	352
Total	247	158	168	168	741
Final analysis set (number of essays: past/future)					
Female (past/future)	120/103	83/83	89/89	90/90	382/365
Male (past/future)	103/79	75/75	79/79	77/76	334/309
Total (essays)	405	316	336	333	1,390

The upper section shows the number of participants at data collection (each contributed one past essay and one future essay). The lower section shows the number of essays included in the final analysis after exclusion of essays containing fewer than five content words, stratified by gender and temporal reference.

Ethics statement

The study was approved by the Research Ethics Committee for the Humanities and Social Sciences of Ochanomizu University (approval no. 2018 − 131; approved on 4 December 2018). Adult participants were recruited through a survey company. Before participation, they received written information regarding the purpose of the study, study procedures, data handling, confidentiality, anonymity, the planned publication of results, and the incentive provided according to the survey company's standard policy. Written informed consent was obtained from all adult participants. For child participants, written informed consent was obtained from their legal guardians before participation. Children received an age-appropriate explanation of the study and provided assent before participation. Participation was voluntary, and children were informed that they could decline participation or withdraw at any time without disadvantage. All procedures were conducted in accordance with the ethical principles of the Declaration of Helsinki and applicable institutional and national guidelines for research involving human participants.

Rarity and value

Two features make the corpus an unusual resource. First, identical paired prompts were administered across the life span, providing a rare basis for direct cross-cohort comparison under constant task conditions. Because both the instructions and the emotional framing ("the most enjoyable event") were held constant, differences in narrative content can be interpreted as reflecting characteristics associated

with age groups rather than differences in elicitation. Second, each participant contributed both a past and a future essay, enabling within-participant comparisons that control for individual differences and isolate the effect of temporal reference. Details of the preprocessing pipeline and the composition of the final analytical corpus are described in the Methods.

Methods

Preprocessing

The dataset comprised 1,482 essays (741 participants × two temporal references), which were morphologically analyzed using MeCab with the UniDic dictionary[34]. Each token was subsequently processed as follows.

1. **Content-word filtering.** Only content words—those whose major part-of-speech was noun, verb, adjective, or adverb—were retained, and all function words (particles, auxiliaries, conjunctions, adnominals, interjections, prefixes, suffixes, and punctuation/symbols) were dropped.
2. **Numeral removal.** Tokens assigned the fine-grained part-of-speech category *numeral* were removed (26 numeral forms in total), eliminating year, grade, and age digits so that numeric strings could not spuriously link documents together.
3. **Lemma normalization.** Each surviving token was normalized to its UniDic lemma, and loanword spelling annotations were stripped.
4. **Stop-lemma removal.** A curated list of high-frequency, low-information function-like lemmas was removed: light verbs (*suru* 'do', *aru* 'exist', *iru* 'be', *naru* 'become'), generic verbs (*iu* 'say', *omou* 'think'), formal nouns (*koto* 'matter', *mono* 'thing', *toki* 'time'), demonstratives (*kore* 'this', *sore* 'that', *koko* 'here'), and degree or evaluative adverbs (*totemo* 'very', *yoi* 'good', *nai* 'not').

Age group was coded as a continuous variable using four equally spaced representative values (elementary school = 10, 20–30s = 30, 40–50s = 50, 60–80s = 70). Essays with fewer than five content tokens were then dropped (91 essays, mostly children's future essays), and terms occurring in fewer than five documents were removed during corpus preparation, which resulted in one additional essay containing no remaining terms and therefore being excluded from the analysis. The final analysis set comprised 1,390 essays, a vocabulary of 1,405 terms, and 37,481 tokens, with a median of 40 content tokens per essay. The composition of the final set remained close to balanced, with only a modest reduction in children's future essays (Table 1).

Structural Topic Model

We fitted a Structural Topic Model (STM)[32,33], which extends standard topic modeling[35–37] by linking topic prevalence and topical word use to document-level covariates. The prevalence model was specified as $\sim s(\text{age}) \times \text{gender} + \text{time_ref}$ and the content model as $\sim \text{gender}$. Age was treated as a continuous variable with a low-degree spline, $s(\cdot)$, to capture potentially nonlinear age-related trends. Gender was

included as an interaction term with age, reflecting our primary interest in whether age-related trajectories differed by gender, whereas temporal reference was included as a main effect to estimate the overall difference between past and future narratives while avoiding unnecessary increases in model complexity. This specification allowed us to examine age-related changes, their moderation by gender, and overall temporal-reference effects within a unified model. The model was estimated with spectral initialization and converged in 14 iterations.

Formally, STM is a generative model[38]. For document d with prevalence covariates $\mathbf{x}_d$ (here the age spline, gender, their interaction, and temporal reference) and content covariate y_d (here gender), the generative process is:

1. Draw the document's topic intensities from a logistic-normal distribution whose mean is a linear function of the prevalence covariates, and map them to proportions θ_d by a softmax function,

where Γ collects the prevalence-regression coefficients and Σ is the topic covariance matrix.

1. Form the topic–word distributions used in document d by a log-linear model in the content covariate,

in which m_v is the baseline log frequency of word v, $\kappa^{(t)}_{kv}$ the topic-specific deviation, $\kappa^{(c)}_{ydv}$ the deviation due to the content covariate, and $\kappa^{(i)}_{ydkv}$ their interaction.

1. For each of the N_d tokens, draw a topic and then a word from that topic,

Setting $\Gamma = \mathbf{0}$ and $\kappa^{(c)} = \kappa^{(i)} = 0$ recovers an ordinary correlated-topic model; it is the prevalence coefficients Γ in Eq. (1) and the content terms $\kappa^{(c)}$, $\kappa^{(i)}$ in Eq. (2) that let

document metadata shape, respectively, which topics appear and which words express them. The parameters were fitted by variational expectation–maximization.

Spectral initialization was used to obtain deterministic starting values from a factorization of the word co-occurrence matrix rather than random seeds, improving reproducibility and reducing the risk of poor local optima. We fitted the model using the stm package (version 1.3.8) in R 4.6.0. Each topic was summarized using both its highest-probability words and FREX words, which balance word frequency and exclusivity within a topic[39]. The effects of the gender content covariate were interpreted using words showing covariate-specific deviations in the estimated topic–word distributions.

Model selection

The number of topics K was selected by grid search over $K \in \{5, 10, 15, 20\}$, using exclusivity, semantic coherence[40], held-out likelihood[41], and residual dispersion as evaluation criteria. Semantic coherence declined monotonically with K, whereas exclusivity and held-out likelihood plateaued and residual

dispersion improved markedly (from 2.05 at $K = 5$ to 1.85 at $K = 10$). We therefore selected $K = 10$ at the elbow point, where gains in held-out likelihood and exclusivity began to plateau while the decline in semantic coherence remained modest.

Effect estimation and supplementary analyses

Covariate effects on topic prevalence were estimated by regressing the model-estimated topic proportions on the covariates, with uncertainty propagated using the method of composition. To probe age-related shifts in future-oriented topics, we estimated effects for topics 2, 6, and 7 using the model ~ age × time_ref.

Supplementary analyses included regression models for an abstractness index (the ratio of abstract to abstract-plus-concrete nouns)[42] and a net-positivity index (positive minus negative words, normalized by essay length), both modeled as functions of age, gender, and temporal reference. Additional analyses included a within-participant continuity analysis, in which cosine similarity was calculated between each participant's paired past and future topic vectors; the paired topic vectors were also clustered using *k*-means. We also re-estimated the model with age included as a content covariate and with $K = 20$ to examine whether the dominant future-planning topic separated into more specific themes at higher resolution.

Utilization of large language models

During this study and the preparation of the manuscript, the authors used large language models to assist with manuscript preparation and computational code writing and debugging. For manuscript preparation, Claude (Anthropic) was used to translate author-written Japanese text into English. Subsequently, ChatGPT (OpenAI) and Claude were used to improve linguistic clarity, grammar, and stylistic consistency during manuscript revision. For the computational analyses, Claude was used to assist with writing and debugging code for data preprocessing, analysis, and visualization. All AI-assisted code was reviewed, tested, and validated by the authors, and all analytical decisions, including model specification, covariate selection, choice of the number of topics, and statistical procedures, were made by the authors. No large language model was used for study design, data collection, interpretation of the results, or formulation of the scientific conclusions. All AI-generated outputs were critically reviewed and edited by the authors, who take full responsibility for the accuracy and content of the manuscript.

Results

Ten interpretable topics emerge along an age axis

With spectral initialization, the model converged in 14 iterations and, without any manual labeling, separated the essays into ten interpretable topics that collectively formed a clear age-related progression (Table 2). The youngest end of the axis was characterized by childhood themes—children's

play (T8: *swim*, *tag*, *friend*, *game*), theme parks and school excursions (T1: *coaster*, *ride*, *excursion*), and school events such as choral performances (T3: *sing*, *song*, *pupil*, *presentation*)—whereas the adult end was characterized by work and research (T2: *colleague*, *research*, *work*), club sports (T5: *final*, *tournament*, *practice*), future planning and later life (T6: *raise*, *pension*, *health*, *independence*), marriage, grandchildren and family (T7: *daughter*, *grandchild*, *ceremony*), sightseeing travel (T9: *tour*, *landmark*, *overseas*), and study abroad and language learning (T10: *study abroad*, *homestay*, *English*).

Table 2
The ten topics extracted by the STM, with interpretive labels and the ten highest-probability words of each topic (translated from the Japanese lemmas).

Topic	Interpretive label	Highest-probability words (top 10)
T1	Theme parks / excursions	USJ, coaster, ride, board, jet, Osaka, excursion, back, bike, souvenir
T2	Work / research	colleague, question, answer, research, people, reply, most, work, occur, increase
T3	School events	sing, song, pupil, study, dance, candle, tune, gathering, presentation, udon
T4	Outdoor / family leisure	hook, fishing, camp, meal, river, school-trip, theme-park, tent, fish, park
T5	Club sports	final, play, athletics, training-camp, affiliation, track-and-field, team, tournament, entry, teammate
T6	Child-rearing / future planning / later life	manage, grow-up, obstacle, build, independence, ideal, gradually, raise, watch-over, most
T7	Marriage / grandchildren / family	state, daughter, grandchild, YouTuber, granddaughter, ceremony, couple, spectating, London, Switzerland
T8	Children's play	swim, tag, play, friend, cousin, sea, game, playtime, home, adult
T9	Sightseeing travel	Britain, gourmet, stroll, history, autumn-leaves, plan, landmark, sightseeing, climb, day-trip
T10	Study abroad / language	culture, homestay, food, Thailand, Japan, study-abroad, language-study, English, foreign-land, Australia

The content covariate (~ gender) further revealed within-topic lexical differences. Within the same topic, words characteristic of women's essays tended to relate to relationships, family, and immediate experience, whereas those characteristic of men's essays tended to relate to objects, competition, and more abstract referents (Table 3). Within the club-sports topic, for example, women's distinctive words included *practice* and *ski*, whereas men's distinctive words included *championship* and *baseball*. These differences represent descriptive tendencies and should not be interpreted as evidence of essential or inherent gender differences.

Table 3
Within-topic lexical differences by gender estimated from the content covariate (∼ gender).

Topic	Interpretive label	Words distinctive of women's essays	Words distinctive of men's essays
T1	Theme parks / excursions	father, airplane, roller-coaster	motorcycle, car, hotel
T2	Work / research	event, book, dog (pet)	research, people, project
T3	School events	study, making, presentation, chorus	participation, pupil, dance, sing
T4	Outdoor / family leisure	river, animal, meal	fishing, camping, family
T5	Club sports	high-school, practice, club, ski	championship, baseball, pro
T6	Child-rearing / future planning / later life	growth, child-rearing, health	the-future, realization, dream
T7	Marriage / grandchildren / family	daughter, son, couple	ceremony, adulthood, spectating
T8	Children's play	cake, adult, cousin	game, swim
T9	Sightseeing travel	plan, overseas, sightseeing	wife, ski, meal
T10	Study abroad / language	America, husband	world, holiday, life

The table lists words showing the strongest gender-specific deviations within each topic (translated from the Japanese lemmas).

Age-by-gender interactions in topic prevalence

We estimated the effects of age and gender on each topic's prevalence and tested the linear age × gender interaction term (using a linear age term rather than a spline because age was represented by only four distinct values). A positive interaction coefficient indicates that the topic became relatively more prevalent among men with increasing age, whereas a negative coefficient indicates a corresponding shift toward women. The interaction was significant for five of the ten topics (Table 4, Fig. 1): two shifted toward men with age (work/research and school events) and three toward women (theme parks/excursions, club sports, and marriage/grandchildren/family). The continuous age curves further showed that several of these interactions involved a crossover. For school events and theme parks, the gender contributing a higher proportion of these topics in childhood was overtaken by the other gender in adulthood, whereas for club sports, topic prevalence increased with age among women but decreased among men. The remaining five topics (T4, T6, T8, T9, and T10) showed no significant interaction.

Table 4
Topics showing a significant age × gender interaction in topic prevalence.

Topic	Interaction coef. *b*	*p*	Increasing prevalence with age
T2 Work / research	+ 0.0020	< .001	Men
T3 School events	+ 0.0019	< .001	Men
T1 Theme parks / excursions	−0.0015	.001	Women
T5 Club sports	−0.0013	.015	Women
T7 Marriage / grandchildren / family	−0.0008	.031	Women

Positive coefficients indicate stronger age-related increases in topic prevalence among men, whereas negative coefficients indicate stronger increases among women. The remaining five topics showed no significant interaction.

Past versus future across age cohorts

We next compared the mean topic composition of past and future essays for each age cohort (Fig. 2). For children, both past and future narratives were characterized by concrete, immediate themes: the past narratives were dominated by children's play (T8, 30%), excursions (T1, 28%), and family leisure (T4, 18%), and the future narratives still featured children's play (T8, 27%) and club sports (T5, 15%). For every adult cohort, by contrast, future narratives were dominated by a single future-planning topic (T6). Two topics stood out for their temporal profile in this composition. In the adult cohorts, the club-sports topic (T5) primarily represented memories of student life of the past—a memory of student days—whereas for children it appeared instead on the future side, as an activity still to come. Sightseeing travel (T9), by contrast, was essentially time-symmetric, appearing at comparable levels in past and future narratives as an ever-present feature of adult life. To quantify the concentration of the mean topic mixture for each age cohort and temporal reference, we computed the share of the top three topics and the effective number of topics, defined as the exponential of the Shannon entropy of the mean topic vector (ranging up to ten when the ten topics are used evenly). Table 5 reports both measures for each age cohort and temporal reference.

Table 5
Concentration of the mean topic mixture by age cohort and temporal reference, quantified as the share of the top three topics and the effective number of topics (the exponential of the Shannon entropy of the mean topic vector; maximum = 10).

Age cohort	Top-three share (%)		Effective no. of topics	
	Past	Future	Past	Future
Elementary	76	56	5.73	7.86
20–30s	65	74	7.48	6.19
40–50s	54	64	8.72	7.12
60–80s	50	70	8.85	6.38

For past narratives, topic breadth increased monotonically with age (Table 5): the effective number of topics rose and the top-three share fell from childhood to the oldest adults. This widening indicates that the reference window of past narratives expands from the recent, concrete events of childhood toward events drawn from across the whole of a longer life. The future side did not show this monotonic broadening. Children were the exception: their future narratives were comparatively broad, because children imagine many concrete prospective activities—more sport, more play, more travel—rather than a single organizing theme. From early adulthood onward the future narratives instead concentrated on the planning topic, staying more concentrated than the contemporaneous past narratives. The contrast was therefore not simply between past and future, but depended on age: with development, past narratives broadened, whereas adult future narratives became increasingly concentrated on the planning topic.

The shifting meaning of “future planning”

The future-planning topic (T6) was dominant in the future narratives of all adult cohorts (about 36%, 28%, and 32% of the future narratives in the twenties to thirties, forties to fifties, and sixties to eighties, respectively), yet its referent shifted systematically with age. Inspection of the future essays in which T6 was most prevalent (i.e., those with the highest topic proportion within each age band) showed that the same topic indexed marriage, child-rearing, and the launch of a career in the twenties to thirties, the children’s independence, loan repayment, and the couple’s later life in the forties to fifties, and health maintenance, pension, grandchildren, and the management of illness and mortality in the sixties to eighties. The shift in referent was thus captured by a single learned topic that retained a stable word distribution while referring to successive life stages.

This descriptive pattern was further supported by covariate-effect estimation (∼ age × time_ref). Within future essays the future-planning (T6) and family (T7) topics increased significantly with age. In contrast, the work/research topic (T2) showed a different age trend in past essays, resulting in a significant past/future interaction, although its decline within future essays alone did not reach significance (Table 6). Consistent with this, the work topic’s share of future essays peaked in the twenties to thirties (23%) and then declined (16%, then 10%), whereas the marriage/family topic (T7) rose monotonically

across future essays (7%, 14%, 19%). Two further checks reinforced the interpretation: an auxiliary model that entered age as a content covariate recovered the marriage-to-health lexical progression directly from the estimated word distributions, and re-estimating the model with $K = 20$ split the single planning topic into an abstract life-planning topic (correlation $r = 0.62$ with the original T6) and a concrete child-rearing/grandchild topic ($r = 0.51$), confirming that these two distinct themes were represented as a single topic at $K = 10$.

Table 6
Age trends in topic prevalence for past and future essays, and their interaction, estimated from the covariate-effect model (~ age × time_ref).

Topic	Past age trend	Future age trend	Interaction (future − past)
T2 Work/research	+ 0.014***	−0.006n.s.	−0.019***
T6 Future planning	+ 0.011***	+ 0.029***	+ 0.019***
T7 Marriage/family	+ 0.016***	+ 0.024***	+ 0.008*
Coefficients represent the change in expected topic proportion per 10-year increase in age. Significance levels: *** $p < .001$, ** $p < .01$, * $p < .05$, .$p < .1$.			
Each stacked bar represents the mean proportions of the ten STM topics.			

How the future is narrated: abstraction, valence, and continuity

Beyond topic content, we examined how past and future events were narrated using each essay's abstractness index and net-positivity index. Future events were narrated more abstractly than past events at every age band: the abstractness index averaged

0.364 for future versus 0.295 for past essays. In a regression on age, gender, and temporal reference, being a future essay raised the abstractness index by 0.066 ($t = 8.78$, $p < .001$), with smaller effects of age (+ 0.0014 per year, $p < .001$) and gender (men slightly more concrete, − 0.034, $p = .021$). This pattern is consistent with the construal-level prediction that psychologically more distant events are represented more abstractly. Children were nonetheless the least abstract overall (future index 0.292), which we interpret not as a counterexample but as a second, orthogonal axis—a vocabulary-development effect captured by the positive age coefficient—superimposed on the within-participant past/future contrast predicted by construal level theory.

Net positivity told a different story. Future essays were slightly more positive than past essays overall (future 0.159 versus past 0.146), and being a future essay was a significant positive predictor (+ 0.047, $p < .001$). The expected age-related rise in positivity, however, was not observed: net positivity declined with age (− 0.0008 per year, $p < .001$), and a negative age × future interaction (− 0.0008, $p = .003$) showed the decline was steeper on the future side, so that the future's positivity advantage was confined mainly to children (0.235) and absent in older adults. The one robust age-related regularity was that the

absolute count of negative words (e.g. illness, death, nursing care) rose with age. Within-participant continuity, measured as the cosine similarity between each participant's past and future topic vectors (overall mean = 0.465 across 667 paired participants), followed a U-shaped pattern across age (0.515, 0.437, 0.429, 0.475), lowest in midlife when narratives shifted most sharply from study and club activities to work and family; a *k*-means clustering of the paired vectors into four types recovered a children's-play persistence type (mostly elementary), a travel persistence type (older, female-leaning), a smooth career-to-planning transition type, and a sharp club-sports-to-planning type that was the most discontinuous and male-leaning, consistent with the significant age × gender interaction in continuity (p = .026). Tracing each participant's dominant past topic to the corresponding dominant future topic showed the same pattern of convergence from the opposite direction: five distinct past topics—club sports, work, family leisure, study abroad, and school events—all had the future-planning topic as their most common destination (in 24% to 50% of cases), whereas travel, children's play, and family topics tended to remain within the same topic.

Discussion

The central pattern we observe—future narratives shifting from work and self-oriented life planning toward family, the next generation, and health—is consistent with socioemotional selectivity theory, in which the perceived contraction of remaining time shifts goals away from open-ended exploration toward emotionally meaningful and close relationships[8,9]. The estimated effects make this concrete: within future essays, the work/research topic (T2) declined with age while the future-planning (T6) and family (T7) topics rose, and the age trend for the work topic differed significantly between past and future essays. Construal level theory provides the complementary account of *how*, rather than *what*, people narrate[14]: greater psychological distance elicits more abstract representation, and because anticipated events are generally more psychologically distant than remembered events, future narratives should therefore be more abstract—which is what we found: the regression showed an increment in abstractness for future essays after controlling for age and gender. That children were the least abstract overall does not contradict this, because the theory concerns the within-person past/future contrast, which held across all age bands, rather than between-cohort differences in overall abstractness.

Not all predictions were borne out, however. The age-related positivity effect[43–46] would lead us to expect older participants to maintain or increase the emotional positivity of their narratives, particularly for future events; instead, net positivity declined with age and fell more steeply on the future side, so that the future's positivity advantage was largely confined to children. The only robust age-related lexical regularity in valence was an increase in the absolute frequency of negative words such as illness, nursing care, and death—the very vocabulary that characterized the older cohorts' future-planning narratives. One reading is that the positivity effect, demonstrated largely in attention and memory paradigms, need not surface in the spontaneous *content* of what older adults choose to narrate when the chosen topic (later life) itself carries negatively valenced referents, even under a prompt that asks for the most enjoyable event. The broader age-related regularities, including the marriage-to-grandchildren

progression and its gendered structure, are broadly consistent with cultural life script accounts of how Japanese adults organize canonical life events across the life course[18,19].

A methodologically notable observation is that a single learned topic can retain a common word distribution while being associated with different life-stage referents across cohorts, reflecting successive life stages through a shared lexical structure. This is precisely what we observed for the future-planning topic, and it has two implications: it allows a compact ten-topic model to summarize the life span, but it also means that a topic's label can conceal an internal developmental gradient. Our supplementary analyses provided evidence that this apparent ambiguity was systematic: an auxiliary model with age as a content covariate recovered the marriage-to-health lexical progression, and refitting the model with $K = 20$ split the planning topic into an abstract life-planning theme and a concrete child-rearing/grandchild theme. The two resolutions are complementary rather than contradictory: $K = 10$ favors interpretability, whereas $K = 20$ provides finer thematic resolution, and the convergence of several distinct past topics onto the single future-planning topic suggests that the lower-resolution topic captures a recurring future-planning structure across adulthood. More generally, this illustrates a practical advantage of estimating topics and covariate effects within one model: the same fitted model supports representative-document inspection, content-covariate re-estimation, and comparison across topic resolutions, allowing an apparent ambiguity in topic labeling to be examined through multiple, complementary analyses rather than resolved by manual recoding.

The gender differences should be interpreted cautiously. Rather than a literal mapping of objects to gender, the data may reflect differences in thematic orientation, with men's essays showing greater emphasis on objects and achievement (motorcycles, championships, projects) and women's essays showing greater emphasis on relationships and settings (family members, child-rearing, shared outings). On this reading, even an apparently object-like word such as "airplane" may function in women's essays as a means of describing a family trip rather than as an object of interest in itself. This relational-versus-object-oriented account remains an exploratory interpretation that would require directly classifying words as object- or relation-referring and testing the gender contras. We therefore treat these gender contrasts as descriptive tendencies rather than evidence of inherent or essential gender differences.

Several limitations bound these interpretations. Most importantly, the data are cross-sectional, so age effects cannot be separated from cohort or period effects; whether an older participant's concern with pensions and end-of-life reflects aging itself or the historical experience of a particular generation cannot be decided here, and the conclusions are therefore correlational and descriptive rather than evidence of developmental causation. Age, although entered as a continuous covariate, was represented by only four discrete band values, limiting the resolution of the estimated age trend. Accordingly, the spline should not be interpreted as providing precise per-year estimates or fine-grained nonlinear developmental trajectories. The two essays from each participant are not independent, and the prevalence regression does not explicitly model this within-participant correlation, which could lead to underestimated standard errors. Morphological analysis and preprocessing introduce some lexical noise —segmentation errors and the particular choices of stop lemmas, numeral removal, and content-word

filtering could affect the assignment or ranking of lower-probability words within some topics—and the choices of *K* and content-covariate specification are not unique. Finally, the sample, while spanning the life course, is modest in size once divided across age cohorts, gender, and temporal reference, and its recruitment limits representativeness. A longitudinal, cohort-sequential design would be required to disentangle age, cohort, and period effects.

Conclusion

Taken together, this work shows that a Structural Topic Model applied to a rare life-span corpus of paired past and future narratives can quantify, without requiring large-scale manual coding, how temporal narratives are reorganized across the life course. The unsupervised model recovered ten interpretable, age-ordered topics; five topics showed significant age × gender interactions in prevalence; and the focus of future narratives shifted with age from work and self-oriented life planning toward family, the next generation, and health, with future narratives consistently more abstract than past narratives. By turning a labor-intensive coding problem into an explicit model with interpretable covariate effects, the approach provides a reproducible analytical framework for studying time perspective across the life span. Because the findings rest on cross-sectional data, they are descriptive rather than causal; applying the same pipeline to longitudinal or cross-cultural corpora would test whether the shift we observe is developmental, generational, or culturally specific.

Declarations

Competing Interests

The authors have no competing interests to declare.

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Author Contribution

I.U. conceived the study, designed the data collection, and collected the essay data. T.T. and I.K. designed the computational analysis. T.T. performed data preprocessing, implemented the analysis code, conducted the structural topic modeling and statistical analyses, prepared all figures and tables, and wrote the original draft of the manuscript. I.U. contributed to the psychological interpretation of the

results. I.U. and I.K. supervised the study and critically revised the manuscript. All authors reviewed and approved the final manuscript.

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Data Availability

The processed dataset underlying the Structural Topic Model analyses contains participant-generated free-text responses. Although direct identifiers have been removed, the dataset may still contain information that could potentially permit re-identification when combined with other information. In accordance with the informed consent provided by participants and the approval of the institutional research ethics committee, the dataset is therefore not publicly available. De-identified research data are available from the corresponding authors upon reasonable request, subject to approval by the institutional ethics committee and applicable data-sharing agreements. Code availability. All preprocessing and analysis scripts used in this study are provided in the Supplementary Information.

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Figures

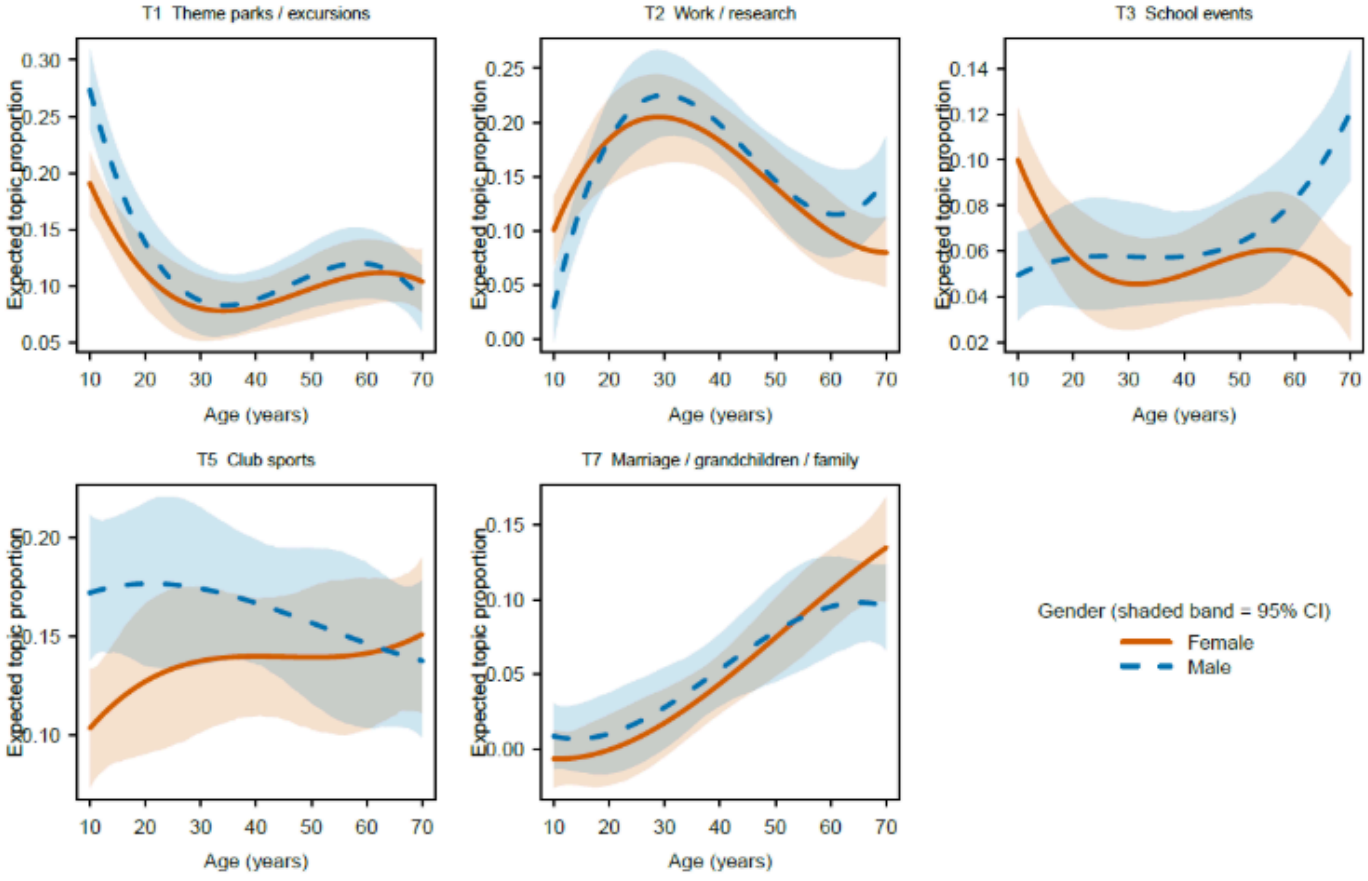


Figure 1

Age-related trends in the expected topic proportions by gender for the five topics showing a significant age × gender interaction (shaded areas indicate 95% confidence bands).

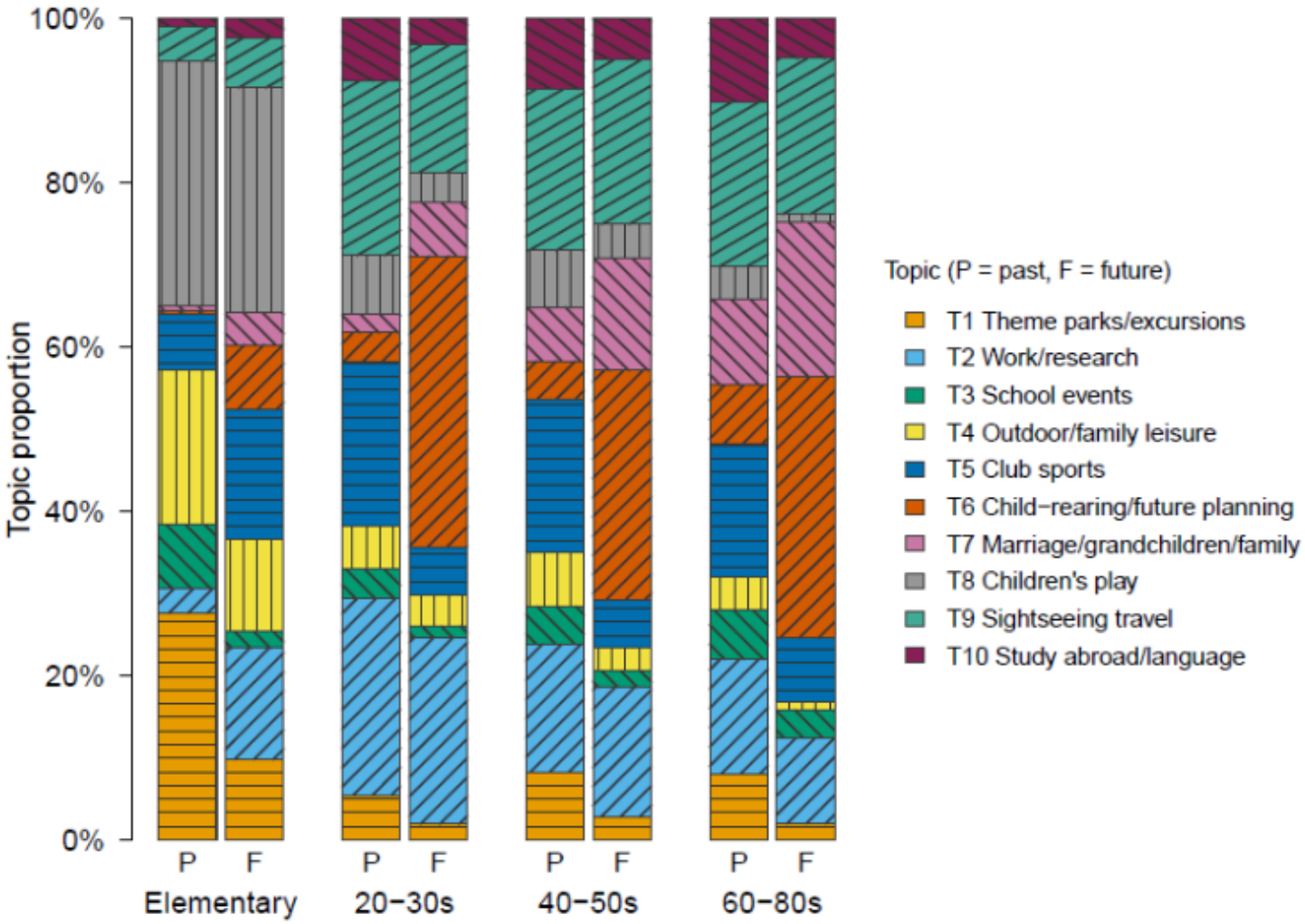


Figure 2

Mean topic composition of past and future essays by age cohort.

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