Memory & Cognition (2018) 46:1178–1193
https://doi.org/10.3758/s13421-018-0830-8

Leveling up the analysis of the reminiscence bump in autobiographical memory: A new approach based on multilevel multinomial models

Daniel Zimprich[1] · Tabea Wolf[1]

Published online: 20 June 2018

Abstract
In many studies of autobiographical memory, participants are asked to generate more than one autobiographical memory. The resulting data then have a hierarchical or multilevel structure, in the sense that the autobiographical memories (Level 1) generated by the same person (Level 2) tend to be more similar. Transferred to an analysis of the reminiscence bump in autobiographical memory, at Level 1 the prediction of whether an autobiographical memory will fall within the reminiscence bump is based on the characteristics of that memory. At Level 2, the prediction of whether an individual will report more autobiographical memories that fall in the reminiscence bump is based on the characteristics of the individual. We suggest a multilevel multinomial model that allows for analyzing whether an autobiographical memory falls in the reminiscence bump at both levels of analysis simultaneously. The data come from 100 older participants who reported up to 33 autobiographical memories. Our results showed that about 12% of the total variance was between persons (Level 2). Moreover, at Level 1, memories of first-time experiences were more likely to fall in the reminiscence bump than were emotionally more positive memories. At Level 2, persons who reported more emotionally positive memories tended to report fewer memories from the life period after the reminiscence bump. In addition, cross-level interactions showed that the effects at Level 1 partly depended on the Level 2 effects. We discuss possible extensions of the model we present and the meaning of our findings for two prominent explanatory approaches to the reminiscence bump, as well as future directions.

Keywords Reminiscence bump · Autobiographical memory · Multilevel multinomial model

A pertinent finding of autobiographical memory research is that autobiographical memories are not evenly distributed across the lifespan: When middle-aged or older adults are asked to recall autobiographical memories, they report more memories of events experienced during their youth and young adulthood than from the life periods before and after (Rubin, Rahhal, & Poon, 1998; Rubin, Wetzler, & Nebes, 1986). This finding, which is commonly referred to as the *reminiscence bump* of autobiographical memory, has been replicated in a number of studies (e.g., Berntsen & Rubin, 2004; Conway, Wang, Hanyu, & Haque, 2005; Wolf & Zimprich, 2016b; Zimprich & Wolf, 2016a, 2016b). In fact, this phenomenon has been observed so frequently and under such a wide variety of procedures that some researchers have concluded that it belongs among the most reliable phenomena in cognitive psychology (Conway & Rubin, 1993).

In the present article, our overarching goal is to introduce an analytical approach based on a multilevel multinomial model that offers a means of examining predictors of the reminiscence bump of autobiographical memory. These predictor variables are located at two levels—namely, the characteristics of the autobiographical memories reported by participants (Level 1) and the characteristics of the person (Level 2) who is remembering these events. To motivate the presentation of the model, we will exemplarily focus on the cognitive explanatory account of the reminiscence bump (e.g., Rubin et al., 1998) and the predictor variables derived from it—extensions to other explanatory accounts are straightforward.

✉ Daniel Zimprich
daniel.zimprich@uni-ulm.de

1 Department of Developmental Psychology, Institute of Psychology and Education, Ulm University, Albert-Einstein-Allee 47, 89081 Ulm, Germany

The reminiscence bump

Research on autobiographical memories has led to the so-called *lifespan retrieval curve* (Conway & Pleydell-Pearce, 2000). When individuals are asked to recall events from their past, events from the first years of life are seldom mentioned (childhood amnesia). By contrast, individuals remember a disproportionately high number of autobiographical events from adolescence and young adulthood, a phenomenon called the *reminiscence bump*. Afterward, during the adult years, the number of reported events declines, until it rises again for memories stemming from the most recent past. The high accessibility of autobiographical memories referring to events experienced during one's youth suggests that the temporal distance of an autobiographical event from the present is not the only factor that governs its recallability. Rather, an event's recallability appears to be strongly related to whether the experience occurred during a specific life period—namely, a person's adolescence or young adult years. Consequently, explanatory accounts of the reminiscence bump have focused on what distinguishes experiences made during adolescence and young adulthood from those that occur in earlier or later life periods.

To give an example, according to a cognitive explanatory account of the reminiscence bump (Rubin et al., 1998), adolescence and young adulthood represent life periods during which many events are experienced for the first time (e.g., the first relationship, with associated events such as the first kiss, etc.). First-time experiences are more distinct than repeated experiences and lead to more distinctive memory traces (Robinson, 1992), which helps increase their recallability (e.g., Eysenck & Eysenck, 1980). Moreover, first-time experiences could function as exemplars for similar events and experiences later in life (Janssen, Rubin, & St. Jacques, 2011; Pillemer, 2001). Therefore, first-time experiences may be recalled more frequently in conjunction with later experiences, which further enhances their recallability (Bjork, 1975). The association between novelty (i.e., whether an autobiographical memory describes a first-time experience) and the reminiscence bump has been examined in a number of studies. Jansari and Parkin (1996), for instance, compared the proportion of word-cued memories for first-time events from earlier life periods (from the ages of 0–20) to the proportion of memories of more recent life periods (10–20 years ago) and found that the earlier life period was associated with a higher proportion of first-time events. Likewise using the cue-word technique, Janssen and Murre (2008) found a reminiscence bump in the distribution of first-time experiences but also of regular events. Using a life history timeline, Demiray, Gülgöz, and Bluck (2009) found a reminiscence bump in the distribution of memories rated as being first-time experiences but not in the distribution of memories referring to last-time experiences. Taken together, these results support the relation between first-time experiences and the reminiscence bump as postulated in the cognitive explanatory account.

A two-level perspective on the reminiscence bump

As we mentioned above, the reminiscence bump has been replicated frequently and in response to a variety of cueing material (e.g., Bohn, 2010; Fitzgerald, 1988; Janssen, Chessa, & Murre, 2005, Rubin & Schulkind, 1997). In most studies, participants were instructed to generate more than one autobiographical memory (for an exception, see Berntsen & Rubin, 2002). For example, Wolf and Zimprich (2016a) asked participants to report autobiographical memories in response to 51 cue words. Focusing on important memories, Glück and Bluck (2007) used the Life Story Questionnaire, in which individuals are required to list up to 15 events that they consider the most important ones in their life.

If participants generate more than one autobiographical memory, the resulting data have a hierarchical or clustered nature, in the sense that the autobiographical memories generated by the same person tend to be more alike in their characteristics than autobiographical memories sampled at random from different persons (cf. Goldstein, 1995). With such a hierarchical data structure, there are two possible units of analysis: namely, the individual autobiographical memory and the individual participant. Thus, one may distinguish two levels of data, with the lower data level (autobiographical memories) nested within the higher one (participants). In what follows, we draw a distinction between these two data levels.

At Level 1, the autobiographical memories of the participants are the unit of analysis. Conceptually, the prediction of whether an autobiographical memory falls within or outside the reminiscence bump is based on the characteristics of the autobiographical memory. On the basis of the cognitive explanatory account outlined above, which draws on novelty (i.e., first-time experiences), one would expect autobiographical memories describing first-time experiences to have a higher likelihood of falling within the reminiscence bump period than to derive from life periods before and after. Because autobiographical memories are nested within participants, Level 1 represents the *within-person* level and captures differences between autobiographical memories. For the characteristics of autobiographical memories at Level 1 to be useful, from both a conceptual and a data-analytic perspective, they must show some variation across the autobiographical memories within participants. For example, there should be autobiographical memories describing first-time experiences as well as autobiographical memories describing other (i.e., not first-time) experiences. An analysis at Level 1 could then lead to the finding that in accordance with the cognitive explanatory account, those autobiographical memories describing first-time experiences are more likely to stem from the period of the reminiscence bump in participants' lives.

At Level 2, persons are the unit of analysis. Conceptually, Level 2 has a different meaning than Level 1. Specifically, Level 2 describes differences between participants, which is why Level 2 represents the *between-person* level. At Level 2, the prediction of whether an individual autobiographical memory falls within or outside the reminiscence bump is based on the characteristics of the participant. Participants may differ, for example, in demographic variables (age, sex, etc.) and, naturally, in many other variables (e.g., personality). What distinguishes the variables located at Level 2 from the variables located at Level 1 is that the Level 2 variables are *constant* across Level 1 units (autobiographical memories) or, equivalently, within persons. For these Level 2 characteristics to be useful, they must show some variation across participants; that is, participants should differ, for example, in sex. An analysis at Level 2 could then, for example, lead to the result that women and men differ in the numbers of memories reported from the reminiscence bump period.[1]

In addition to genuine individual-difference variables (e.g., demographic variables or differences in personality), it is common practice in multilevel analyses to form new individual-difference variables by averaging the Level 1 variables within a Level 2 unit to form so-called "context means" (Bryk & Raudenbush, 1992). For example, one could calculate the proportion of autobiographical memories describing first-time experiences for every participant. This proportion of first-time experiences then would represent a Level 2 variable; that is, it would be constant within a participant. In further pursuing the cognitive explanatory account of the reminiscence bump, one might expect that those participants with a higher proportion of memories of first-time experiences would report more autobiographical memories from the reminiscence bump period than participants with a lower proportion of memories of first-time experiences.

Thus, explanatory accounts of the reminiscence bumps may lead to predictions at Level 1, which refer to the characteristics of the autobiographical memories, and to predictions at Level 2, which refer to the characteristics of the participants. To illustrate, on the basis of the cognitive explanatory account, one would expect that an autobiographical memory describing a first-time experience would be more likely to fall into the reminiscence bump period—a Level 1 or within-person prediction. Also, one would expect that a participant who recalled a high proportion of autobiographical memories describing first-time experiences would be more likely to report more autobiographical memories from the reminiscence bump period—a Level 2 or between-person prediction.

The conceptual difference between Level 1 and Level 2 variables becomes somewhat blurred once *cross-level interactions* are taken into account. That is, Level 1 variables and Level 2 variables may interact to create specific effects. For example, an interaction between autobiographical memories describing first-time events (Level 1) and sex (Level 2) would imply that the change in probability of an autobiographical memory falling within the reminiscence bump due to its novelty would be different for women than for men. A Level 1 variable might also interact with its contextual mean (Level 2), which would lead to a so-called *contextual model* (Bryk & Raudenbush, 1992). For example, a contextual model could involve an interaction between autobiographical memories describing first-time experiences (Level 1) and the proportion of first-time experiences that a person reports (Level 2)—such that, for example, the effect at Level 1 would be smaller for high values of Level 2. Such an interaction would imply that for participants reporting many first-time experiences, the fact that a single autobiographical memory describes a first-time experience would be less predictive that the autobiographical memory would fall within the reminiscence bump.

A multilevel multinomial model

An analysis of data exhibiting a hierarchical nature should take into account their multilevel structure. During the last decades, several analysis models for multilevel data have been developed and described using different names—for example, random-effects models (Laird & Ware, 1982), multilevel models (Goldstein, 1995), variance component models (Dempster, Rubin, & Tsutakawa, 1981), or hierarchical linear models (Bryk & Raudenbush, 1992).

For an analysis of the reminiscence bump, a natural starting point would be to model the probabilities that an autobiographical memory falls within versus outside the reminiscence bump period. The two categories (inside vs. outside the reminiscence bump) would be based on the age at which an experience described in the autobiographical memory occurred. Doing so would lead to a logistic regression model (e.g., Christensen, 1997). However, a logistic regression model treats autobiographical memories falling in the *pre*bump period the same as it treats autobiographical memories falling in the *post*bump period. Thus, potentially important information would be lost. An alternative would be an ordered logit model, which can handle more than two categories (e.g., McCullagh, 1980). The ordered logit regression model, however, would treat categories in either an ascending or a descending order. This would imply, for example, that the proportion of first-time experiences should be smallest in the prebump period, medium during the reminiscence bump, and largest in the postbump period. On the basis of the cognitive account, however, we would expect the intermediate category—that is, the reminiscence bump period—to show the greatest proportion of first-time events.

A model that takes into account that prebump, bump, and postbump autobiographical memories may be *qualitatively* different (but *not in a given order*) is the multinomial

[1] The distinction between variables that vary within persons and variables that vary between persons, of course, also transfers to experimentally manipulated variables. For example, a within-person manipulation could involve using emotionally positive versus emotionally neutral cue words to elicit autobiographical memories in the same participant (e.g., Maki, Janssen, Uemiya, & Naka, 2013). A between-person manipulation would use emotionally positive cue words in one group of participants and emotionally negative cue words in another group.

regression model, which treats different categories as nominal (e.g., Long, 1997). Basically, a multinomial regression model can be thought of as simultaneously estimating logistic regression models for all possible comparisons among the prebump, bump, and postbump categories of autobiographical memories. Because the autobiographical memory data exhibit a two-level structure (Level 1: autobiographical memories; Level 2: individuals), an extension of the multinomial regression model would be required that can handle the hierarchical nature of the data. Hartzel, Agresti, and Caffo (2001), among others, have developed such an extension of the multinomial model.[2] In what follows, we will base our presentation of the multilevel multinomial regression model mainly on Hedeker (2003) and Hedeker and Gibbons (2006).

Let the (unordered) categorical variable y denote whether an autobiographical memory stems from an age before the reminiscence bump (prebump), an age within the reminiscence bump, or an age after the reminiscence bump (postbump). More specifically, let a_{ij} denote the age at which the event described in autobiographical memory j reported by person i occurred. For instance, if the reminiscence bump period is defined to lie between the ages of 10 and 30 (as reported by, e.g., Conway & Haque, 1999; Demiray et al., 2009), the categories of y are given as

$$y_{ij} = \begin{cases} \mathrm{A} & \text{if } 0 \le a_{\mathrm{ij}} \le 10 \\ \mathrm{B} & \text{if } 11 \le a_{ij} \le 30 \\ \mathrm{C} & \text{if } a_{ij} \ge 31 \end{cases} \tag{1}$$

Hence, an autobiographical memory falls in category "A" if the event or experience it describes happened during the prebump life period, category "B" if the event or experience happened during the bump period, and "C" if the event or experience happened during the postbump period. Note that the letters A, B, and C are used here for ease of presentation (and do not affect the parameter estimates). Because the categories are nominal, one could use any numbers or letters, as long as the categories are mutually exclusive and each category receives a unique identifier.

Let $p_{ij\mathrm{A}}$ denote the probability that autobiographical memory j of individual i falls in category A (the prebump life period)—that is, the probability that y_{ij} = A. Analogously, let $p_{ij\mathrm{B}}$ denote the probability that it falls in category B (the bump period), and $p_{ij\mathrm{C}}$ denote the probability that it falls in category C (the postbump period). Because probabilities are limited to the interval [0, 1], which is difficult to handle statistically, for multinomial models generalized logits $\eta_{ij\mathrm{A}}$, $\eta_{ij\mathrm{B}}$, and $\eta_{ij\mathrm{C}}$ are constructed that can vary between −∞ and ∞. The logit of $p_{ij\mathrm{A}}$ is given as (Lindsey, 1997)

$$\operatorname{logit}\left(p_{ij\mathrm{A}}\right) = \eta_{ij\mathrm{A}} = \log\left(\frac{p_{ij\mathrm{A}}}{p_{ij\mathrm{B}}}\right) \tag{2}$$

where the denominator is the probability of the reference category—that is, the category that the category in question is compared to. Although the choice of reference category is arbitrary, in the present context it makes sense to designate category B (the reminiscence bump period category) as the reference category, because this allows investigating what distinguishes autobiographical memories from the reminiscence bump from those that derive from earlier or later life periods. By analogy, the two other generalized logits are

$$\operatorname{logit}\left(p_{ij\mathrm{B}}\right) = \eta_{ij\mathrm{B}} = \log\left(\frac{p_{ij\mathrm{B}}}{p_{ij\mathrm{B}}}\right) = \log(1) = 0 \quad \text{and} \quad \operatorname{logit}\left(p_{ij\mathrm{C}}\right) = \eta_{ij\mathrm{C}} = \log\left(\frac{p_{ij\mathrm{C}}}{p_{ij\mathrm{B}}}\right) \tag{3}$$

showing that the generalized logit of the reference category (category B) is zero.

In the context of generalized linear models—of which multinomial models are one representative—the logit function is called the *link function* (Lindsey, 1997). Generalized logits are then accounted for by regression models. Importantly, for every category that is not the reference category, a separate regression model is estimated that compares the category in question with the reference category. For the comparison between category A (prebump) and the reference category B (bump), the regression equation is (Long, 1997)

$$\eta_{ij\mathrm{A}} = \mathbf{x}_i^{'}\boldsymbol{\beta}_{\mathrm{A}} \tag{4}$$

where $\mathbf{x}_i$ is a vector of covariates ("predictors") measured in individual i, and $\boldsymbol{\beta}_{\mathrm{A}}$ is a vector of regression parameters comparing category A (prebump) with the reference category B (bump). Typically, the first element of the covariate vector contains a value of 1 for the intercept estimation. The comparison between category C (postbump) and the reference category is modeled by the equation

$$\eta_{ij\mathrm{C}} = \mathbf{x}_i^{'}\boldsymbol{\beta}_{\mathrm{C}} \tag{5}$$

where $\boldsymbol{\beta}_{\mathrm{C}}$ is the vector of regression parameters comparing categories C (postbump) and B (bump). Note that the parameter estimates gathered in $\boldsymbol{\beta}_{\mathrm{A}}$ and $\boldsymbol{\beta}_{\mathrm{C}}$ are expected to be different, because the pre- and postbump categories differ qualitatively from the reference bump category, but also from each other. Comparable to "classic" multiple regression models, the multinomial regression model is multivariate in nature; that is, several predictors can be included simultaneously. Moreover, because the model is multivariate, the associations among the predictor variables are taken into account.

What has been described so far is a multinomial regression model that does not consider the hierarchical or clustered nature of the data—with autobiographical memories being nested within individuals. To take the influence of individuals

[2] Hartzel et al. also provide SAS code for fitting random-effects multinomial models at www.statmod.org/smij/Vol1/Iss2/Hartzel/Data.txt.

on their autobiographical memories into account, random subject effects are included in the multinomial regression model. A simple extension of the regression models given in Eqs. 4 and 5 contains individual-specific influences by including a random intercept—that is,

$$\eta_{ij\mathrm{A}} = b_{0\mathrm{A}i} + \mathbf{x}_i^{'}\boldsymbol{\beta}_\mathrm{A} \tag{6}$$

and

$$\eta_{ij\mathrm{C}} = b_{0\mathrm{C}i} + \mathbf{x}_i^{'}\boldsymbol{\beta}_\mathrm{C} \tag{7}$$

where $b_{0\mathrm{A}i}$ in Eq. 6 is the random intercept of individual i in the regression model comparing category A with the reference category, and $b_{0\mathrm{C}i}$ in Eq. 7 is the random intercept of individual i in the regression model comparing category C with the reference category. Across individuals, without loss of generality, the random intercepts are assumed to be normally distributed with 0 means and variances $\sigma^2_{b_{0\mathrm{A}}}$ and $\sigma^2_{b_{0\mathrm{C}}}$, respectively (Goldstein, 1995). These variances capture the amount of individual difference in the random intercepts of the regression models in Eqs. 6 and 7—if they are statistically significantly different from 0, this indicates reliable individual differences. The covariance between the random intercepts is captured by $\sigma_{b_{0\mathrm{A}}b_{0\mathrm{C}}}$, which represents the amount that the individual differences represented by the random intercepts are associated. Together, these assumptions can be expressed as

$$\begin{pmatrix} b_{0\mathrm{A}i} \\ b_{0\mathrm{C}i} \end{pmatrix} \sim MVN(\mathbf{0}, \boldsymbol{\Sigma}) = MVN\left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma^2_{b_{0\mathrm{A}}} & \sigma_{b_{0\mathrm{A}}b_{0\mathrm{C}}} \\ \sigma_{b_{0\mathrm{A}}b_{0\mathrm{C}}} & \sigma^2_{b_{0\mathrm{C}}} \end{pmatrix}\right], \tag{8}$$

where MVN denotes multivariate normality, $\mathbf{0}$ is the vector of means of the random intercepts, and $\boldsymbol{\Sigma}$ is the variance–covariance matrix of the random intercepts.

For random-intercept models, it is frequently of interest to express the amount of variance that the data contain at Levels 1 and 2. As Hedeker and Gibbons (2006, p. 222) outlined, for the multinomial model with random intercepts, the Level 1 variance is given by $\frac{\pi^2}{3}$, which is the variance for a standard logistic distribution. For the regression model comparing category A (prebump) to the reference category (bump), the intraclass correlation r_{icc}, which is the ratio of the Level 2 variance $\sigma^2_{b_{0\mathrm{A}}}$ to the total variance (Level 2 *plus* Level 1 variance), is calculated as

$$r_{\mathrm{icc}} = \frac{\sigma^2_{b_{0\mathrm{A}}}}{\sigma^2_{b_{0\mathrm{A}}} + \pi^2/3}. \tag{9}$$

The intraclass correlation for the regression model comparing category C (postbump) to the reference category is calculated analogously, after replacing $\sigma^2_{b_{0\mathrm{A}}}$ with $\sigma^2_{b_{0\mathrm{C}}}$. An intraclass correlation of 0 would indicate that all variance was at Level 1—that is, within persons—which would render a multilevel model unnecessary. An intraclass correlation of 1, in turn, would indicate that all variance was at Level 2 (between persons), implying perfect dependency of the autobiographical memories within a participant (Bryk & Raudenbush, 1992).

Aims of the present research

As we outlined above, a multilevel multinomial regression model (Hartzel et al., 2001; Hedeker, 2003; Hedeker & Gibbons, 2006) appears well-suited to address two pertinent questions of autobiographical memory research simultaneously and, from a statistical perspective, more adequately. From a statistical perspective, multilevel multinomial regression models are possibly more adequate because the fact that autobiographical memories are nested within persons is taken into account. Once a participant provides more than one autobiographical memory, hierarchical data result that necessarily contain some amount of dependency (Bryk & Raudenbush, 1992; Goldstein, 1995). From a substantive perspective, our approach allows for investigating two types of questions that center on the reminiscence bump phenomenon. First, the question of what characterizes the autobiographical memories falling into the reminiscence bump is tackled. Specifically, what distinguishes autobiographical memories from the reminiscence bump period from autobiographical memories falling in an earlier (prebump) or a later (postbump) age range? Note that this first question is addressed at Level 1, or the within-person level. Second, the question of what characterizes the individuals who report many (i.e., a high proportion of) autobiographical memories falling in the reminiscence bump is addressed. What differentiates such persons from persons who report more autobiographical memories falling in an earlier or a later age range? Note that this second question—which is investigated less often in empirical research (see, e.g., Wolf & Zimprich, 2016b)—directly relates to explanatory accounts of the reminiscence bump, although it does so more implicitly, because it refers to differences between individuals (e.g., Conway & Pleydell-Pearce, 2000). It is addressed at Level 2, or the between-person level. Multilevel multinomial regression models can address both types of questions simultaneously. Predictor variables of the reminiscence bump are also located at different data levels (e.g., the novelty of an autobiographical memory vs. the proportion of autobiographical memories describing a first-time experience a person has reported) and, as such, may have different effects, or may even interact, which has the potential to provide new insights into the reminiscence bump phenomenon. In what follows, we describe the data set that will serve to illustrate the suggested analytical approach.

Method

Participants

The sample comprised $N = 100$ older adults who, on average, were 73 years old ($SD = 4.98$ years, min. 65 years, max. 84 years). Of these 100 older adults, 63 (63%) were female.[3] The majority of the participants (59%) reported being married. On a Likert-type scale ranging from 1 (*excellent*) to 5 (*poor*), their subjective health was rated at 2.45 ($SD = 0.77$), on average, whereas their subjective memory functioning was rated at 2.49 ($SD = 0.70$). About half of the sample (51%) reported having a secondary general school certificate ("Hauptschulabschluss"), which is equivalent to 9 years of formal education. Fifteen participants reported having a university-entrance diploma.

Procedure

Older adults were interviewed individually. Participants were shown a cue word printed on a small card (33 cue words in total) and were asked to report an autobiographical memory that came to their mind that was evoked by the cue word. The order of the cue words was random. Participants were instructed to report events that were at least 10 years old, to avoid the recency effect typically found in autobiographical memory. After participants had described the memory, they were asked whether it was an event or experience that had happened for the first time and, subsequently, were required to judge the emotional quality of the reported event, on a scale ranging from 1 (*very negative*) to 5 (*very positive*). Then, the next cue word was presented. After all events had been described, the interviewer went through the recalled events again and asked the participants for their age at the time of each event. The cue words were drawn from the Berlin Affective Word List (BAWL-R; Võ et al., 2009) and were high in imageability and emotionally neutral.

Statistical modeling

A multilevel multinomial model was used to analyze the autobiographical memory data (Hedeker, 2003; Hedeker & Gibbons, 2006; Stroup, 2013). Three categories of autobiographical memories were created, based on the age at which the event or experience described in the autobiographical memory took place. To foreshadow results, on the basis of Fig. 1 we defined the reminiscence bump in the present study to lie between the age boundaries of 11 and 25 years. As a consequence, the following age boundaries were used to define the three categories of prebump (category A), bump (B), and postbump (C) memories:

$$\begin{aligned}
&\text{Category A (Prebump)}: && 0 \text{ years} < \text{Age of AM} \leq 10 \text{ years},\\
&\text{Category B (Bump)}: && 11 \text{ years} \leq \text{Age of AM} \leq 25 \text{ years},\\
&\text{Category C (Postbump)}: && 26 \text{ years} \leq \text{Age of AM},
\end{aligned}$$

where AM denotes autobiographical memory.

Apart from the predictor variables, we included sex and age as demographic variables to be controlled for. Although sex has not been shown to have consistent effects on the reminiscence bump (see Janssen et al., 2005; Rubin, Schulkind, & Rahhal, 1999), age has effects on the shape and the location of the bump (Janssen, Gralak, & Murre, 2011; Zimprich & Wolf, 2016b). Because the (linear) effects of both demographic variables were statistically controlled, the effects of the other predictor variables reflect "net" effects after taking sex- and age-related differences into account. As a predictor variable derived from the cognitive account, the question of whether an autobiographical memory described a first-time experience was used. To illustrate the potential benefits of our multivariate approach, we additionally included the emotional quality of autobiographical memories as a second predictor variable. Prior to the analyses, the proportion of memories describing first-time experiences and the average emotional quality were calculated for every participant in order to form context means of these variables (see above). Thus, first-time experiences entered the model at two levels, at Level 1 as whether the individual autobiographical memory described a first-time experience, and at Level 2 as the proportion of autobiographical memories describing a first-time experience. Likewise, at Level 1 emotional quality reflects the emotional valence of an individual autobiographical memory, whereas at Level 2 it reflects the average emotional valence of the autobiographical memories that a participant generated. In line with common practice, the Level 1 variables were centered within persons by subtracting the participant's mean, whereas the Level 2 variables were centered across persons by subtracting the sample mean (Wang & Maxwell, 2015).[4] Similarly, age was grand-mean centered by subtracting the sample's age mean (73 years) from an individual participant's age. Sex was entered dummy-coded as 0 (*male*) and 1 (*female*).

The estimation of parameters in a multilevel multinomial model—as a special case of generalized linear mixed models—can follow different routes (cf. Stroup, 2013). As compared to linear models (based on the normality assumption), the likelihood function of multilevel multinomial models is more complicated and requires integration over a product of likelihoods, which makes direct maximization

[3] The present data are part of a larger data set that has been analyzed elsewhere with a different focus (Wolf & Zimprich, 2016b).

[4] The effects of group-mean centering (i.e., within-person centering in the present context) and grand-mean centering (i.e., between-person centering) are that the within-person and between-person parts of a predictor variable are independent or uncorrelated.

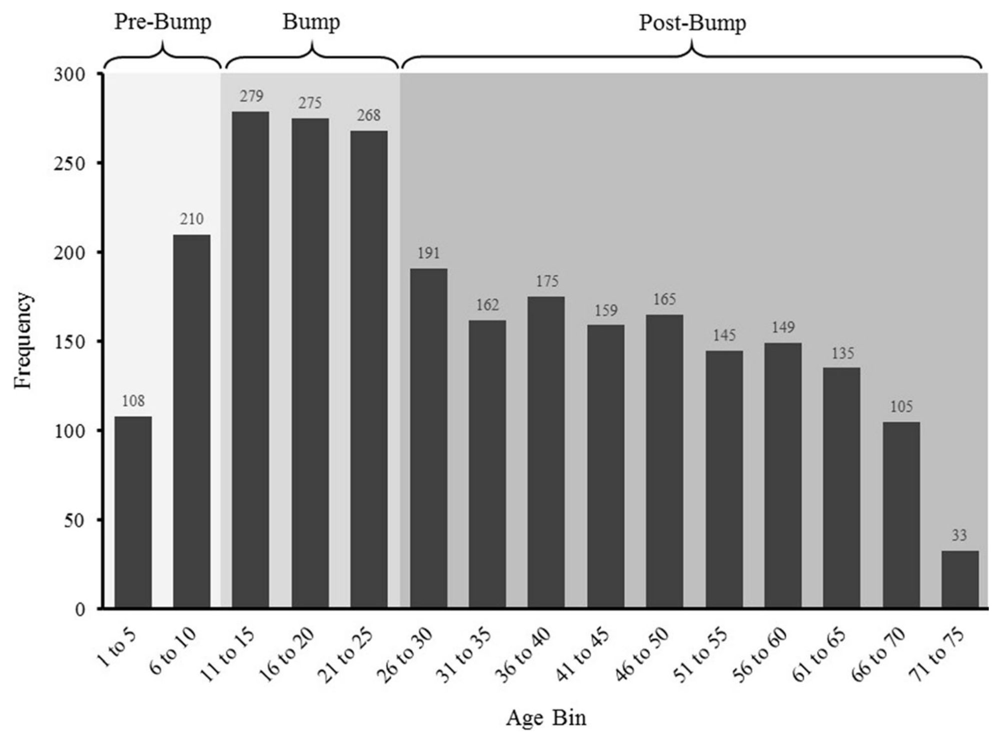

Fig. 1 Distribution of autobiographical memories, aggregated across persons into 5-year age bins. The different shaded areas represent prebump memories ($0 \leq \text{age} \leq 10$), bump memories ($11 \leq \text{age} \leq 25$), and postbump memories ($26 \leq \text{age}$)

impossible. Using an *approximation* of integrals, however, allows for parameter estimation (see McCulloch, 1997). In practice, two approaches are common: namely, Gauss–Hermite quadrature (e.g., McCulloch & Searle, 2001, chap. 10) and Laplace approximation (e.g., Raudenbush, Yang, & Yosef, 2000). The former is implemented, for example, in the SAS NLMIXED procedure; the latter can be accessed, for example, as part of the SAS GLIMMIX procedure (SAS, 2014).[5] Markov chain Monte Carlo (MCMC) algorithms represent an alternative to likelihood-based methods but are relatively computer-intensive (Zhao, Staudenmayer, Coull, & Wand, 2006).

The data were analyzed using SAS NLMIXED (SAS Institute Inc., 2014) using Gauss–Hermite quadrature with 15 quadrature points. As the criteria for model fit, the Akaike information criterion (AIC; Akaike, 1974) and the Bayesian information criterion (BIC; Schwarz, 1978) were used. Both are based on − 2 times the log-likelihood of the data given the model in question, plus a penalty factor for introducing additional parameters, which thus rewards parsimony—with the AIC penalizing the number of parameters less strongly than the BIC. A thorough discussion of the properties of both the AIC and BIC can be found in Vrieze (2012). In addition, we calculated conditional R-squared according to Nakagawa and Schielzeth (2013) as a measure of the variance (in the metric of logits, $\eta_{ij\mathrm{A}}$ and $\eta_{ij\mathrm{C}}$) explained by the model.

[5] The Laplace approximation can be shown to be equivalent to the Gauss–Hermite procedure with one quadrature point (Stroup, 2013, chap. 4).

Results

Descriptive statistics

Figure 1 shows the distribution of autobiographical memories generated by the 100 participants in the present study, aggregated into 5-year age bins and across participants. Due to missing values (some participants were unable to recall an autobiographical memory to some cue words), there were not 100 (sample size) × 33 (number of cue words) = 3,300 autobiographical memories in total, but 2,559 autobiographical memories (ranging from 15 to 33 per participant).[6] On the basis of Fig. 1, we defined the reminiscence bump as falling between the age boundaries of 11 and 25 years, because the corresponding three age bins showed the highest frequencies.

Table 1 contains descriptive statistics at both Level 1 and Level 2 regarding the autobiographical memories generated by the 100 participants in the present study. Of the 2,559 autobiographical memories, 318 (12.4%) fell in the prebump category, whereas 822 (32.1%) and 1,419 (55.5%) fell in the bump and postbump categories, respectively. In total, 1,160 of the autobiographical memories (45.3%) were categorized by participants as describing first-time experiences. Whereas 120 (37.7%) of the prebump memories described first-time

[6] Because multilevel models are based on the so-called "long" data format (in contrast to the more typical "wide" format), in which every autobiographical memory of every person constitutes a row in the data set, missing data in the outcome variable are handled automatically (see Bryk & Raudenbush, 1992).

Table 1 Descriptive statistics of autobiographical memories (Level 1 and Level 2)

			Within-Person (Level 1)			Between-Person (Level 2)	
Category		Total	First-Time		Emot. Quality	First-Time	Emot. Quality
Prebump (A)	*N*	318	120	Mean	2.84	.47	2.99
	%	12.4	37.7	SD	1.26	.12	0.30
Bump (B)	*N*	822	410	Mean	3.13	.46	2.97
	%	32.1	49.9	SD	1.29	.11	0.29
Postbump (C)	*N*	1,419	630	Mean	2.71	.46	2.91
	%	55.5	44.4	SD	1.32	.11	0.27
Total	*N*	2,559	1,160	Mean	2.86	.46	2.94
	%	100	45.3	SD	1.32	.11	0.28

experiences, 410 (49.9%) of the bump memories and 630 (44.4%) of the postbump memories, respectively, described first-time experiences (see Table 1). The emotional quality of the prebump autobiographical memories was 2.84, on average. For the bump and postbump memories, these averages were 3.13 and 2.71, respectively.

With respect to Level 2, the mean proportion of first-time experiences that participants reported was .46 overall, but there was considerable variability between participants (*SD* = .11). This average proportions of first-time experiences differed only minimally across the prebump, bump, and postbump categories (.47, .46, .46). Participants described autobiographical memories with an average emotional quality of 2.94. There were small differences across the prebump, bump, and postbump categories, with the first showing the highest average and the last showing the lowest.

Multilevel multinomial regression models

In a first model (Model 0), only fixed intercepts were estimated; that is, neither explanatory variables nor random effects were included. Table 2 shows the parameter estimates for the comparisons of prebump (A) with bump (B) and postbump (C) with bump (B). The statistically significant intercept estimate for the prebump category was $\beta_{0A} = -.949$. For an interpretation of this estimate, two different but related calculations are helpful. First, if the estimate is transformed back to the probability scale—with the use of the postbump intercept estimate of $\beta_{0C} = .546$—one gets

$$p_{ij\mathrm{A}} = \frac{\exp(\beta_{0\mathrm{A}})}{1 + \exp(\beta_{0\mathrm{A}}) + \exp(\beta_{0\mathrm{C}})} = \frac{\exp(-0.949)}{1 + \exp(-0.949) + \exp(0.546)} = 0.124,$$

implying that 12.4% of the autobiographical memories are predicted to fall into the prebump category—which, in this case, because no predictor variables were included, exactly equals the observed value (see Table 1). For the postbump intercept estimate, a similar calculation leads to $p_{ij\mathrm{C}} = .555$. Therefore, the probability of an autobiographical memory falling within the bump is $p_{ij\mathrm{B}} = 1 - .124 - .555 = .321$ (cf. Table 1).

As an alternative, an odds ratio (OR) can be calculated as

$$OR_{ij\mathrm{A}} = \exp(\beta_{0\mathrm{A}}) = \exp(-0.949) = 0.387,$$

implying that the odds of an autobiographical memory falling in the prebump category are 0.387 times the odds of an autobiographical memory falling in the bump category. For the postbump intercept estimate, a similar calculation leads to $\mathrm{OR}_{ij\mathrm{C}} = 1.73$, showing that the odds for an autobiographical memory to fall in the postbump category are 1.73 times the odds for the bump category. Because only intercepts and no predictor variables were included, Model 0 did not account for any variance ($R^2 = 0$ for both submodels).

In the next model (Model 1), random effects for the intercepts were added. As Table 2 shows, the random-effect variances were statistically different from zero, implying that there were reliable individual differences. In other words, participants differed reliably in their proportions of prebump and postbump autobiographical memories. The intraclass correlations (see Eq. 9) were .13 and .10 for the prebump and postbump regressions. This means that 13% of the variance in the comparison between the prebump and bump categories of autobiographical memories was at Level 2 and, thus, reflected between-person differences. Similarly, 10% of the variance in the comparison between the postbump and bump categories of autobiographical memories reflected between-person differences. The random effects showed a negative correlation (− .59), indicating that participants who reported (relatively) more memories from the prebump category tended to report (relatively) fewer memories from the postbump category (and vice versa).[7] Relative to Model 0, the

[7] This negative correlation is, at least in part, due to the design of the study. Participants were asked to report autobiographical memories in response to 33 cue words. Although not all participants did so, the total number of memories a participant reported was, on average, close to 33, which might have induce a negative correlation between the categories. Given an (almost fixed) total number of memories, if (relatively) more memories falling in the prebump category were generated, this would imply that (relatively) fewer memories would fall in the other categories (bump and postbump).

Table 2 Parameter estimates for each model tested

Regressor	0		1		2		3		4	
	Pre-Bump	Post-Bump	Pre-Bump	Post-Bump	Pre-Bump	Post-Bump	Pre-Bump	Post-Bump	Pre-Bump	Post-Bump
Fixed effects										
Intercept	− 0.949*	0.546*	− 1.220*	0.528*	− 1.488*	0.472*	− 1.489*	0.453*	− 1.490*	0.452*
b: Age					− .014	.005	− .017	.004	− .017	.003
b: Sex (0 = male, 1 = female)					.402*	.083	.413*	.133	.413*	.131
w: First time							− .586*	− .234*	− .606*	− .234*
b: First time							.417	− .359*	.455	− .344*
w × b: First time									.642*	− .975
w: Emotional quality							− .195*	− .228*	− .186*	− .229*
b: Emotional quality							.135	− .678*	.128	− .675*
w × b: Emotional quality									− .139	.182*
Random effects										
Intercept variance			.482*	.378*	.455*	.366*	.462*	.326*	.465*	.327*
Intercept correlation			− .586*		− .643*		− .639*		− .643*	
Model fits										
AIC	4,870.7		4,673.2		4,677.4		4,626.5		4,611.1	
BIC	4,882.4		4,686.2		4,700.9		4,670.8		4,665.8	
R^2	0	0	.128	.103	.149	.105	.228	.203	.251	.233

"w:" denotes a Level 1 (or within-person) effect, "b:" denotes a Level 2 (or between-person) effect; AIC = Akaike information criterion (smaller is better); BIC = Bayesian information criterion (smaller is better); R^2 = conditional *R*-squared according to Nakagawa & Schielzeth (2013). $^*p < .05$.

intercept estimates have changed (e.g., − 0.949 vs. − 1.220 in the prebump model), which is due to the difference between marginal and conditional models.[8] Eventually, the fit of Model 1 was significantly better than that of Model 0 (see the AIC and BIC values in Table 2), which implies that the inclusion of random effects led to an improved description of the data. Also, Model 1 accounted for 13% and 10% of the total variance, respectively—which, in this case, equals the intraclass correlations (see Nakagawa & Schielzeth, 2013, Eq. 30).

In Model 2, age and sex were entered as Level 2 demographic variables to be (statistically) controlled for. As Table 2 shows, age did not have a statistically significant effect. In addition, sex did not affect the postbump category significantly. By contrast, sex had a statistically significant effect on the prebump category, in the sense that women reported more autobiographical memories from their childhood years (age 1 to 10) than did men. More specifically, for men the probability of reporting an autobiographical memory stemming from the prebump category was .08, whereas for women it was .11.[9] The other parameter estimates remained basically unchanged as compared to the previous model. Contrasted with Model 1, the model fit slightly decreased according to the AIC and BIC, which was due to the mostly nonsignificant effects of age and sex. The amount of variance accounted for increased slightly in both the prebump-versus-bump model and the postbump-versus-bump model.

Next, in Model 3, the Level 1 and Level 2 effects of first-time experiences and emotional quality were included. As Table 2 shows, the statistically significant effect of first-time experiences was − .586 in the prebump regression, implying that, as compared to the bump category, autobiographical

[8] In generalized linear mixed models, one distinguishes between marginal and conditional models. In contrast to normally distributed data, for non-Gaussian data the observed (or *marginal*) distribution of the outcome variable is not the same as the distribution of the outcome variable *conditional* on the random effects (cf. Stroup, 2013). Moreover, the larger the random variance, the larger this discrepancy becomes. Put simply, the reason for this is that the *logit of the mean* of the individual values of the outcome variable is not the same as the *mean of the logit* of the individual values of the outcome variable (Hedeker & Gibbons, 2006). Therefore, the fixed-effect estimates change once random effects are included—as we did in moving from Model 0 (only fixed effects) to Model 1 (including random intercepts as well). A more extensive discussion of marginal versus conditional models can, for example, be found in Diggle, Heagerty, Liang, and Zeger (2002). Hedeker, du Toit, Demirtas, and Gibbons (2018), among others, describe an approach to obtaining marginal probability estimates based on the parameter estimates from a conditional model.

[9] More precisely, this sex difference holds for participants of average age (mean-centered age of 0) and with random intercepts of zero. To compute these probabilities, on the basis of the Table 1 values, one calculates for men (sex = 0),

$$p_{ij\mathrm{A}} = \frac{\exp(\beta_{0\mathrm{A}} + \beta_{1\mathrm{A}}\mathrm{age} + \beta_{2\mathrm{A}}\mathrm{sex})}{1 + \exp(\beta_{0\mathrm{A}} + \beta_{1\mathrm{A}}\mathrm{age} + \beta_{2\mathrm{A}}\mathrm{sex}) + \exp(\beta_{0\mathrm{C}} + \beta_{1\mathrm{C}}\mathrm{age} + \beta_{2\mathrm{C}}\mathrm{sex})}$$
$$= \frac{\exp(-1.488 - 0.014 \times 0 + 0.402 \times 0)}{1 + \exp(-1.488 - 0.014 \times 0 + 0.402 \times 0) + \exp(0.528 + 0.005 \times 0 + 0.083 \times 0)}$$
$$= 0.077,$$

whereas for a woman (sex = 1),

$$p_{ij\mathrm{A}} = \frac{\exp(\beta_{0\mathrm{A}} + \beta_{1\mathrm{A}}\mathrm{age} + \beta_{2\mathrm{A}}\mathrm{sex})}{1 + \exp(\beta_{0\mathrm{A}} + \beta_{1\mathrm{A}}\mathrm{age} + \beta_{2\mathrm{A}}\mathrm{sex}) + \exp(\beta_{0\mathrm{C}} + \beta_{1\mathrm{C}}\mathrm{age} + \beta_{2\mathrm{C}}\mathrm{sex})}$$
$$= \frac{\exp(-1.488 - 0.014 \times 0 + 0.402 \times 1)}{1 + \exp(-1.488 - 0.014 \times 0 + 0.402 \times 1) + \exp(0.528 + 0.005 \times 0 + 0.083 \times 1)}$$
$$= 0.106.$$

In terms of an odds ratio, one has OR = $\exp(\beta_{2\mathrm{A}} \times \mathrm{sex}) = \exp(0.340) = 1.41$, implying that the odds of a woman (of average age) reporting an autobiographical memory from the prebump category are about 1.4 times the odds of a man (of average age) doing so.

memories describing first-time experiences were less likely to fall in the prebump category (OR: 0.56). Moreover, with respect to the prebump versus bump categories, the emotional quality of an autobiographical memory had a significant effect, in the sense that emotionally more positive memories were less likely to fall in the prebump than in the bump category. The OR of this effect was 0.82, implying that (because emotional valence is a continuous variable) with every unit that the emotional valence of an autobiographical memory increases, the odds for this autobiographical memory to fall in the prebump as compared to the bump category decrease by a factor of 0.82.[10] At the between-person level, the effect of neither first-time experiences nor emotional valence became statistically significant, indicating that persons who reported more autobiographical memories describing first-time events and more positive autobiographical memories did not report significantly more autobiographical memories from the prebump than from the bump category.

Turning to the postbump-with-bump comparison, the Level 1 effects of first-time experiences and emotional quality were also significant and negative, showing that postbump memories were less likely to describe first-time experiences (OR: 0.79) and included memories that were emotionally less positive than bump memories (OR: 0.80). At Level 2, both the effects of first-time experiences and emotional quality became significant, implying that participants who reported a higher proportion of autobiographical memories describing first-time experiences and, on average, more positive emotional quality also reported fewer memories from the postbump than from the bump category (ORs: 0.70 and 0.51). As before, the other parameters were largely the same as in the previous model. The model fit, however, increased substantially after taking into account the within- and between-person effects of first-time experiences and the emotional quality of autobiographical memories. Also, the amount of variance accounted for became considerably larger in both submodels.

In a final model (Model 4), cross-level interactions were added by estimating the interactions of the Level 1 variables with their respective context means (Level 2). Two of these interactions became statistically significant, whereas the other parameter estimates remained largely unchanged (see Table 2). First, in the prebump-versus-bump model, a positive interaction occurred between whether an autobiographical memory described a first-time experience (Level 1) and the proportion of autobiographical memories describing first-time experiences that a participant generated (Level 2)—with the Level 1 effect being negative and the Level 2 effect being positive (but not statistically significant). This interaction implies that the negative Level 1 effect of whether an autobiographical memory describes a first-time experience is smaller—that is, less negative—for participants who report a higher proportion of first-time experiences. In other words, for participants who report many autobiographical memories describing first-time experiences (Level 2), it is less likely for an individual autobiographical memory describing a first-time experience (Level 1) to fall in the bump (as compared to the prebump) category. The cross-level interaction is depicted in Fig. 2, using the Johnson–Neyman technique as described in Preacher, Curran, and Bauer (2006).

In the postbump-versus-bump model, the interaction between the emotional quality of a single autobiographical memory and the average emotional quality of all a participant's autobiographical memories was positive—with both the Level 1 and Level 2 effects being negative and statistically significant. This interaction implies that the negative Level 1 effect of (within-person) emotional quality is smaller—that is, less negative—for participants who, on average, report emotionally more positive autobiographical memories. In other words, for participants who report many positive autobiographical memories, it is less likely that an individual positive autobiographical memory will fall within the bump.[11] In turn, for these same participants it is more likely that an individual positive autobiographical memory will fall within the postbump range.

Using the Johnson–Neyman technique, this cross-level interaction is shown in Fig. 3.

With the inclusion of the cross-level interactions, the model fit was improved according to both the AIC and the BIC. The amount of explained variance increased somewhat in both submodels.

[10] To exemplify this association between the predictor variable and the prebump versus bump categories, the change in (predicted) odds ratios and the related probability estimates in dependence on the (mean-centered) value of emotional valence are given in the table below.

Emotional Valence*	Odds Ratio	Probability
− 2	1.48	.71
− 1	1.22	.43
0	1.00	.18
1	0.82	.06
2	0.68	.02

*Mean-centered at Level 1

To illustrate, if the (mean-centered) emotional valence of an autobiographical memory is − 2 (implying an emotionally negative memory), the odds that it will fall in the prebump as opposed to the bump category are 1.48. In turn, if the (mean-centered) emotional valence of an autobiographical memory is 2 (implying an emotionally positive memory), the odds that it will fall in the prebump as opposed to the bump category are 0.68.

[11] Note that a positive average emotional quality can arise from most autobiographical memories reported by a participant being positive and/or from some of the autobiographical memories reported being exceptionally positive. To distinguish between these two possibilities, one could include the standard deviation (or a comparable quantity) of the emotional quality of the autobiographical memories that a participant reported as a between-person predictor in the model. Doing so, however, was beyond the scope of the present study.

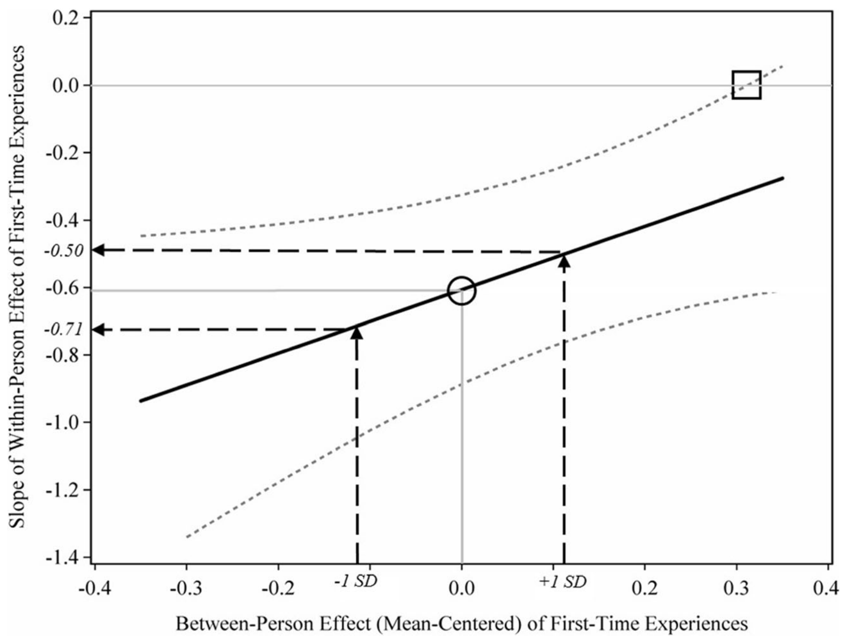

Fig. 2 Cross-level interaction of the within- and between-person effects of whether an autobiographical memory describes a first-time experience in the *pre*bump model. The black line represents the slope of the within-person effect, with 95% confidence limits shown as dotted gray lines. The black circle represents the slope of the within-person effect (− 0.606) at the average between-person effect (0), as estimated in Model 4. The black square represents the between-person effect (0.312) at which the slope of the within-person effect is no longer statistically different from zero (because the 95% confidence limit includes zero). The broken arrows illustrate the within-person effects of first-time experiences for an individual who is one standard deviation below (− 1 *SD*) or above (+ 1 *SD*) the average between-person effect. As is illustrated by the numbers in italics, for a between-person effect of the proportion of autobiographical memories describing first-time experiences one standard deviation *below* the average, the within-person effect is − 0.71, whereas for a between-person effect one standard deviation *above* the average, the within-person effect is − 0.50

Discussion

In the present study, we set out to shed some light on the reminiscence bump in autobiographical memory research by introducing a novel analytical approach. By distinguishing two levels of data and two levels of analysis, we simultaneously modeled which characteristics of the individual autobiographical memories contribute to the reminiscence bump (Level 1) and which characteristics of the participants contribute to having a more (or less) pronounced reminiscence bump (Level 2).

Methodological considerations

A pertinent question with respect to a new analysis approach for data that hitherto have been analyzed using other approaches is: What are the benefits of the new approach? We argue here that the new approach is statistically more adequate, in that it takes the data dependency typically arising in autobiographical memory studies—if participants report more than one autobiographical memory—into account. As our results show, the amount of data dependency is substantial, with intraclass correlations around .12. That is, about 12% of the total variance was between persons—a source of variance (or data dependency) that would be ignored if random effects were not included. Ignoring data dependency may lead to biased parameter estimates and biased standard error estimates of the parameters (Bryk & Raudenbush, 1992; Diggle, Heagerty, Liang, & Zeger, 2002; Hedeker & Gibbons, 2006; Zimprich, 2010).

Moreover, our analysis approach is multivariate, as opposed to the univariate analysis approaches that have been used in many studies investigating the reminiscence bump. The estimate of the effect of a predictor variable (e.g., whether an autobiographical memory describes a first-time experience) is determined not only by its relationship with the outcome variable (in our case, the prebump, bump, and postbump categories), but also by the mutual relationships among the predictor variables. These relationships among predictor variables come into play at both levels of analysis. For example, in the data we analyzed, at the between-person level the proportion of first-time experiences and the average emotional quality were positively correlated (r = .27), implying that those participants who reported more autobiographical memories describing first-time experiences tended to also report more positive autobiographical memories. Consequently, these two predictor variables are not independent from each other, which is taken into account using a multivariate model. In addition, by including different predictor variables—such as the novelty and emotional quality of events—

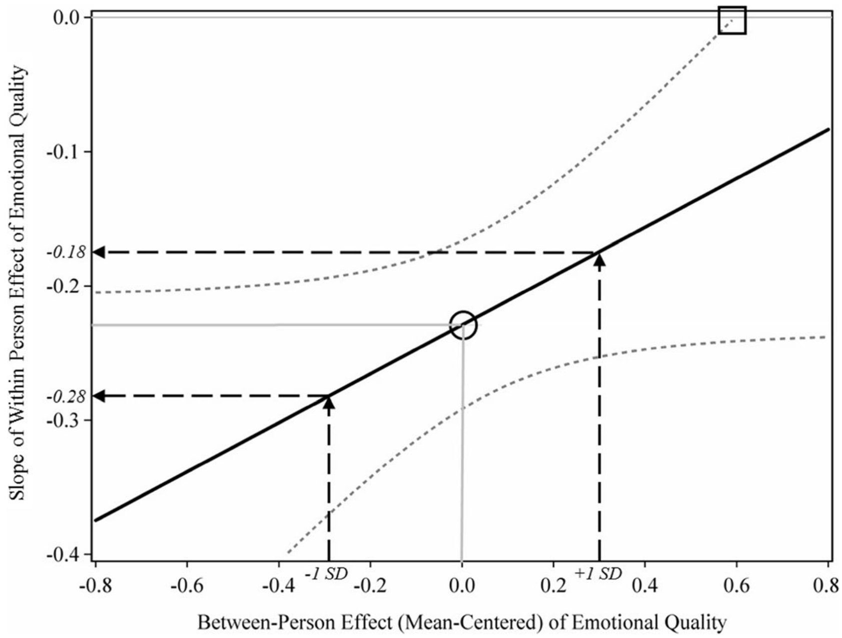

Fig. 3 Cross-level interaction of the within- and between-person effects of the emotional quality of an autobiographical memory in the *post*bump model. The black line represents the slope of the within-person effect, with 95% confidence limits shown as dotted gray lines. The black circle represents the slope of the within-person effect (− 0.229) at the average between-person effect (0), as estimated in Model 4. The black square represents the between-person effect (0.596) at which the slope of the within-person effect is no longer statistically different from zero (because the 95% confidence limit includes zero). The broken arrows illustrate the within-person effects of emotional quality for an individual who is one standard deviation below (− 1 *SD*) or above (+ 1 *SD*) the average between-person effect. As is illustrated by the numbers in italics, for a between-person effect of emotional quality one standard deviation *below* the average, the within-person effect is − 0.28, whereas for a between-person effect of emotional quality one standard deviation *above* the average, the within-person effect is − 0.18

simultaneously, a multivariate approach offers the possibility to examine several explanatory approaches and their relative merits at the same time. We will return to this issue later.

From a more substantive perspective, distinguishing different levels of data has the conceptual advantage of allowing for hypothesis testing at both the within- and between-person levels. For example, according to a cognitive-explanatory account (Rubin et al., 1998), the reminiscence bump is triggered by first-time experiences mainly occurring during one's youth and being more easily recallable. On the basis of this account, hypotheses at two different levels may be deduced. First, within persons, the reminiscence bump should comprise (relatively more) autobiographical memories describing first-time experiences (Level 1)—this is what most previous studies have examined, although, frequently, possible data dependency has been ignored. Second, between persons, those individuals reporting (relatively) more autobiographical memories describing first-time experiences should report more memories falling within the reminiscence bump (Level 2), leading to a more pronounced reminiscence bump. This hypothesis has only seldom been tested (but see, e.g., Wolf & Zimprich, 2016b), although it represents a second and, from the perspective of individual differences in autobiographical memory, important deduction from the cognitive-explanatory account.

Explaining the reminiscence bump

As we outlined in the introduction, explanatory accounts of the reminiscence bump have often focused on what distinguishes experiences made during adolescence and young adulthood from those of other life periods. In the present study, we have used the cognitive-explanatory account (e.g., Rubin et al., 1998) as an example to illustrate our analytical approach. On the basis of this account, we expected that autobiographical memory describing first-time experiences would more likely stem from the reminiscence bump period (Level 1 prediction). At the same time, we expected that participants who reported greater proportions of autobiographical memories describing first-time experiences would show a more pronounced reminiscence bump—as would be indicated by (relatively) more autobiographical memories falling within the reminiscence bump period (Level 2 prediction). Indeed, we found the autobiographical memories referring to first-time experiences did show a greater likelihood of stemming from the reminiscence bump period than from the prebump or postbump period (Level 1). In addition, we found that higher proportions of first-time experiences led to a more pronounced reminiscence bump—at least with regard to the postbump model (Level 2). Thus, the predictions derived from the cognitive account were substantiated by our data at the level of events recalled (Level 1) and, to some extent, at the level of participants (Level 2). Importantly, a statistically significant cross-level interaction indicated that higher proportions of first-time experiences reduced the likelihood of memories of first-time experiences falling in the bump as compared to the prebump period. This, in turn, implies that the fewer first-time experiences a person recalls, the greater is the probability that an autobiographical memory (describing a first-time experience) will fall in the reminiscence bump (instead of the prebump period), as is shown in Fig. 1. By contrast, we observed no cross-level interaction regarding memories of first-time events with respect to the bump-versus-postbump comparison model—presumably because the probability of experiencing first-time events naturally decreases across adulthood. Taking these results together, our findings extend the assumptions raised by the cognitive account, in that the question of whether the reminiscence bump is characterized by a greater number of first-time experiences also depends on how many first-time experiences a person recalls. The finding of a cross-level interaction implies that the distribution of autobiographical memories is qualitatively different for different individuals. For persons who report many first-time experiences, the cognitive account has less explanatory power, because for those persons first-time experiences are less discriminative for an individual autobiographical memory to fall within the bump period.

Other explanatory accounts of the reminiscence bump (for a review of explanatory accounts, see, e.g., Berntsen & Rubin, 2002; Conway & Pleydell-Pearce, 2000; Rubin et al., 1998) also lead to predictions at different levels. In their life script account, for instance, Rubin and Berntsen (2003) postulated that the recall of autobiographical memories is shaped by culturally shared life scripts, which allocate the majority of important life events to young adulthood. On the basis of this account, one would expect autobiographical memories that individuals consider to be important for their life to show a higher likelihood of falling in the reminiscence bump period (Level 1 prediction). This association has been examined before. For instance, by asking participants for their single most important autobiographical memory, Berntsen and Rubin (2002) found a reminiscence bump in the aggregate distribution of participants' most important memory. Including more than one personally important memory per person, Glück and Bluck (2007) also reported a reminiscence bump in the aggregate memory distribution of important memories. However, their approach did not account for the hierarchical structure of the data. Moreover, the association between the importance of memories and the reminiscence bump has not been examined at Level 2. Using multilevel multinomial models, the importance of memories could be included by calculating either the individual proportion of important autobiographical memories or the mean importance of the memories reported by a participant. On the basis of the life script account, one would hypothesize that participants who reported greater proportions of important autobiographical memories would show a more pronounced reminiscence bump, and likewise that the reminiscence bump would become more pronounced for persons who perceived their memories, on average, as being more important.

Apart from the importance of events, the life script account predicts an association between the emotional quality of events and the reminiscence bump: Because normative life script events typically represent emotionally positive experiences (i.e., marriage), the reminiscence bump period is considered to include higher proportions of positive memories than other life periods do (Level 1 prediction). In line with this prediction, Berntsen and Rubin (2002) found a reminiscence bump in the aggregate distribution of memories for participants' happiest memory, but not for the distribution of their saddest autobiographical memory (see also Zaragoza Scherman, Salgado, Shao, & Berntsen, 2015). On the basis of more than one positive and, respectively, negative autobiographical memory per participant, Glück and Bluck (2007) found a pronounced reminiscence bump in the distribution of positive memories and a small bump in the distribution of negative memories (see also Alea, Ali, & Marcano, 2014). In the present research, we included the emotional quality as a possible predictor variable. In line with previous research, we found the reminiscence bump to be associated with emotionally more positive autobiographical memories than were the prebump and postbump periods (Level 1). In contrast to previous research, we examined this association at the level of participants, as well (Level 2). Regarding individual differences, we found a significant effect of the emotional quality of autobiographical memories with respect to the postbump versus bump categories: Individuals who reported, on average, emotionally more positive autobiographical memories also recalled (relatively) more memories from the reminiscence bump than from the postbump life period. Thus, the predicted association between the emotional valence of autobiographical memories and the reminiscence bump was substantiated at the level of the remembered events as well as at the level of the person remembering these events. However, a significant cross-level interaction indicated that reporting emotionally more positive experiences reduced the within-person effect (see Fig. 2), which implies that the likelihood that an autobiographical memory will fall within the reminiscence bump (as compared to the postbump) decreases if individuals report, on average, emotionally more positive events.

Taken together, our results support the assumptions of two different explanatory accounts of the reminiscence bump, which postulate that specific characteristics of an event increase its long-term recallability. These predictions held at both the within- and the between-person levels. Importantly, however, we found cross-level interactions that imply that the distribution of autobiographical memories is qualitatively different for different individuals. More precisely, for persons who report many first-time experiences or, on average, emotionally more positive memories, the predictions derived from two different accounts have less explanatory power, because for those persons the novelty and emotional quality of memories are less discriminative for an individual autobiographical memory to fall within the bump. Only focusing on the characteristics of autobiographical memories (and not the individual who is remembering those memories) may thus overestimate those characteristics' associations with the reminiscence bump.

Limitations, future directions, and conclusion

Although the present data serve only as an exemplar to illustrate the analytical approach we suggested, limitations regarding our sample and study design need to be taken into account. In the present research, the data came from 100 older participants who reported up to 33 autobiographical memories in response to cue words. As Hox and Maas (2001) have demonstrated, in multilevel models the sample size represents a critical issue for the accuracy of the between-person model when intraclass correlations are in the low to moderate range (as in the present study). Therefore, our Level 2 predictions should ideally be tested using a larger sample size. Also, in the present study we used the cue word technique to elicit autobiographical memories, which typically leads to an early reminiscence bump located between the ages of 10 and 25 years (see, e.g., Alea et al., 2014; Janssen, Gralak, & Murre, 2011; Janssen, Rubin, & St. Jacques, 2011; Wolf & Zimprich, 2016b). Other cueing material may lead to a differently located or differently shaped reminiscence bump (for a review, see Koppel & Berntsen, 2015), which can be examined with the present approach after adjusting the age boundaries of the bump accordingly.

With respect to multilevel multinomial models, there are a number of extensions of the relatively basic model we presented here. Comparable to linear mixed models (e.g., Bryk & Raudenbush, 1992; Goldstein, 1995), in *generalized* linear mixed models (of which the multilevel multinomial model used in the present study represents a special case) one may distinguish more than two levels of analyses, given a corresponding design of the study (e.g., Gibbons & Hedeker, 1997; Li & Hedeker, 2012; Raman & Hedeker, 2005). For example, characteristics of autobiographical memories (Level 1) could be nested within individuals (Level 2), who, in turn, could belong to dyads (Level 3)—which typically also show some data dependency. As another example, the characteristics of autobiographical memories (Level 1) could be measured at two or more measurement occasions (Level 2) nested within individuals (Level 3).

Another extension of the models used in the present article would be to include more random effects (cf. Hedeker & Gibbons, 2006; Stroup, 2013; Zimprich, 2010). Although in the present study only intercepts were considered random, the slopes of the within-person effects could also be treated as random. For the data from the present study, for instance, one could model the effect of an autobiographical memory describing a first-time experience as random. This would acknowledge the idea that persons may differ with respect to the effect of how much the prebump and postbump life periods are characterized by first-time experiences. For example, in some persons the reminiscence bump may consist almost exclusively of memories of first-time experiences, whereas in other persons it may consist of other autobiographical memories as well. We did so (results not shown), but the random slope variances did not reach statistical significance, implying that the individual differences were not reliable and that these random effects were unnecessary to adequately describing the data of the present study.

Eventually, the inclusion of additional predictor variables derived from other explanatory approaches of the reminiscence bump will be an obvious next step. For example, elsewhere we have shown that, across the lifespan, the use of autobiographical memories for specific purposes changes (Wolf, 2014; Wolf & Zimprich, 2014, 2015), which leads to the question of whether memories from the bump period are used for different purposes than are prebump or postbump memories. Also, by including predictor variables derived from different explanatory approaches simultaneously, one might compare and evaluate the amounts to which they account for the reminiscence bump.

To summarize, the analysis approach presented in the present article might be refined in many respects—from both statistical and substantive perspectives—and, hence, it represents but a first step into examining within-person and between-person predictors of the reminiscence bump in autobiographical memory. In that sense, the present study has only scratched the surface of the capabilities the multilevel multinomial model offers as an analytical framework for measuring and structuring between- and within-person differences in autobiographical memory. We expect to see more of this kind of analysis in the future, given its suitability and significance for autobiographical memory research.

References

Akaike, H. (1974). A new look at the statistical model identification. *IEEE Transactions on Automatic Control*, *AC-19*, 716–723. https://doi.org/10.1109/TAC.1974.1100705

Alea, N., Ali, S., & Marcano, B. (2014). The bumps in Trinidadian life: Reminiscence bumps for positive and negative life events. *Applied Cognitive Psychology*, *28*, 174–184.

Berntsen, D., & Rubin, D. C. (2002). Emotionally charged autobiographical memories across the life span: The recall of happy, sad, traumatic and involuntary memories. *Psychology and Aging*, *17*, 636–652. https://doi.org/10.1037/0882-7974.17.4.636

Berntsen, D., & Rubin, D. C. (2004). Cultural life scripts structure recall from autobiographical memory. *Memory & Cognition*, *32*, 427–442. https://doi.org/10.3758/BF03195836

Bjork, R. A. (1975). Retrieval as a memory modifier: An interpretation of negative recency and related phenomena. In R. L. Solso (Ed.), *Information processing and cognition: The Loyola Symposium* (pp. 123–144). Hillsdale, NJ: Erlbaum.

Bohn, A. (2010). Generational differences in cultural life scripts and life story memories of younger and older adults. *Applied Cognitive Psychology*, *24*, 1324–1345.

Bryk, A. S., & Raudenbush, S. W. (1992). *Hierarchical linear models*. Newbury Park, CA: Sage.

Christensen, R. (1997). *Log-linear models and logistic regression* (2nd ed.). New York, NY: Springer.

Conway, M. A., & Haque, S. (1999). Overshadowing the reminiscence bump: Memories of a struggle for independence. *Journal of Adult Development*, *6*, 35–44.

Conway, M. A., & Pleydell-Pearce, C. W. (2000). The construction of autobiographical memories in the self-memory system. *Psychological Review*, *107*, 261–288. https://doi.org/10.1037/0033-295X.107.2.261

Conway, M. A., & Rubin, D. C. (1993). The structure of autobiographical memory. In A. E. Collins, S. E. Gathercole, M. A. Conway, & P. E. M. Morris (Eds.), *Theories of memory* (pp. 103–137). Hove, UK: Erlbaum.

Conway, M. A., Wang, Q., Hanyu, K., & Haque, S. (2005). A cross-cultural investigation of autobiographical memory: On the universality and cultural variation of the reminiscence bump. *Journal of Cross-Cultural Psychology*, *36*, 739–749.

Demiray, B., Gülgöz, S., & Bluck, S. (2009). Examining the life story account of the reminiscence bump: Why we remember more from young adulthood. *Memory*, *17*, 708–723.

Dempster, A. P., Rubin, D. B., & Tsutakawa, R. K. (1981). Estimation in covariance components models. *Journal of the American Statistical Association*, *76*, 341–353.

Diggle, P. J., Heagerty, P., Liang, K.-Y., & Zeger, S. L. (2002). *Analysis of longitudinal data.* Oxford, UK: Oxford University Press.

Eysenck, M. W., & Eysenck, M. C. (1980). Effects of processing depth, distinctiveness, and word frequency on retention. *British Journal of Psychology*, *71*, 263–274.

Fitzgerald, J. M. (1988). Vivid memories and the reminiscence phenomenon: The role of a self narrative. *Human Development*, *31*, 261–273.

Gibbons, R. D., & Hedeker, D. (1997). Random-effects probit and logistic regression models for three-level data. *Biometrics*, *53*, 1527–1537.

Glück, J., & Bluck, S. (2007). Looking back across the life span: A life story account of the reminiscence bump. *Memory & Cognition*, *35*, 1928–1939.

Goldstein, H. (1995). *Multilevel statistical models* (2nd ed.). London, UK: Arnold.

Hartzel, J., Agresti, A., & Caffo, B. (2001). Multinomial logit random effects models. *Statistical Modelling*, *1*, 81–102.

Hedeker, D. (2003). A mixed-effects multinomial logistic regression model. *Statistics in Medicine*, *21*, 1433–1446.

Hedeker, D., du Toit, S. H. C., Demirtas, H., & Gibbons, R. D. (2018). A note on marginalization of regression parameters from mixed models of binary outcomes. *Biometrics*, *74*, 354–361. https://doi.org/10.1111/biom.12707

Hedeker, D., & Gibbons, R. D. (2006). *Longitudinal data analysis*. New York, NY: Wiley.

Hox, J. J., & Maas, C. J. M. (2001). The accuracy of multilevel structural equation modeling with pseudobalanced groups and small samples. *Structural Equation Modeling*, *8*, 157–174.

Jansari, A., & Parkin, A. J. (1996). Things that go bump in your life: Explaining the reminiscence bump in autobiographical memory. *Psychology and Aging*, *11*, 85–91.

Janssen, S. M. J., Chessa, A. G., & Murre, J. M. J. (2005). The reminiscence bump in autobiographical memory: Effects of age, gender, education, and culture. *Memory*, *13*, 658–668.

Janssen, S. M. J., Gralak, A., & Murre, J. M. J. (2011). A model for removing the increased recall of recent events from the temporal distribution of autobiographical memory. *Behavior Research Methods*, *43*, 916–930. https://doi.org/10.3758/s13428-011-0110-z

Janssen, S. M. J., & Murre, J. M. J. (2008). Reminiscence bump in autobiographical memory: Unexplained by novelty, emotionality, valence, or importance of personal events. *Quarterly Journal of Experimental Psychology*, *61*, 1847–1860.

Janssen, S. M. J., Rubin, D. C., & St. Jacques, J. L. (2011). The temporal distribution of autobiographical memory: Changes in reliving and vividness over the life span do not explain the reminiscence bump. *Memory & Cognition*, *39*, 1–11.

Koppel, J., & Berntsen, D. (2015). The peaks of life: The differential temporal locations of the reminiscence bump across disparate cueing methods. *Journal of Applied Research in Memory and Cognition*, *4*, 66–80.

Laird, N. M., & Ware, J. H. (1982). Random-effects models for longitudinal data. *Biometrics*, *38*, 963–974.

Li, X., & Hedeker, D. (2012). A three-level mixed-effects location scale model with an application to Ecological Momentary Assessment (EMA) data. *Statistics in Medicine*, *31*, 3192–3210.

Lindsey, J. K. (1997). *Applying generalized linear models*. New York, NY: Springer.

Long, J. S. (1997). *Regression models for categorical and limited dependent variables*. Thousand Oaks, CA: Sage.

Maki, Y., Janssen, S. M. J., Uemiya, A., & Naka, M. (2013). The phenomenology and temporal distributions of autobiographical memories elicited with emotional and neutral cue words. *Memory*, *21*, 286–300.

McCullagh, P. (1980). Regression models of ordinal data (with discussion). *Journal of the Royal Statistical Society, Series B*, *42*, 109–142.

McCulloch, C. (1997). Maximum likelihood algorithms for generalized linear mixed models. *Journal of the American Statistical Association*, *92*, 162–170.

McCulloch, C. E., & Searle, S. R. (2001). *Generalized, linear, and mixed models*. New York, NY: Wiley.

Nakagawa, S., & Schielzeth, H. (2013). A general and simple method for obtaining R^2 from generalized linear mixed effects models. *Methods in Ecology and Evolution*, *4*, 133–142.

Pillemer, D. B. (2001). Momentous events and the life story. *Review of General Psychology*, *5*, 123–134.

Preacher, K. J., Curran, P. J., & Bauer, D. J. (2006). Computational tools for probing interaction effects in multiple linear regression, multilevel modeling, and latent curve analysis. *Journal of Educational and Behavioral Statistics*, *31*, 437–448.

Raman, R., & Hedeker, D. (2005). Mixed-effects regression models for three-level ordinal response data. *Statistics in Medicine*, *24*, 3331–3345.

Raudenbush, S. W., Yang, M. L., & Yosef, M. (2000). Maximum likelihood for generalized linear models with nested random effects via high-order, multivariate Laplace approximation. *Journal of Computational and Graphical Statistics*, *9*, 141–157.

Robinson, J. A. (1992). First experience memories: Contexts and function in personal histories. In M. A. Conway, D. C. Rubin, H. Spinnler, & W. A. Wager (Eds.), *Theoretical perspectives on autobiographical memory* (pp. 223–239). Dordrecht, The Netherlands: Kluwer.

Rubin, D. C., & Berntsen, D. (2003). Life scripts help to maintain autobiographical memories of highly positive, but not highly negative, events. *Memory & Cognition*, *31*, 1–14. https://doi.org/10.3758/BF03196077

Rubin, D. C., Rahhal, T. A., & Poon, L. W. (1998). Things learned in early adulthood are remembered best. *Memory & Cognition*, *26*, 3–19.

Rubin, D. C., & Schulkind, M. D. (1997). The distribution of autobiographical memories across the lifespan. *Memory & Cognition*, *25*, 859–866.

Rubin, D. C., Schulkind, M. D., & Rahhal, T. A. (1999). A study of gender differences in autobiographical memory: Broken down by age and sex. *Journal of Adult Development*, *6*, 61–71.

Rubin, D. C., Wetzler, S. E., & Nebes, R. D. (1986). Autobiographical memory across the adult lifespan. In D. C. Rubin (Ed.), *Autobiographical memory* (pp. 202–221). Cambridge, UK: Cambridge University Press.

SAS Institute Inc. (2014). *SAS/STAT® 13.2 user's guide*. Cary, NC: SAS Institute Inc.

Schwarz, G. (1978). Estimating the dimension of a model. *Annals of Statistics*, *6*, 461–464. https://doi.org/10.1214/aos/1176344136

Stroup, W. W. (2013). *Generalized linear mixed models: Modern concepts, methods and applications*. Boca Raton, FL: CRC Press.

Võ, M. L.-H., Conrad, M., Kuchinke, L., Urton, K., Hofmann, M. J., & Jacobs, A. M. (2009). The Berlin Affective Word List Reloaded (BAWL-R). *Behavior Research Methods*, *41*, 534–538. https://doi.org/10.3758/BRM.41.2.534

Vrieze, S. I. (2012). Model selection and psychological theory: A discussion of the differences between the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). *Psychological Methods*, *17*, 228–243. https://doi.org/10.1037/a0027127

Wang, L., & Maxwell, S. E. (2015). On disaggregating between-person and within-person effects with longitudinal data using multilevel models. *Psychological Methods*, *20*, 63–83.

Wolf, T. (2014). Nostalgie und die Funktionen des autobiographischen Gedächtnisses. *Zeitschrift für Gerontologie und Geriatrie*, *47*, 557–562.

Wolf, T., & Zimprich, D. (2014). Funktionen des autobiographischen Gedächtnisses bei jungen und älteren Erwachsenen. *Zeitschrift für Entwicklungspsychologie und Pädagogische Psychologie*, *46*, 201–210.

Wolf, T., & Zimprich, D. (2015). Differences in the use of autobiographical memory across the adult lifespan. *Memory*, *23*, 1238–1254.

Wolf, T., & Zimprich, D. (2016a). The distribution and the functions of autobiographical memories: Why do older adults remember autobiographical memories from their youth? *European Journal of Ageing*, *13*, 241–250.

Wolf, T., & Zimprich, D. (2016b). How can individual differences in autobiographical memory distributions of older adults be explained? *Memory*, *24*, 1287–1299.

Zaragoza Scherman, A., Salgado, S., Shao, Z., & Berntsen, D. (2015). Life span distribution and content of positive and negative autobiographical memories across cultures. *Psychology of Consciousness: Theory, Research, and Practice*, *2*, 475–489.

Zhao, Y., Staudenmayer, J., Coull, B. A., & Wand, M. P. (2006). General design Bayesian generalized linear mixed models. *Statistical Science*, *21*, 35–51.

Zimprich, D. (2010). Modeling change in skewed variables using mixed beta regression models. *Research in Human Development*, *7*, 9–26.

Zimprich, D., & Wolf, T. (2016a). The distribution of memories for popular songs in old age: An individual differences approach. *Psychology of Music*, *44*, 640–657.

Zimprich, D., & Wolf, T. (2016b). Modeling individual differences in autobiographical memory distributions using mixed logitnormal regression. *Applied Cognitive Psychology*, *30*, 360–374.