Does Activity Engagement Protect Against Cognitive Decline in Old Age? Methodological and Analytical Considerations

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The literature about relationships between activity engagement and cognitive performance is abundant yet inconclusive. Some studies report that higher activity engagement leads to lower cognitive decline; others report no functional links, or that higher cognitive performance leads to less decline in activity engagement. We first discuss some methodological and analytical features that may contribute to the divergent findings. We then apply a longitudinal dynamic structural equation model to five repeated measurements of the Swiss Interdisciplinary Longitudinal Study on the Oldest Old. Performance on perceptual speed and verbal fluency tasks was analyzed in relation to six different activity composite scores. Results suggest that increased media and leisure activity engagement may lessen decline in perceptual speed, but not in verbal fluency or performance, whereas cognitive performance does not affect change in activity engagement.

In recent years, a somewhat bewildering body of literature addressing the nature and magnitude of associations between various indicators of activity engagement on the one hand and various aspects of cognitive performance on the other hand has been accumulating. The results pertaining to the magnitude of and the potential causal relationships behind the associations are quite mixed at best, if not controversial (e.g., Hertzog, Hultsch, & Dixon, 1999; Hultsch, Hertzog, Small, & Dixon, 1999; Kramer, Bherer, Colcombe, Dong, & Greenough, 2004; Pushkar et al., 1999; Pushkar-Gold et al., 1995; Salthouse, Berish, & Miles, 2002). We believe that a number of methodological and analytical considerations might account for some of the divergence in extant results.

Methodological Considerations

Across existing empirical studies, theoretical definitions and subsequent operationalizations of activity engagement are highly variable. Whereas some studies focus on general activities (e.g., regular vs sporadic), others center on specific domains (e.g., cognitive, physical, or household). Moreover, studies that use an overall activity engagement or lifestyle index often differ in what exactly that index represents, how it was empirically obtained, and how the index is implemented in the analyses. Although there is probably greater consensus around the substantive meaning and the empirical measurement of particular cognitive performances, given the over one-century-old tradition of psychometrics, the definition and construction of activity scores seems more disputable. This gap calls for explicit definitions of the activity scores that are analyzed in empirical investigations.

Precise definitions of the analyzed activity scores further clarify the role of covariates that might or should have been included in the analyses. Indeed, the role of additional participants’ information in the analyses may also be a source of disagreement across empirical examinations of activity–cognition relations (Hertzog et al., 1999; Mackinnon, Christensen, Hofer, Korten, & Jorm, 2003; Newson & Kemps, 2005). For example, gender and socioeconomic status may significantly affect not only the frequency of engagement in specific activities, but also cognitive performance. Thus, spurious relationships may emerge if these covariates are not accounted for. Furthermore, in samples of old and very old adults, knowledge about the participants’ physiological functioning is essential. In particular, general health status as well as vision and hearing functioning may influence the likelihood of engaging in some activities, while at the same time it may correlate with cognitive performance for extraneous reasons (Lindenberger & Baltes, 1994). Not accounting for gender, socioeconomic status, health status, vision, and hearing may hence introduce spurious relations between activities and cognition, or it may confound the results.

Analytical Considerations

Even with the assumption that independent studies all agreed with respect to the methodological considerations outlined herein, and that the same underlying processes were in play, the results drawn from such studies may still vary as a function of the chosen analytical procedure. Indeed, the particular analytical strategy (i.e., statistical model) adopted is an often-cited reason for divergent results in this research field (e.g., Hertzog et al., 1999; Hultsch et al., 1999). Extant reports rely on various data-analytical techniques, including hierarchical multiple regression models that include change scores at the manifest, observed level (e.g., Newson & Kemps, 2005); latent longitudinal structural equation models (e.g., Pushkar-Gold et al., 1995); latent cross-lagged regression models (e.g., Aartsen, Smits, van Tilburg, Knipscheer, & Deeg, 2002); latent growth models (e.g., Mackinnon et al., 2003); and a particular structural equation model proposed by McArdle (2001) and McArdle and Hamagami (2001) called the Dual Change Score.
Latent cross-lagged regression models are similar to latent longitudinal models, but they presuppose that all variables have been assessed at two time points and that all earlier factor scores may influence later factor scores. These models define the same factors at two time points and regress the factors at Time 2 on those at Time 1. Of particular interest are the regression weights that each factor at Time 1 has on other factors at Time 2 over and above the autocorrelations. Aartsen, Smits, van Tilburg, Knipscheer, & Deeg (2002) applied a series of bivariate latent cross-lagged regression models between one of three everyday activities (social, experiential, and developmental) and one of five cognitive functioning scores (the Mini-Mental State Examination, from Folstein, Folstein, & McHugh, 1975; immediate recall; learning; fluid intelligence; and information-processing speed). Their sample consisted of 2,076 participants (Time 1, age $M = 68.7$; $SD = 8.3$ years) of the Longitudinal Aging Study Amsterdam (Deeg, Knipscheer, & van Tilburg, et al., 1993), who were assessed twice. The results indicated that, over the 6-year period elapsed between the two waves, none of the three activities at Time 1 influenced any of the cognitive scores at Time 2. The only cognitive score that influenced engagement in an activity was information-processing speed, affecting developmental activities (i.e., following a course and engaging in outdoor sports), which suggests that participants with good cognitive functioning may prefer cognitively demanding activities. These models, however, do not explicitly define change, so that the understanding of the models’ outcomes when two variables with differing change functions are analyzed is not intuitive, because they do not estimate the reciprocal influences in the presence of systematic change components (although change is usually implied, this model does not explicitly include its expectations). Moreover, psychometric properties of the variables (such as their reliabilities, i.e., amount of error variance, and stabilities, i.e., amount of true interindividual differences in change) may confound the results (e.g., Rogosa, 1980).

Latent growth models are typically applied to repeated measures over at least three occasions. In general, two factors are defined over the longitudinal assessment. The first is usually called the level or intercept, and it defines the reliable portion of the typical performance at a precise point in time (often, Occasion 1). The second factor is usually called the change or slope, and it defines the reliable, systematic long-term deviations around the level or intercept. The functional form of change is represented by the factorial loadings of the change factor on the repeated measurements. These loadings may either be fixed to known values in accordance with predefined mathematical functions (e.g., linear, quadratic, exponential, or Weibull) or estimated empirically. This model strategy offers a very flexible and useful analysis of change, because it explicitly models systematic change components. Mackinnon and associates (2003) adopted a latent growth modeling strategy to investigate the relationships between levels and changes of an overall activity composite score (including physical, rest, interest and hobby related, and planned activities) and cognitive performance (memory, speed, and crystallized intelligence) in a sample of 887 older adults, aged 70 years or older, who were assessed three times over 7 years. The researchers’ main results were that an overall decrease in activity engagement correlated with deteriorations in all three cognitive domains and that, among those who participated during the whole study, individuals whose activity engagement remained stable experienced the same decrease on the three cognitive domains as individuals whose activity diminished. The authors concluded that activity engagement does not protect against cognitive decline. Furthermore, they specified that the direction of the possible causation between activities and cognition was not resolvable, because latent growth models examine concurrent associations between changes, and not lead–lag relations between variables.
Motivated by the flexibility of latent growth models and by the desire to disentangle the directionality of influences within a given limited system of variables, McArdle and Hamagami (McArdle, 2001; McArdle & Hamagami, 2001; also see McArdle et al., 2004) developed the Dual Change Score Model (DCSM), which combines several features of the models just described. In particular, in a bivariate setting, the model contains the explicit and flexible definition of change inherent in latent growth models as well as, in conceptual analogy to the cross-lagged regression models, the inclusion of coupling effects of earlier measurements on later changes. The bivariate DCSM (BDCSM) explicitly separates true from error variance independently for the two variables of analysis, models the variables’ systematic change around the intercept, and simultaneously includes competing hypotheses about lead–lag effects between the two variables. What makes the BDCSM special, however, is that it simultaneously estimates (a) the systematic change patterns of both variables, (b) each variable’s autoproportional effect, and (c) the coupling effect that each variable may exert on the changes of the other variables. These coupling effects are not defined, as is the case for cross-lagged regression models, from Time 1 to Time 2 values, but from Time t values to the reliable portion of change occurring between times t and t + Δt, where Δt represents the time interval of analysis (usually set to 1 time unit). In other words, the explicit definition of change is an inherent, rather than inferred, part of the model, and each variable may affect its own as well as the other variable’s change.

Lövdén, Ghisletta, and Lindenberger (2005) applied the BDCSM to three repeated measurements of the 516 adults (age, M = 85.04, SD = 8.68) of the Berlin Aging Study (P. B. Baltes & Mayer, 1999). Of particular interest were the longitudinal associations between a composite score of overall social participation (M. M. Baltes, Maas, Wilms, Borchelt, & Little, 1999) and one of perceptual speed. The main findings indicated that, over the 6-year period examined, both social participation and perceptual speed decreased and previous scores of social participation influenced subsequent changes in perceptual speed, whereas the opposite did not hold. On the basis of these dynamic (state affecting change) across-domain lead–lag effects, the authors concluded that, to a certain degree, an active lifestyle may alleviate decline in perceptual speed.

Objectives

In this study we intend to investigate further the relationships between engagement in various types of activities and performance in two cognitive domains in a sample of very old individuals. To address the methodological considerations outlined herein, we investigated six types of different activities organized by type. We computed first an exploratory (or unrestricted) and then a confirmatory (or restricted) maximum likelihood factor analysis to simplify the activity space and to estimate composite activity scores. We specified the exploratory factor analysis with Promax rotation and the Kaiser–Guttman rule (i.e., one component for each eigenvalue > 1). We specified the confirmatory factor analysis according to the solution of the exploratory factor analysis: \( \chi^2(N = 529, df = 39) = 45.72, p = .213 \). (The factor analysis reported here considered the 16 activities as normally distributed and applied listwise deletion to handle incomplete data. We also computed exploratory factor analyses that applied full information maximum likelihood, or FIIML, estimation to handle incomplete data or considered the 16 activities as categorical variables. All solutions converged to the factorial representation shown in Table 1.)

The final confirmatory factor solution was quite good: \( \chi^2(N = 529, df = 87) = 248.43, \) root mean square error of approximation (RMSEA) = 0.051, value for test of close fit of RMSEA, \( p < .05 = 0.39 \), standardized root mean residual = 0.045,

METHODS

Participants

The Swiss Interdisciplinary Longitudinal Study on the Oldest Old (SWILSO-O, Lalive d’Epinder, Pin, & Spini, 2001) is a multicohort interdisciplinary study on aging in the French-speaking region of Switzerland, and it involves sociology, social and cognitive psychology, social medicine, and epidemiology. Two cohorts were assessed on an approximately yearly basis, the first for nine waves from 1994 to 2004, with 340 participants at inception, and the second for five waves from 1999 to 2004, initially with 377 participants. The starting samples of each cohort were stratified by sex and region (urban vs semirural) and composed of community-dwelling participants between about 80 and 85 years of age. Several domains were assessed during the interviews (social, health-related, familial, professional, cognitive, etc.).

Because the cognitive measures were introduced in the SWILSO-O in 1999, we could only include the waves from that year onward. More specifically, our sample consisted of the fifth to the ninth wave of the first cohort and the first to the fifth wave of the second cohort (i.e., all waves during which the cohorts were assessed in parallel). Moreover, because the cognitive tasks were only administered to participants able to respond, we did not include participants for whom answers were obtained by a proxy. Because longitudinal selectivity effects in SWILSO-O are weak (Ghisletta & Spini, 2004) and cohort analyses revealed no cohort effects, we merged the two cohorts into a unique analysis.

Activity Engagement

Participants were asked with which frequency (everyday, at least once a week, at least once a month, at least once a year, never) they engaged in a total of 16 activities. Table 1 lists the activities organized by type.

We computed first an exploratory (or unrestricted) and then a confirmatory (or restricted) maximum likelihood factor analysis to simplify the activity space and to estimate composite activity scores. We specified the exploratory factor analysis with Promax rotation and the Kaiser–Guttman rule (i.e., one component for each eigenvalue > 1). We specified the confirmatory factor analysis according to the solution of the exploratory factor analysis: \( \chi^2(N = 529, df = 39) = 45.72, p = .213 \). (The factor analysis reported here considered the 16 activities as normally distributed and applied listwise deletion to handle incomplete data. We also computed exploratory factor analyses that applied full information maximum likelihood, or FIIML, estimation to handle incomplete data or considered the 16 activities as categorical variables. All solutions converged to the factorial representation shown in Table 1.)

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goodness-of-fit index = 0.96. Its factorial representation is shown in Table 1. We computed composite activity scores by averaging the activity scores of each type.

**Cognitive Performance**

Two cognitive tasks were administered in the SWILSO-O. The first was the Cross Out Test of the revised Woodcock–Johnson Psycho-Educational Battery (Woodcock & Johnson, 1989). This variable assesses perceptual speed. Each item consisted of a line in which a target figure on the left was to be identified among a series of similar but different distracting figures. There were 19 distracting figures, in which the target appeared five times in random order mixed with 5 other distracting figures appearing less frequently. The final score consisted of the total number of correctly identified target figures within 3 min.

The second cognitive variable was the Category Fruit Test (Cardébat, Doyon, Puel, Goulet, & Joanette, 1990). Participants had 2 min to name as many different fruits as possible. The final score consisted of the total number of different fruits named. For further details on the cognitive variables, see Ghisletta and de Ribaupierre (2005).

**Covariates**

To control for potentially confounding covariates, we ensured that all models included initial chronological age, sex, socioeconomic status (SES), hearing, vision, and general health values. In the sample there were 274 women and 255 men. The SES indicator accounted for income, occupational status, and number of years of education to classify participants in lower (n = 289), middle (n = 185), or upper (n = 55) status. Hearing functioning was a composite score of difficulties understanding other persons, difficulties having a conversation with someone, and general hearing problems. About half of the participants in the sample (n = 293) reported having no functional problems with hearing, and very few (n = 9) reported having major problems with hearing. Visual functioning consisted of general problems with vision and general visual capacities. The majority of participants (n = 381) reported no functional problems, and a minority (n = 19) reported serious problems with vision. Finally, general health summarized one’s self-assessed health (on a 5-point Likert scale) and one’s general health status in accordance with the multidimensional classification proposed by Guilley, Armi, Ghisletta, and Lalive (2004). In particular, the classification consisted of three states along a general health continuum: robustness, frailty without affecting activities of daily living (ADLs), and ADL dependence. Only 69 participants considered themselves in very good health and were considered robust, but only 4 were considered ADL dependent and reported to be in bad health. The majority of participants were classified as frail (n = 248), and over half of them (n = 131) considered themselves in satisfactory health. All covariates were self-assessed.

To facilitate the interpretation of the results, we scaled the activity and the cognitive composite scores to the T metric to have $M = 50$ and $SD = 10$ at Wave 1. We scaled the subsequent longitudinal scores with respect to Wave 1 to retain longitudinal changes in mean and variances. We also rescaled the covariates to facilitate interpretations: age was centered around its mean; sex was coded 0 for men and 1 for women; SES was coded −1 for lower, 0 for middle, and 1 for upper; and hearing, vision, and general health were scaled to have a mean of zero. Table 2 presents the descriptive statistics of age and of all cognitive and activity composite scores by occasion of measurement.

**Statistical Procedures**

We applied the BDCSM (McArdle, 2001; McArdle & Hamagami, 2001). Figure 1 depicts a graphical representation of the BDCSM where manifest (i.e., observed) variables are

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| Table 1. List of Activities Organized by Type |
|-----------------|-----------------|-----------------|
| I. Media        | II. Leisure     | III. Manual     |
| 1. Listen to the radio | 5. Play games (cards, board games, chess, Scrabble) | 7. Do gardening |
| 2. Watch television | 6. Do crossword puzzles | 8. Do craftwork (knit, fix, or mend) |
| 3. Read the newspaper | | 9. Go for walks (besides shopping and going on errands) |
| 4. Read books or magazines | | 10. Do gymnastics or other physical exercise (besides walking) |

<table>
<thead>
<tr>
<th>IV. External–physical</th>
<th>V. Social</th>
<th>VI. Religious</th>
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<tr>
<td>11. Visit coffees, tea rooms, restaurants</td>
<td>12. Participate in trips or outings</td>
<td>15. Pray</td>
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<tr>
<td>13. Attend cultural events (theater, music, cinema)</td>
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<td>16. Attend religious services (go to church or temple, listen to or watch on the radio or television)</td>
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| Table 2. Descriptive Statistics of the Cognitive and Activity Variables by Occasion of Measurement |
|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|
| Variable        | T1              | T2              | T3              | T4              | T5              |
| Age (years)     | 83.38 (2.64)    | 84.73 (2.64)    | 85.57 (2.59)    | 86.45 (2.54)    | 87.78 (2.54)    |
| Cross Out       | 50.00 (10.00)   | 47.46 (8.12)    | 49.58 (9.10)    | 49.41 (8.23)    | 49.09 (8.26)    |
| Category        | 50.00 (10.00)   | 50.29 (9.74)    | 50.32 (10.21)   | 51.73 (11.47)   | 51.02 (11.10)   |
| Media           | 50.00 (10.00)   | 50.10 (9.80)    | 49.32 (10.33)   | 49.31 (11.48)   | 49.41 (11.25)   |
| Leisure         | 50.00 (10.00)   | 50.15 (9.76)    | 50.27 (9.67)    | 49.81 (10.40)   | 50.00 (10.53)   |
| Manual          | 50.00 (10.00)   | 49.12 (9.54)    | 48.60 (10.09)   | 49.35 (9.72)    | 48.92 (10.00)   |
| External–physical | 50.00 (10.00)   | 50.25 (9.54)    | 49.57 (9.67)    | 49.12 (10.40)   | 49.34 (10.53)   |
| Social          | 50.00 (10.00)   | 49.59 (9.83)    | 49.09 (9.83)    | 49.37 (9.43)    | 48.30 (10.62)   |
| Religious       | 50.00 (10.00)   | 50.14 (10.93)   | 49.82 (10.72)   | 49.56 (10.75)   | 50.31 (10.59)   |

Note: Here, n refers to occasion-specific sample size. For each variable, means (with standard deviations in parentheses) are presented. T = time; T1, n = 529; T2, n = 404; T3, n = 337; T4, n = 283; T5, n = 226.
represented by squares, latent variables (e.g., factors) by circles, regression weights by one-headed arrows, and variance and covariances by two-headed arrows; the triangle is used to allow the inclusion of means and intercepts. The regression weights that are unlabeled have value 1 and are not estimated. Ten manifest variables are represented; five are for activities \((A_1 - A_5)\) and five are for cognition \((C_1 - C_5)\). Affecting each manifest variable is an unlabeled latent variable, which indicates the unreliable portion of variance of that variable (e.g., error or residual, indicated as \(R\)). Often it is assumed that \(R\) does not change in size across time. Both time series of manifest variables define a level factor, labeled \(L\) and anchored at Time 1, to represent the reliable portion of variance at Time 1.

Between each adjacent pair of manifest variables is a latent variable labeled \(\Delta A\) or \(\Delta C\), which represents the change occurring between those two measurements. The change scores are latent and free of common measurement problems because unreliability has been removed from all measurements (in particular, latent change scores are not liable to the criticism of difference scores computed on manifest variables directly; cf. Rogosa, 1980). The common portion of variance of all change scores is represented by the overall change factor, labeled \(C\).

A second effect on the latent change scores comes from the previous measurement, and this is represented by the autoproportionality parameter, \(\beta\). Finally, in the bivariate setting, a third effect on the latent change scores comes from the previous measurements of the other variable, and this is represented by the coupling parameter, \(\gamma\). The \(\beta\) and \(\gamma\) parameters are considered dynamic because they are inherent parts of the expectations of latent change scores by linking previous state measurements to changes. We can summarize the expectations for a score \(A\) at time \(t\) in the following equation:

\[
A_{n[t]} = A_{n[t-1]} + \beta_n \times A_{n[t-1]} + \gamma_{C\rightarrow A} \times C_{n[t-1]} + CA_n
\]

where \(A_{n[t]}\) and \(A_{n[t-1]}\) represent the activity score for person \(n\) at time \(t\) and \(t - 1\), respectively, \(\beta_n\) is the activity autoproportionality parameter, \(\gamma_{C\rightarrow A}\) is the coupling parameter from cognition to activity, \(C_{n[t-1]}\) is the cognitive score for person \(n\) at time \(t - 1\), and \(CA_n\) is the constant change component on activity for person \(n\). In the end, this model defines change as being made up of (a) a constant, linear component \((CA_n)\), (b) an autoproportionality component \((\beta_n)\), and (c) a coupling effect from the other variable in the system \((\gamma_{C\rightarrow A})\).

We can consider the model to be an extension of a latent growth model. Indeed, if dynamic parameters \(\beta\) and \(\gamma\) are set equal to zero, the model is a latent growth model with a linear growth function. We can interpret all parameters about level and residual variance analogously (i.e., \(M_L\), the mean of level, is the sample average score at Time 1 and \(Var_L\), the variance of level, represents individual differences around the sample average). However, the meaning of the change factor is different. Whereas in a latent growth model change represents the only influence of change across time, the change factor in the BDGSM represents the constant, linear portion of change, once controlling for the effects of previous scores of that same variable (by means of the \(\beta\) parameter) and of the other variable (by means of the \(\gamma\) parameter). As a consequence, the mean and variance of change \((M_C\) and \(Var_C\), respectively) represent the sample average and the magnitude of individual differences around the sample mean of the linear portion of change that is independent of the immediately preceding values.

To test the relations between each activity and each cognitive marker, we applied a series of BDGSMs and focused especially on the autoproportional \(\beta\) and the cross-lagged \(\gamma\) parameters. A reliable effect of activity on change in cognition (or of cognition on change in activity) would be captured by coupling parameter \(\gamma_{A\rightarrow C}\) (or \(\gamma_{C\rightarrow A}\)). To simplify estimation, we assumed that all \(\beta\)s, \(\gamma\)s, and residual variances \(R_A\) and \(R_C\) have constant value across time. Relaxing these assumptions did not contribute to ameliorations in statistical fits. We regressed the level and the change factors on the covariates. We also estimated the means, variances, and intercorrelations of the covariates (for simplicity, the figure represents only one covariate: Cov). We defined change over occasions of measurement (although other time bases, such as chronological age, are possible; cf. McArdle, 2001; McArdle & Hamagami, 2001; McArdle & Nesselroade, 2003). For further details on the BDGSM, see McArdle and colleagues (2004) and Ghisletta and Lindenberger (2003, 2005).

We implemented the model with AMOS. Basic (Arbuckle & Wothke, 1995), and a sample input script is available from us on request. In face of the incomplete data caused by longitudinal attrition, we applied FIML estimation (Finkbeiner, 1979), available in AMOS. Basic, which constitutes the most easily implemented state-of-the-art method of handling missingness. (Other state-of-the-art methods to handle incomplete data include multiple imputation and various Bayesian approaches; however, these are not easily implemented in structural equation modeling software—although cf. WinBUGS.
by Spiegelhalter, Thomas, Best, & Lunn, 2004.) FIML estimation produces more precise and less biased population estimates than do other common ways of dealing with missing values (e.g., listwise deletion, regression imputation, mean imputation; see, e.g., Schafer & Graham, 2002), especially when the researcher includes covariates that are informative of dropout (e.g., age, health, SES; cf. Ghisletta & Spini, 2004).

### Results

Table 3 depicts the models’ statistical fits in terms of $\chi^2$ and RMSEA (Browne & Cudeck, 1993), as well as the substantively important autoproportional ($\beta_c$ and $\beta_a$) and coupling parameters ($\gamma_{C\rightarrow A}$ and $\gamma_{A\rightarrow C}$) of the six BDCSMs involving the cross-out variable and each activity composite variable. All models fit very well (all RMSEAs < 0.05). Because of the number of models we tested, we adopted a stringent significance criterion ($\alpha = 0.01$).

In all bivariate models, the cross-out variable manifested a reliable and negative autoproportion (ranging from $-1.274$ to $-1.146$), meaning that those participants with higher scores tended to have the largest declines. In all pairwise combinations, cross-out performance did not significantly influence changes in activity scores. However, media and leisure activity scores positively influenced changes in cross-out scores (0.458 and 0.530, $p<.01$). This suggests that, although there is an overall decline in cross-out scores (i.e., negative $\beta$), higher engagement in media and leisure activities tends to slow down cognitive decline.

The category variable did not manifest a reliable autoproportion effect when we analyzed it in conjunction with any activity score. No reliable coupling effects were detected between previous scores of activity engagement and changes in category scores or between previous category scores and changes in activity engagement. Consequently, we did not include details concerning BDCSMs fitted to category. However, the BDCSM described very well the bivariate systems involving category and each of the six activity scores: $\chi^2(N = 529, df = 81)$ ranged from 90.557 to 142.412 and RMSEAs ranged from 0.015 to 0.038.

Table 4 presents the main parameters of the two BDCSMs presenting the most interesting dynamics, those on cross-out and media activities (columns 2 and 3) and cross-out and leisure activities (columns 4 and 5). The estimates about the Cross Out Test are very similar when we analyze them in conjunction with either media or leisure activity. In particular, we note that change in cross-out score between two adjacent occasions is defined by a relatively high constant component (mean of the slope), a strong negative autoproportion effect when we analyzed it in conjunction with any activity score, and a relatively strong positive coupling component associated to previous activity scores ($\gamma_{A\rightarrow C}$). For media and leisure, not much change occurred. Indeed, the constant change (mean of the slope), the autoproportional ($\beta$), and the cognitive coupling ($\gamma_{C\rightarrow A}$) components were all nonsignificant.

### Discussion

We investigated the relatively short-term (1-year) dynamic relationships between a wide array of activities and scores on two cognitive markers, the Cross Out Test and the Category Fruit Test, typically construed as representing perceptual speed and verbal fluency, respectively. All analyses included...
statistical control of potentially confounding covariates (initial age, sex, socioeconomic status, vision, hearing, and general health) that might have distorted the activity–cognition relations. Indeed, our scope was to uncover one kind of dynamic association between cognitive performance and activity engagement that is not the expression of spurious or background associations attributable to important covariates. Moreover, including these covariates further strengthened the estimation algorithm adopted to adjust for incomplete data. We applied the BDSCM because it models potentially different patterns of systematic change and different reliabilities of each activity and each cognitive variable, estimates each variable’s autoproportional effect (i.e., effects of state of one variable on its subsequent change), estimates the effect that each variable exerts on the upcoming change in the other variable (i.e., coupling effects), and can be estimated with any structural equation modeling software. This allows for the simultaneous testing of what have been considered competitive hypotheses about the relation between activity engagement and cognitive performance in old age. In other words, this model allows researchers to test simultaneously the influence that activity engagement may exert on short-term cognitive decline and the influence that cognitive performance may exercise on activity engagement.

Our results suggest differential relations for the two cognitive tasks. Over and above its autoproportional effects, changes in performance on the cross-out task are influenced by previous scores of engagement in media and leisure activities. The effects were beneficial, in that higher previous activity engagement contributes to gentler declines in cross-out performance. The only other study using the same analytical approach in this context (Lövdén et al., 2005) led to the conclusion that higher engagement in social participation (conceived in a larger sense than here) alleviates decline in perceptual speed. Thus, results converge in unraveling an effect of engagement in activities on decline in perceptual speed. The present study extends this finding by suggesting the effect to be localized to the media and leisure domains. Media (listening to the radio, watching television, or reading the newspaper, books, or magazines) and leisure activities (playing games such as chess or Scrabble and doing crossword puzzles) are the most cognitively demanding activities of those analyzed here, suggesting that complexity may be a key feature distinguishing the relationships between different activities and cognitive performance (cf. Schooler, 1984).

The cross-out task is indicative of perceptual speed, which in old age is a sensitive marker of cognitive aging in general (e.g., Lindenberger, Mayr, & Kliegl, 1993; Salthouse, 1996). In a life-span perspective, performance on perceptual speed tasks has repeatedly been shown to be decreasing after an individual reaches the age of 25–30 years (e.g., Lindenberger, Hommel, Aschersleben, Prinz, & Baltes, P. B., 2004; Park et al., 2002; Schaie, 2005). Decline in perceptual speed performance is hence not novel in old age and represents an almost lifelong (at least from young adulthood onward) normative process. This may render the general evolution in perceptual speed performance more susceptible to influences from other domains, such as activity engagement.

Note that SWILSO-O is an observational study, and activity engagement was neither experimentally controlled nor manipulated. Hence, we are not saying that one can prevent or reverse decline in speed by adopting a more engaged lifestyle. The effects of the activities on change in speed performance were considerably smaller than the negative autoproportional effects of the cross-out variable. (Although all variables were standardized to a T metric, a strict comparison of the effect size between autoproportional β and coupling γ parameters is not possible. However, given the great discrepancies between β_L and γ_A→C, it is highly unlikely that change in cognition is predominantly dependent on previous states of activity rather than on previous states of cognition.) This indicates that although engagement in media and leisure activities may alleviate decline in cross-out performance, this effect is probably exceeded by the general decreasing trend of performance in this cognitive task. This picture is consistent with an overall decline in perceptual speed performance, decline that might be alleviated to some extent by engaging more in media and leisure activities.

The results pertaining to the category task indicate that change in verbal fluency does not depend on its previous scores and confirms that changes in activities are not related to previous activity scores. Moreover, no reliable coupling effects were obtained between activity engagement and category performance. Hence, we can say that there is no reliable dynamic effect between the short-term evolution of activity engagement and verbal fluency performance. However, different conceptualization of the activity or the category measures, as well as alternative considerations of covariates, may yield to the extension of the activity–cognition link to verbal fluency. The category task assesses verbal fluency, which is more resistant to cognitive decline than is perceptual speed (e.g., Schaie, 2005). Not being able to recall common words during oral language production may represent a more novel alteration that occurs predominantly in very old age and is directly attributable to old-age processes. Those affected by decline in this cognitive domain are more likely to develop dementia than are high performers (e.g., Lövdén, Bergman, Adolfsson, Lindenberger, & Nilsson, 2005). Consequently, when decline in verbal fluency is experienced, it may be too late or even impossible to engage in beneficial long-term processes, such as compensatory behaviors (Bäckman & Dixon, 1992), that moreover may require longer time spans for activation than the duration of this study allows.

In conclusion, the relationships between activity engagement and cognitive performance are quite complex. Activities that differ with respect to the amount of intellectual stimulation needed for active engagement relate differentially to different cognitive performance tasks. Future work in this line of research would benefit from the analysis of specific, rather than general, activities, the assessment of cognitive performance on a wider range of intellectual domains than presented here, the consideration of covariates that potentially alter the activity–cognition relation, the inclusion of additional information that might mediate the activity–cognition relations (e.g., compensatory behaviors, personality characteristics, neurophysiological indicators), the recognition of potential group heterogeneity (e.g., presence of subgroups abiding to different laws), and the application of analytical tools capable of accounting for differential intrinsic properties (e.g., change pattern, reliability) of both activity and cognitive
variables as well as competing hypotheses about influences on change.

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