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Working memory and fluid intelligence are differentially related to categories of urban fabric in older adults: Results from the Berlin aging study

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ABSTRACT

Urbanization is Globally increasing at a rapid rate but its consequences for mental health, including cognitive functioning, are not well understood. In particular, little is known about the effects of different morphological features associated with urban development, such as variations in the densities of urban fabric (i.e., degrees of ground sealing). We investigated associations of episodic memory, working memory, and fluid intelligence with different densities of urban fabric, obtained from the European Urban Atlas, in a structural equation model framework. We used data on 1053 healthy participants aged 61–88 years (mean age 70.33; SD = 3.75; 51% female) drawn from the Berlin Aging Study II. All participants were living within the city of Berlin, Germany. Our data include the precise geographical coordinates of every household, thereby permitting the calculation of the share of each density type of urban fabric within a 1-km radius around the household. We found these types to be significantly related to working memory and fluid intelligence. No significant association emerged for episodic memory. All results were robust against the inclusion of a set of covariates known to be related to cognitive performance. We discuss the idea of enrichment effects due to morphological features of urban development as one possible mechanism.

1. Introduction

Worldwide, urbanization is on the rise, with more than half of the world's population now living in urban areas, which is estimated to rise to about 68% by 2050 (UN Department of Economic and Social Affairs, 2018). The long-term impact of urbanization is, however, not fully understood yet.

Multiple studies have looked at the impacts of built as opposed to natural/green environments on cognition (Ohly et al., 2016; Stevenson, Schilhab, & Bentsen, 2018), generally finding that cognitive performance improves after exposure to natural settings, be it via real-life experiences or digital presentations such as videos or photographs. The Attention Restoration Theory (ART) by Kaplan (Kaplan & Kaplan, 1989), a prominent theory in the field, suggests that natural environments impose less cognitive load and, thereby, restore attention capacity, which, in turn, benefits overall well-being. However, these studies typically focus on short-term effects of acute exposure to natural or urban settings after a specific and demanding cognitive task.

Long-term exposure to an environment, however, may paint a very different picture. A strand of research looked explicitly at rural-urban

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differences in cognitive functioning, with most studies focusing on older adults, possibly guided by the rationale that as individuals age, decreases in cognitive functionality make them more vulnerable to environmental demands and stressors; a phenomenon that has been termed "environmental docility" (Lawton & Simon, 1968). By now, a number of studies have been published suggesting that cognitive performance in older participants is higher in individuals living in urban as opposed to rural settings. In the Czech Republic, for example, citizens from Prague outperformed individuals from towns and villages in tests assessing verbal memory, executive functioning, and attention (Stepankova Georgi et al., 2019), although these groups were otherwise the same in terms of age, gender, education, and leisure activities. In Ireland, urban residents revealed better performance than rural residents in terms of global cognition and executive function, again after controlling for sociodemographic characteristics, health, and lifestyle factors (Cassarino, O'Sullivan, Kenny, & Setti, 2016). In another study using the same Irish sample, medium-high densely populated (census data) areas were likewise associated with better performance (Cassarino, O'Sullivan, Kenny, & Setti, 2018). Similar findings have been obtained across different societies/cultural settings: Mexico (Saenz, Downer, Garcia, & Wong, 2018), India (Xu, Ostbye, Vorderstrasse, Dupre, & Wu, 2018), and Taiwan (Chiao, 2017).

Another, more recent strand of research has gone beyond the urban-rural divide (which is usually defined based on the density of inhabitants in a particular region) to assess certain morphological characteristics of the local living environment in a small radius around the home address of participants. Two studies from the UK focused on the occurrence of dementia and cognitive impairment (quantified by means of MMSE scores), reporting increased odds of dementia and cognitive impairment in the highest quartile of availability of natural environment and a reduction of odds of dementia (60%) when land use around the home address was mixed. This indicates that a close integration of residential, commercial, and recreational uses with a variety of facilities, services, and resources in local areas promotes cognitive performance (Wu et al., 2015). In a follow-up study from the UK, a similar pattern was found, with higher levels of land use mix being associated with a decrease of odds of cognitive impairment (but here no association with dementia was observed). However, living in areas with high availability of natural environment reduced the odds of cognitive impairment (Wu et al., 2017). The authors interpret their findings as indicating that there might be a non-linear relationship, suggesting that environments with especially low or high levels of land use diversity might be associated with a lack or an overload of cognitive stimulation, each of which may be detrimental to cognition in later life.

A similar, inverse U-shape relationship has been suggested by a study from the Netherlands, where urbanicity was quantified as the number of residential and commercial addresses in a radius of 1 km around the home address (Wörn, Ellwardt, Aartsen, & Huisman, 2017). Here, medium levels of urbanicity were positively associated with processing speed. For the other cognitive tasks, namely MMSE and an auditory verbal learning task, urbanicity was linearly associated with better cognitive performance, with the exception of problem solving, which was not associated at all. However, the authors caution their conclusions, since the Netherlands are a highly urbanized country, yielding little variation in the degree of urbanicity. In contrast to the Dutch findings on processing speed, a study from the US found a positive linear relationship between land dedicated to retail and processing speed, yet generally worse overall cognition in a dementia screening instrument with increasing social destination density, walking destination density, and intersection density (Besser et al., 2018). A report using data from Japan finds a negative association between a measure capturing street integration and MMSE scores (Koohsari et al., 2019).

To sum up, there seems to be a relatively high degree of consistency across research in different countries and cultural settings comparing urban with rural environments (mainly derived based on population density) and associations with cognitive performance and cognitive impairment. However, the picture becomes more complex and contradictory as soon as studies attempt to investigate and identify the actual underlying morphological features associated with the urban vs. rural difference, such as availability of nature, land use diversity, retail density, or street morphology. This could be due to the fact that many studies that have investigated associations between morphological features of the environment and cognition so far are based on data that have been acquired with a focus on the urban vs rural divide, while not controlling for different features within an urban area, since the urban-rural distinction is typically made based on the density of inhabitants. However, different morphological features and architectural aspects of the city itself might exert divergent effects. To understand this further, a more detailed assessment of city features needs to be looked at. Proposals have been made that the aspects of the urban environment could function as training and stimulating environment for cognitive performance (Cassarino & Setti, 2015). However, the exact layout of an optimal urban environment is yet to be understood. Another aspect that might contribute to the heterogeneity of results is that studies oftentimes relied on dementia screening instruments, which are very coarse and cannot discriminate between different cognitive domains, which might in fact be differentially associated with the urban environment (Koohsari et al., 2019). Also, many previous studies treated cognitive test data on a manifest level albeit analyses at the latent construct yield more reliable and valid results, as they express the shared variance among measures of the same constructs and control for measurement error (see e.g., Saenz, Downer, Garcia, & Wong, 2017; Wörn et al., 2017). In order to address these concerns, the aims of the study were twofold. First, we only used data from healthy older adults who are all living in the same urban area, the city of Berlin in Germany. Within this highly diverse urban setting, our data allow us to explicitly model the coverage of different land use categories around the home address. By this, we aim at specifically associating building-related aspects of the urban environment to cognitive performance. Second, cognitive performance was assessed with three different cognitive tests per domain, enabling a latent variable approach. By this, we aim at assessing cognitive performance on a sophisticated and detailed level in order to differentially associate cognitive domains to different land use categories, that is specific features of the urban environment. Our combined data include the precise geographical coordinates of every household, which allows us to calculate the share of each density type of urban fabric in a 1-km radius around the household.

2. Materials and methods

2.1. Participants and study design

We had to exclude 11 individuals from the analysis due to unplausible data entries for the respective variables, resulting in a final sample size of $n = 1042$.

Fig. 1 shows how the participants included in the present analyses were derived from the total sample of older individuals of the Berlin Aging Study (BASE-II, Bertram, Bockenhoff, et al., 2014). The analyses reported in the present paper refer to 1042 individuals aged 61–88 years (mean age in years 70.34; SD = 3.71; 51% female).

Participants had an average of 14 years of formal education (SD = 3.0). None of the participants took any medication that may have affected memory function or had a history of head injuries, medical (e.g., heart attack), neurological (e.g., epilepsy), or psychiatric disorders (e.g., depression). The study was approved of by the ethics committees of German Psychological Society, the Ethics Committee of the Max Planck Institute for Human Development and the Ethics Committee of the Charité – Universitätsmedizin Berlin.

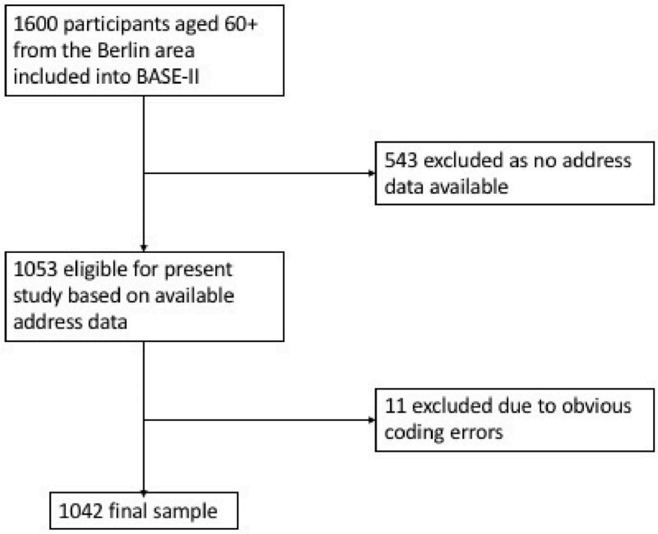

Fig. 1. Flowchart depicting the sample selection for the present study from the original sample of the older cohort from the Berlin Aging Study II (BASE-II, Bertram, Bockenhoff, et al., 2014).

2.2. Measures

2.2.1. Cognitive measures

Assessment of the variables used in the present study took place in a larger assessment of cognitive variables within the BASE–II–study. For a detailed description of the cognitive assessment see (Bertram, Bockenhoff, et al., 2014). In the present study we focussed on cognitive variables assessing episodic memory, working memory, and fluid intelligence (Duzel et al., 2016).

2.2.1.1. Episodic memory. Scene Encoding Task. Participants performed an incidental encoding task with 88 complex, grey-scaled images, displaying 44 indoor and 44 outdoor scenes of neutral emotional valence. Next, participants performed a subjective indoor/outdoor rating on each image indicated by button presses. In the first retrieval test (2.5 h after encoding), 44 old images (22 indoor – 22 outdoor) already presented at encoding were randomly presented together with 44 novel distractor images (22 indoor – 22 outdoor) for 2.5 s. After the presentation of each image, participants had to rate their confidence of recognizing the image as old with the rating scale ranging from 1 = sure that new to 5 = sure that old. No time restriction for confidence in recognition ratings were imposed. Recognition memory performance was assessed as hits minus false alarms.

Verbal Learning and Memory Test. Subjects first learned a 15-word list that was auditorily presented via headphones. The task was composed of five learning trials each followed by a free recall period. After initial learning, a 15-word distractor list, containing semantically unrelated words was presented, followed by a free recall phase of the distractor items. Next, participants were again asked to freely recall only items presented in the initial list. Another free recall test was administered after a delay of 30 min. Also, participants faced a recognition task, in which the 15 originally learned words had to be chosen amongst a total of 30 words.

Face–Profession Task. The task assesses associative binding on the basis of recognition of incidentally encoded face–profession pairs. 45 face–profession pairs were presented sequentially each for 3.5 s on the computer screen and participants were asked to indicate whether the face matched the profession or not via pressing a button. At retrieval, 54 face–profession pairs consisting of 27 old pairs, 9 new pairs, and 18 newly arranged pairs (an already seen face was matched with a new profession) were presented. Participants had to rate how confident they were that they had seen the matched pairs before, ranging from 1 = not sure to 3 = very sure. Recognition memory for the rearranged pairs (hits minus false alarms) were assessed as outcome.

2.2.1.2. Working memory. Spatial Updating Task. In each block of this task, a display of two or three 3-by-3 grids was shown for 4 s. In each of these grids, one blue dot was presented in one of the nine locations. Those two/or three locations had to be memorized and updated according to shifting operations that were indicated by arrows appearing below the corresponding field. After six shifting operations, the resulting end position had to be correctly indicated. 8 trials with two grids and 8 trials with three grids were conducted and used for scoring. The average percentage of correct placements was used as outcome.

Letter Updating Task. Subjects were randomly presented with letters A-B-C-D in a sequence of 7, 9, 11, or 13 letters. Once a sequence stopped, subjects had to recall the last three letters in correct order by pressing buttons on the button box corresponding to A, B, C, and D. 16 test trials were administered.

Number-N-Back task. Three one-digit numbers (0–9) were presented sequentially in three cells presented horizontally followed by the next sequence of three digits. This cycle was repeated 30 times. In each cycle, two-choice decisions on whether the current stimulus matched the stimulus shown three steps earlier had to be made.

2.2.1.3. Fluid intelligence. Practical Problem Task. The task consisted of 18 items depicting everyday problems such as the times in a bus schedule, instructions for medication, a warranty for a technical appliance, a rail map, as well as other forms and tables. For each item, the problem was presented in the upper part of the screen with five alternative solutions shown in the lower part. Participants had to click on one of the alternatives in order to solve the problem indicated. The test phase terminated when subjects made three consecutive errors to solve the problems presented, or when they reached the maximum time limit of 10 min, or after they reached the last test item. The number of correctly solved problems was assessed as outcome.

Figural Analogies. 22 items in this test follow the format "A is to B as C is to ?". The complete figure was presented in the upper left part of the screen. Participants had to apply the same rule as the one applying to the complete figure pair to choose one of five alternative responses presented in the lower part of the screen. The test phase terminated when subjects made three consecutive errors, when they reached the maximum time limit of 10 min, or after they reached the last test item. The score was based on the total number of correct responses.

Letter Series Task. The task consisted of 22 items. Each item contained five letters followed by a question mark (e.g., c e g i k ?). The test phase terminated when subjects made three consecutive false responses, when they reached the maximum time limit of 6 min, or after they reached the last item of the test. The score was based on the total number of correct responses.

2.2.2. Urban land use data

The georeferencing data was taken from the European Urban Atlas, provided by the European Environment Agency, which maps urban land use in Europe, including data for major German cities (European Environment Agency, 2016). The dataset contains polygon features representing real-world features characterised by very small areas. All areas greater than 0.25 ha or 10-m feature length for the reference year 2006 were assigned exclusively to well-defined land use categories.

Within the present study we aimed at focusing on whether urban fabric within a 1-km radius around the current home address of participants might exert a positive influence on cognitive abilities. Geodata were extracted within R (R Core Team, 2021) using the sf package (Pebesma, 2018). The classification system from the European Environment Agency allows for categorizing different dimensions concerning urban fabric mainly based on the degree of soil sealing. This refers to the amount of the ground that is covered by an impermeable material, such as concrete or tarmac. In the areas classified as urban fabric, residential areas are predominant, but also business districts with at least partial residential use are included. The different subclasses of urban fabric represented in the European Urban Atlas are distinguished by their degree of soil sealing rather than by type of building. In the present analyses we considered five distinct categories with different degrees of urbanicity. The categories are continuous urban fabric with more than 80% of the soil sealed, discontinuous dense urban fabric with 50–80% of the soil sealed, discontinuous medium density urban fabric with 30–50% of the soil sealed, discontinuous low density urban fabric with 10–30% of the soil sealed, and discontinuous very low density urban fabric with less than 10% of the soil sealed. Usually, these categories have been applied as a composite score representing urban fabric on a broader level. However, as we were specifically interested in whether or not urbanicity can be found as exerting a positive relation to cognition, we preferred the more fine-grained categories described above. We additionally included urban green, forests, and water within a 1-km radius around the current home address into our analyses. Categories were defined according to the European Urban Atlas. Urban green is defined as public areas within the cities that are predominantly used for recreational purposes such as gardens or zoos. Private gardens are always excluded as well as forests or green areas unless they are surrounded from at least two sides by urban areas and traces of recreational use are visible. Forests are defined as areas with broad leaved forests with ground coverage of tree canopy >30% and tree height > 5 m, including bushes and shrubs. Lastly, water is defined as water bodies visible that exceed the extend of 1 ha (European Environment Agency, 2016). The radius of 1 km around the home address has already been applied in another study making use of this sample as this radius describes a walkable distance for older individuals (Kühn et al., 2017).

2.2.3. Covariates: demographic information, personality, mental health, (social) environment, physical health

Sex was dummy-coded with 0 = female and 1 = male. *Age* was assessed as years since birth. As an approximation of the *socio-economic status* we computed the household income as the monthly net amount of income which has been adjusted to the size of the household based on the OECD-modified equivalence scale (Hagenaars, de Vos, & Zaidi, 1994).

To assess *openness* and *extraversion* we used a 3-item subscale as a short form of the Big Five Inventory (Lang, John, Lüdtke, Schupp, & Wagner, 2011).

Depression was assessed with the Geriatric Depression Scale (Yesavage et al., 1982). *Loneliness* was assessed using 7 items from the UCLA loneliness scale (Russell, 1996). We also assessed *general satisfaction with life* using the Satisfaction with Life Scale (Diener, Emmons, Larsen, & Griffin, 1985).

To assess *social participation*, we used 8 single items from the BASE-II study. Activities assessed were participation in cultural events, visits to the cinema, musical and artistic activities, meeting with friends or neighbours, working as volunteer, helping friends or neighbours, political commitment, and going to church. Answers were first categorized as "every month or more often" and "less than once a month" and coded as 1 and 0. For the parsimony of the model, we combined the social activities into one social activity score building an unspecific sumscore from the single items ranging from 0 (social participation in all of the 8 activities less than once a month) to 8 (regular participation in all of the 8 activities).

Population density was assessed as inhabitants per urban planning area in 2012 divided by area in hectare [ha].

To approximate objective health of study participants, we used two well-established measures, namely Body Mass Index (BMI) and grip strength. The *BMI* as a measure of obesity as well as underweight and normal body weight was calculated as a composite score from height and weight (BMI = person's weight in kilograms divided by his or her height in meters squared). *Grip strength* was measured with a dynamometer (Smedley, ranging from 0 to 100 kg). Participants were asked "to grasp with as much force as possible". Three measurements for each hand were taken, with the highest value being selected for later analysis.

2.2.3.1. Statistical analysis.

Data preparation. Overall, 17.6% of missing data were the maximal proportion of data missing, with exceptions for extraversion and openness with 20.0% and 33.0% missing, respectively. Missing data in the present study are not due to attrition or non-compliance, but rather due to the fact that the cognitive and socio-economic assessment were conducted at different time points and not all participants completed both assessments. Although samples here do overlap to a great extent, this is not true for all variables. Hence, in our analyses we applied full information maximum likelihood (FIML) estimation. Meeting the assumption that data are missing at random (Little & Rubin, 1987), FIML yields unbiased parameter estimates and standard errors. We used robust maximum likelihood estimation (mlr) to account for deviations from normality.

In a confirmatory factor analysis framework, we set up a three-factor model of cognitive abilities, allowing for the three latent factors to be correlated. Each factor was composed of three manifest indicators represented by the actual data from the cognitive tasks (Working memory: spatial updating, letter updating, and number-*n*-back; episodic memory: face-profession task, verbal learning and memory, scene encoding; fluid intelligence: practical problems, figural analogies, and letter series). Land use categories as well as social participation variables were added as covariates on latent level. Our main variables of interest, i.e., the land use categories, were tested for statistical significance by calculating the χ^2-difference test. As we used MLR estimator, we uses the Satorra-Bentler scaled chi-square difference test (Satorra & Bentler, 2010). For model identification, effects-coding method was used according to Little, Slegers, and Card (2006). As criteria for model fit, we report the Comparative Fit Index (CFI), and the Root Mean Square Error of Approximation (RMSEA). Values of the CFI above 0.95 denote a well-fitting model, whereas for the RMSEA values less than 0.06 may be interpreted as acceptable model fit (Hu & Bentler, 1999). Throughout the analyses we used SPSS Version 26, R (3.1.1) and Mplus version 8.0 (Muthén & Muthén, 1998-2017).

3. Results

In a first step, we fitted a three-factor model to the cognitive variables. Latent factors were allowed to be correlated. A model with three indicators for each latent factor, fitted the data well ($\chi^2 = 59.80$, $df = 24$ $p < 0.001$, $RMSEA = 0.041$ (90% CI: 0.028–0.054), $CFI = 0.98$). Factor loadings for all indicators were significant. The three latent factors were substantially correlated with fluid/working memory r = 0.83, fluid/episodic memory r = 0.66, and working memory/episodic memory r = 0.68. Fig. 2 depicts the three-factor confirmatory model of the cognitive abilities in our study.

Cognitive abilities are well known to be influenced by social and mental health aspects as well as physical health. In order to control for this known influence, we entered social participation, mental, and physical health as covariates (for description of variables see methods section). A distinct pattern for each cognitive ability emerged (see Table 1 for standardized factor loadings and confidence intervals).

Episodic memory had a significant relation with social participation variables, indicating that socially involved individuals exhibit better episodic memory performance. Satisfaction with life was negatively related with episodic memory. For working memory, social participation was not significant. We found a positive association for the fluid intelligence factor with social participation. Again, a negative relation emerged for satisfaction with life. Overall, the model fitted the data well ($\chi^2 = 125.64$, $df = 96$ $p = 0.02$, $RMSEA = 0.017$ (90% CI: 007–0.025), $CFI = 0.99$).

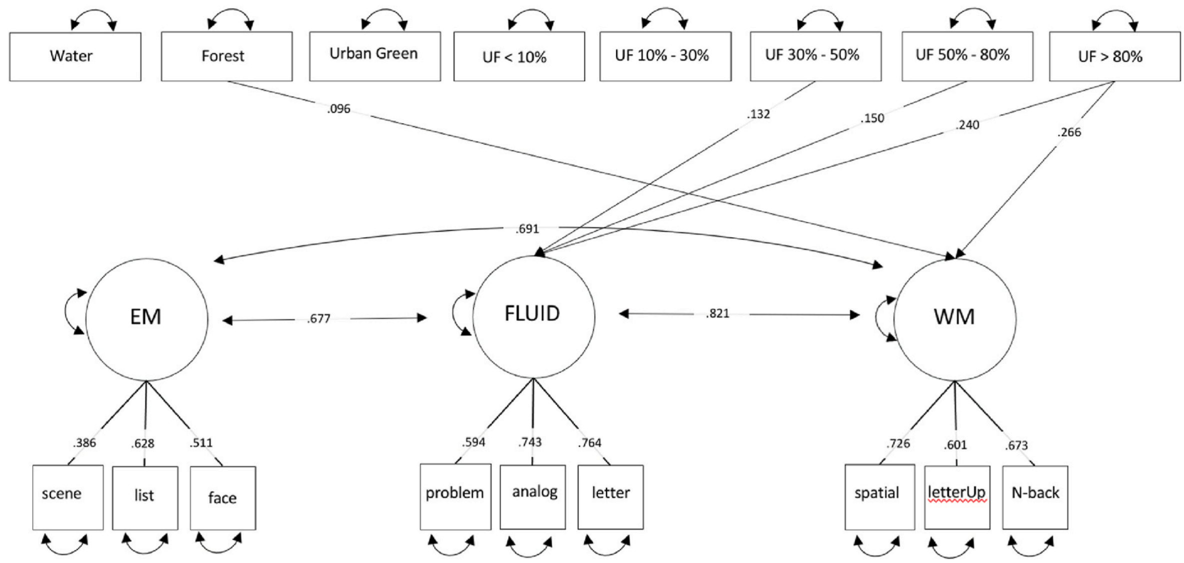

Fig. 2. Confirmatory three-factor models of cognitive abilities. Fluid = Fluid intelligence, WM = working memory, EM = episodic memory, UF = Urban fabric with the respective percentage of soil sealed. We report standardized factor loadings and correlations. Manifest indicators are represented by squares, latent variables are represented by circles.

Table 1
Standardized factors of the covariates loading on the three cognitive ability-factors episodic memory, working memory, and fluid intelligence for model I.

Variable	Factor		
	Episodic memory	Working memory	Fluid intelligence
	Model I	Model I	Model I
Age in years	−.21* (−.30; −.12)	−.10* (−.17; −.10)	−.14* (−.22; −.07)
Household income	.21* (.12; .29)	.18* (.10; .25)	.26* (.19; .33)
Sex	−.24* (−.40; −.09)	.01 (−.13; .15)	.07 (−.06; .19)
Population density	−.03 (−.11; .06)	.04 (−.04; .11)	.06 (−.01; .13)
Social participation	0.16* (0.05; 0.26)	0.08 (−0.01; 0.17)	0.16*(0.08; 0.25)
Openness	−.01 (−.12; .10)	−.06 (−.16; .04)	−.03 (−.11; .06)
Extraversion	−.08 (−.18; .02)	−.09* (−.18; −.003)	−.1* (−.18; −.02)
Loneliness	−.03 (−.14; .07)	−.08 (−.17; .01)	.02 (−.08; .11)
Satisfaction with life	−.13* (−.22; −.03)	−.04 (−.13; .05)	−.10* (−.18; −.01)
depression	.07 (−.03; .18)	.04 (−.05; .12)	−.03 (−.10; .05)
BMI	.05 (−.05; .14)	.002 (−.09; .08)	.03 (−.05; .11)
Grip strength	.12 (−.03; .27)	.17* (.04; .31)	.15* (.02; .28)

Note: We report standardized factor loadings with 95% confidence intervals; * = $p < 0.05$; Sex was dichotomously assessed with 0 = female and 1 = male; Land use categories according to the European Urban Atlas, provided by the European Environment Agency; Depression was measured with the Geriatric depression scale; Openness and Extraversion with a short form of the Big Five Inventory; Loneliness = UCLA Loneliness scale; Satisfaction with life = Diener's satisfaction with life scale; BMI = Body Mass Index.

We then added the land use categories described above to our model in a third step while still controlling for all the covariates of the previous model. Although social participation turned not out to be significant for all cognitive factors, we kept the nonsignificant paths to the model as all covariates were chosen on sound theoretical grounds. As we were adding specific land use categories to the model in an exploratory fashion, we wanted to be sure to not discount commonly known influential covariates. We acknowledge that this approach was at the possible expense of the parsimony of the model. However, as the model fitted the data well, we found this acceptable ($\chi^2 = 188.84$, $df = 144$ $p < 0.01$, $RMSEA = 0.017$ (90% CI: 009–0.024), $CFI = 0.98$). Standardized factor loadings and confidence intervals for the model including urban land use categories are depicted in Table 2. We also report $\Delta\chi^2$ and Δdf after separately constraining the land use categories to zero in order to test each path for statistical significance.

We found a distinct pattern of relations between the cognitive ability factors and the urban land use categories. While there was no significant relation between urban land use categories and episodic memory, we found a significant positive relation between working memory and urban fabric with more than 80% of the soil being sealed. For the categories with urban fabric with 50–80% of the soil being sealed and urban fabric with medium density (30–50%) we found p-values of $p = 0.069$ and $p = 0.075$, respectively, indicating associations not systematically difference from zero. For the fluid intelligence factor, we found a positive and significant relation with three different categories of urban fabric. Namely, the three categories with the highest percentage of soil sealed with buildings (80%, 50–80%, and 30–50%) were significantly related to fluid intelligence, indicating that individuals living in strongly urbanized areas exhibit better performance on fluid intelligence tasks. Urban fabric with low density (10–30%), exhibited a p-value of $p = 0.052$. We then, in a next step, tested whether the differences in the respective associations between land use categories and each of the cognitive domains differed significantly between domains. We constrained each pairing to be equal and assessed any potential decrement in fit of the Satorra-Bentler scaled chi-square difference for df = 1. We did so, as a significant difference from zero in specific associations is not automatically equal to significant differences between associations, but needs to be tested for (Gelman & Stern, 2006). The chi-square differences can be seen in Table 3. We tested the difference in the associations between urban land use categories and working memory and fluid intelligence, respectively, and found them to be not statistically significant. The results reported are of special interest as we observed the specific differentiation in a sample from the metropolitan area of Berlin, hence, an area where all participants were in some way exposed to urbanicity.

4. Discussion

The present analyses aimed at assessing the association between three cognitive domains (namely, fluid intelligence, working memory, episodic memory) and urban land use categories on the latent level in a sample of older adults living in the city of Berlin, Germany. The main

Table 2
Standardized factors of the covariates loading on the three cognitive ability-factors episodic memory, working memory, and fluid intelligence in model II.

Variable	Episodic memory	$\Delta\chi^{2a}$	Working memory	$\Delta\chi^{2\ a}$	Fluid intelligence	$\Delta\chi^{2}$ a
	Model II		Model II		Model II	
Age in years	−.21* (−.30; −.12)		−.1* (−.17; −.01)		−.15* (−.22; −.08)	
Household income	.21* (.12; .30)		.17* (.09; .24)		.24* (.17; .32)	
Sex	−.25* (−.40; −.10)		.12 (−.13; .15)		.06 (−.07; .19)	
Population density	−.07 (−.22; .09)		−.1 (−.22; .04)		−.03 (−.14; .09)	
Social participation	0.15* (0.05; 0.26)		0.07 (−0.02; 0.16)		0.15* (0.06; 0.26)	
Openness	−.01 (−.12; .10)		−.07 (−.16; .03)		−.04 (−.12; .04)	
Extraversion	−.08 (−.18; .02)		−.1* (−.19; −.01)		−.1* (−.18; −.02)	
Loneliness	−.03 (−.14; .07)		−.1* (−.19; −.003)		.002 (−.09; .09)	
Satisfaction with life	−.12* (−.22; −.03)		−.05 (−.14; .04)		−.11* (−.20; −.03)	
depression	.08 (−.02; .19)		.04 (−.04; .13)		−.03 (−.10; .05)	
BMI	.05 (−.05; .14)		.01 (−.08; .09)		.04 (−.04; .11)	
Grip strength	.12 (−.03; .28)		.16* (.02; .3)		.15* (−.02; .28)	
Land use categories						
Urban Fabric (UF)						
Continuous UF > 80%	.1 (−.09; .27)	0.8	.27* (.12; .41)	11.9*	.24* (.1; .38)	9.5*
Discontinuous Dense UF (50–80%)	.13 (−.01; .27)	2.3	.11 (−.01; .23)	2.5	.15* (.05; .26)	5.8*
Discontinuous medium density UF (30–50%)	.04 (−.09; .16)	0.3	.10 (−.01; .21)	2.6	.13* (.04; .23)	6.4*
Discontinuous low density UF (10–30%)	.04 (−.05; .13)	0.9	.04 (−.05; .13)	0.99	.08 (−.002; .16)	2.6
Discontinuous very low density UF <10%	.03 (−.13; .17)	0.06	.05 (−.05; .15)	1.2	−.003 (−.08; .08)	0.01
Urban Green	.05 (−.05; .15)	0.99	.02 (−.06; .1)	0.4	.001 (−.09; .09)	0.04
Forest	.04 (−.07; .16)	0.6	.1 (−.001; .19)	3.7	.08 (−.02; .17)	2.9
Water	−.003 (−.11; .11)	0.01	−.01 (−.09; .08)	0.1	.06 (−.03; .15)	1.5

Note: We report standardized factor loadings with 95% confidence intervals; * = $p < 0.05$; [a] represents the Satorra-Bentler scaled chi-square difference after constraining the respective path to zero to the comparison model with all covariates included and the land use categories estimated freely. Δdf = 1 for all tests. Sex was dichotomously assessed with 0 = female and 1 = male; Land use categories according to the European Urban Atlas, provided by the European Environment Agency; Depression was measured with the Geriatric depression scale; Openness and Extraversion with a short form of the Big Five Inventory; Loneliness = UCLA Loneliness scale; Satisfaction with life = Diener's satisfaction with life scale; BMI = Body Mass Index; Model I and II are different in terms of the inclusion of land use categories as predictors.

Table 3
Satorra-Bentler scaled chi-square difference after constraining the respective path to zero to the comparison model with all covariates included, the land use categories estimated freely and no path constrained to be equal. Δdf = 1 for all constraints.

Domains compared / Land use category	$\Delta\chi^2$ fluid intelligence and working memory	$\Delta\chi^2$ working memory and episodic memory	$\Delta\chi^2$ fluid intelligence and episodic memory
Continuous UF > 80%	0.86	11.96*	9.54*
Discontinuous dense UF (50–80%)	0.04	2.45	5.69*
Discontinuous medium density UF (30–50%)	0.05	2.63	6.56*
Discontinuous low density UF (10–30%)	0.25	0.96	3.93*
Discontinuous very low density (<10%)	2.49	1.18	0.003

Note: UF = Urban fabric with the respective percentage of soil sealed. * = $p <$ 0.05.

focus was on assessing the differential association between different levels of urbanization and cognitive performance within one city rather than on the difference between urban and rural dwellings.

We will, first, discuss the results referring to land use categories and cognitive performance. We will then turn to the discussion of socio-demographic and lifestyle variables.

In our model, we found categories of urban fabric to be significantly related to working memory and fluid intelligence. Working memory performance was significantly associated with the land use category indicating the highest density of urban fabric. Fluid intelligence was even more strongly associated with urbanicity, namely, with the three categories with the highest percentage of soil sealed with buildings. No significant relations emerged for episodic memory. We discuss two explanations, both requiring further research.

First, in older age, fluid intelligence is known to decrease as a process of normal aging (Kievit et al., 2016; Zimprich & Martin, 2002). However, extent and speed of decline may well be influenced by individual behaviour and living environment (Hultsch, Hertzog, Small, & Dixon, 1999). Activity and training have been identified as beneficial for maintaining fluid intelligence levels in older age. One possible explanation for the positive association between fluid intelligence and land use categories with high urban fabric density might reflect that. An immediate living environment that is complex and demanding might represent a constant training environment for fluid abilities. Navigating in neighbourhoods with high building density might be more demanding, especially in a city such as Berlin where street networks are rather winding (and not checkerboard like in Manhattan, for example). Hence, the potential complexity of the neighbourhood might act as a constant, daily training opportunity (Cassarino & Setti, 2015). Actual navigation might be more demanding, but also directions might entail more turns which are more demanding to remember. The complexity of the physical environment itself and its structure and appearance could, hence, act as a daily training space having positive impact on cognitive performance over and above the use of facilities (Cassarino & Setti, 2016). Coming from a cross-cultural perspective, Linnell and Caparos (2020) found that attention and perceptual processes vary between urbanized and remotely living individuals starting in early childhood, leading to the conclusion that the urban environment per se has an effect on cognitive performance (Bremner et al., 2016; Linnell, Caparos, de Fockert, & Davidoff, 2013). This also fits to the distinction made by Stine-Morrow et al. (2014), distinguishing between training and enrichment. Whereas training is referred to as an intervention that targets specific skills via explicit instructions, enrichment describes the embeddedness into a complex and demanding environment that exerts influence on a broad level without explicit instructions. We suggest that the neighbourhoods in our study might represent such aspects of enriched environment, characterised by densely built and twisty urban areas.

One has to bear in mind, however, that the urban fabric categories only describe the percentage of soil sealed. Morphological features that further describe the surrounding are not included. Neighbourhoods described with the same land use categories might, in fact, look very different in terms of buildings, layout of buildings, and use. Hence, we cannot directly infer that higher percentage of soil sealed necessarily represents a more complex environment. A potentially useful scale to further shed light on morphological features within the same land use category could come from Suarez-Rubio and Krenn (2018), who developed a set of indicators to describe urbanization over and above the land use categories of the Urban Atlas. Because our data all come from the same region (city of Berlin), we feel that it is reasonable to assume that differences in land use categories do reflect differences in complexity as data are from the same cityscape but different neighbourhoods. In order to potentially isolate specific features of “city demands” it is desirable that futures studies would contrast different areas matched for underlying complexity.

Interestingly, no effect was found for episodic memory. Although all three cognitive constructs are strongly correlated, the correlation between working memory and fluid intelligence is stronger (0.82) than the correlation between episodic and fluid (0.68) and working memory (0.69). Hence, the cognitive aspects associated with urban fabric might tap into the common aspects of fluid intelligence and working memory, but are distinct from episodic memory. It has been repeatedly found that working-memory performance is one of the best predictors for intelligence (e.g., von Bastian & Oberauer, 2014), suggesting that working-memory and intelligence might share a substantial amount of variance. This notion does not account for the underlying mechanisms explaining the association, however, it provides an explanation for the differential relations between cognitive domains. Another possible explanation could simply lie in the selection of episodic memory tasks.

Our second explanation for the results of the present study aims at our urban land use categories potentially reflecting higher standards of living. This would suggest that the association found might reflect beneficial effects of living standards reflected in the urban development. Although we added a substantial set of potential confounding variables, our covariates control for social and financial aspects and not for potential systematic differences in the morphology of buildings accompanying different socio-economic groups. We do not know, whether the buildings our participants live in are single family houses or apartment blocks, because categories are defined by their degree of soil sealing and not by the type of building. Neighbourhoods described by the same urban land use category, might differ considerably with respect to building type ranging from large apartment blocks to single-family houses with private gardens. Urban features might act as promoting cognitive functioning, e.g., in terms of enrichment, as long as they are not outweighed by negative aspects of urbanicity, such as air and noise pollution. Negative effects of air and noise pollution on cognitive function have been reported in older adults (Tzivian et al., 2017). Air and noise pollution, in turn, are positively correlated with urbanization (Kim et al., 2012), however, differentially associated with urban morphological features (Tang & Wang, 2007). Hence, we speculate that in our sample morphological features fostering cognitive performance (i.e., enrichment) outweighed negative aspects such as air and noise pollution, implying that neighbourhoods in the present study might have been characterized by single-family houses with private gardens maybe even located in traffic-calmed areas. If this was the case, our results would point to unique positive aspects of those type of urban development over and above socio-economic selection bias, as we controlled for them in our sample. However, this interpretation remains speculative and needs additional data from future studies. While the associations between cognitive domain and land use categories exhibited a differential pattern for each domain, the differences between domains were only significant between fluid intelligence and episodic memory as well as working memory and episodic memory, but only in the highest soil sealed category fort the latter. Hence, although distinct on descriptive level, this is not corroborated by means of inferential statistics. This unique pattern for episodic memory might, again, reflect the fact that either working memory and fluid intelligence have more in common that, in turn, is related to urban land use categories. This would point to a “real” difference between the domains. Or, again, this could simply lie in the selection of episodic memory tasks. Future studies are needed to shed some light on this question.

Population density was not significantly related to any of the three cognitive measures. This is interesting as many previous studies have used population density as measure for the urban-rural categorization (Besteher, Gaser, Spalthoff, & Nenadic, 2017; Haddad et al., 2015; Lederbogen et al., 2011). Our study, focusing on land use categories, suggests that population density might be one aspect typical for the distinction between urban and rural areas, however, does not function as a sufficient description of the differences between urban and rural environments. Population density and morphological features should be treated as different entities describing distinct associations between cognitive performance rather than as proxies for each other.

We will now, for the remainder of the text, briefly discuss the associations between cognitive performance and socio-demographics and lifestyle choices. Results for our socio-demographic variables fit into existing literature and therefore generally validate our data. Older individuals performed worse, whereas higher income was associated with better performance. We found women to significantly outperform men on episodic memory; while working memory and fluid intelligence measures did not differ significantly. Two recent meta-analyses reviewed sex differences in cognitive performance and concluded that they are present under certain conditions and should, hence, always be reported. As our study was not primarily interested in sex differences, we refer the interested reader to Voyer, Saint Aubin, Altman, and Gallant (2021) and Asperholm, Högman, Rafi, and Herlitz (2019) for an in-depth discussion of this aspect.

A substantive body of literature shows the importance of social participation and cognitive performance in older age. Hence, we added social participation variables as covariate to our model to ensure that potential associations between urban land use categories and cognitive performance were not driven by confounding social and cultural participation. This is especially important in a study where different land use aspects of urban development are focus of the analyses, because social and cultural activities may often co-occur in areas with high levels of building development. Social participation has been repeatedly found to be significantly associated with cognitive performance in old age (Hultsch et al., 1999; Park, Gutchess, Meade, & Stine-Morrow, 2007), which we, generally speaking, replicated in our study. To control for another set of potential confounders on individual-level, we added indicators for mental and physical health to our covariates, namely BMI, grip strength, and depression. Grip strength (as a proxy for overall physical health) was positively associated with cognitive performance whereas no association emerged for depression and BMI and cognitive performance. Participants of the Berlin Aging Study have been screened at study entry for not having a history of mental illnesses and, hence, represent an overall mentally healthy sample. To control for a last set of potential confounders, we added extraversion and openness as two broad personality traits as well as loneliness and satisfaction with life to our list of covariates. It is feasible to assume that different personalities use urban infrastructure in different ways or that personality functions as self-selection-mechanism into specific long-term living conditions (Diener, Sandvik, Pavot, & Fujita, 1992; Jokela, 2020) By including aspects of personality on top of social participation variables, we wanted to control for a potential association between urban features and cognition that rather mirrors differences in personality.

4.1. Limitations

Our study has some limitations. Generally, we cannot make any inferences on causality as we used cross-sectional data, without experimental variation in urban land use around respondents' home addresses. We acknowledge that this should be taken into account in future studies to further understand the underlying mechanism of the association found in the present study. With respect to cognitive performance, this would not only be an interesting route to follow in terms of understanding, but also in terms of prevention, as cognitive impairment represents a challenging condition to aging societies. Hence, longitudinal studies are needed. Also, although we did control for a couple of social and sociodemographic variables known to influence cognitive performance, future studies could include some additional variables of potential interest, e.g. the duration of living in that same area or an urban vs rural upbringing which has been shown to affect cognitive performance in adulthood (see e.g., Hirst, Cassarino, Kenny, Newell, & Setti, 2022; Linnell et al., 2013). Of course, one has to balance the inclusion of potentially influential variables and the requirement of a preferably parsimonious model.

As noted above, we can only speculate about the underlying mechanisms driving the association between cognition and land use categories in the present study. One aspect that should be included in future studies is a more detailed description of land use categories in terms of type of building, architecture, and use. Also, studies need to explore whether the association can be broken down into single features or is rather described by a conglomerate of features forming the environment "urban"; upholding the motto: the city is greater than the sum of its parts.

4.2. Conclusion

Overall, we conclude that the results of our study significantly contribute to the current literature on cognitive performance and urbanicity. As a unique contribution, we assessed the differential effect of different urban fabric densities, aiming at further exploring the association on a more fine-grained level by focusing on a relatively homogeneous urban sample of a single city. Our results suggest that different gradations of urbanicity are differentially related to cognitive performance. Our study adds further evidence to the notion that urban environments need a differentiated approach to understand its impact on cognition. Understanding the underlying mechanisms of the results of our study could provide urban planning and architecture with valid information on how to integrate and support successful cognitive performance of inhabitants into cities of the future.

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Declaration of competing interest

None.

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