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Mnemonic but not contextual feedback signals defy dedifferentiation in the aging early visual cortex

https://doi.org/10.1523/JNEUROSCI.0607-23.2023

Received: 13 June 2023 Revised: 18 November 2023 Accepted: 18 December 2023

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1	Mnemonic but not contextual feedback signals defy dedifferentiation in the
2	aging early visual cortex
3	Abbreviated Title: Dedifferentiation in feedback signals
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22	Number of figures: 6
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Introduction: 691 27

Discussion: 1618 28

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Conflict of interests: The authors declare no competing financial interests. 30

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32 Acknowledgments: This work was funded by a European Research Council Starting Grant 33 (ERC-2018-StG-PIVOTAL-758898). The work of YLS is also supported by the German Research Foundation (Project ID 327654276, SFB 1315, "Mechanisms and Disturbances in 34 Memory Consolidation: From Synapses to Systems") and the Hessisches Ministerium für 35 Wissenschaft und Kunst (HMWK; project "The Adaptive Mind"). The work of JO is funded 36 by the Volkswagen Stiftung (project: 9B326). LM has received funding for this project from 37 the Biotechnology and Biological Science Research Council (BBSRC) BB/V010956/1 38 ('Layer-specific cortical feedback dynamics'). We thank members of the LISCO lab (PI: 39 weinoscharter YLS) for their helpful feedback on this project, and especially all participants for their 40 41 committed participation in this study. 42 43

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46 Abstract

Perception is an intricate interplay between feedforward visual input and internally generated 47 feedback signals that comprise concurrent contextual and time-distant mnemonic (episodic 48 and semantic) information. Yet, an unresolved question is how the composition of feedback 49 50 signals changes across the lifespan and to what extent feedback signals undergo age-related dedifferentiation, i.e., a decline in neural specificity. Previous research on this topic has 51 focused on feedforward perceptual representation and episodic memory reinstatement, 52 suggesting reduced fidelity of neural representations at the item and category levels. In this 53 fMRI study, we combined an occlusion paradigm that filters feedforward input to the visual 54 cortex and multivariate analysis techniques to investigate the information content in cortical 55 feedback, focusing on age-related differences in its composition. We further asked to what 56 extent differentiation in feedback signals (in the occluded region) is correlated to 57 58 differentiation in feedforward signals. Comparing younger (18 - 30 years) and older female and male adults (65 -75 years), we found that contextual but not mnemonic feedback was 59 prone to age-related dedifferentiation. Semantic feedback signals were even better 60 differentiated in older adults, highlighting the growing importance of generalized knowledge 61 across age. We also found that differentiation in feedforward signals was correlated with 62 63 differentiation in episodic but not semantic feedback signals. Our results provide evidence for age-related adjustments in the composition of feedback signals and underscore the importance 64 of examining dedifferentiation in aging for both feedforward and feedback processing. 65 66

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Significance Statement

Cognitive decline in aging is related to reduced neural specificity (dedifferentiation) in the brain, which has mainly been examined in feedforward processing. Using an occlusion paradigm, we tested whether there is dedifferentiation in contextual and mnemonic feedback signals internally generated in the early visual cortex to aid perception. Older adults' contextual but not mnemonic feedback signals suffered from dedifferentiation, with semantic mnemonic representations being even better differentiated in older age. Neural differentiation between feedforward and episodic feedback signals was positively correlated in both age groups. In sum, these results highlight the growing importance of semantic knowledge across the lifespan and imply that the impact of dedifferentiation on cognition highly depends on the euroscente nature of the recruited information.

100 Introduction

Throughout the lifespan, our brain undergoes structural and functional changes. A notable 101 pattern emerges within the memory systems as we approach later stages of life: episodic 102 memory tends to decline, while semantic memory is mostly preserved (Shing et al., 2008; 103 104 Ofen and Shing, 2013; Lalla et al., 2022). At the same time, the notion of *dedifferentiation* has emerged in the literature as an important factor contributing to age-related functional 105 106 changes in cognition. Age-related dedifferentiation refers to the finding that neural representations become less distinct with advancing age and, therefore, less representative of 107 the evoking stimulus. Support for this view comes from non-human animal (Schmolesky et 108 al., 2000; Yang et al., 2008, 2009) and human neuroimaging studies, which showed that 109 neural selectivity for visual stimuli declines with age (Voss et al., 2008; Zheng et al., 2018; 110 Koen et al., 2019, 2020). The visual system has been widely used for studying neural 111 differentiation (Park et al., 2004; Payer et al., 2006; Carp et al., 2010, 2011a, 2011b). Its 112 hierarchical and retinotopic organization allows the mapping of the visual field onto brain 113 voxels, which enables nuanced control of the feedforward input reaching a given portion of 114 the visual cortex. In this study, we combined nuanced control with multivariate analysis 115 techniques to enable us to test the influence of internal models on the constellation and quality 116 117 of perceptual representations.

State-of-the-art models of perception recognize the brain's heavy reliance on internal 118 representations of the outside world that are formed early in life and updated throughout the 119 120 lifespan (Berkes et al., 2011; Larkum, 2013; Shin et al., 2021). The predictive processing framework integrates this influence, postulating that feedback signals travel from higher-level 121 brain areas to the earliest sensory regions (Rao and Ballard, 1999; Friston, 2005; Clark, 2013). 122 Importantly, neural units and long-range connections transmitting internally generated 123 feedback signals are distinct from and proportionally more numerous than pathways 124 125 transmitting external feedforward visual input (Markov et al., 2014). As a result, feedback

signals can traverse the visual hierarchy and powerfully drive disambiguation of the percept at
early stages. Thus, exploring to what extent age-related dedifferentiation manifests in these
top-down directed perceptual processing streams can provide key insights into the interplay
between mnemonic and perceptual systems.

So far, several studies have investigated age-related dedifferentiation in feedback 130 signals mostly in the form of memory reinstatement (Bowman et al., 2019; Deng et al., 2021; 131 Katsumi et al., 2021; St-Laurent et al., 2011, 2014). The overall finding is that 132 dedifferentiation affects the older brains' integrity by acting on both feedforward sensory 133 input and internally generated representations of information. A recent study by Ortiz-Tudela 134 and colleagues (2023) showed that feedback signals carry information of different natures. 135 More concretely, their results showed that concurrent contextual and time-distant mnemonic 136 information coexist as feedback signals in primary and secondary visual cortices V1 and V2. 137 Concurrent contextual information refers to visual input that does not reach a given brain 138 region via feedforward but lateral connections. Time-distant mnemonic information describes 139 content drawn from stored knowledge acquired in the past. They found that mnemonic 140 episodic and semantic components explained different portions of the variance of the 141 multivariate neural pattern of feedback signals. Such compositional complexity of feedback 142 143 signals has not been considered in studies of age-related dedifferentiation so far. In this study, we combined an occlusion paradigm with fMRI and multivariate pattern 144

analysis to examine: 1) if concurrent contextual and time-distant mnemonic information can
be decoded in feedback signals within V1 and V2 of older adults, as it was found in younger
adults; 2) if feedback signals in older adults are less differentiated; and 3) how the
relationship between feedforward and feedback signals is characterized across age. We
hypothesized to find contextual and mnemonic information in older adults' V1 and V2
feedback signals. Compared to contextual feedback, we expected mnemonic episodic, but not
semantic, feedback to be impacted by age-related dedifferentiation, as episodic memory

152	decline is a well-established aging phenomenon. Finally, we predicted a positive relationship
153	between feedforward and feedback signals in older compared to younger adults. To our
154	knowledge, this is the first study that examined the detailed interplay of feedforward and
155	feedback components in a cross-sectional lifespan sample.
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157	Materials and Methods
158	Reanalysis of published data and registration
159	The current study is an extension of a previous study by Ortiz-Tudela et al. (2023),
160	which reported data from 30 younger participants. We collected additional data from younger
161	adults to match the sample size of older adults. All reported results for younger adults in this
162	study refer to the topped-up sample. We pre-registered the study prior to data collection on
163	the OSF platform. The preregistration is available at <u>https://doi.org/10.17605/OSF.IO/X7B6Z</u> ,
164	and any deviations from it are indicated in the corresponding sections.
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aphantasia. Additionally, we recruited 46 healthy older adults between 65 and 74 years of age 178 via E-Mail advertisements to attendees of the University study program for the third age and 179 via invitation letters to residents within the required age range. We excluded two participants 180 due to low training performance (< 80%) on day one, another one due to low retrieval 181 performance (< 25%) in the post-scan phase on day two, two due to MRI incompatibility, one 182 due to technical issues during scanning, and one participant due to no-show on day two. The 183 final sample included 36 younger adults (23 female, M = 24.18 years, SD = 2.54) and 39 old 184 adults (18 female, M = 69.28 years, SD = 2.99). Before participation, we screened all 185 participants for MRI compatibility, visual capacity, and state of health via phone. We tested 186 older adults additionally with a phone-compatible version of the Mini-Mental State 187 Examination (Folstein et al., 1975) and invited them only if they correctly responded to 16 out 188 of 18 questions. All participants gave written informed consent as approved by the 189 Department for Psychology ethics committee at Goethe University Frankfurt (Protocol 190 number: 2019-38). For their participation, participants received either course credits (only for 191 psychology students) or monetary compensation (8€/h for behavioral tests and 10€/h for the 192 fMRI session). 193

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195 Stimuli and materials

The stimulus set consisted of the same cartoon image material as in the study from 196 Ortiz-Tudela et al. (2023) and is available at https://github.com/ortiztud/feedbes. It comprised 197 198 16 indoor room images (e.g., bathroom, kitchen, electronic store) and four object images (i.e., bathtub, oven, bed, and TV). With this material, we created two sets of object-room category 199 pairs. One set consisted of eight combinations with minimal semantic relation (e.g., "bed" in 200 "bathroom"), providing the stimulus material for the episodic trials. The episodic nature of 201 202 these combinations is given by the need to create new associative memories binding object 203 and room context, which must be retrieved 24 hours later during the fMRI scan. The other set

consisted of eight combinations with maximal semantic relation (e.g., "oven" in "kitchen"), 204 205 providing the stimulus material for the semantic trials. Note that the same four objects were 206 used for episodic and semantic trials, but the rooms were unique for each trial type. This was done to ensure comparability between the retrieved object content for episodic and semantic 207 208 trials and to equate the difficulty between the pairings as much as possible. Object-room combinations and the assignment of room categories to either episodic or semantic trials were 209 210 counterbalanced across participants. Thereby, we preserved the required (in)congruent relationships in the respective stimulus sets and ensured that every object would be presented 211 in every possible room and in episodic trials as well as semantic trials across the entire 212 sample. Importantly, the objects were always placed in the lower right corner of the room. 213 Depending on the task, they were either visible or hidden behind a white patch that occluded 214 the respective corner. Previous studies successfully used such an occlusion paradigm to 215 separate feedback signals from feedforward visual input (Smith and Muckli, 2010; Muckli et 216 al., 2015; Morgan et al., 2019). During the learning phase on day one, we presented the 217 stimuli on a 60 Hz monitor (resolution 1680 x 1050, full HD) approximately 60 cm from the 218 participant's head. Subjects responded using a standard QWERTY keyboard. In the scanner, 219 participants saw the stimuli on a 60 Hz monitor (resolution 1920 x 1080, full HD) via a coil-220 221 mounted mirror with an approximate total distance of 162 cm to the participants' eye. The size of the stimuli spanned 16.4° x 12.1° of visual angle. 222

223

224 **Procedure**

For younger adults, the procedure was identical to the original study (see Ortiz-Tudela et al., 2023). All necessary adjustments to ensure that older adults could manage the task as similarly as younger adults are specified in the corresponding sections. The procedure was split into two sessions across two consecutive days.

Day one 230

The first session took place in a quiet testing room. Participants started the first session 231 by answering a set of questionnaires, including the Vividness of Visual Imagery 232 Questionnaire (Marks, 1973), the Spot-the-Word test (Baddeley et al., 1993), the Digit 233 Symbol test, which is a subtest of the Wechsler Adult Intelligence Scale (Wechsler, 1981), 234 and the Health Dynamics Inventory (Saunders and Wojcik, 2004). After that, they proceeded 235 NUSCI with the learning phase. 236

237

Learning phase 238

In the learning phase, the participant's task was to study and remember the episodic 239 object-room pairs, i.e., combinations with minimal semantic relation (Figure 1A). Younger 240 and older participants underwent five and nine learning cycles, respectively, in which the 241 object-room pairs were presented for 10 s sequentially and repeated ten times. The number of 242 additional learning cycles was piloted to make sure that old adults could reach the threshold 243 of at least 80% accuracy in the final block in order to compensate for the known decline of 244 episodic memory in older adults (Shing et al., 2008). We instructed participants to memorize 245 the object-room combinations and as many details as possible, including the object's exact 246 247 position in the lower right corner. At the end of each learning block, their memory of the object-room pairings and the object's position was tested. In a 4AFC format, we presented a 248 previously studied room with a white occluder and the four available objects; participants 249 250 selected one object by pressing a number key, ranging from 1 to 4, on the keyboard with their left hand. We tested the remembered position by presenting the same room with the correct 251 but slightly displaced object and asked the participants to move the object to its original place 252 by pressing the arrow key corresponding to the moving direction with their right hand. While 253 younger adults pressed the keys independently within a 2-s time window, older adults 254 255 indicated their choice verbally, and the experimenter pressed the keys on their behalf within a

4-s time window. We adjusted the procedure after observing in pilots that some older adultsstruggled to coordinate choice and response in time.

After completing all learning cycles, we familiarized participants with the structure 258 and timing of the scanner task on day two. In this task, the episodic rooms with the occluder 259 were presented sequentially for four seconds each; participants were instructed to fixate on the 260 cross in the center of the screen and to reinstate and hold the room in mind, including the 261 learned object in its original position. After each trial, participants rated the vividness of the 262 retrieved object on a 4-point Likert scale. Younger adults entered their ratings via the 263 keyboard, and older adults responded verbally. Finally, all participants conducted another 264 265 learning block to refresh their memory for the object-room pairs. Unlike in the preregistration announced, participants did not additionally draw the objects on a printed version of the 266 occluded rooms due to time limitations. 267

268

269 **Day two**

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The second session took place at the Brain Imaging Center (Frankfurt am Main).

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272 **Pre-scan phase**

273 Before entering the scanner, we introduced participants to the semantic object-room pairings (Figure 1B), with all rooms being novel to the participants. The eight new room 274 images appeared one after another, always with the occluder, and participants had to name 275 276 one among the four studied objects with the best semantic fit. The experimenter gave feedback on incorrect object choices. Unlike the episodic object-room pairings, the semantic 277 278 room images were never directly shown together with the objects to participants. Older adults were exposed to the semantic rooms for two more rounds and received additional practice. In 279 this practice, we presented both episodic and semantic rooms with occluder in random order, 280 281 and participants had to indicate the correct associated object, which was, depending on the

room, semantically or episodically retrieved. We added this practice to ensure that older
adults would understand the alternating order of episodic and semantic trials in the occlusion
task during scanning and would retrieve the required object depending on the presented room.

286 Scanning phase

The reported structure of the scanning session was identical to the one in Ortiz-Tudela 287 et al. (2023). The scanning sequences were distributed across two blocks of approximately 50 288 minutes, with a ten-minute break in between these two blocks. The break allowed participants 289 to go to the bathroom and refresh themselves to prevent discomfort and unwanted 290 movements. In block one, participants performed two occlusion task runs, a structural scan 291 and a functional retinotopy run. In block two, participants performed two more occlusion task 292 runs, another structural scan, another functional retinotopy scan, and a sensory template run. 293 One additional functional scan and one additional anatomical scan were collected but not used 294 for this project, and thus, they are not discussed further. 295

296

Occlusion task. Each of the four occlusion task runs presented all episodic and semantic 297 rooms intermixed. We optimized the presentation order using the MATLAB toolbox easy-298 299 optimize-x by Spunt (2016) to obtain the most efficient design for detecting activation differences between episodic and semantic trials. A white patch occluded the lower right 300 corner of the rooms, and a fixation cross designed to minimize unwanted eve movements 301 302 (Thaler et al., 2013) on a small white square covered the foveal region. In each run, all 16 rooms were repeated six times with a presentation duration of 4 s and an inter-trial interval of 303 304 2 s. Each run lasted 576 s. While the room images flashed at a 5 Hz frequency, the white patches and the fixation cross remained stable, helping the participants focus their gaze on the 305 center of the room. We asked participants not to move, to focus on the fixation cross, and to 306 307 retrieve the associated object as vividly as possible. When an episodic room (studied on day

one) was presented, they had to retrieve the object that was studied together with this room on
day one (i.e., episodic trial). When a semantic room (introduced on day two) was shown, the
object with the best semantic fit had to be retrieved (i.e., semantic trial). This procedure
ensured the comparability of episodic and semantic trials, with the main difference being the
mnemonic retrieval route accessed by the participants.

313

Sensory Template. In order to compare feedback with feedforward signals, we ran an 314 additional task in which we showed the 16 correct object-room pairings 12 times (without 315 occlusions) for 1.5 s with an inter-trial interval of 1 s. The run lasted 480 s. We optimized the 316 presentation order, as in the occlusion task runs, using easy-optimize-x (Spunt, 2016). 317 Participants fixated on the cross in the center of the screen and performed a 1-back task, 318 which served as a cover task to ensure attention was paid to the stimuli. Whenever they 319 detected image repetitions, they had to press a button with the index finger on an MRI-320 compatible button box. 321

322

Functional Retinotopy and Target Area Mapping. We used standard stimulation 323 procedures to demarcate the early visual cortex (EVC) primary and secondary subfields V1 324 325 and V2. For eccentricity mapping, we showed flashing and expanding contrast-reversing checkerboard rings (9 cycles, 56 seconds/ expansion). For polar angle mapping, we showed a 326 flashing and rotating contrast-reversing checkerboard wedge (eight clockwise rotations, 64 327 328 seconds/ rotation). Through target area mapping, we identified voxels that topographically represented the lower right corner within areas V1 and V2. To this end, we used two different 329 checkerboard patterns. The first pattern spanned 1° of visual angle along the inner boundary 330 of the occluded lower right corner, and the other pattern covered the remaining inside of the 331 occluded region. Voxels that represented the boundary of the occluder were eventually 332 333 excluded from further analyses to prevent spillover from adjacent receptive fields and to have

a buffer for small misalignments across functional runs (Smith and Muckli, 2010). For further
details, see the identical procedure in Ortiz-Tudela et al. (2023).

336

337 Post-scan phase

After both scanning blocks, we asked participants to do one last retrieval task on a 338 laptop outside the scanner. Identical to the memory test for object-room pairings and object 339 position on day one, each occluded room was presented together with the four available 340 object options. The presentation order was sequential, with all rooms from the episodic set 341 showing first, followed by all semantic rooms. As on day one, younger adults pressed the 342 number and arrow keys themselves with their left hand and within 2s, and older adults 343 communicated their decision verbally to the experimenter, who pressed the keys on their 344 behalf within 4s. 345

346

347 MRI setup and data acquisition

We scanned participants with a 3.0 Tesla Siemens MAGNETOM Prisma scanner with 348 a 32-channel head coil system. 3D structural scans (MPRAGE sequence; resolution: 1 x 1 x 1 349 mm; iPAT factor: 2) were acquired in both blocks for anatomical reference. Echo-planar 350 351 imaging sequences (EPI; TE=38ms; TR = 800ms, resolution = $2 \times 2 \times 2 \text{ mm}$; MB factor = 8; flip angle= 52° ; field of view = 208 mm; 72 axial slices, phase encoding direction = AP) were 352 applied to measure the brains' blood oxygen level-dependent (BOLD) response. After the first 353 354 occlusion task run in each block, we acquired five extra volumes for each phase-encoding direction to allow susceptibility distortion correction in EPI sequences. 355

356

357 Behavioral data analysis

We conducted all behavioral analyses in R (version 4.0.3; R Core Team, 2020) and used the results to explore the data and to identify participants performing below a threshold of 80%.

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362 **fMRI data analysis**

363 Preprocessing

Except for the retinotopic and target mapping runs, we preprocessed the fMRI data using fMRIPREP 20.1.1 (Esteban et al., 2019, 2020). fMRIPREP's output provides a CCOlicensed citation boilerplate that includes all preprocessing details. As requested by fMRIPREP's authors, an unchanged copy is available in the corresponding OSF repository. The preprocessing of retinotopic and target mapping runs was conducted in BrainVoyager 21.4 (Brain Innovation) for Linux and included slice time correction, 3D motion correction, and temporal high-pass filtering at 0.01 Hz with linear detrending.

371

372 **ROI definitions**

We defined regions of interest as the subset of voxels in the left EVC for V1 and V2, 373 topographically representing the room images' lower right corner. In this corner, the object 374 375 was either presented as feedforward visual input (in the sensory template run) or covered (in the occlusion task runs). Covering the corner removed any meaningful feedforward visual 376 stimulation because all the trials in the occlusion task included the same-sized white patch in 377 378 the identical position. We conducted all further analyses on this particular subset of voxels. We created masks for early visual areas V1 and V2 using standard retinotopic mapping 379 procedures (see Retinotopic and Target mapping section) and manual delineation of the 380 subfields. The resulting masks were restricted exclusively to the voxels representing the 381 room's lower right corner using the target mapping run (see Ortiz-Tudela et al. (2023) for a 382 383 detailed procedure description).

384

385 Generalized linear model

We extracted single-trial beta estimates by applying a Least Squares Separate (LSS) 386 approach, where each trial is modeled as a separate regressor (Mumford et al., 2012; 387 Abdulrahman and Henson, 2016). For each of the four occlusion task runs, we computed 96 388 GLMs. A single GLM comprised one regressor for the onset of the current trial, 16 regressors 389 for the onsets of each room, six raw head motion regressors (three for displacement and three 390 for rotation), and three regressors for global, WM, and CSF intensities. For the sensory 391 template run, we conducted 192 GLMs with the same combination of regressor coefficients. 392 In our preregistration, we planned to include six additional nuisance regressors for volume-to-393 volume eye motion measures in each spatial axis for each eye. We extracted the eye bulbs of 394 each participant using Eye State fMRI (Brodoehl et al., 2016) to compute directional vectors 395 for each eye along the anteroposterior axis in a three-dimensional space (x,y,z). However, in 396 our older adults sample, due to large head sizes, the EPI's field of view (208 mm) did not 397 always include a sufficient portion of the eye bulbs to calculate those directional vectors 398 reliably. Thus, to provide comparability of findings across age groups, we decided not to 399 include regressors for eye motion in either sample. 400

401

402 Multi-voxel pattern analysis

We applied multivariate pattern analysis (MVPA) to decode the different components of feedback signals in nonstimulated voxels of V1 and V2 during the occlusion task. We used binary linear support vector machine (SVM) classifiers with a 4-fold leave-one-run out crossvalidation procedure. We trained classifiers on three of four occlusion task runs (288 trials) and tested on the remaining run (96 trials). We repeated this train-test procedure for all four runs and averaged the resulting classification accuracies across folds. All classification analyses were performed separately for episodic and semantic trials. Figure 2 illustrates the 410 classification schemes we adopted to decode the specific feedback components, i.e., contextual and mnemonic. Contextual refers to the visual information provided by the room 411 image surrounding the occluded region. This contextual information is fed through lateral 412 connections to the adjacent nonstimulated receptive fields, where it can be used to 413 414 disambiguate the percept and aid the retrieval of the associated object. To capture contextual information in V1 and V2, we trained a classifier with and tested on "same object – different 415 room" combinations (i.e., the two class labels share the object but differ in the room) so that 416 only contextual feedback could provide the classifier with information to discriminate 417 between room and object. Mnemonic refers to the object information retrieved through an 418 episodic or semantic route and transmitted to nonstimulated receptive fields in V1 and V2. 419 We trained another classifier based on a cross-classification schema to decode mnemonic 420 information. The training set consisted of "different object – different room" combinations 421 (i.e., the two class labels neither share the object nor the room), in which the classifier learned 422 to discriminate between object and room using both feedback information types. A classifier 423 tested in this set could use either (or both) the object and the room to discriminate the classes. 424 However, when tested on a different subset of rooms that shared the same objects across 425 training and test sets, above-chance classification could be achieved only by relying on the 426 427 mnemonic object information. We chose this more conservative cross-classification schema as it prevents using any learned room information and enables classification solely on object 428 information. Note that an alternative classification schema would be training a classifier with 429 and testing on "different object - same set of rooms" combinations. However, this 430 combination was not part of the experimental design and would lead to interference if a 431 particular room cues two different objects. We performed all decoding analyses with The 432 Decoding Toolbox (Hebart et al. (2015). We averaged classification estimates across 433 participants and tested for significance using a two-step bootstrapping approach (Stelzer et al., 434 435 2013). An accuracy distribution was created for each participant by randomly permuting the

trial labels 100 times and calculating classification accuracies for each iteration. We drew a 436 random sample (with replacement) from each distribution and averaged across participants 437 1000 times, thus creating a null distribution of 1000 average accuracies. If classification 438 estimates were larger than 99.9% of the accuracies in the null distribution (p < .001), they 439 were considered significant. For age group comparisons, we used linear mixed effect models 440 (LMMs, lmer function in the *lme4* package; Bates et al., 2015) instead of ANOVAs, as 441 written in the preregistration, to control for additional variance attributed to participants. Age 442 group (older versus younger), trial type (episodic versus semantic), and ROI (V1 versus V2) 443 were included as predictors and random intercepts were specified per subject. For main effect 444 445 testing, we calculated type-II Wald F tests using the Anova function in the car package (Fox and Weisberg, 2019) and type-III Wald F tests for interaction testing. Confidence intervals 446 were determined using the confint function from the stats package (R Core Team, 2020). 447

448

449 Representational similarity analysis

For each participant, we used single-trial beta estimates to compute Representational
Dissimilarity Matrices (RDMs) between every pair of individual trials (Kriegeskorte et al.,
2008). We calculated all RDMs using The Decoding Toolbox (Hebart et al., 2015). As
distance measures, we used the cross-validated Mahalanobis distance for the occlusion task
RDMs and Pearson r for the single-run sensory template RDMs.

455

456 *Model correlations*

To investigate to what extent contextual and mnemonic information is represented in feedback signals within both ROIs, we created two model RDMs that reflected the ideal correlation pattern for each feedback component (see Figure 3). Both model matrices were equally sized as the individual neural RDMs, spanning 96x96 trials (48 episodic and semantic trials, respectively). The contextual model had zero values for "same object – same room"

cells because we expected those combinations to have the lowest dis-similarity and maximal 462 values (i.e., ones) for the remaining high dissimilarity cells. The diagonal, containing only 463 zeros, was excluded from all analyses. In the mnemonic model, we expected the lowest 464 dissimilarity for "same object - different room" cells, therefore having zero values. "Different 465 object – different room" cells had maximal values representing the highest dissimilarity. 466 "Same object – same room" cells were removed as the low dissimilarity between the same 467 rooms would artificially reduce the final dissimilarity measure, which should be solely based 468 on the object. Both models were Spearman rank correlated with all individual RDMs. 469 Correlating the dissimilarity matrices results in correlation values that can range from zero to 470 one, with low values representing low similarity between the model and individual RDMs and 471 high values representing high similarity between the model and individual RDMs. The 472 correlation coefficients were Fisher-z transformed and compared against zero using Wilcoxon 473 signed-rank tests (wilcox.test function from stats package, R Core Team, 2020). As for 474 MVPA, we performed age comparisons using LMMs with random intercepts per participant, 475 and model (object versus room), trials (episodic versus semantic), and age (older versus 476 younger) as predictors. 477

478

479 *Differentiation index*

Similar to the procedure in Koen et al. (2019), we calculated Differentiation indices 480 (DIs) to obtain a measure for the specificity of neural responses. For the DI calculation, we 481 482 used the dissimilarity values from the individual neural RDMs and subtracted the average within from the average between dissimilarities. Within dissimilarity refers to the pairwise 483 distance of trials that share the same object, for example, TV versus TV, whereas between 484 dissimilarity refers to the pairwise distance of trails comprising different objects, for example, 485 TV versus bathtub. Thus, well-preserved neural differentiation is represented by higher DIs 486 487 resulting from lower within and higher between dissimilarities. We computed DIs for each

participant, occlusion task trials (episodic or semantic), and ROI. We followed the same procedure for the sensory template runs. DIs for the occlusion task are henceforth referred to as feedback DIs, and DIs for the sensory template run as feedforward DIs. We contrasted the resulting indices against zero with one-sided Wilcoxon tests and conducted age group comparisons separately for feedforward and feedback DIs using LMMs with age (older versus younger), trial type (episodic versus semantic), and ROI (V1 versus V2) as predictors and random intercepts per subject.

495

496 Correlation of feedforward and feedback differentiation indices

We transformed all feedforward and feedback DIs into z-scores. Note that a single 497 feedforward DI was computed per participant and ROI as the 1-back task in the sensory 498 template run did not include a distinction between episodic and semantic trials. Outliers were 499 500 defined as DIs above or below 3.29 standard deviations (signaling the most extreme 0.1%) from the mean and excluded from further analyses. For younger adults, we removed two 501 feedforward and two feedback outliers from DI data of ROI V2, and for older adults, we 502 excluded two feedforward and one feedback outlier from DI data of ROI V1. Finally, we 503 Spearman correlated (one-sided) the average feedforward DIs with episodic and semantic 504 505 feedback DIs separately for age groups and ROIs. All p-values were adjusted using the Benjamini & Hochberg correction (Park et al., 2010). 506

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- 508

Results

509 **Behavioral results**

510 Training performance on day one

511 Both age groups learned the object-room associations successfully across their designated

number of learning cycles, i.e., five for younger and nine for older adults, plus one refresher

513 cycle at the end of the session. All participants crossed the threshold of at least 80% learning

514 performance either in the last training or in the refresher cycle at the latest. Figure 4 shows the 515 learning progress of both age groups for object recognition and object position memory,

516 respectively.

517

518 Post-scan memory performance on day two

After being scanned, we tested participants' memory for object-room associations and object 519 position to ensure they maintained the required retrieval performance during scanning. On 520 average, both age groups performed above 80 % in both trial types (episodic: $M_{\text{younger}} = .81$, 521 $SD_{younger} = .16; M_{older} = .86, SD_{older} = .16; semantic: M_{younger} = .84, SD_{younger} = .15, M_{older} = .95,$ 522 523 $SD_{older} = .07$). Unpaired two-sided t-tests showed no differences across age groups in episodic trials for either object memory (t(68.49) = -1.43, p = .156) or object position ($M_{younger} = .77$, 524 $SD_{vounger} = .18, M_{older} = .78, SD_{older} = .21, t(69.95) = -0.24, p = .805)$. The mean recognition 525 memory performance for objects from semantic trials was better for older compared to 526 younger participants (t(43.77) = -3.61, p < .001). 527

528

529 fMRI results

The previous study with only younger adults (Ortiz-Tudela et al., 2023) showed that 530 531 contextual and mnemonic feedback signals contributed to the activation pattern in nonstimulated voxels of the primary and secondary visual cortices V1 and V2. Interestingly, 532 the extent to which mnemonic feedback signals fed down to these early cortices depended 533 534 critically on the retrieval route. That is, only episodic mnemonic content was represented but not semantic mnemonic content. This difference in content was revealed through RSA, which 535 was conducted after observing that the initial MVPA decoding approach was only sensitive to 536 contextual information and failed to capture mnemonic information. 537 Notably, the lifespan trajectories of episodic and semantic memory are different; 538

semantic memory remains relatively stable across age with later and less decline than episodic

memory (Li et al., 2004; Rönnlund et al., 2005). We, therefore, hypothesized that the 540 individual components of feedback would also change with age. More concretely, we 541 expected that the amount of episodic feedback would be reduced in older adults. Semantic 542 feedback, on the contrary, should be less affected by age-related changes as semantic memory 543 content tends to be relatively preserved in older age (Nyberg et al., 2003, 2012; Haitas et al., 544 2021). Hence, we anticipated less or no decay in semantic feedback signals compared to 545 episodic feedback signals. For contextual feedback signals, we expected no substantial 546 differences between age groups because the contextual visual input was identical and 547 immediately available, and any visual impairment was corrected for all participants with 548 appropriate MRI-compatible glasses. 549

550

551 Decoding contextual (and mnemonic) feedback signals

Following the previous study by Ortiz-Tudela et al. (2023), we addressed our 552 hypothesis first with a classifier-based approach. We set up two classification schemes to 553 decode contextual and mnemonic information, respectively, from nonstimulated voxels of V1 554 and V2 (for details about classifier arrangements, see MVPA section). The first classifier 555 arrangement aimed at capturing contextual room information. In both age groups, the 556 557 classifier performed above chance level (.50) for both episodic and semantic trials in both ROIs (younger adults: $V1_{epi} = .69$, $V2_{epi} = .68$, $V1_{sem} = .65$, $V2_{sem} = .66$; older adults: $V1_{epi} = .68$ 558 .58, $V2_{epi} = .58$, $V1_{sem} = .58$, $V2_{sem} = .58$, all p's < .001; one-sided one-sample t-test). Linear 559 560 mixed model analysis revealed a significant main effect of age on contextual room information, with classification accuracy in older adults being lower than in younger adults (β 561 = -0.077, 95% CI [-0.111, -0.043], t = -4.424, p < .001). These results replicate and extend 562 previous findings by showing that contextual information is a reliably traceable constituent of 563 feedback signals in nonstimulated voxels of early visual areas not only in younger but also in 564 565 older adults. Although we did not anticipate a significant age effect on contextual feedback,

the result is in line with some studies that found an age-related decrease in neural specificity
within feedback signals (St-Laurent et al., 2014; Trelle et al., 2019).

The second classifier arrangement aimed at capturing mnemonic object information. 568 The classifier did not perform above chance level (.50) in younger or older adults. Therefore, 569 we were unable to look further into age comparisons (younger adults: $V1_{epi} = .49$, $V2_{epi} = .47$, 570 $V1_{sem} = .49, V2_{sem} = .49;$ older adults: $V1_{epi} = .51, V2_{epi} = .51, V1_{sem} = .50, V2_{sem} = .51, all$ 571 p's>.05, one-sided one-sample t-test). This classification failure in older adults replicates the 572 previous study's finding with younger adults (Ortiz-Tudela et al., 2023). Nevertheless, this 573 null result does not rule out the possibility of mnemonic object information existence in 574 feedback signals. We reasoned that the classifier might have failed to decode object 575 information at test because it might have learned to classify primarily based on room 576 information and consequently could not generalize its' knowledge to a test set of new rooms. 577 578

579 Coexistence of contextual and mnemonic feedback signals revealed by RSA

Similar to the previous study, we addressed the null result for decoding mnemonic 580 information by using RSA, which enabled the identification of different sources of variance 581 within the same data (Ortiz-Tudela et al., 2023). We correlated individual RDMs from 582 583 episodic and semantic trials of both ROIs with two model RDMs that represent ideal dissimilarity correlation patterns for room (contextual model) and object categories 584 (mnemonic model; see RSA section for further details about RDM model specifications). 585 586 Figures 5 A) and B) show the correlations with both model RDMs for younger and older adults, respectively. Correlating the contextual room model with episodic RDMs resulted in a 587 moderate relationship for younger (rhov₁ = .31, rhov₂ = .33, both p's < .001) and a weaker 588 relationship for older participants ($rho_{V1} = .15$, $rho_{V2} = .20$, both p's < .001). We observed a 589 similar age pattern in the correlations between the contextual room model with semantic 590 591 RDMs: moderate for younger and weaker for older participants (younger: $rho_{V1} = .31$, $rho_{V2} =$

592 .30, both *p*'s <.001; older: $rho_{V1} = .14$, $rho_{V2} = .16$, both *p*'s < .001). Interestingly, correlating 593 the mnemonic model with episodic RDMs resulted in a low positive relationship for both age 594 groups (younger: $rho_{V1} = .08$, $rho_{V2} = .11$, both *p*'s < .001; older: $rho_{V1} = .06$, $rho_{V2} = .08$, both 595 *p*'s < .001), whereas correlating the mnemonic model with semantic RDMs resulted in 596 different relationships for the two age groups: In younger adults, a low negative relationship 597 emerged ($rho_{V1} = -.03$, *p* < .001, $rho_{v2} = -.01$, *p* = .009) but in older adults, the correlation 598 turned out positive ($rho_{V1} = .01$, *p* = .037, $rho_{v2} = .02$, *p* < .001).

Testing these observations formally, LMM analysis revealed a significant three-way 599 interaction between model, trial type, and age ($\beta = -0.093, 95\%$ CI [-0.183, -0.003], t = -600 2.023, p = 0.043). We further investigated the interaction by running LMMs separately for the 601 two models. For the contextual model, only a main effect of age emerged ($\beta = 0.153$, 95% CI 602 [0.114, 0.191], t = 7.793, p < .001) but no significant interaction between age and trial type (β 603 = 0.006, 95% CI [-0.046, 0.059], t = 0.252, p = .800). In particular, older adults, compared to 604 younger adults, showed lower correlations between the contextual model with both episodic 605 and semantic RDMs. For the mnemonic model, we found a significant interaction between 606 age and trial type ($\beta = -0.073$, 95% CI [-0.103, -0.044], t = -4.859, p < .001), indicating that 607 the difference between younger and older age groups was larger in semantic trials (t(276) =608 609 4.42, p < .001) than in episodic trials (t(276) = -2.37, p = .018), specifically because younger adults showed lower correlation estimates in the negative direction, while older adults showed 610 higher, positive correlation estimates. 611

Taken together, these findings are in line with our classification results by showing that 1) contextual information is present in feedback signals in both age groups, trial types, and ROIs, and 2) the amount of contextual information is overall reduced in older adults early visual areas V1 and V2, suggesting dedifferentiation of contextual feedback signals. In contrast to our classification results and in line with the original study with younger adults only, RSA revealed that mnemonic information exists in both younger and older adults'

primary and secondary cortices. Interestingly, episodic feedback was comparably well
reinstated in younger and older adults, whereas semantic feedback was more reliably
reinstated in older but not in younger participants. Even though these results are contrary to
our expectations, they lend support to previous research showing that older adults rely on
semantic knowledge more extensively, especially benefiting from it when learning new
information in line with their prior knowledge (Badham and Maylor, 2014; Mohanty et al.,
2016; Lalla et al., 2022).

In our preregistration, we included a variance partitioning approach to further explore 625 the unique contribution of different sources of information on activation patterns, particularly 626 627 the age differences therein. However, in observation of dedifferentiation, the reduced contextual feedback results indicated a higher noise level in older adults' brains. Thus, the 628 amount of variance that could be explained is presumably lower in older adults and, 629 consequently, not comparable to the amount of variance available in younger adults. 630 Consequently, we did not pursue this analysis to prevent inappropriate interpretations when 631 comparing the amount of variance between age groups. 632

633

634 Dedifferentiation in mnemonic feedback signals and feedforward visual input

So far, we have provided empirical evidence for the existence of contextual and 635 mnemonic feedback signals not only in younger but also in older adults. We further showed 636 that the composition of feedback signals changes over the lifespan. Compared to younger 637 638 adults, contextual feedback was reduced, episodic feedback was similar, and semantic feedback was stronger in older adults. To further characterize dedifferentiation in mnemonic 639 640 feedback (i.e., specificity in object information), we calculated DIs for each trial type and ROI. DIs were tested against zero and compared across age groups. Following previous 641 research on age-related episodic memory decline, we expected primarily episodic feedback to 642

suffer from age-related dedifferentiation; that is, older adults would have lower DIs inepisodic trials than younger adults.

Figures 5 C) and D) show feedback DIs for younger and older adults, respectively. 645 Feedback DIs for both age groups were significantly different from zero (younger adults: 646 $V1_{epi} = 25.34$, z = 4.43, p < .001; $V2_{epi} = 22.05$, z = 5.64, p < .001; $V1_{sem} = -3.87$, z = -3.30, p 647 <.001; V2_{sem} = -3.69, z = -2.29, p = .010; older adults: V1_{epi} = 10.71, z = 5.70, p < .001; V2_{epi} = .010; older adults: V1_{epi} = .010; older adults: .000; older adult 648 $= 3.41, z = 6.09, p < .001; V1_{sem} = .50, z = 1.65, p = .049; V2_{sem} = 1.15, z = 2.74, p = .002;$ 649 one-sided Wilcoxon test). LMM analyses resulted in a significant two-way interaction 650 between age and trial type ($\beta = -6.75466, 95\%$ CI [-10.521, -2.969], t = -3.478, p < .001). The 651 difference between age groups was higher in semantic trials (t(284) = 3.21, p = .001) 652 compared to episodic trials (t(284) = -3.61, p < .001), with younger adults having lower 653 semantic DIs than older adults. This finding is in line with the RSA model correlation results 654 suggesting that episodic feedback does not show compromise in neural specificity in older 655 age. Interestingly, semantic feedback signals even increased in DIs, such that the neural 656 specificity for this mnemonic content improves in older age. To complement those findings, 657 we explored neural differentiation within our ROIs when the objects were presented as 658 feedforward visual input during the sensory template run (i.e., episodic and semantic object-659 660 room pairings were consecutively presented during scanning; for details, see Sensory Template in the methods section). All feedforward DIs were different from zero (younger 661 adults: $V1_{epi} = .021$, z = 6.08; $V2_{epi} = .014$, z = 5.64; $V1_{sem} = .024$, z = 6.23; $V2_{sem} = .012$, z = 0.012, 662 5.56; older adults: $V1_{epi} = .009$, z = 5.25; $V2_{epi} = .009$, z = 5.65; $V1_{sem} = .006$, z = 4.10; $V2_{sem}$ 663 = .005, z = 4.42; all p's < .001, one-sided Wilcoxon test). Through LMM analysis, we 664 observed a significant main effect of age on neural differentiation ($\beta < .001$, 95% CI 665 [0.009338798, 0.027471357], t = 3.936, p < .001), meaning that feedforward DIs were lower 666 in older compared to younger adults. Therewith, we replicated previous research and 667

668 contributed additional evidence for age-related neural dedifferentiation at the item level in the669 early visual areas V1 and V2.

670

671 Relating feedforward and feedback components across age

It has been suggested that dedifferentiation could result from a general age-related 672 deficient dopaminergic modulation (Li et al., 2001; Abdulrahman et al., 2017). If the 673 underlying mechanism for age-related dedifferentiation is general across brain areas and 674 pathways, feedforward and feedback signals might be impacted to a comparable extent. Based 675 on this assumption, we expected to find a positive relationship between neural specificity in 676 feedforward and individual feedback components as age increases. To this end, we correlated 677 the feedforward DIs with DIs for episodic and semantic feedback separately per age group 678 and ROI. The correlation between feedforward and semantic feedback DIs (see Figure 6) 679 680 neither resulted in a significant relationship in older (rhov₁ = -.11, p = .736, rhov₂ = .11, p = .736, rhov₂ = .11, p = .736, rhov₂ = .11, p = .736, rhov₁ = .11, p = .736, rhov₂ = .11, .334) nor in younger adults (rho_{V1} = -.3, p = .179, rho_{v2} = -.05, p = .616). A different picture 681 emerged when we correlated feedforward with episodic feedback DIs. In older adults, we 682 observed a low positive relationship between feedforward and episodic feedback DIs in V1 683 and V2 (rho_{V1} = .34, p = .044, rho_{v2} = .35, p = .044), whereas, in younger adults, this positive 684 685 relationship appeared only in V1 (rho_{V1} = .41, p = .035, rho_{V2} = .18, p = .215). This pattern supports the hypothesis that the putative mechanism of dedifferentiation (e.g., dopaminergic 686 modulation) impacts both feedforward and feedback signals but points out that this is only 687 688 true for a specific component of the feedback signal. Specifically, mnemonic content retrieved through an episodic route was especially prone to age-related changes in the neural 689 690 mechanism that fosters dedifferentiation, while semantic content was spared. Furthermore, this result implies that certain brain areas, such as V1, are more affected by dedifferentiation 691 than others. 692

694

Discussion

The present study examined age-related changes in the composition of feedback signals in the 695 early visual areas of younger and older adults. We combined an occlusion paradigm with 696 multivariate fMRI pattern analysis, allowing us to isolate and examine concurrent contextual 697 and time-distant mnemonic information in feedback signals in V1 and V2. As the first study 698 that scrutinized age-related differences in feedback signals, four main findings emerged. 699 First, concurrent contextual and time-distant mnemonic information coexist as 700 feedback signals in V1 and V2 of both younger and older adults. By this, we replicated 701 previous research that identified contextual (Smith and Muckli, 2010; Muckli et al., 2015) and 702 mnemonic (episodic or semantic) information in feedback signals (Ortiz-Tudela et al., 2023) 703 in younger adults' visual cortex occluded from feedforward visual input and extended this 704 finding to older adults. As occlusions are ubiquitous in everyday life, both young and 705 706 senescent visual systems must overcome the perceptual challenge of disambiguating uncertain visual input. Feedback signals facilitate this process by carrying information from the 707 708 concurrent surroundings and internally retrieved time-distant memory representations to "fill in the blank" in the case of occlusion. 709 Second, decoding accuracy of contextual feedback was reduced in older adults' V1 710 711 and V2. Lower correlations between a contextual feedback model and multivariate activation patterns in older adults supported this finding. Reduced classification accuracy and 712 (dis)similarity measures have been previously interpreted to indicate age-related 713 714 dedifferentiation in neural representations (Abdulrahman et al., 2017; Trelle et al., 2019; Folville et al., 2020). Our results showed that contextual feedback is prone to age-related 715 716 dedifferentiation. Common age-related changes in the neural circuitry within the visual cortex 717 could account for this reduction. For example, demyelination, reduced spine, and synapse densities may lead to dendritic and axonal regressions, which may hamper the integrity of 718 719 neural signal that is transferred via lateral intracortical connections to adjacent receptive fields

(Smith and Muckli, 2010; Larkum, 2013; Danka Mohammed, 2021). However, the exact 720 721 nature and impact of age-related decline in micro-structure integrity within early visual regions is not fully known and needs to be examined in future research. Additionally, an 722 increased baseline noise level in older adults' EVC has been shown to compromise perceptual 723 processing (Li et al., 2001; Tran et al., 2020). In line with this, we found feedforward DIs to 724 be significantly lower in older adults, probably rendering the transmitted contextual feedback 725 less representative of the original input. Future studies should consider including diffusion 726 tensor imaging to obtain measures for the structural integrity of lateral neural connections to 727 account for such changes (Voss et al., 2008). 728

729 Despite the compromised lateral transfer of contextual information, the representational quality of mnemonic feedback could nevertheless be preserved due to 730 compensatory mechanisms (Park et al., 2001). For example, older adults have been shown to 731 recruit more neural resources at low task demand levels as a compensatory strategy, 732 improving neural distinctiveness (Reuter-Lorenz and Cappell, 2008; Carp et al., 2010). This 733 observation may be important to consider with our third main finding: episodic feedback 734 remained well differentiated across age groups, whereas semantic feedback was even better 735 differentiated in older adults than in younger adults. The maintenance of episodic feedback 736 737 signals was unexpected for several reasons. Age-related episodic memory decline is well established in the aging literature, as well as the notion that older adults tend to retrieve only 738 the gist of a previously experienced episode; namely, contextual details are lost while the 739 740 central aspects are preserved (Koutstaal and Schacter, 1997; Old and Naveh-Benjamin, 2008; Nyberg et al., 2012; Abadie et al., 2021). Interestingly, while there is evidence for reduced 741 742 episodic memory reinstatement in the visual cortex (Zheng et al., 2018), some studies found neural reinstatement of episodic memory content as age-invariant (Wang et al., 2016; Thakral 743 et al., 2017, 2019). According to the *Lifetime Experience Hypothesis* by Koen and Rugg 744 745 (2019), the absence of age-related dedifferentiation could be explained by high familiarity

with the stimulus material in both age groups, attenuating differences in neural specificity of 746 747 episodically retrieved feedback. Furthermore, our training procedure might have contributed to the well-differentiated episodic feedback, which was also mirrored by very high post-scan 748 recognition memory performance for episodic object-room combinations. Older adults 749 received four additional learning cycles for encoding the episodic set on day one. These 750 additional cycles, together with the relatively small training set (eight object-room 751 752 combinations), could have provided older adults the opportunity to compensate for any 753 attentional or binding deficits during encoding and eventually diminished effects of dedifferentiation, leading to a comparable behavioral performance (for a similar pattern, see 754 St-Laurent et al., 2014). Furthermore, we assume that due to our recruiting strategy through 755 the university, the older adults were positively biased, characterized by youth-like memory 756 integrity and distinctiveness of neural representations (Fandakova et al., 2015; Zhang et al., 757 758 2020; Katsumi et al., 2021). Taken together, our results show that episodic feedback is not compromised when performance level is matched between age groups. 759

In terms of semantic feedback, we expected no age difference or only slightly less 760 differentiation in older compared to younger adults. Somewhat surprisingly, our results 761 showed that semantic feedback was even better differentiated in older than younger adults. 762 763 This finding supports studies suggesting that the semantic memory system remains relatively intact in older adults, even with improvements in some domains (Laumann Long and Shaw, 764 2000; Levine et al., 2002; Lalla et al., 2022). Interestingly, while most studies investigated 765 766 dedifferentiation using episodic retrieval tasks, the only study that employed an additional semantic task did not find neural dedifferentiation, pointing to the preservation of generalized 767 768 knowledge in older age (St-Laurent et al., 2011). Moreover, the ecological validity of our stimulus material, as well as the congruity between semantic object-room pairs, might have 769 770 helped older adults at retrieval and thereby enhanced neural differentiation of semantic 771 feedback (Badham and Maylor, 2014; Mohanty et al., 2016; Brod and Shing, 2019). Although

772 the semantic set was not as extensively trained as the episodic set, the semantic post-scan 773 retrieval performance was better in older adults than younger adults, which underlines the growing impact of semantic knowledge over the lifespan and supports previously reported 774 relationship between higher neural differentiation and better memory retrieval (Katsumi et al., 775 776 2021). Nevertheless, it should also be noted that the poorer post-scan memory performance of younger adults for semantic trials could have been a by-product of the different response 777 778 formats between age groups. Younger adults entered their responses with their left hand within 2 seconds time window, potentially leading to some premature response errors (note 779 that two errors would already result in a performance level of 75%). In contrast, older adults 780 verbally indicated the objects within 4 s, and the responses were entered by the experimenter. 781 In addition to the growing relevance of semantic memory, a decline in inhibitory 782 control might challenge older adults to suppress accessing semantic information, which 783 784 happens largely automatically (Karl Healey et al., 2013; Vachon et al., 2019). At the same time, intensified recruitment of semantic knowledge could compensate for deterioration 785 elsewhere, such as feedforward perception and contextual feedback. Future research should 786 employ longitudinal study designs to track changes in feedback signals as they may emerge 787 gradually over the lifespan. To further scrutinize the sources and compensatory mechanisms 788 789 that may underlie age-related changes in feedback composition, connectivity analysis techniques such as psychophysiological interaction analysis or deep neural networks could be 790 utilized (cf. Deng et al., 2021; Ortiz-Tudela et al., 2023). 791

Fourth, while differentiation of feedforward visual input was overall reduced in older adults, the extent of differentiation was positively related to episodic feedback signals in both older adults' V1 and V2 and younger adults' V1. That is, the retrieval of better-differentiated information through an episodic route correlated with better differentiation of visual input in early visual areas across age groups. This result partly met our hypothesis predicting a positive relationship between neural differentiation in feedforward and feedback signals,

798 especially in older adults. Age-invariant relationships between neural selectivity at perception 799 and retrieval have been demonstrated before (Johnson et al., 2015; Hill et al., 2021; Katsumi et al., 2021). In line with this research, our findings suggest that regardless of age, neural 800 specificity during feedforward processing is correlated with neural specificity of feedback. 801 802 We extend this postulation by demonstrating that this age-invariant relationship is only present for information retrieved episodically but not semantically and that it holds even in 803 the absence of reduced neural differentiation of episodic feedback. The lack of relation 804 between feedforward and semantic feedback aligns well with Park et al. (2010), who showed 805 that neural specificity was associated with measures of fluid processing ability but not 806 crystallized knowledge. A possible interpretation is that as accumulated knowledge increases, 807 it is less dependent on the quality of neural differentiation in feedforward visual input. On the 808 contrary, episodic memory ability is more variable across the lifespan, and the integrity of 809 810 stored episodic content depends on the initial quality of neural differentiation at perception. Hence, episodic memory is more prone to differences in neural selectivity regardless of age. 811 In sum, we demonstrated the coexistence of concurrent contextual and time-distant 812 mnemonic information in feedback signals in early visual areas V1 and V2 across age. 813 Furthermore, we showed that individual feedback components follow distinct trajectories 814 815 regarding neural dedifferentiation. Episodic feedback signals were comparably differentiated across age, whereas semantic feedback signals showed better neural differentiation in older 816 adults than in younger adults, probably reflecting the lifelong accumulation of generalized 817 818 knowledge. Notably, while feedforward differentiation was reduced in older adults, it was positively correlated with episodic feedback in both age groups. This suggests that measuring 819 820 dedifferentiation of internally generated signals depends on the nature of the retrieved information. Our findings have important implications for the investigation of memory 821 reinstatement and aging, highlighting dissociations among different components of feedback 822 823 signals across the lifespan.

825 **References**

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Figure Legends

- ar Figure 1. Schematic overview of training and test phases across days. A) During day one training, participants studied room-object combinations with minimal semantic relation, i.e., the episodic set. The target objects were always placed in the lower right corner of the room image. After each training cycle, we tested object memory with a 4AFC format, followed by memory for the objects' original position. B) On day two, participants were introduced to the semantic set consisting of new room images and verbally indicated the object with maximal semantic relation to the room. During scanning, the occlusion task showed rooms from both episodic and semantic sets with a white occluder hiding the area of the target object. Participants were asked to focus on the cross in the center of the screen and to reinstate and hold the entire room in mind, including the associated object, with as much detail as possible.
- Figure 2. Classification setup. All trials used for decoding analyses stem from the occlusion task performed in the scanner on day two. Note that the objects were never shown during the

actual task (shown here only for illustration purposes). We performed decoding on voxels in 1045 1046 V1 and V2 that represented the occluded lower right corner. A) To decode contextual 1047 information, we provided the classifier with a training set of different rooms associated with the same objects (solid box). Based on this arrangement, the classifier could use only the 1048 1049 contextual room information in feedback signals to distinguish trials of the upper stack from trials of the lower stack. The test set (dashed box) comprised the same object-room 1050 1051 combinations from a separate run from the training set. B) To decode mnemonic information, the classifier was trained with two trial sets of different rooms associated with different 1052 objects (solid box). Here the classifier could use contextual and mnemonic feedback to learn 1053 1054 to distinguish the upper from the lower stack. When tested on a set of new rooms that shared the same object (dashed box), only the mnemonic feedback that was consistent (across 1055 training and test sets) could provide sufficient information to discriminate between them. 1056 1057 Figure 3. Model RDMs. Two model RDMs representing an ideal neural response pattern were created and correlated with the neural RDM of a participant. For illustration purposes, 1058 reduced model matrices spanning 24x24 trials instead of 96x96 trials are plotted. Cells 1059 represent four object-room pairings (TV-Room A, TV-Room B, Bed-Room A, Bed-Room B) 1060 containing either zeros (= lowest possible dis-similarity) or ones (= highest possible dis-1061 1062 similarity). In the left panel mnemonic model, "same object – different room" cells are colored in red, indicating zeros since retrieving the same object should ideally result in the 1063 lowest possible dissimilar neural signal. "Different object - different room" cells are colored 1064 1065 in blue, indicating ones since retrieving different objects should ideally result in the highest possible dissimilar neural signal. "Same object - same room" cells are colored in white and 1066 1067 were removed from the correlation analysis to prevent the coefficient from being artificially lowered through room similarity. In the right panel contextual model, "same object – same 1068 1069 room" cells are colored in red, indicating zeros since perceiving the same room images should 1070 ideally result in the lowest possible dissimilar neural signal. "Same object – different room"

1071 cells are colored in blue, indicating ones since perceiving different rooms should ideally result
1072 in the highest possible dissimilar neural signal. The diagonal cells are colored in white and
1073 were removed from the correlation analysis to prevent the coefficient from being artificially
1074 lowered through overall similarity.

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Figure 4. Memory performance across learning cycles on day one. The proportion of correct responses for object recognition (upper panel) and position memory (lower panel) across five learning cycles for younger (left panel) and nine learning cycles for older adults (right panel), plus one refresher cycle at the end of the session, respectively. The dashed red line indicates the threshold of 80% that had to be crossed, either in the last or the refresher cycle of the object recognition task, to be included for fMRI analysis.

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Figure 5. Model correlations and feedback differentiation indices. The upper panel shows 1083 Spearman correlations (z scores) for A) younger and B) older participants between individual 1084 RDMs and two model RDMs representing ideal dissimilarity correlation patterns for context 1085 (contextual model) and object categories (mnemonic model), respectively. Correlations are 1086 1087 separately shown for episodic and semantic trials in ROIs V1 and V2. The lower panel shows 1088 differentiation indices separately for episodic and semantic mnemonic feedback for C) younger and D) older participants in both ROIs V1 and V2. The dashed vertical line indicates 1089 1090 zero.

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Figure 6. Relationship between visual feedforward and mnemonic feedback DIs. Spearman correlations between average feedforward DIs and episodic and semantic feedback DIs are plotted for younger (left panel) and older adults (right panel) and separately for ROIs V1 (top) and V2 (bottom). Darker colors and solid lines represent episodic feedback DIs, and lighter colors and dashed lines represent semantic feedback DIs. Shaded ribbons represent the 95%

- 1097 confidence intervals. Average feedforward DIs were positively related to episodic feedback
- 1098 DIs in younger adults' V1 and older adults' V1 and V2.

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Meurosci Accepted Manus

A) Contextual

B) Mnemonic









Meurosci Accepted Mark







