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Increasing Social Inequalities in Educational Attainment Over Adolescence Follow Increasing Inequalities in Working Memory

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ABSTRACT

By the end of primary school, the poorest UK pupils are around a year behind their peers in terms of educational attainment. This gap doubles by the age of 16. Using longitudinal data from the demographically representative Study of Cognition, Adolescents, and Mobile Phones (SCAMP), we previously showed that working memory (WM) gaps also widen during adolescence. In the current study, SCAMP data were linked with data from the UK Department for Education's National Pupil Database ($n = 2726$). Analyses showed that differences in WM skill development mediated some of the widening socioeconomic gradient in educational attainment during adolescence. Interestingly, some (parental occupation and income poverty), but not all aspects of socioeconomic status (parental education), predicted individual differences in academic progress via WM. While correlational, these results provide an important starting point for understanding different ways in which socioeconomic status might impact attainment during adolescence.

Early adolescence is characterized by rapid cognitive development and is viewed as both a window for increased opportunities for intervention and for increased vulnerability to environmental factors (Fuhrmann et al. 2015). Working memory (WM, see Table 1 for Glossary of abbreviations), the short-term storage and manipulation of information (Engle and Kane 2004), shows one of the most protracted developmental trajectories of all cognitive skills, not reaching maturation until the mid-20s (Lee et al. 2013; Ferguson et al. 2021). WM shows a high level of individual differences (Jarrold and Towse 2006), which reliably associate with academic achievement (Ahmed et al. 2019; Albert et al. 2020; Donati, Meaburn, and Dumontheil 2019). While some of these differences are driven by genetic variation (Donati, Dumontheil, and Meaburn 2019), WM responds to training (Melby-Lervåg et al. 2016) and is susceptible to environmental factors including the experience of familial, economic and neighborhood adversity in childhood (Mooney et al. 2021).

We previously demonstrated that WM may continue to be vulnerable to adversity during adolescence: In the Study of Cognition, Adolescents, and Mobile Phones (SCAMP)—a large longitudinal cohort study of adolescents from London (England; $n = 2726$)—we showed that socioeconomic status (SES) linked differences in WM increased between 12 and 14 years (Perry et al. 2026). The present study aimed to extend this work and test the relationship between SES, WM, and attainment during adolescence.

In another United Kingdom (UK) cohort ($n = 5383$), Donati, Meaburn, and Dumontheil (2019) showed that, after controlling

TABLE 1 | A glossary of acronyms used in this paper.

Category	Acronym	Stands for	Definition
Socioeconomic status related terms	FSM	Free school meals status	An indicator of household income poverty
	SES	Socioeconomic status	An individual's relative social or financial position
Academic attainment related term	GCSE	Graduate Certificate of Secondary Education	Standardized national exams taken at the end of compulsory education at age 16 in England
	NPD	National Pupil Database	Department for Education's data store, covering education, skills and children's services data for individual learners in England
	SAT	Standard Assessment Test	Statutory national curriculum tests for taken at the end of primary school in England
Cognitive terms	BDS	Backward Digit Span	A verbal working memory task
	EF	Executive function	Cognitive control skills
	SWM	Spatial Working Memory	A spatial working memory task
	WM	Working memory	The short-term storage and manipulation of information
Statistical terms	CFA	Confirmatory Factor Analysis	A statistical technique used to create latent factors (new variables that reflect shared variance across a range of measures)
	CI	Confidence interval	The range of values within which the true population value is expected to fall
	CFI	Comparative Fit Index	A statistic used to indicate how well a structural equation model fits your data. Values > 0.90 are considered acceptable.
	FDR	False Discovery Rate	A method to control the statistical significance threshold for multiple comparisons
	RMSEA	Root Mean Square Error of Approximation	A statistic used to indicate how well a structural equation model fits your data. Values < 0.10 are considered acceptable.
	SEM	Structural Equation Model(ling)	A statistical technique used to model relationships between measured variables and latent factors
	SRMR	Standardized Root Mean Square Residual	A statistic used to indicate how well a structural equation model fits your data. Values < 0.10 are considered acceptable

for measures of SES, age, visuospatial reasoning, and vocabulary, WM measured at 11 years old predicted maths, science, and English attainment at 16 (full models R^2 range = 0.65–0.71). Similarly, having accounted for SES and a range of demographic factors, Ahmed et al. (2019) found that age 5 WM, but not other executive functions (EFs; cognitive control skills), continued to predict attainment during adolescence (full models R^2 range = 0.36–0.50). In the UK, the attainment gap between high and low SES students doubles during secondary education (Education Policy Institute 2023). This study seeks to understand whether the increasing attainment gap could be partly explained by increasing inequalities in WM development over adolescence.

Only one previous study has explored whether WM might be on the causal pathway from SES to attainment. Albert et al. (2020) found that EF (at 8–9 years) partially mediated the association of a composite measure of parental education and income with attainment in reading and maths at 13. This effect was strongest when WM, specifically verbal WM, was the mediator compared to measures of planning or inhibition, with verbal WM explaining 11% of the SES effect on maths and 7% on reading attainment. However, since the researchers did not take concurrent measures of WM and attainment, it is possible that the covariance of WM with attainment drove this effect. Demonstrating that WM growth mediates attainment progress over time would give a more convincing indication of causality.

It has been argued that some WM measures are better predictors of attainment than others for example, complex versus simple span tasks (Jarvis and Gathercole 2003) and verbal rather than visuospatial tasks (Albert et al. 2020, but see Gilmore and Cragg 2018 for a different view). Further, Donati, Meaburn, and Dumontheil (2019) showed that the relationship between cognitive skills and academic progress over adolescence is better captured with statistical models that treat academic subjects separately. Hence, we compared models treating measures of WM and measures of attainment separately to those treating them together to better understand the specificity of associations in this age group.

We also aimed to further understand the nature of social inequalities in cognitive and educational outcomes during adolescence. Perry et al. (2026) show that some SES gaps in WM widen during early adolescence. We found that, controlling for other aspects of SES, age, gender and age 12 WM, Free School Meals status (FSM; an indicator of household poverty) and parent occupation predicted WM development from 12 to 14 years (full models R^2 range across WM measures = 0.13–0.28). However, as in Hackman et al. (2014), parental education and area deprivation were not significantly related to WM development. As associations between all these SES indices and attainment have been reported in previous studies of UK adolescents (Chevalier et al. 2013; Donati, Meaburn, and Dumontheil 2019; McDool 2017; Ermisch and Francesconi 2001), some but not all social inequalities in attainment might operate via WM.

Using longitudinal cohort data on adolescents from England, we analyzed associations between SES, WM and academic attainment with a focus on specific pathways. We predicted that we would replicate Donati, Meaburn, and Dumontheil's (2019) finding that adolescent WM skills significantly predict age 16 attainment, controlling for SES and prior attainment, here focusing on change in WM skills during early adolescence (H1). We anticipated that change in WM would significantly predict academic progress in all core subjects (maths, English, and science; H2), in line with Donati, Meaburn, and Dumontheil's (2019) findings. While our previous analyses of this dataset indicated that only FSM and parental occupation associated with change in WM, we expected that all SES indices would nevertheless predict educational attainment progress, given the associations between a range of SES indices and attainment in UK adolescents reported elsewhere (Chevalier et al. 2013; Donati, Meaburn, and Dumontheil 2019; McDool 2017; Ermisch and Francesconi 2001) (H3). Finally, we hypothesized that we would replicate Albert et al.'s (2020) finding that WM partially mediates the association between SES and adolescent attainment, here focusing on change in WM and attainment (H4).

1 | Methods

The original SCAMP study protocol and subsequent amendments were approved by The North West-Haydock Research Ethics Committee. Ethical approval for the linkage of SCAMP data with National Pupil Database (NPD) data for the purposes of RCP's PhD project was granted by the Imperial College London Research Ethics Committee (Protocol number 14IC2067, version 4, July 29, 2014).

1.1 | Participants and Design

Participants were 2726 state school educated pupils (54% female) from the Greater London area who participated in the Study of Cognition, Adolescents, and Mobile Phones (SCAMP). SCAMP followed a regionally representative sample of adolescents from London (England) through secondary education. All but two SCAMP participants completed their age 16 assessments in 2017, 2018, or 2019, before the Covid pandemic.

Participants completed a battery of demographic questionnaires and cognitive tasks during class in their first year of secondary school (T1, M_{age} = 12.06 years, SD = 0.38) and again approximately 2 years later (T2, M_{age} = 14.29, SD = 0.48). These data were linked with the UK Department for Education's NPD.

Participants were included in this study if they were present at both testing sessions (whether or not they had complete data for that session) and were successfully identified in the NPD. See Perry et al. (2026) for further details on the included participants and descriptions of the measures and tasks, and Toledano et al. (2018) for a description of the full cohort (N = 6905).

1.2 | Measures

1.2.1 | Socioeconomic Status

The SES indices used in this study were highest parental occupation based on the Office for National Statistics (2010) classification system (0 = long-term employed/never worked to 8 = large employers, higher managerial, and administrative), how many of the pupil's parents attended university (0, 1, or 2), area-level deprivation (quintiles based on proportion of male unemployment, lack of car ownership, overcrowding, and head of households in low occupational classes in postcode area reported in

2011 census following Carstairs and Morris 1990), and FSM status (yes/no; an indicator of household poverty). The first three indicators were based on adolescent reports at age 12 and FSM was from the NPD. All were coded so that a higher score indicates higher SES.

1.2.2 | Working Memory

The SCAMP battery included three computerized measures of WM: one verbal, the Backward Digit Span (BDS), and two visuospatial, the Corsi and Spatial WM (SWM) tasks. Corsi tries to find individuals' maximum spans, while the SWM involves strategic searching.

The metrics used for BDS and Corsi were individuals' spans, obtained using a staircase procedure, and for the SWM, total number of errors. The latter was transformed so that higher scores reflect better WM in all cases. As there was variability in age at T1 and T2 testing, age was regressed out from T1 and T2 WM measures prior to the main analysis.

1.2.3 | Academic Attainment

English pupils sit Graduate Certificate of Secondary Education (GCSE) examinations in English language, maths, and science, in their final year of compulsory secondary education (Year 11; age 16). GCSEs are graded on a scale of 1–9 (4 = pass mark). All models controlled for attainment at the end of the final year of primary school (Year 6; age 11). At this stage, pupils sit Standard Assessment Tests (SATs) in maths and reading and teacher-assessed grades for writing and science are recorded. Teacher assessments are on a scale of 2–6 and SATs are on a scale of 3–6 (4 = average and expected standard as specified by the UK government). On all measures, higher grades reflect higher achievement.

1.3 | Analysis

All analyses were run in Rstudio 2024.04 + 1748. A series of structural equation models (SEMs) were run using lavaan with Full Information Maximum Likelihood estimation due to the presence of missing data (Figure 1). *N* for all models was 2726.

In a first step, SEMs treated all key variables as factors (Models 1a–2a), having previously confirmed that WM, SES and academic attainment measures loaded well onto single factors (Figure S1) and that key variables were correlated (Table S1). Then, we assessed whether models using individual measures of WM and attainment (Model 3a) and SES (Model 4a) fit the data better. In each specific effects model, we estimated the covariance between measures of the same construct taken at the same point in time (e.g., between T1 WM measures; Table S2).

Following Cribbie (2007), the Benjamini and Hochberg (1995) false-discovery-rate (FDR) correction procedure was applied to multiple paths tested within the same model that fall under the same family of associations (e.g., all SES→WM paths tested within a given model).

We confirmed that observed associations were not better explained by ethnicity, first language status and gender—factors correlated with SES and attainment in SCAMP (see Filippi et al. 2026; Perry et al. 2026)—by running models controlling for these variables (Models 1b–4b, Supporting Analysis A and Table S3–S5).

Finally, as an exploratory analysis, we controlled for school quality to adjust for clustering by school and to isolate the effects of SES on attainment from school quality effects on attainment (Supporting Analysis B and Figures S2–S4).

We interpret R^2 values, robust Comparative Fit Index (CFI) and Root Mean Square Error of Approximation (RMSEA) estimates for each model.

2 | Results

2.1 | Descriptives Statistics

Compared to the national figures, a higher percentage of the study sample met or exceeded the expected attainment standard across subjects at age 11 and at age 16 (Table 2). Performance higher than the national average is typical of pupils from London (Farquharson et al. 2022).

2.2 | Structural Equation Models

2.2.1 | Model 1a. Does SES Predict Age 16 Attainment Controlling for Age 11 Attainment?

We first confirmed that SES significantly predicted age 16 attainment controlling for age 11 attainment. Model fit was acceptable (Table 3). SES and prior attainment were significant predictors of age 16 attainment (all p's < 0.001); however, the effect of prior attainment (standardized β [95% confidence intervals, CI] = 0.74 [0.71–0.76], raw β = 1.22 [1.13–1.31]) was nearly four times larger than the effect of SES (standardized β = 0.15 [0.10–0.19], raw β = 0.25 [0.17–0.32]) (Figure 2). A 1 SD increase (equivalent to a change from the 50th to the 84th percentile) in SES associated with a change from the 50th to the 56th age 16 attainment percentile, while a 1 SD change in age 11 attainment associated with a change from the 50th to the 77th age 16 attainment percentile (Supporting Analysis C).

2.2.2 | Model 2a. Does Change in WM in Early Adolescence Predict Age 16 Attainment Controlling for Age 11 Attainment and SES? (H1)

We then tested H1 following the latent change score modeling procedure described in Kievit et al. (2018). Adding WM improved the model fit according to RMSEA. CFI was unchanged (Table 3). Change in WM from early (M_{age} = 12.06) to mid-adolescence (M_{age} = 14.29) explained a significant amount of variance in age 16 attainment, consistent with H1

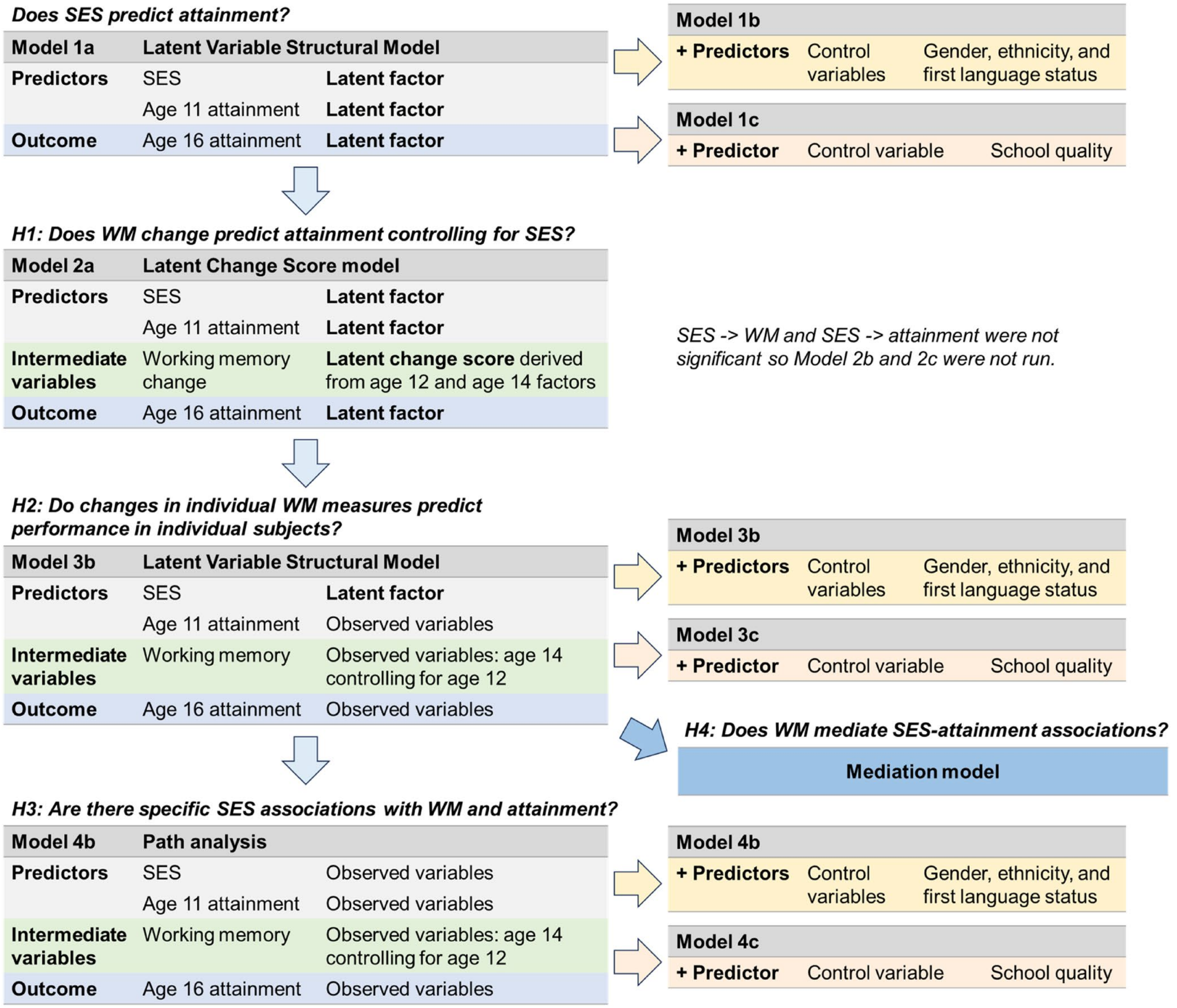

FIGURE 1 | A flowchart outlining the models run and the sequence in which they were run.

TABLE 2 | Attainment scores at age 11 and 16 in the SCAMP sample, compared to national results.

	Age 11			Age 16		
	Standard Achievement Tests (SATs) / Teacher assessments			General Certificate of Secondary Education (GCSE) exams		
	M (SD)	Met or exceeded expected standard		M (SD)	Met or exceeded expected standard	
	SCAMP	SCAMP	England	SCAMP	SCAMP	England
Reading	4.41 (0.75)	91%	86%			
Writing	4.29 (0.71)	92%	85%			
English				5.13 (1.78)	80%	70%
Maths	4.49 (0.85)	91%	83%	5.16 (2.08)	80%	71%
Science	4.32 (0.66)	91%	88%	5.32 (2.05)	81%	55%

Note: The England columns refer to results for all pupils who sat their SATs in 2013 and their GCSE exams in 2018 (Department for Education 2013; Ofqual 2018). The grey shades were mentioned to show there is no English assessment at age 11 and no reading and writing assessments at age 16.

TABLE 3 | Model fit indices.

Model	R^2	Chi-squared test (χ^2)	SRMR	CFI	RMSEA [90% CI]
1a	0.64[a]	χ^2 (41) = 911.32, p < 0.001	0.04	0.94	0.09 [0.09–0.10]
2a	0.75	χ^2 (114) = 1083.82, p < 0.001	0.04	0.94	0.06 [0.06–0.06]
3a[a]	Maths = 0.54	χ^2 (87) = 1479.89, p < 0.001	0.16	0.91	0.09 [0.08–0.09]
	Science = 0.46				
	English = 0.40				
4a	Maths = 0.54	χ^2 (67) = 1412.43, p < 0.001	0.16	0.91	0.10 [0.09–0.10]
	Science = 0.45				
	English = 0.38				

Note: Values > 0.90 for CFI and < 0.10 for RMSEA are considered acceptable following Fabrigar et al. (1999) and Schumacker and Lomax (2010). χ^2 is not interpreted due to issues of over sensitivity to minor model misspecification in the case of large samples. SRMR is not interpreted due to issues of inflation in structural equation models that accommodate missing data (McNeish and Matta 2025).
Abbreviations: CFI, comparative fit index; RMSEA, root mean square error of approximation; SRMR, standardized root mean square residual.
[a]Model 3a was rerun with only within-subject paths from age 11 to age 16 attainment and model fit worsened (χ^2 (95) = 2287.37, p < 0.001, SRMR = 0.18, CFI = 0.87, RMSEA = 0.10 [0.10, 0.10]), so between-subject paths were retained.

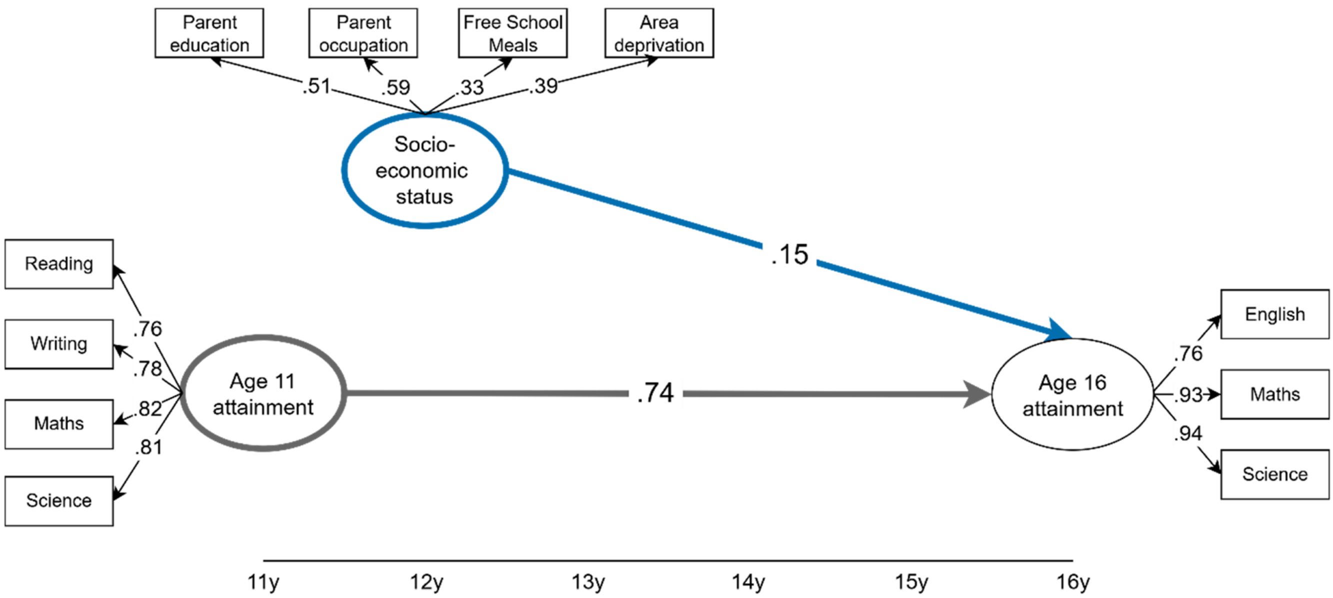

FIGURE 2 | Path diagram of structural equation model 1a assessing whether socio-economic status predicts attainment at 16 when controlling for prior attainment at age 11. Values on the paths are standardized parameter estimates. The *x*-axis scale shows the average age at which these measures were taken.

(Figure 3). This association was small but more than twice that of the SES–attainment association, which was reduced compared to Model 1a and became non-significant. As a latent factor, SES also did not significantly associate with change in WM over adolescence.

2.2.3 | Model 3a. Does Change in WM Predict Performance in Individual Subjects? (H2)

WM and attainment measures were included separately in Model 3a. Model fit was marginal and worse than previous models (Table 3). This was likely due to the presence of non-significant paths from reading and writing at age 11 to age 16 maths. Removing all between-subject paths worsened model fit (Table 3). Since only removing the non-significant attainment paths was not theoretically motivated, they were retained.

SES had small but significant longitudinal associations with all age-14 WM measures and attainment in all subjects at age 16 (controlling for earlier measures; Figure 4). In terms of attainment, SES effects were slightly larger on English and science than maths (Table 4).

As expected, all WM measures significantly predicted progress in all core subjects (H2). BDS and SWM associations with attainment were similar across subjects, while the Corsi span

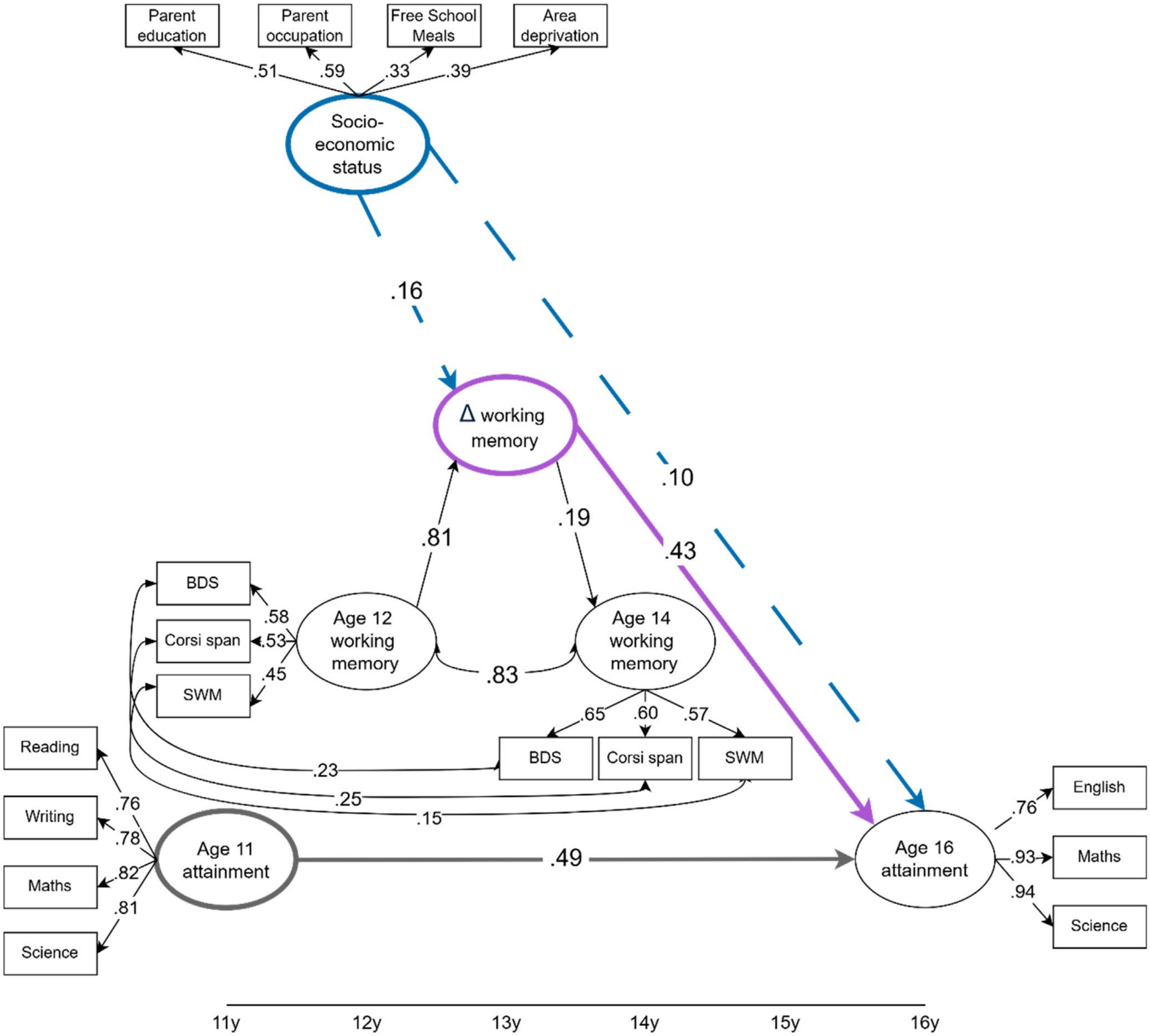

FIGURE 3 | Path diagram of the latent change score Model 2a run to establish whether change in latent measures of working memory over early to mid-adolescence predicts attainment at 16, controlling for socioeconomic status and prior attainment. Filled paths are significant at $p < 0.05$, dashed paths are not significant. Values on the paths are standardized parameter estimates. Color and emboldening are used to highlight the paths central to our predictions. BDS, backward digit span; SWM, spatial working memory. The *x*-axis scale shows the average age at which these measures were taken.

had larger beta coefficients with maths and science than with English (although CIs overlapped; Table 4).

All paths described above remained significant after FDR correction (Table 4).

2.2.4 | Model 4a. Are There Specific SES Associations With WM and Attainment? (H3)

SES indices as well as WM and attainment measures were included separately in Model 4. Model fit was marginal and RMSEA was slightly worse than the previous model (Table 3), likely due to the presence of multiple non-significant paths (reading and writing at age 11 to age 16 maths and some SES effects indicated in Table 5).

As found in previous analyses of these data (Perry et al. 2026), area deprivation and parent education level were not significantly related to change in any WM measure (age 14 controlling for age 12); only parent occupation and FSM predicted change in WM over adolescence (Figure 5 and Table 5). More specifically, BDS span and SWM were significantly predicted by FSM and Corsi span was predicted by parent highest occupation. Only the SES to BDS path remained significant after FDR correction.

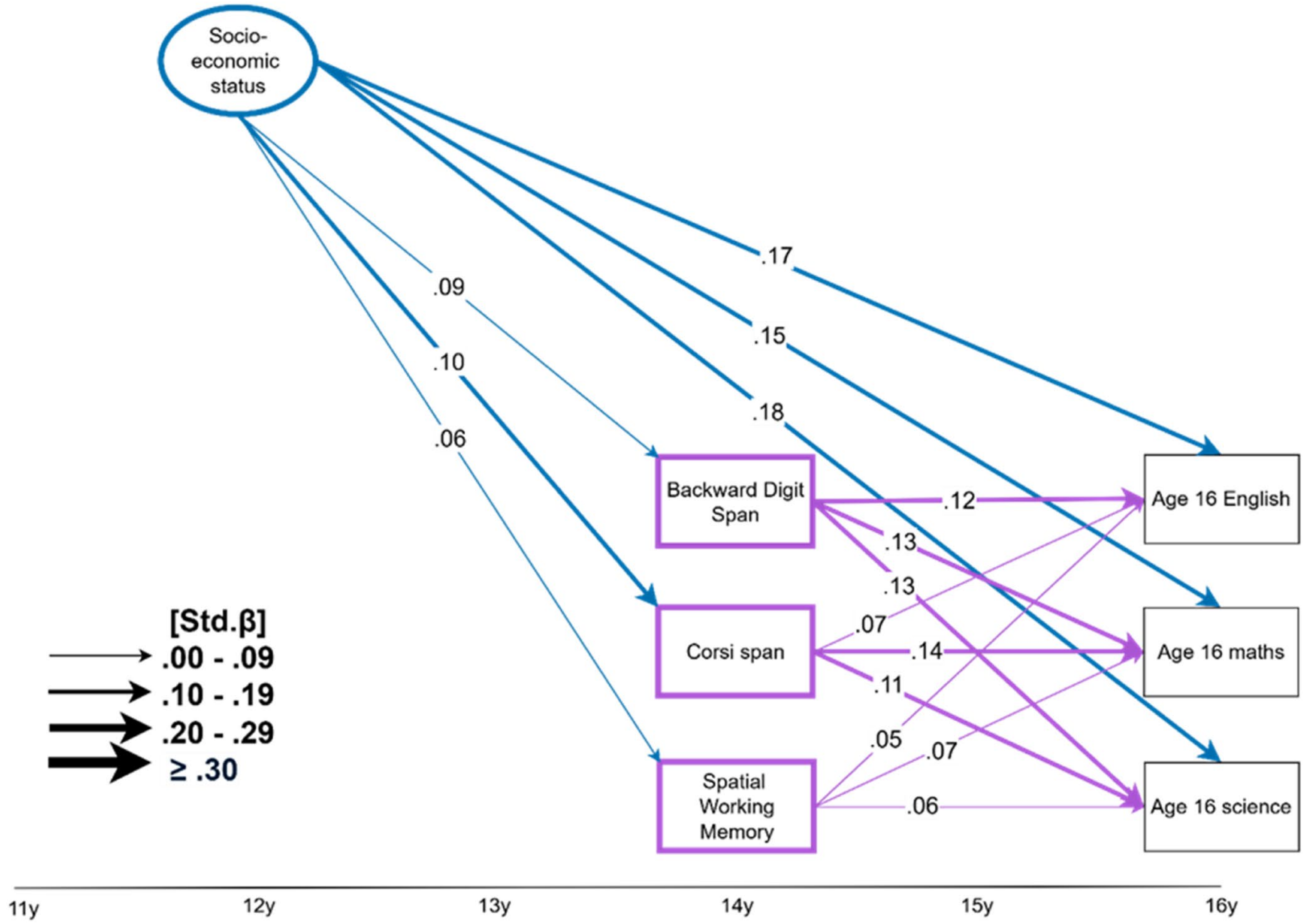

FIGURE 4 | Path diagram of the structural equation model 3a, evaluating specific associations between working memory and age 16 attainment measures. Only regression paths central to our predictions are shown to aid with readability, but this model included T1 WM→T2 WM and Age 14→Age 16 attainment measures predictions. Please see Table 4 for all regression paths estimated in this model. The scale shows the average age (years) at which these measures were taken. Color distinguishes the SES (blue), academic attainment (gray), and WM predictors (purple). Strength of association is indicated by the thickness of arrows. All paths were significant at uncorrected $p < 0.05$.

Contrary to predictions, area deprivation did not predict attainment in any subject at age 16. All other SES indices significantly predicted attainment in each subject, except for parental occupation, which did not significantly directly predict age 16 maths attainment (Figure 5 and Table 5). These results are therefore mostly consistent with H3, in that most SES indices predicted attainment. In addition, all WM change to attainment paths were small and significant, as in Model 3a (Table 5). All significant SES-attainment and WM-attainment paths remained so after FDR correction.

2.2.5 | Does WM Mediate SES-Attainment Associations? (H4)

50,000 Montecarlo simulations were run using semTools to estimate 95% CIs for the indirect and total effects. All mediation paths were tested within the same SEM (Model 3a; the best fitting model with significant paths from SES to WM and SES to attainment, see Figure S5 for the mediation formula).

Change in scores on the three WM measures over adolescence mediated 11% of the SES effect on age 16 English attainment (BDS: 6%; Corsi: 4%; SWM: 1%), 17% for maths (BDS: 7%; Corsi: 8%; SWM: 2%) and 13% for science (BDS: 6%; Corsi: 5%; SWM: 2%) (Figure 6). CIs for the indirect paths did not cross zero, except for the indirect effects of SES on English attainment via Corsi span and SWM. No CIs for the direct paths crossed zero and $c' < c$ for all school subjects, indicating partial mediation. These results are partially consistent with H4: change in all WM measures partially mediated the association between SES and maths and science attainment at age 16. However, only change in verbal WM span mediated the relationship between SES and English attainment.

3 | Discussion

This study explored relationships between SES, change in WM and academic attainment over adolescence. We first showed that SES predicts academic attainment at age 16, controlling for age 11 attainment (full model $R^2 = 0.64$), indicating a growing SES gradient between 11 and 16 years. Change in WM between 12 and 14 years partially mediated the increase in the socioeconomic attainment gradient. However, this effect was only apparent when we looked at subject-specific pathways. Specific

TABLE 4 | Standardized and unstandardised coefficients for the associations of interest between socioeconomic status factor, T2 working memory measures and age 16 attainment in Model 3a.

Path	Std. β [95% CIs]	Raw β [95% CIs]
Socioeconomic status factor→T2 BDS span	**0.09 [0.04–0.14]***	0.09 [0.04–0.13]
Socioeconomic status factor→T2 Corsi span	**0.10 [0.02–0.18]***	0.09 [0.02–0.16]
Socioeconomic status factor→T2 SWM	**0.06 [0.02–0.18]***	0.80 [0.08–1.45]
Socioeconomic status factor→Age 16 English	**0.17 [0.13–0.22]***	0.29 [0.21–0.37]
Socioeconomic status factor→Age 16 maths	**0.15 [0.11–0.19]***	0.28 [0.20–0.36]
Socioeconomic status factor→Age 16 science	**0.18 [0.13–0.22]***	0.33 [0.25–0.42]
Age 14 BDS span→Age 16 English	**0.12 [0.09–0.16]***	0.22 [0.15–0.28]
Age 14 BDS span→Age 16 maths	**0.13 [0.09–0.16]***	0.25 [0.19–0.32]
Age 14 BDS span→Age 16 science	**0.13 [0.10–0.17]***	0.27 [0.20–0.34]
Age 14 Corsi span→Age 16 English	**0.07 [0.02–0.12]***	0.13 [0.03–0.23]
Age 14 Corsi span→Age 16 maths	**0.14 [0.10–0.19]***	0.31 [0.21–0.40]
Age 14 Corsi span→Age 16 science	**0.11 [0.06–0.16]***	0.23 [0.13–0.33]
Age 14 SWM→Age 16 English	**0.05 [0.01–0.09]***	0.01 [0.00–0.01]
Age 14 SWM→Age 16 maths	**0.07 [0.03–0.10]***	0.01 [0.01–0.02]
Age 14 SWM→Age 16 science	**0.06 [0.03–0.10]***	0.01 [0.00–0.02]

Note: Bold standardized β indicate p-values < 0.05 after FDR correction.
Abbreviations: BDS, backward digit span; CIs, confidence intervals; SWM, spatial working memory task.
*$p < 0.05$.
**$p < 0.01$.
***$p < 0.001$.

associations were also observed between SES indices, verbal and visuospatial WM, and academic subjects.

Consistent with national trends (Education Policy Institute 2023), our results suggest that SES continues to impact academic progression during adolescence in England. Supplementary analyses showed that supposed SES effects were not driven by school quality, gender, ethnicity, or first language status. Adding latent change in WM from 12 to 14 years old explained 11% of additional variance in age 16 attainment, with a medium-sized association between change in WM and change in attainment.

Previous longitudinal studies in this area were limited as they did not have repeated measures of cognition and attainment, so any associations they observed could be due to residual confounding. Donati, Meaburn, and Dumontheil (2019) observed that a latent factor of different WM measures collected at ages 10–17 years explained significant variance in age 16 attainment in English, maths, and Science, controlling for age 11 attainment. Here we extend these findings to show that changes in WM skills over adolescence are associated with change in attainment in the three core subjects, providing stronger evidence for a developmental relationship between WM and attainment.

Our model explained most variance in maths (54%) and least in English (40%) progress, partly because maths showed particularly strong longitudinal stability (see Table S1). The SES factor had similar strength associations with longitudinal change in attainment across science, maths, and English. A 1 SD change on the SES factor (equivalent to an increase from the 50th to the 84th SES percentile) was associated with an increase of around a third of a GCSE grade. Significant associations between SES and specific school subjects suggest that SES is related to individual differences in the development of skills and knowledge uniquely assessed in English, maths, and science over adolescence. This may reflect that growing up in a low SES family limits students from pursuing learning experiences that align with their interests and strengths (e.g., Tucker-Drob and Briley 2012). The relationship of SES with change in scores on a latent factor of attainment was smaller and non-significant, suggesting SES is not related to the development of generic academic skills during this period.

This study is unique in that we were able to isolate associations of SES with attainment and WM during adolescence from effects that unfold earlier in development. Without controlling for prior attainment, Albert et al. (2020) found verbal WM, but not visuospatial WM, partially mediated the relationship between SES and maths and English (reading) attainment during adolescence. We extend on this work to show that change in both verbal and visuospatial WM accounts for some of the relationship between SES and change in attainment in maths and science from 11 to 16 years (mediation ratios = 11%–17%) but only verbal WM mediated the SES to English attainment relationship.

TABLE 5 | Standardized and unstandardised coefficients for the associations between socioeconomic status indices, T2 working memory measures and attainment at age 16 in English, maths, and science in Model 4a.

	Age 16 English		Age 16 Maths		Age 16 Science		Age 14 BDS span		Age 14 Corsi span		Age 14 SWM	
	Std. β [95% CIs]	Raw β [95% CIs]	Std. β [95% CIs]	Raw β [95% CIs]	Std. β [95% CIs]	Raw β [95% CIs]	Std. β [95% CIs]	Raw β [95% CIs]	Std. β [95% CIs]	Raw β [95% CIs]	Std. β [95% CIs]	Raw β [95% CIs]
Parent education	**0.06**** **[0.02–0.10]**	0.12 [0.04–0.19]	**0.06**** **[0.02–0.09]**	0.13 [0.05 to 0.20]	**0.07**** **[0.03–0.10]**	0.14 [0.06–0.22]	0.02 [−0.02 to 0.06]	0.02 [−0.02 to 0.07]	0.00 [−0.07 to 0.07]	0.00 [−0.07 to 0.07]	−0.03 [−0.08 to 0.02]	−0.40 [−1.08 to 0.30]
Parent occupation	**0.05**** **[0.02–0.09]**	0.05 [0.01–0.08]	0.03 [−0.01 to 0.06]	0.02 [−0.01 to 0.06]	**0.05**** **[0.02–0.09]**	0.05 [0.02–0.09]	0.04 [0.00–0.08]	0.02 [0.00–0.04]	0.08* [0.01–0.14]	0.04 [0.01–0.06]	0.04 [−0.01 to 0.08]	0.23 [−0.52 to 0.05]
FSM	**0.07***** **[0.04–0.10]**	0.30 [0.16–0.43]	**0.09***** **[0.06–0.12]**	0.43 [0.29–0.57]	**0.09***** **[0.05–0.12]**	0.41 [0.26–0.56]	**0.06**** **[0.02–0.09]**	0.14 [0.05–0.22]	0.02 [−0.03 to 0.08]	0.05 [−0.07 to 0.17]	0.05* [0.01–0.09]	1.47 [0.21–2.73]
Area deprivation	0.02 [0.01–0.06]	0.03 [0.01–0.08]	0.02 [−0.01 to 0.05]	0.03 [−0.02 to 0.07]	0.01 [−0.02 to 0.04]	0.02 [−0.03 to 0.07]	0.01 [−0.03 to 0.04]	0.00 [−0.02 to 0.03]	0.02 [−0.04 to 0.09]	0.02 [−0.03 to 0.06]	0.03 [−0.01 to 0.07]	0.30 [−0.11 to 0.70]
Age 14 BDS span	**0.13***** **[0.09–0.16]**	0.22 [0.16–0.29]	**0.13***** **[0.10–0.16]**	0.26 [0.19–0.32]	**0.14***** **[0.10–0.17]**	0.27 [0.20–0.34]						
Age 14 Corsi span	**0.08**** **[0.03–0.13]**	0.14 [0.05–0.24]	**0.15***** **[0.10–0.16]**	0.32 [0.23–0.42]	**0.11***** **[0.07–0.16]**	0.25 [0.15–0.35]						
Age 14 SWM	**0.05**** **[0.01–0.09]**	0.01 [0.00–0.01]	**0.07***** **[0.04–0.10]**	0.01 [0.01–0.02]	**0.07***** **[0.03–0.10]**	0.01 [0.01–0.02]						

Note: Bold standardized β indicate p-values < 0.05 after FDR correction.
Abbreviations: BDS, backward digit span; CIs, confidence intervals; SWM, spatial working memory task.
*$p < 0.05$.
**$p < 0.01$.
***$p < 0.001$.

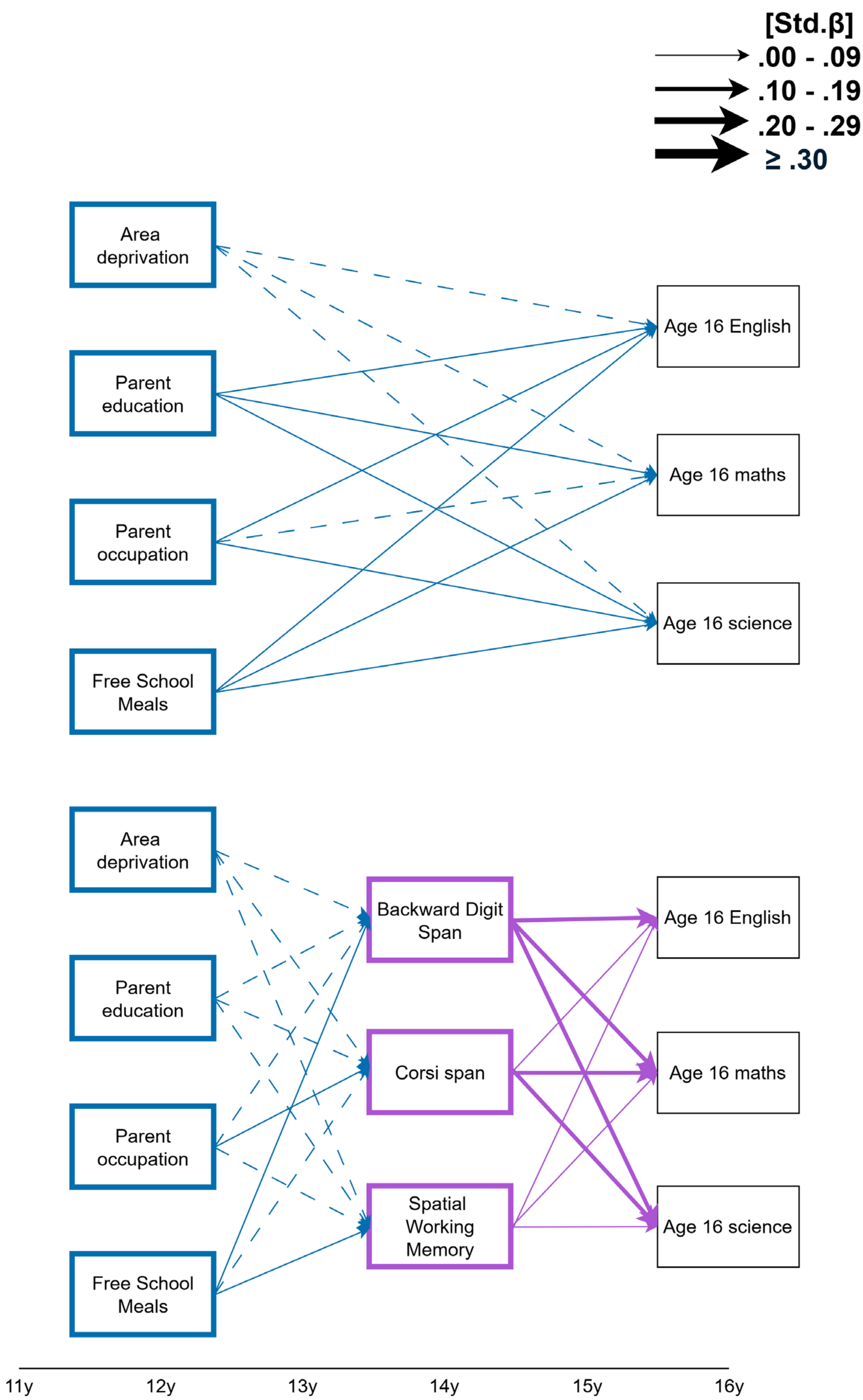

FIGURE 5 | Diagram of the paths tested in structural equation Model 4a, evaluating specific associations between socioeconomic status indices and working memory and age 16 attainment measures. Only regression paths central to our predictions are shown and we have split the model up into its key components to aid with readability. Please see Table 5 for all regression paths estimated in this model. The *x*-axis scale shows the average age at which these measures were taken. Color distinguishes the SES (blue), academic attainment (gray), and WM (purple) variables and associated parameter estimates. Strength of association is indicated by the thickness of arrows. Filled paths are significant at uncorrected $p < 0.05$, dashed paths are not significant.

Another contribution of this study is to demonstrate that treating WM measures separately (as opposed to grouping them as a latent factor) better captures the full extent of socioeconomic effects. Since our models provided inconsistent evidence for SES effects on WM, a replication of the mediation effect observed here is needed.

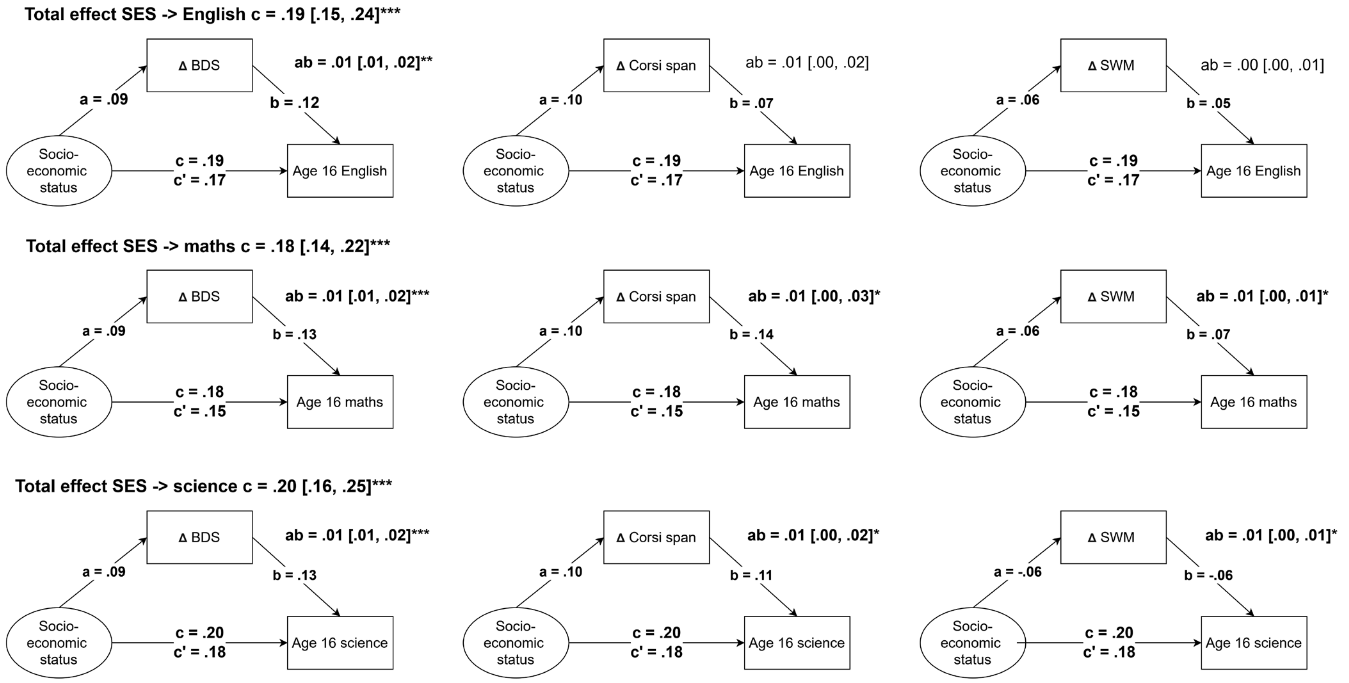

FIGURE 6 | Standardized beta estimates and Montecarlo 95% CIs for the mediation tested within Model 3a. *c* is the total effect of the socioeconomic status factor on age 16 attainment, *c′* is the direct effect of socioeconomic status on attainment (i.e., the effect of socioeconomic status on attainment not via working memory), ab is the indirect effect of socioeconomic status via change in working memory. Significant effects are in bold and the significance levels of total and indirect effects are indicated using asterisks: $^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. Table 4 shows the significance levels of *a*, *b* and *c* paths. BDS, backward digit span; SWM, spatial working memory task.

Our findings should also be interpreted with the understanding that WM measures are not pure tests of the skill they intend to measure. Our previous research in this sample (Perry et al. 2026) showed that WM tasks, and not other EF tasks, show an increasing SES gradient during adolescence, suggesting that our results are not explained by other executive demands of the tasks. However, we were unable to isolate WM demands from the other skills the tasks tap (e.g., language; Pluck et al. 2021) due to a lack of available measures in this dataset.

By looking at the pathways from different SES indices to attainment via cognition, we provide important new evidence needed to inform a mechanistic understanding of social inequalities in attainment during adolescence. In this study, parental occupation and household poverty (FSM) predicted attainment in the three core subjects at 16 and change in performance on one or more WM measures. Studies in younger children have similarly found that parental occupation and income have independent effects on educational attainment and cognitive skills (Pensiero and Schoon 2019; Schoon et al. 2021). However, since we looked at growth in cognitive skills and attainment, the causal explanation for our findings must be activities/experiences that take place in adolescence. Partial mediations of SES-attainment effects by WM suggest that families' sociocultural and economic resources have separable promotive effects on adolescent cognitive development, with downstream consequences for academic outcomes (see Bukodi and Goldthorpe 2013).

Consistent with a US longitudinal study (Hackman et al. 2014), we found no significant increase in the parental education gradient in WM over adolescence. However, parental education had direct associations with change in attainment during adolescence, which may be explained by parents' ability to help with schoolwork and academic pressure (e.g., Davis-Kean et al. 2019) and genetic influences on attainment (e.g., in von Stumm et al. 2020 genome-wide polygenic scores predicted 14% of the variance in age 16 attainment). Parent education effects are likely to be weaker in SCAMP compared to older UK datasets and datasets from other countries as increasing numbers of adults in the UK hold a first degree (Bolton 2024), thanks to reduced financial barriers to accessing higher education.

We observed no effects of area deprivation on changes in WM (as in Hackman et al. 2014) or change in attainment during adolescence. This is consistent with a systematic review which showed that area deprivation has smaller effects on attainment than other SES indicators (Sirin 2005). Studies of neighborhood deprivation and adolescent attainment typically only account for parent education when trying to remove the confounding effect of family level factors (e.g., McDool 2017; Nieuwenhuis et al. 2021; Weinberg et al. 2019) and may therefore not fully isolate neighborhood effects.

Mediation effects were weak in this study; only 11%–17% of the relationship between SES and educational attainment was mediated by performance on the WM tasks. This may in part be because we looked at change in a single aspect of cognition over just 2 years. Other processes at work likely include SES pupils' decreasing confidence in their intelligence and ability to grow their skills and increasing disillusionment with education as they progress through school (Caro et al. 2009; Brummelman and Sedikides 2023; Guo 1998). Increased rates of ADHD traits and reduced duration and poorer quality of sleep are also thought to partly explain SES effects on attainment (Buckhalt 2011; van Poortvliet 2024).

In sum, this study has shown that SES-related gaps in attainment widen during adolescence and that this effect could be partly explained by widening gaps in WM. Both verbal and visuospatial WM predicted attainment in maths, science, and English; however, only verbal WM mediated some of the attainment gap in English. Parental education, parental occupation, and household poverty, but not area deprivation, were unique predictors of attainment at age 16, while only parental occupation and household poverty appeared to predict attainment via WM. These results provide a starting point for understanding different pathways from SES to attainment during adolescence. Further research exploring the mechanisms behind educational inequalities in adolescence is needed to help understand how best to support low SES pupils to succeed in schools and beyond.

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Ethics Statement

The original SCAMP study protocol and subsequent amendments were approved by The North West-Haydock Research Ethics Committee. Ethical approval for the linkage of SCAMP data with National Pupil Database data for the purposes of RCP's PhD project was granted by the Imperial College London Research Ethics Committee (Protocol number 14IC2067, version 4, July 29, 2014). A data sharing agreement was drawn up between Birkbeck College and Imperial College, granting RCP permission to securely store and analyze a pseudonymised extract of SCAMP data.

Consent

For data collection in schools, informed consent was first obtained from head teachers and eligible families were provided with information about the study. Students from the SCAMP schools were enrolled into the study if their parents consented to their participation. Parents also consented to data linkage at the stage of first enrolling in the study.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

SCAMP data are not publicly available. However, some data can be shared on request subject to approval by the SCAMP Data Access Committee. Data access requests should be directed to Dr. Mireille B Toledano (Principal Investigator; m.toledano@imperial.ac.uk). The code for the analyses described in this paper will be made available on OSF.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section. **Figure S1:** Path diagrams showing the loadings and error variances for (a) the socioeconomic status factor, (b) the T1 working memory factor, (c) the T2 working memory factor, (d) the age 11 attainment factor, and (e) the age 16 attainment factor. **Table S1:** Correlation matrix for the predictor, mediating, and control variables. **Table S2:** Covariance matrices for the standardized correlations between (a) age 11 attainment measures, (b) socio-economic status (SES) measures, (c) T1 working memory measures, (d) T2 working memory measures, and (e) age 16 attainment measures in models 2 and 3. **Supporting Analysis A**. Controlling for gender, ethnicity, and first language. **Table S3:** Parameter estimates from Model 1b. **Table S4:** Parameter estimates from Model 3b for (a) paths to attainment and (b) paths to working memory. **Table S5:** Parameter estimates from Model 4b for (a) paths to attainment and (b) paths to working memory. **Supporting Analysis B**. Controlling for school quality. **Figure S2:** Path diagram of structural equation Model 1c with the addition of school quality as a covariate of socio-economic status and a predictor of age 16 attainment. **Figure S3:** Path diagram of structural equation Model 3c with the addition of school quality as a covariate of SES and a predictor of age 16 attainment. **Figure S4:** Path diagram of structural equation Model 4c with the addition of school quality as a covariate of SES and a predictor of age 16 attainment. **Supporting Analysis C**. Converting standardized betas into percentages of a grade. **Figure S5:** Mediation formula.