



OPEN

A genetic risk score of alleles related to MGUS interacts with socioeconomic position in a population-based cohort

Lisa Baak¹, Mirjam Frank¹, Jan Dürig², Ulrich Dührsen², Per Hoffmann³, Markus M. Nöthen³, Nico Dragano⁴, Raimund Erbel¹, Karl-Heinz Jöckel¹ & Børge Schmidt¹✉

Environmental, genetic, and social factors are suggested to jointly influence monoclonal gammopathy of undetermined significance (MGUS), a precursor of multiple myeloma. Aim of this study was to investigate interactions between MGUS-related genetic variants and socioeconomic position (SEP) indicators education and income on MGUS in a population-based study. Two different MGUS-related genetic risk allele sum scores (GRS) were calculated based on recent genome-wide meta-analyses. Odds Ratios (OR) were estimated in 4329 participants including 238 MGUS cases to assess associations and multiplicative interaction. The relative excess risk due to interaction (RERI) was calculated to assess additive interaction. Both GRSs were associated with MGUS. A multiplicative interaction between one GRS and education was observed with genetic effects of OR 1.34 (95% CI 1.11–1.62) per risk allele in the highest and OR 1.06 (95% CI 0.86–1.31) in the lowest education group. A RERI of 0.10 (95% CI 0.05–0.14) also indicated additive interaction. Further, additive GRS by income interaction (RERI 0.07; 95% CI 0.01–0.13) for the same GRS was also indicated. Results indicate interaction between MGUS-related genetic risk and SEP. Non-genetic MGUS risk factors more common in higher education groups may influence the expression of MGUS-related genetic variants.

Monoclonal gammopathy of undetermined significance (MGUS) is an asymptomatic premalignant plasma-cell dyscrasia that is characterised by the presence of a monoclonal immunoglobulin (M-Protein). The prevalence of MGUS increases from age 50 onwards and its clinical relevance lies in the inherent risk of progression to hematologic malignancies such as multiple myeloma or other lymphoproliferative disorders as well as amyloidosis or light-chain deposition disease at an annual rate of ~1%^{1,2}.

Case reports of familial clustering of multiple myeloma and case-control as well as cohort studies have provided strong evidence for increased risk of MGUS or multiple myeloma in first-degree relatives of affected patients^{3–8}. In addition, several genome-wide association studies (GWASs) have identified multiple risk loci for MGUS and multiple myeloma. So far, common genetic variants at 23 loci have been associated with multiple myeloma risk^{9–13}, which have also been shown to be at least weakly associated with MGUS^{14–16}. However, genetic susceptibility of MGUS has only been studied to a limited extent, with two interrelated GWASs each identifying 10 different risk loci with suggestive evidence of genome-wide association^{15,17}. Like other polygenic risk factors for complex disorders, MGUS-related risk alleles only show small to moderate individual effects on the respective outcome. One explanation for this are possible gene-environment interactions.

Although preventable risk factors for MGUS are still largely unknown, inequalities in socioeconomic position (SEP) are discussed alongside other factors such as obesity, diabetes, smoking, diet, and other lifestyle factors as well as pesticide exposure and occupational factors^{18–23}. However, most studies on modifiable risk factors have shown inconclusive results. So far, only one population-based study have indicated a positive association between SEP and MGUS while considering other discussed risk factors potentially mediating this effect²³. As SEP can serve as a context defining variable that describes overall differences in risk-associated environments

¹Institute for Medical Informatics, Biometry and Epidemiology, University Hospital Essen, University of Duisburg-Essen, Hufelandstr. 55, 45122 Essen, Germany. ²Department of Haematology, University Hospital Essen, University of Duisburg-Essen, Essen, Germany. ³Institute of Human Genetics, School of Medicine and University Hospital Bonn, University of Bonn, Bonn, Germany. ⁴Institute of Medical Sociology, Medical Faculty, Centre for Health and Society, University of Düsseldorf, Düsseldorf, Germany. ✉email: boerge.schmidt@uk-essen.de

and health behaviours, it is hypothesized that SEP may affect disease via its influence on the social distribution of specific risk factors, which in turn have an impact on gene expression (i.e., gene-environment interaction)^{24,25}.

The aim of this study was (1) to replicate the cumulative effect of genetic risk allele sum scores (GRSs) predisposing to MGUS using an independent sample of MGUS cases and (2) to investigate possible interactions between the GRSs and indicators of SEP (i.e., education and income) in a population based study cohort, where positive associations between indicators of SEP and MGUS have already been shown²³. We calculated two separate MGUS GRSs each comprising 10 different risk loci from previous GWASs published in 2017¹⁷ and 2019¹⁵. To explore whether any detected GRS by SEP interactions are mediated by underlying interactions with other suggested MGUS risk factors, risk factors that were available for analysis in the study population (i.e., obesity, diabetes, smoking, dietary factors such as low fish, vegetable, and fruit consumption) were included in the analysis. As MGUS is one of the most common premalignant disorders in the general population, gaining a better understanding of the underlying causes and their interaction is important for the identification of factors suitable for disease prevention.

Methods

Study population. The present study is based on data of the prospective population-based Heinz Nixdorf Recall Study. The design and rationale of the study has been described in detail elsewhere²⁶. Briefly, 4814 participants aged 45–75 years were recruited from 2000 to 2003 from three adjacent cities (Bochum, Essen, Mülheim/Ruhr) in an urban region in the western part of Germany. The first follow-up examination took place after a median time of ~5.1 years between 2005 and 2008, the second follow-up took place ~10.3 years after baseline between 2010 and 2015. The baseline response proportion of invited random sample of the population was 55.8%²⁷. The study was approved by the ethics committee of the University of Duisburg-Essen and comprises extended quality management procedures including a certification according to DIN ISO 9001:2000. Written informed consent was obtained from all participants.

Monoclonal gammopathy of undetermined significance (MGUS). Serum samples were collected at baseline and prospectively at the 5-year and the 10-year follow-up examination at each visit and stored at –80 °C. MGUS was assessed using standard serum electrophoresis combined with parallel screening immunofixation electrophoresis (scIFE) using pentavalent antisera (Hydragel 12 IF, Penta-Kit, Sebia, Fulda, Germany). In samples showing a visible or suspected monoclonal band, confirmatory IFE was performed using antisera against γ , α , μ , κ , and λ immunoglobulin chains. Results were assessed by a trained physician and MGUS cases were defined according to the International Myeloma Working Group criteria (i.e., including information on the detectable monoclonal protein on SPE and/or IFE, monoclonal protein concentration, laboratory results, and disease history)²⁸.

Free kappa (κ) and free lambda (λ) immunoglobulin light chains (FLC) were determined using a Dade Behring BNII automated nephelometer (Siemens, Germany) utilizing a commercially available kit (FREELITE, The Binding Site Ltd, Birmingham, UK). Published ranges for κ and λ FLC were used as reference (3.3–19.4 mg/L and 5.7–26.3 mg/L, respectively)²⁹. A pathological κ/λ FLC ratio was defined as <0.26 or >1.65 for participants with an estimated glomerular filtration rate (eGFR) of >30 mL/min and as <0.37 or >3.1 for participants with an eGFR of <30 mL/min³⁰.

Genetic data. Lymphocyte DNA was extracted from EDTA venous blood samples using the Chemagic Magnetic Separation Module I (Chemagen, Baesweiler, Germany) and genotyped using different Illumina microarrays according to the manufacturer's protocols. Data from different Illumina genome-wide chips were imputed and then combined (Omni1-Quad $n=779$, Omni1S $n=1348$, HumanCoreExome $n=1747$, Illumina OmniExpressv1.0 $n=457$) resulting in a population of $n=4331$ participants with an imputation quality of >0.97 for all selected SNPs. Prior to imputation, quality control was applied separately for each chip on subject level including sex-, ethnicity- and relatedness-checks, excluding subjects with missing genotype data $>5\%$. Further, SNPs with a minor allele frequency (MAF) $<1\%$, a missing genotype frequency $>5\%$ or a deviation from Hardy-Weinberg Equilibrium (HWE) ($p < 10^{-5}$) were excluded. Imputation was carried out using IMPUTE v.2.3.1³¹ with reference data from 1000 Phase 3, release October 2014.

Two unweighted genetic risk allele sum scores for MGUS were constructed based on previous genome-wide association studies (GWAS) published in 2017¹⁷ (GRS_{MGUS2017}) and 2019¹⁵ (GRS_{MGUS2019}). Each GWAS had identified 10 loci associated with MGUS at a p value threshold of $<10^{-5}$. Of the GRS_{MGUS2017} risk loci, one SNP (rs10744861) was not available for 3874 participants. Therefore, we used rs1816225 as a proxy marker for those participants, which was in linkage disequilibrium of $r^2=0.86$, based on European populations (CEU, TSI, FIN, GBR and IBS). Likewise, rs74998556 was used as a proxy marker with $r^2=0.73$ for one SNP (rs74998556) of the GRS_{MGUS2019} score that was not available for 457 participants. The GRSs were then calculated by summing the total number of risk alleles for each individual across the selected SNPs.

Indicators of SEP. Information on education and income was assessed by standardized face-to-face interviews at baseline examination. Education was defined as total years of formal education by combining school and vocational training according to the International Standard Classification of Education (ISCED-97)³². Education was included in all SEP stratified analyses categorized into four groups with the lowest educational group of ≤ 10 years (equivalent to a basic school degree with no vocational training) and the highest educational group of ≥ 18 years of education. For all regression models including SEP indicators education was dichotomized into low education (<14 years) vs. high education (≥ 14 years). Income was defined as the monthly household equivalent income calculated by dividing the total household net income by a weighting factor for each house-

hold member³³. Income was included in all SEP stratified analyses as a categorized variable using sex-specific quartiles. Income was dichotomized using sex specific medians for all regression models including SEP indicators. To take into account different mechanisms causing health inequalities, both SEP indicators were analysed separately^{34,35}.

Potential risk factors. Data on potential risk factors for MGUS were collected at study baseline (i.e., smoking, obesity, diabetes, low dietary intake of fish, vegetables, and fruits). Information on smoking was dichotomised into one group comprising current and past smoking (smoking cigarettes during the past year or having a history of smoking before the past year), and the second group of never smoking. Obesity was defined according to WHO criteria for individuals having a body mass index of 30 or more, utilizing standardized measurements of height and weight (kg/m²). Diabetes mellitus was defined as either of the following criteria: nonfasting glucose levels of 200 mg/dL or greater, fasting blood glucose levels of greater than 125 mg/dL, a reported history of diabetes mellitus, or intake of glucose lowering drugs. Dietary intake was assessed by a validated food frequency questionnaire (FFQ)³⁶. Frequency of consumption was assessed using a five-point scale with the categories daily, 4–6 times/week, 1–3 times/week, 1–3 times/month, and hardly ever/never for each food item. Based on the FFQ, information for boiled vegetable, raw vegetable, and fruit consumption was dichotomized into low consumption (1–3 times/week or less) vs. high consumption (at least 4–6 times/week). Fish consumption was dichotomized into low consumption (1–3 times/month) vs. high consumption (at least 1–3 times/week)³⁷.

Statistical analyses. For the main analyses, 4329 participants with non-missing information on MGUS and genetic variants were included (Figure S1). Additional missing information on education (n = 12) and income (n = 267), smoking status (n = 6), obesity (n = 21), and dietary factors (n = 65–71) led to the exclusion of these participants from the respective analyses. Participants with missing information on income or education did not differ in rates of MGUS or in the GRS distribution compared to the analysis population. All analyses included both, prevalent MGUS cases at baseline and incident MGUS cases at the 5- and 10-year follow-up examination (i.e., having MGUS at least at one of the three examination dates).

First, age- and sex-adjusted logistic regression models were fitted to calculate odds ratios (OR) and their corresponding 95% confidence intervals (95% CI) to detect associations of the two SEP indicators and the two GRSs with MGUS in four separate regression models. In addition, the age- and sex-adjusted effect of the two GRSs on MGUS was also calculated stratified by SEP groups.

Second, to assess GRSxSEP interactions on the multiplicative scale, the GRS and SEP main effects as well as GRSxSEP interaction terms were included separately for the SEP indicators education and income as dichotomized variables in the regression models (base models). The regression coefficient of the interaction term in the logistic regression models calculated here reflect interaction on a multiplicative scale; however, it has been proposed that interaction described as departure from additivity of effects on disease events is better suited for indicating biological interaction³⁸. Hence, the relative excess risk due to interaction (RERI) and the corresponding 95% CI was calculated to estimate interaction on the additive scale utilizing the regression coefficients of the logistic regression models including interaction terms.

Third, single reference joint effects of the GRS and SEP indicators were assessed by grouping GRS tertiles and SEP categories in all possible combinations into dummy variables that were then entered in regression models with the group of lowest GRS and lowest SEP as reference.

Finally, to investigate whether suspected GRSxSEP interactions were mediated by underlying interactions involving other potential MGUS risk factors, the base model was extended by GRS by risk factor and SEP by risk factor interaction terms and respective main effects in separate models for each risk factor. Single SNP analyses were performed accordingly assuming an additive genetic model. All analyses were performed using the statistical computing software R v3.5.3³⁹ and Plink v1.07 for single SNP analyses for Windows⁴⁰.

Results

Characteristics of the study population are presented in Table 1. The total number of MGUS cases was 238 (5.5%) with women having a lower risk of MGUS than men. Clinical characteristics of MGUS cases are presented in Table S1. Mean values and standard deviations of MGUS-GRSs were 5.3 ± 2.0 (GRS_{MGUS2017}) and 9.0 ± 1.9 (GRS_{MGUS2019}), respectively. Both GRSs showed slightly higher average numbers of risk alleles for participants diagnosed with MGUS compared to non-MGUS participants.

As expected, single SNP associations showed no genome-wide significance; however, magnitude and direction of effects were consistent to those reported in the original GWAS for 9/10 of the GRS_{MGUS2017}-SNPs and 7/10 of the GRS_{MGUS2019}-SNPs (Tables S2–S3). Both GRSs were associated with MGUS risk (GRS_{MGUS2017}: OR, 1.08; 95% CI, 1.01–1.15; and GRS_{MGUS2019}: OR, 1.12; 95% CI 1.04–1.20 per additional risk allele; Table 2). Both SEP indicators were also associated with MGUS in separate logistic regression models (Table 2). With the low education group (< 14 years of training) as reference, an OR of 1.43 (95% CI 1.07–1.90) was observed for the high education group (≥ 14 years of training). Similarly, the high income group (income > sex-specific median) showed an OR of 1.38 (95% CI 1.05–1.82) (Table 2).

Stratified analyses for the genetic effect on MGUS indicated stronger effects of the GRS_{MGUS2017} in higher SEP groups (Fig. 1), with the strongest effect in the highest education group (OR 1.34; 95% CI 1.11–1.62 per additional risk allele). A similar, although less pronounced trend of GRS_{MGUS2017} effects was observed for income quartiles with higher associations in Q2–Q4 compared to the lowest quartile. Associations of the GRS_{MGUS2019} were also stronger in the highest education group compared to the lower education groups; however, a strong effect of GRS_{MGUS2019} was also observed in the lowest education group. No clear trend was observed for the GRS_{MGUS2019} effect stratified by income (Fig. 1).

	All	MGUS	no MGUS
<i>n</i>	4329 (100%)	238 (5.5%)	4091 (94.5%)
Age (years)*	59.6 (± 7.8)	61.9 (± 7.7)	59.5 (± 7.8)
Sex (female)†	2165 (50.0%)	94 (39.5%)	2071 (50.6%)
GRS _{MGUS2017} *	5.3 (± 2.0)	5.6 (± 2.1)	5.3 (± 2.0)
GRS _{MGUS2019} *	9.0 (± 1.9)	9.3 (± 2.0)	8.9 (± 1.9)
Education (years of training)‡ [n _{miss} = 12]			
< = 10 years	486 (11.3%)	20 (8.4%)	466 (11.4%)
11–13 years	2409 (55.8%)	119 (50.2%)	2290 (56.1%)
14–17 years	972 (22.5%)	66 (27.8%)	906 (22.2%)
> = 18 years	450 (10.4%)	32 (13.5%)	418 (10.2%)
Income (€/month)‡ [n _{miss} = 267]			
Current or past smoking† [n _{miss} = 6]	2517 (58.2%)	149 (62.6%)	2368 (60.0%)
Obesity† (BMI ≥ 30) [n _{miss} = 21]	1177 (29.1%)	74 (31.2%)	1103 (27.1%)
Diabetes mellitus†	588 (13.6%)	43 (18.1%)	545 (13.3%)
Dietary factors			
Low fish consumption† [n _{miss} = 69]	2694 (63.2%)	148 (63.0%)	2546 (63.3%)
Low boiled vegetables consumption† [n _{miss} = 67]	2695 (63.2%)	157 (66.8%)	2538 (63.0%)
Low raw vegetables consumption† [n _{miss} = 71]	2937 (69.0%)	169 (72.2%)	2768 (68.8%)
Low fruit consumption† [n _{miss} = 65]	1316 (30.8%)	74 (31.5%)	1242 (30.8%)

Table 1. Characteristics of the study population stratified by MGUS status. *Mean (± sd), †Number(%), ‡Median (quartile range).

Model	n (n _{case})	OR (95%CI)	P
GRS _{MGUS2017}	4329 (238)	1.08 (1.01; 1.15)	0.02
GRS _{MGUS2019}	4329 (238)	1.12 (1.04; 1.20)	1.44*10 ⁻³
Education (≥ 14 years)	4317 (237)	1.43 (1.07; 1.90)	0.02
Income (high)	4062 (222)	1.38 (1.05; 1.82)	0.02

Table 2. Sex- and age adjusted odds ratios (OR) and 95% confidence intervals (95% CI) for the main effects on MGUS status in four separate logistic regression models including either the MGUS-associated genetic risk scores (GRS), dichotomized education or income (lower category as reference).

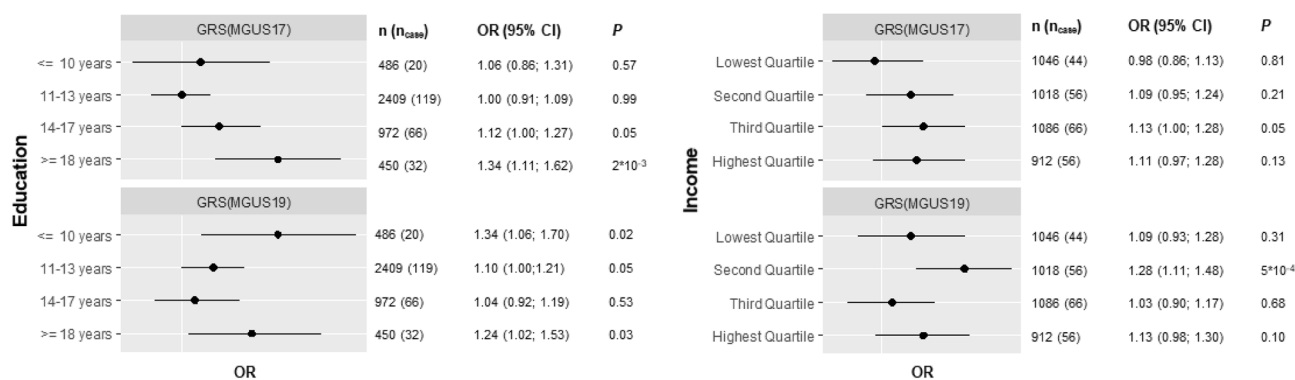


Figure 1. Sex- and age-adjusted odds ratios (OR) and 95% confidence intervals (95% CI) for the effect of genetic risk scores GRS_{MGUS2017} or GRS_{MGUS2019} on MGUS status, stratified by education groups (years) and income quartiles in logistic regression models.

In analyses modelling the interaction between the GRSs and SEP, indication for a GRS_{MGUS2017} by education interaction was observed on the multiplicative scale showing an OR_{interaction} of 1.17 (95% CI 1.03–1.33) per additional risk allele for high (≥ 14 years) compared to low (< 14 years) education (Table 3). The RERI reflecting additive GRS_{MGUS2017} by education interaction effect on MGUS was 0.10 (95% CI 0.05–0.14) for high (≥ 14 years) vs. low (< 14 years) education (Table 3). Further, there was also indication for additive GRS_{MGUS2017} by income

	MGUS-Education+GRS _{MGUS2017} (<i>n</i> =431/ <i>n</i> _{ref} =237)		MGUS-Education+GRS _{MGUS2019} (<i>n</i> =431/ <i>n</i> _{ref} =237)		MGUS-Income+GRS _{MGUS2017} (<i>n</i> =406/ <i>n</i> _{ref} =222)		MGUS-Income+GRS _{MGUS2019} (<i>n</i> =406/ <i>n</i> _{ref} =222)	
	OR (95% CI)	<i>P</i>	OR (95% CI)	<i>P</i>	OR (95% CI)	<i>P</i>	OR (95% CI)	<i>P</i>
Age	1.04 (1.02; 1.06)	2.49*10 ⁻⁰⁶	1.04 (1.03; 1.06)	1.98*10 ⁻⁰⁶	1.04 (1.02; 1.06)	4.22*10 ⁻⁰⁶	1.04 (1.03; 1.06)	2.73*10 ⁻⁰⁶
Sex (male)	1.39 (1.05; 1.86)	0.02	1.41 (1.07; 1.89)	0.02	1.60 (1.21; 2.12)	9.90*10 ⁻³	1.62 (1.23; 2.16)	6.88*10 ⁻⁴
GRS _{MGUS2017}	1.01 (0.93; 1.10)	0.81			1.04 (0.94; 1.14)	0.44		
GRS _{MGUS2019}			1.14 (1.04; 1.24)	5*10 ⁻³			1.19 (1.07; 1.32)	1.34*10 ⁻³
Education (≥ 14 years)	0.58 (0.26; 1.27)	0.17	1.95 (0.52; 7.23)	0.32				
Education x GRS _{MGUS2017}	1.17 (1.03; 1.33)	0.02						
Education x GRS _{MGUS2019}			0.97 (0.84; 1.11)	0.64				
Income (> median)					0.89 (0.40; 1.95)	0.76	3.62 (0.94; 14.09)	0.06
Income x GRS _{MGUS2017}					1.08 (0.95; 1.24)	0.24		
Income x GRS _{MGUS2019}							0.90 (0.78; 1.04)	0.16
RERI (95% CI)	0.10 (0.05; 0.14)		0.06 (-0.03; 0.14)		0.07 (0.01; 0.13)		0.07 (-0.14; 0.28)	

Table 3. Sex- and age-adjusted odds ratios (OR) and 95% confidence intervals (95% CI) for the effects on MGUS status in logistic regression models including main effects and interaction terms of the genetic effect (GRS_{MGUS}) and dichotomised education or income as indicators of socioeconomic position (SEP) with the lower SEP category as reference group (relative excess risk due to interaction, RERI).

interaction on MGUS (RERI: 0.07; 95% CI 0.01–0.13 for high compared to low income). No indication for interaction was observed for using GRS_{MGUS2019} in the analyses (Table 3).

The analysis of single reference joint effects of GRS_{MGUS2017} and SEP indicators on MGUS showed an increasing trend of effect size estimates with increasing years of education in groups with the highest GRS_{MGUS2017} tertile (Table 4). Compared to the reference group with the lowest education and lowest GRS_{MGUS2017} tertile, participants within the highest GRS_{MGUS2017} tertile and highest education category showed on average a fivefold higher MGUS risk (OR 4.99; 95% CI 1.87–15.77). Single reference joint effect analyses of income and GRS_{MGUS2017} also indicated the strongest MGUS risk for participants within the highest income quartile and highest GRS_{MGUS2017} tertile compared to the reference group (Table 4).

The addition of interaction terms with other potential MGUS-risk factors (i.e., smoking, obesity, diabetes, low dietary intake of fish, vegetables, and fruits) to the logistic regression model including the GRS_{MGUS2017} × Education interaction term did not substantially change the effect size estimate of the GRS_{MGUS2017} × Education interaction, neither on the multiplicative nor on the additive scale (Table 5).

In the single SNP interaction analysis using education as SEP indicator, 7 of the 10 SNPs included in the GRS_{MGUS2017} were directionally consistent to the overall GRS_{MGUS2017} by education interaction effect on the multiplicative scale (Table S4), while this was true for 8 of the 10 SNPs regarding interaction on the additive scale. SNP rs3118053 presented the strongest indication for interaction with education on both scales.

Discussion

The aim of this study was (1) the replication of cumulative genetic risk factors predisposing to MGUS and (2) to investigate possible interactions between genetic risk allele sum scores and indicators of SEP and their impact on MGUS in a population-based study cohort employing MGUS cases not included in previous GWAS. Associations of two different sum scores of MGUS-related genetic variants with MGUS were observed. In addition, results gave indication for positive interaction between one MGUS-related GRS (GRS_{MGUS2017}) and SEP indicator education on both the additive and multiplicative scale and for income on the additive scale, resulting in stronger associations between MGUS-related genetic risk and MGUS in higher SEP groups. Effect size estimates for the GRS_{MGUS2017} by education interaction remained unchanged after including discussed MGUS risk factors (i.e., smoking, obesity, diabetes, low dietary intake of fish, vegetables, and fruits) into regression analysis, suggesting that these factors do not explain the observed GRS_{MGUS2017} by education interaction. Further, results of stratified analyses support the suspected interaction with the strongest genetic effect on MGUS observed in the highest education group. In addition, joint effects of all possible combinations of GRS_{MGUS2017} tertiles and education groups showed the strongest effect on MGUS for participants with highest genetic risk within the highest education group.

In the present study, the cumulative effect of MGUS-related genetic risk alleles reported in two different GWAS by Thomsen et al.^{15,17} was replicated utilising cumulative GRSS. The associations between SNPs effect

	n (n _{case})	OR	95%CI	P
Education				
Education ≤ 10 years				
GRS _{MGUS2017} lower tertile	160 (5)	Ref
GRS _{MGUS2017} middle tertile	188 (10)	1.77	0.62; 5.81	0.31
GRS _{MGUS2017} highest tertile	138 (5)	1.22	0.33; 4.47	0.76
Education 11–13 years				
GRS _{MGUS2017} lower tertile	791 (45)	2.07	0.88; 6.07	0.13
GRS _{MGUS2017} middle tertile	870 (39)	1.62	0.68; 4.77	0.32
GRS _{MGUS2017} highest tertile	748 (35)	1.68	0.70; 4.97	0.29
Education 14–17 years				
GRS _{MGUS2017} lower tertile	347 (20)	1.94	0.75; 6.01	0.20
GRS _{MGUS2017} middle tertile	326 (18)	1.88	0.72; 5.86	0.23
GRS _{MGUS2017} highest tertile	299 (28)	3.20	1.29; 9.71	0.02
Education ≥ 18 years				
GRS _{MGUS2017} lower tertile	147 (7)	1.84	0.57; 6.45	0.31
GRS _{MGUS2017} middle tertile	160 (8)	1.93	0.62; 6.61	0.26
GRS _{MGUS2017} highest tertile	143 (17)	4.99	1.87; 15.77	2.59*10 ⁻³
Income				
Income Q1				
GRS _{MGUS2017} lower tertile	338 (15)	Ref
GRS _{MGUS2017} middle tertile	360 (21)	1.34	0.71; 2.80	0.34
GRS _{MGUS2017} highest tertile	348 (8)	0.51	0.20; 1.20	0.13
Income Q2				
GRS _{MGUS2017} lower tertile	358 (18)	1.24	0.61; 2.53	0.56
GRS _{MGUS2017} middle tertile	359 (16)	1.07	0.52; 2.23	0.85
GRS _{MGUS2017} highest tertile	301 (22)	1.85	0.95; 3.72	0.07
Income Q3				
GRS _{MGUS2017} lower tertile	357 (18)	1.29	0.64; 2.64	0.48
GRS _{MGUS2017} middle tertile	404 (19)	1.21	0.60; 2.46	0.60
GRS _{MGUS2017} highest tertile	325 (29)	1.29	1.25; 4.59	0.01
Income Q4				
GRS _{MGUS2017} lower tertile	315 (21)	1.77	0.89; 3.57	0.10
GRS _{MGUS2017} middle tertile	318 (14)	1.14	0.54; 2.42	0.74
GRS _{MGUS2017} highest tertile	279 (21)	2.01	1.02; 2.07	0.05

Table 4. Sex- and age-adjusted odds ratios (OR) and 95% confidence intervals (95% CI) for the single reference joint effects of the genetic effect (GRS_{MGUS2017}) and SEP indicators on MGUS status calculated separately for income and education with the group of being in the low genetic risk score tertile and the lowest SEP category as reference.

MGUS risk factor	n (n _{case})	OR (95% CI) _(GRSxE)	P _(GRSxE)	RERI (95% CI)
Base model	4317 (237)	1.17 (1.03; 1.34)	0.02	0.10 (0.05; 0.14)
Current or past smoking	4317 (237)	1.19 (1.04; 1.36)	0.01	0.07 (-0.01; 0.16)
Obesity	4298 (236)	1.17 (1.03; 1.34)	0.02	0.09 (0.04; 0.15)
Diabetes mellitus	4317 (237)	1.18 (1.03; 1.34)	0.01	0.11 (0.05; 0.16)
Low fish consumption	4252 (234)	1.18 (1.03; 1.34)	0.02	0.10 (0.03; 0.17)
Low boiled vegetables consumption	4254 (234)	1.17 (1.03; 1.34)	0.02	0.07 (-0.01; 0.15)
Low raw vegetables consumption	4250 (233)	1.19 (1.04; 1.36)	0.01	0.14 (0.06; 0.22)
Low fruit consumption	4256 (234)	1.17 (1.03; 1.34)	0.02	0.10 (0.04; 0.15)

Table 5. Changes in the interaction effect of the genetic effect (GRS_{MGUS2017}) by dichotomised education (E) on MGUS (base model) in separate sex- and age-adjusted logistic regression models additionally including the main effects and respective interaction terms for each potential risk factor (odds ratios, OR; 95% confidence intervals, 95% CI; relative excess risk due to interaction, RERI).

alleles and MGUS in both previous studies have been reported to reach suggestive evidence of genome-wide association ($p < 10^{-5}$), probably due to small numbers of MGUS cases. The first GWAS from 2017 comprised 243 MGUS cases and 1285 controls from Germany with a replication of three SNPs in an independent Czech cohort of 294 cases and 272 controls. The second GWAS from 2019 comprised in total 992 MGUS cases and 2900 controls based on three different data sets including the previously mentioned German cohort, a Czech cohort of 288 cases and 600 controls and additionally a Swedish cohort including 461 cases and 1,025 controls. Since none of the 10 loci associated with MGUS risk identified in the first GWAS were replicated in the second (probably due to fluctuations of allele frequencies in smaller GWAS samples), we decided a priori to investigate associations of the reported SNP sets separately in our study population. Another recent GWAS including 754 MGUS cases from Mayo Clinic and MD Anderson could only replicate one of the reported MGUS risk loci¹⁶. This lack of replication may be explained by underlying population differences and differences in the distribution MGUS risk types between study populations. However, both MGUS-related genetic sum scores showed an association with MGUS in our study population with $GRS_{MGUS2019}$ showing a slightly stronger association with MGUS than the $GRS_{MGUS2017}$. In contrast to the present study, the underlying genetic variants of the GRSs calculated here were identified in GWAS in which MGUS cases were mainly not selected from MGUS screening studies, but from clinical MGUS collectives.

The main finding of this study is the indication for stronger associations between $GRS_{MGUS2017}$ and MGUS in groups of higher SEP. Results of stratified analyses revealed the strongest genetic effect of $GRS_{MGUS2017}$ on MGUS in the highest education group and joint effects of all possible combinations of $GRS_{MGUS2017}$ tertiles and education groups showed the strongest effect on MGUS for participants with highest genetic risk within the highest education group. These findings together with the effect size estimates for the $GRS_{MGUS2017}$ by education interaction term and the RERI estimate gave strong indication for positive interaction that is more than the product and the sum of both independent variables, meaning that the presence of these underlying genetic variants is accompanied with a higher risk for developing MGUS in higher educational groups. Results for interaction between SEP indicator income and $GRS_{MGUS2017}$ were less pronounced; however, we still observed an indication for additive interaction between $GRS_{MGUS2017}$ and income and stronger associations of $GRS_{MGUS2017}$ with MGUS in higher income groups. SEP stratified analyses of $GRS_{MGUS2019}$ on MGUS showed more heterogeneous results across the strata. However, it showed also stronger associations in the highest education group compared to all other groups.

As SEP usually has no direct effect on disease, but influences disease development indirectly via risk factors that are unequally distributed across SEP groups²³, results of the present analysis indicate that MGUS risk factors more prevalent in higher SEP groups may also impact the expression of MGUS-related genetic effects. However, since the inclusion of potential MGUS risk factors that were available for analysis did not explain the observed $GRS_{MGUS2017}$ by education interaction, other risk factors for MGUS not included in the analysis may be underlying the observed interaction effect. In previous studies, stronger genetic effects on health risks in higher SEP groups have also been explained by a lack of competing non-genetic risk factors in higher SEP groups⁴¹. However, in the present study both, a higher overall MGUS risk as well as stronger MGUS-related genetic effects were observed in higher SEP groups. The stronger overall MGUS risk in higher SEP groups suggests some sort of MGUS risk factor that is more prevalent in higher SEP groups and that may also affect MGUS risk via its interaction with MGUS-related genetic factors.

Besides its population-based study design, strengths of this study include the assessment of both prevalent and incident MGUS cases over a 10-year follow-up period using a sensitive diagnostic screening approach, the inclusion of two different SEP indicators as well as the inclusion of other potential MGUS risk factors into analyses. Moreover, interaction analyses were not merely based on testing $GRS \times SEP$ interaction terms and additional RERI calculation, but also on stratified analyses and analyses of joint effects. A limitation of the study is the lack of urine protein measurements as well as imaging and bone marrow biopsy results for giving more detailed information on MGUS diagnosis and its severity. Thus, a small fraction of MGUS cases and rare plasma cell dyscrasias might have been missed. Moreover, due to the sample size the statistical power for single SNP analyses was limited. Furthermore, complex interdependencies of the analysed risk factors cannot be ruled out for contributing to the observed $GRS \times SEP$ interaction. However, with regard to potential model overfitting the sample size of the study was not suitable for simultaneously exploring potential interactions between all factors included in the analysis.

In conclusion, results of the present study provide further evidence for associations of previously reported genetic variants for MGUS risk and indicate stronger associations between one MGUS-related GRS ($GRS_{MGUS2017}$) and MGUS in higher SEP groups in a population-based study sample. This suggests that the genetic risk related to MGUS may not act independently from potentially preventable risk factors. However, the present study was not able to identify potential MGUS risk factors underlying the observed GRS by SEP interaction, indicating the existence of unknown risk factors for MGUS not included in the analysis that are more common in people with higher SEP that seem to influence the expression of MGUS-associated genetic variants. However, further studies are needed to investigate MGUS risk factors including genetic variants and SEP effects on MGUS to reliably identify more distinct subgroups with higher exposure-specific disease risk and to gain further insights into the biology of MGUS.

Data availability

Due to data security reasons (i.e., data contain potentially participant identifying information), the Heinz Nixdorf Recall Study does not allow sharing data as a public use file. However, others can access the data used upon request, which is the same way the authors of the present paper obtained the data. Data requests can be addressed to: recall@uk-essen.de.

Received: 13 September 2021; Accepted: 4 March 2022

Published online: 15 March 2022

References

- Kyle, R. A. *et al.* A long-term study of prognosis in monoclonal gammopathy of undetermined significance. *N. Engl. J. Med.* **346**, 564–569 (2002).
- Dispenzieri, A. *et al.* Prevalence and risk of progression of light-chain monoclonal gammopathy of undetermined significance: A retrospective population-based cohort study. *Lancet* **375**, 1721–1728 (2010).
- Kristinsson, S. Y. *et al.* Patterns of hematologic malignancies and solid tumors among 37,838 first-degree relatives of 13,896 patients with multiple myeloma in Sweden. *Int. J. Cancer* <https://doi.org/10.1002/ijc.24514> (2009).
- Landgren, O. *et al.* Risk of plasma cell and lymphoproliferative disorders among 14,621 first-degree relatives of 4458 patients with monoclonal gammopathy of undetermined significance in Sweden. *Blood* <https://doi.org/10.1182/blood-2008-12-191676> (2009).
- Greenberg, A. J., Rajkumar, S. V. & Vachon, C. M. Familial monoclonal gammopathy of undetermined significance and multiple myeloma: Epidemiology, risk factors, and biological characteristics. *Blood* <https://doi.org/10.1182/blood-2011-11-387324> (2012).
- Clay-Gilmour, A. I. *et al.* Risk of MGUS in relatives of multiple myeloma cases by clinical and tumor characteristics. *Leukemia* <https://doi.org/10.1038/s41375-018-0246-2> (2019).
- Vachon, C. M. *et al.* Increased risk of monoclonal gammopathy in first-degree relatives of patients with multiple myeloma or monoclonal gammopathy of undetermined significance. *Blood* <https://doi.org/10.1182/blood-2008-12-192575> (2009).
- Morgan, G. J. *et al.* Inherited genetic susceptibility to multiple myeloma. *Leukemia* <https://doi.org/10.1038/leu.2013.344> (2014).
- Went, M. *et al.* Identification of multiple risk loci and regulatory mechanisms influencing susceptibility to multiple myeloma. *Nat. Commun.* **9**, 3707 (2018).
- Broderick, P. *et al.* Common variation at 3p22.1 and 7p15.3 influences multiple myeloma risk. *Nat. Genet.* <https://doi.org/10.1038/ng.993> (2012).
- Chubb, D. *et al.* Common variation at 3q26.2, 6p21.33, 17p11.2 and 22q13.1 influences multiple myeloma risk. *Nat. Genet.* <https://doi.org/10.1038/ng.2733> (2013).
- Mitchell, J. S. *et al.* Genome-wide association study identifies multiple susceptibility loci for multiple myeloma. *Nat. Commun.* <https://doi.org/10.1038/ncomms12050> (2016).
- Swaminathan, B. *et al.* Variants in ELL2 influencing immunoglobulin levels associate with multiple myeloma. *Nat. Commun.* <https://doi.org/10.1038/ncomms8213> (2015).
- Weinhold, N. *et al.* Inherited genetic susceptibility to monoclonal gammopathy of unknown significance. *Blood* **123**, 2513–2517 (2014).
- Thomsen, H. *et al.* Genome-wide association study of monoclonal gammopathy of unknown significance (MGUS): Comparison with multiple myeloma. *Leukemia* <https://doi.org/10.1038/s41375-019-0396-x> (2019).
- Clay-Gilmour, A. I. *et al.* Coinherited genetics of multiple myeloma and its precursor, monoclonal gammopathy of undetermined significance. *Blood Adv.* <https://doi.org/10.1182/bloodadvances.2020001435> (2020).
- Thomsen, H. *et al.* Genomewide association study on monoclonal gammopathy of unknown significance (MGUS). *Eur. J. Haematol.* <https://doi.org/10.1111/ejh.12892> (2017).
- Thordardottir, M. *et al.* Obesity and risk of monoclonal gammopathy of undetermined significance and progression to multiple myeloma: A population-based study. *Blood Adv.* **1**, 2186–2192 (2017).
- Landgren, O. *et al.* Obesity is associated with an increased risk of monoclonal gammopathy of undetermined significance among black and white women. *Blood* <https://doi.org/10.1182/blood-2010-01-262394> (2010).
- Landgren, O. *et al.* Pesticide exposure and risk of monoclonal gammopathy of undetermined significance in the Agricultural Health Study. *Blood* **113**, 6386–6391 (2009).
- Boursi, B., Weiss, B. M., Haynes, K., Mamtani, R. & Yang, Y. X. Reappraisal of risk factors for monoclonal gammopathy of undetermined significance. *Am. J. Hematol.* <https://doi.org/10.1002/ajh.24355> (2016).
- Pasqualetti, P. *et al.* Tobacco smoking and risk of haematological malignancies in adults: A case-control study. *Br. J. Haematol.* <https://doi.org/10.1046/j.1365-2141.1997.942910.x> (1997).
- Schmidt, B. *et al.* Socioeconomic position is positively associated with monoclonal gammopathy of undetermined significance in a population-based cohort study. *Ann. Hematol.* <https://doi.org/10.1007/s00277-019-03825-5> (2019).
- Johnson, W. *et al.* Education reduces the effects of genetic susceptibilities to poor physical health. *Int. J. Epidemiol.* <https://doi.org/10.1093/ije/dyp314> (2010).
- Schmidt, B. *et al.* Socioeconomic status interacts with the genetic effect of a chromosome 9p21.3 common variant to influence coronary artery calcification and incident coronary events in the Heinz Nixdorf recall study (risk factors, evaluation of coronary calcium, and lifes). *Circ. Cardiovasc. Genet.* <https://doi.org/10.1161/CIRCGENETICS.116.001441> (2017).
- Schmermund, A. *et al.* Assessment of clinically silent atherosclerotic disease and established and novel risk factors for predicting myocardial infarction and cardiac death in healthy middle-aged subjects: Rationale and design of the Heinz Nixdorf RECALL study. *Am. Heart J.* <https://doi.org/10.1067/mhj.2002.123579> (2002).
- Stang, A. *et al.* Baseline recruitment and analyses of nonresponse of the Heinz Nixdorf Recall Study: Identifiability of phone numbers as the major determinant of response. *Eur. J. Epidemiol.* <https://doi.org/10.1007/s10654-005-5529-z> (2005).
- International Myeloma Working Group. Criteria for the classification of monoclonal gammopathies, multiple myeloma and related disorders. *Br. J. Haematol.* <https://doi.org/10.1046/j.1365-2141.2003.04355.x> (2003).
- Katzmann, J. A. *et al.* Serum reference intervals and diagnostic ranges for free κ and free λ immunoglobulin light chains: Relative sensitivity for detection of monoclonal light chains. *Clin. Chem.* <https://doi.org/10.1093/clinchem/48.9.1437> (2002).
- Hutchison, C. A. *et al.* Serum free light chain measurement aids the diagnosis of myeloma in patients with severe renal failure. *BMC Nephrol.* <https://doi.org/10.1186/1471-2369-9-11> (2008).
- Howie, B., Marchini, J. & Stephens, M. Genotype imputation with thousands of genomes. *G3 Genes Genomes Genet.* <https://doi.org/10.1534/g3.111.001198> (2011).
- UNESCO. *ISCED 1997 - International Standard Classification of Education*. *Annals of Physics* (2006).
- Hagenaars, A. *Poverty statistics in the late 1980s: research base on micro-data*. (EUR-OP, 1994).
- Galobardes, B., Shaw, M., Lawlor, D. A., Lynch, J. W. & Smith, G. D. Indicators of socioeconomic position (part 1). *J. Epidemiol. Community Health* <https://doi.org/10.1136/jech.2004.023531> (2006).
- Geyer, S., Hemström, Ö., Peter, R. & Vägerö, D. Education, income, and occupational class cannot be used interchangeably in social epidemiology. Empirical evidence against a common practice. *J. Epidemiol. Community Health* <https://doi.org/10.1136/jech.2005.041319> (2006).
- Winkler, G. & Döring, A. Validation of a short qualitative food frequency list used in several German large scale surveys. *Z. Ernährungswiss.* <https://doi.org/10.1007/PL00007377> (1998).
- Muff, C. *et al.* Is the co-occurrence of smoking and poor consumption of fruits and vegetables confounded by socioeconomic conditions?. *Int. J. Public Health* <https://doi.org/10.1007/s00038-010-0152-5> (2010).
- Knol, M. J. & VanderWeele, T. J. Recommendations for presenting analyses of effect modification and interaction. *Int. J. Epidemiol.* <https://doi.org/10.1093/ije/dyr218> (2012).

39. 3.5.1., R. D. C. T. A Language and Environment for Statistical Computing. *R Found. Stat. Comput.* (2018).
40. Purcell, S. *et al.* PLINK: A tool set for whole-genome association and population-based linkage analyses. *Am. J. Hum. Genet.* <https://doi.org/10.1086/519795> (2007).
41. Emmel, C. *et al.* A genetic sum score of effect alleles associated with serum lipid concentrations interacts with educational attainment. *Sci. Rep.* <https://doi.org/10.1038/s41598-021-95970-z> (2021).

Acknowledgements

We are indebted to all study participants and to both the dedicated personnel of the study center of the Heinz Nixdorf Recall study and to the investigative group, in particular to U. Slomiany, U. Roggenbuck, E. M. Beck, A. Öffner, S. Münkler, R. Peter, and H. Hirche. Advisory Board: Meinertz T., Hamburg, Germany (Chair); Bode C., Freiburg, Germany; deFeyter P. J., Rotterdam, Netherlands; Güntert B, Halli, Austria; Gutzwiller F., Bern, Switzerland; Heinen H., Bonn, Germany; Hess O., Bern, Switzerland; Klein B., Essen, Germany; Löwel H., Neuherberg, Germany; Reiser M., Munich, Germany; Schmidt G., Essen, Germany; Schwaiger M., Munich, Germany; Steinmüller C., Bonn, Germany; Theorell T., Stockholm, Sweden; Willich S. N., Berlin, Germany.

Author contributions

B.S. formed the study concept. J.D., U.D., P.H., M.M.N., N.D., R.E., and K.H.J. contributed to data acquisition or genotyping. L.B. performed the statistical analysis. L.B. and B.S. drafted the manuscript. All authors contributed to the interpretation of results, revised the paper draft and approved the final manuscript.

Funding

Open Access funding enabled and organized by Projekt DEAL. The authors thank the Heinz Nixdorf Foundation [Chairman: Martin Nixdorf; Past Chairman: Dr jur. Gerhard Schmidt (†)], for their generous support of this study. Parts of the study were also supported by the German Research Council (DFG) [DFG project: EI 969/2-3, ER 155/6-1;6-2, HO 3314/2-1;2-2;2-3;4-3, INST 58219/32-1, JO 170/8-1, KN 885/3-1, PE 2309/2-1, SI 236/8-1;9-1;10-1,], the German Ministry of Education and Science [BMBF project: 01EG0401, 01GI0856, 01GI0860, 01GS0820_WB2-C, 01ER1001D, 01GI0205], the Ministry of Innovation, Science, Research and Technology, North Rhine-Westphalia (MIWFT-NRW).

Competing interests

The authors declare no competing interests.

Additional information

Supplementary Information The online version contains supplementary material available at <https://doi.org/10.1038/s41598-022-08294-x>.

Correspondence and requests for materials should be addressed to B.S.

Reprints and permissions information is available at www.nature.com/reprints.

Publisher's note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.



Open Access This article is licensed under a Creative Commons Attribution 4.0 International License, which permits use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if changes were made. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit <http://creativecommons.org/licenses/by/4.0/>.

© The Author(s) 2022

DuEPublico

Duisburg-Essen Publications online

UNIVERSITÄT
DUISBURG
ESSEN

Offen im Denken

ub | universitäts
bibliothek

This text is made available via DuEPublico, the institutional repository of the University of Duisburg-Essen. This version may eventually differ from another version distributed by a commercial publisher.

DOI: 10.1038/s41598-022-08294-x

URN: urn:nbn:de:hbz:465-20240209-131743-5



This work may be used under a Creative Commons Attribution 4.0 License (CC BY 4.0).