ORIGINAL ARTICLE

Population-specific validation and comparison of the performance of 77- and 313-variant polygenic risk scores for breast cancer risk prediction

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Abstract

Background: The polygenic risk score (PRS) allows the quantification of the polygenic effect of many low-penetrance alleles on the risk of breast cancer (BC). This study aimed to evaluate the performance of two sets comprising 77 or 313 low-penetrance loci (PRS77 and PRS313) in patients with BC in the Czech population.

Methods: In a retrospective case-control study, variants were genotyped from both the PRS77 and PRS313 sets in 1329 patients with BC and 1324 noncancer controls, all women without germline pathogenic variants in BC predisposition genes. Odds ratios (ORs) were calculated according to the categorical PRS in individual deciles. Weighted Cox regression analysis was used to estimate the hazard ratio (HR) per standard deviation (SD) increase in PRS.

Results: The distributions of standardized PRSs in patients and controls were significantly different ($p < 2.2 \times 10^{-16}$) with both sets. PRS313 outperformed PRS77 in categorical and continuous PRS analyses. For patients in the highest 2.5% of PRS313, the risk reached an OR of 3.05 (95% CI, 1.66–5.89; $p = 1.76 \times 10^{-4}$). The continuous risk was estimated as an $HR_{per\ SD}$ of 1.64 (95% CI, 1.49–1.81; $p < 2.0 \times 10^{-16}$), which resulted in an absolute risk of 21.03% at age 80 years for

individuals in the 95th percentile of PRS313. Discordant categorization into PRS deciles was observed in 248 individuals (9.3%).

Conclusions: Both PRS77 and PRS313 are able to stratify individuals according to their BC risk in the Czech population. PRS313 shows better discriminatory ability. The results support the potential clinical utility of using PRS313 in individualized BC risk prediction.

KEYWORDS
breast cancer, germline genetic testing, polygenic risk score, PRS77, PRS313

INTRODUCTION

Breast cancer (BC) is the most prevalent oncologic disease, with a cumulative lifetime risk exceeding 10% in females in developed countries.[1] The risk of BC depends on various environmental and biological factors, among which family BC history is one of the strongest predictors.[2]

Although sporadic cases with no family history of BC comprise a majority of patients, 5%–10% of cases of BC can be explained by the presence of germline pathogenic variants (PVs) in high and moderate BC predisposition genes.[3] Compared to patients with sporadic BC, patients with hereditary BC are characterized by a different spectrum of BC subtypes: tumor development at an earlier age, increased risk of second primary cancers, and increased prevalence of breast, ovarian, and other related cancer types in relatives.[4] However, more than 80% of patients with a positive BC family history are not carriers of a PV in established cancer predisposition genes.[3]

Recent studies have suggested that part of the missing heritability in cases of BC can be attributed to the interplay among low-penetrance variants, usually single-nucleotide polymorphisms (SNPs).[5,6] Although each such SNP can modify BC risk only very slightly (but statistically significantly), their combined predictive power, expressed as a polygenic risk score (PRS), may lead to exceeding relative risk (RR) thresholds for moderate (RR, >2) or even high (RR, >4) BC risk.[7–9]

The PRS expresses BC risk at a level of polygenic genetic background, which summarizes the overall contributions of individual SNPs multiplied by the corresponding allelic dosages.[9–11] PRS values are assumed to be distributed normally among a correspondingly large group of individuals.[12,13] Because allelic frequencies of SNPs considered for the PRS differ in various populations, the raw PRS value must be compared to the mean PRS in the corresponding population.

The PRS may improve the stratification of BC risk in personalized medicine in assessing the proper management and timing of BC prevention.[14] To date, several SNP sets have been created on the basis of data from the Collaborative Oncological Gene-Environment Study and OncoArray.[10,15–17] Sets of 77 SNPs[10] and 313 SNPs[16] have been developed from a sample of women of European descent[8] and represent the gold standard in PRS analysis in female patients with BC. Nevertheless, the proband sample on which the sets were tested was heavily biased toward women of Western/Northern European descent. Before the application of these sets for BC risk

prediction in other populations, the SNP sets need to be validated and standardized accordingly.

The focus of this study was to calculate and compare the predictive performance of the PRS from the sets of 77 SNPs[10] and 313 SNPs[16] and to test each set on samples from 1698 Czech female patients with BC and 1459 noncancer female control individuals. Carriers of PVs in known BC predisposition genes were excluded from both groups before the analysis.

MATERIALS AND METHODS

Study participants

The patient cohort consisted of 1698 female patients with BC (aged 20–80 years), including 481 patients with BC indicated for germline genetic testing on the basis of national testing guidelines[18] and 1217 nonindicated patients with BC who underwent germline genetic testing within clinical research projects. All patients with BC were enrolled at the General University Hospital (GUH) in Prague between 1997 and 2023. The control group consisted of 1459 noncancer individuals, including the following subgroups: (1) 405 healthy female volunteers (aged 60–80 years) with no family cancer history were enrolled at the GUH in Prague, Masaryk Memorial Cancer Institute (MMCI), and AGEL Laboratories between 2019 and 2023; and (2) 1054 women without cancer unselected for family cancer history (aged 20–80 years, enrolled between 2015 and 2023) included 97 female volunteers from the MMCI and 957 females enrolled at the GUH in Prague from patients tested because of various noncancer conditions (mainly cardiomyopathy and diabetes mellitus). All study participants were Czechs (Central Europeans). All participants signed informed consent forms for study participation, which was approved by the Ethics Committee of the GUH in Prague. All samples were anonymized before testing. Carriers of PVs in BC predisposition genes were excluded from PRS analysis.

Next-generation sequencing panel analysis

Genomic DNA was isolated from peripheral venous blood. All DNA samples were tested by targeted custom-designed next-generation

sequencing (NGS) panels (KAPA HyperCap; Roche, Basel, Switzerland). The CZECANCA panel (Czech Cancer Panel for Clinical Application) has been used to exclude carriers of PVs in established BC predisposition genes, and the PRSMAN panel was designed to genotype variants for the PRS analysis.

The CZECANCA panel targeted 226 known and candidate cancer predisposition genes and was described in detail previously.[19–21]

The PRSMAN panel was designed to target 883 PRS-associated variants in breast, ovarian, and other cancer types that were published by July 2020 (Table S1).[8,10,15–17,22–35] The Roche probe design algorithm excluded 39 SNPs from the PRSMAN panel before its production. The final 844 targeted SNPs are listed in Table S2.

The NGS libraries were prepared with KAPA HyperPlus/EvoPlus Library Preparation Kits (Roche) according to the manufacturer with minor modifications described previously.[19,21,36] The target regions were captured with pooled CZECANCA and PRSMAN panels in a 2:1 ratio. Sequencing was performed with NextSeq 500 instruments (Illumina, San Diego, California).

Description of 77- and 313-SNP sets

We validated sets of 77 and 313 SNPs (henceforth referred to as PRS77 and PRS313) developed by Mavaddat et al. in 2015 and 2019.[10,16] Although all PRS77 SNPs were successfully genotyped, 48 SNPs from the PRS313 set were excluded from further analysis: 22 SNPs because of panel design restrictions (two of which were substituted by other SNPs in linkage disequilibrium covered in the PRSMAN panel; Table S3), 24 SNPs because of their localization in repetitive sequences, and two SNPs that did not match the allele specification in the PRS313 definition. Finally, 267 out of the 313 SNPs were genotyped by the PRSMAN panel. The overlap between the sets consisted of 15 SNPs.

Bioinformatics analysis

Raw NGS data were processed by an in-house bioinformatics pipeline as described previously.[19] The sequencing data in the FASTQ format were generated from NextSeq with the Illumina BaseSpace Sequence Hub (https://support.illumina.com/sequencing/sequencing_software/basespace.html). The FASTQ files were then mapped to the hg19 reference genome with NovoAlign version 2.08.03 (http://www.novocraft.com/products/novoalign). GATK version 3.3 HaplotypeCaller (https://github.com/broadinstitute/gatk-docs) was used for PRS SNP calling.

Via in-house scripts a call rate filter was applied, which excluded samples or SNPs with a call rate of <95% due to observed read coverages of <10× from further analysis. The set of SNPs was tested for Hardy–Weinberg equilibrium (HWE). Identity-by-state analysis was performed in PLINK version 1.90b6.26 (https://www.cog-genomics.org/plink) to prevent duplicated samples. Missing genotypes were substituted by the corresponding observed allele frequencies across patients and controls as described previously.[37] Created VCF files were used for subsequent PRS calculations.

PRS calculation

An individual's raw PRS was calculated as follows:

$$PRS = \sum_{i=1}^{N} \log OR_i \times \text{number of effect alleles,}$$

namely the sum of the corresponding log OR and the number of observed effect alleles, which took the values 0, 1, or 2 (or dosage in case of imputation), per SNP. PRS calculation was performed in two steps: the first considered data from controls only to determine the mean and standard deviation (SD), and the second was performed to retrieve normalized PRS values both from control and patient data. PRS values were calculated separately for the PRS77 and PRS313 SNP sets, with the effect sizes of individual SNPs as published in the Polygenic Score (PGS) Catalog (PGS000001 for PRS77; PGS000004 for PRS313).[38]

Statistical analysis

Statistical analyses were performed with R version 4.2.0 (https://cran.r-project.org/). Differences between the standardized PRS values of patients and controls were assessed via the two-sided t-test, with p values of less than .05 considered statistically significant.

We compared the numbers of patients and controls in distinct deciles of the PRS to the reference middle quintile (5th and 6th deciles) to assess the OR in the respective groups. Statistical significance was calculated by the Fisher exact test in R.

The association of the PRS with BC development was determined by weighted Cox regression analysis with age at diagnosis as the time-dependent variable. To account for the oversampling of cases of BC in our retrospective study sample, real-world incidence rates in the Czech Republic in the years 2012–2022 collected by the Czech National Cancer Registry[39] were mimicked with the weighted cohort approach proposed by Antoniou et al.[40] Absolute age-specific risks of BC at distinct standardized PRS percentiles were estimated as a proportional hazards assumption in age-stratified Cox regression models as described by Zhang et al.[41] Age-specific cumulative BC risks were calculated as described previously.[27,42]

RESULTS

Selection of samples for PRS analysis and SNP validation

The initial sample set included 1698 patients with BC (aged 20–80 years) and 1459 controls (aged 20–80 years). Of these, 311

patients with BC (18.3%) and 55 control individuals (3.8%) harbored any germline PV in the established BC predisposition genes (i.e., *BRCA1*, *BRCA2*, *CHEK2*, *ATM*, *BARD1*, *BRIP1*, *MLH1*, *MSH6*, *NBN*, *NF1*, *PALB2*, *PMS2*, *PTEN*, *RAD51C*, *RAD51D*, and *TP53*; data not shown) and were excluded from subsequent PRS analyses. Thus, data from 1387 PV-negative patients with BC and 1404 PV-negative controls were considered for further analyses. The call rate filter excluded 43 patients and 0 controls for the PRS77 data set and 57 patients and 80 controls for the PRS313 data set. However, for the sake of direct comparability, only probands who passed the call rate filters for *both* the PRS77 and PRS313 data sets were included in further analyses, which yielded final data sets of 1329 patients with BC and 1324 controls (mean age, 56 and 54 years, respectively; $p = .15$ in the two-sided Welch *t*-test; Figure S1). The noncancer controls included two subsets with and without selection for family cancer history. The statistical analysis of raw PRS values in these subsets for PRS77 and PRS313 showed no statistically significant differences ($p = .06$ for PRS77; $p = .16$ for PRS313), and hence both control subsets were combined for further analyses.

All SNPs passed the call rate filter with a threshold of >95% for PRS77. Regarding the 267 SNPs genotyped within the PRS313 set, eight SNPs did not pass the quality filters for variant calling recommended by GATK, the SNP-specific call rate filter excluded a further 16 SNPs, and two SNPs did not pass HWE control, which resulted in a final set of 241 loci for further PRS313 analyses.

Association between PRS and BC risk

The distributions of standardized PRSs in patient and control samples are shown in Figure 1. Standardized PRS77 values ranged from −2.56 to 4.35 (mean, 0.34) in patient samples and −2.80 to 3.75 (mean, 0) in control samples. Standardized PRS313 values ranged from −2.85 to 3.72 (mean, 0.48) in patient samples and −3.34 to 3.13 (mean, 0) in control samples. For both SNP sets, the mean PRS of patient samples was statistically significantly increased compared to the mean PRS of control samples (PRS77, $p < 2.2 \times 10^{-16}$; PRS313, $p < 2.2 \times 10^{-16}$).

We calculated ORs for patients and control individuals binned by decile of the standardized PRS (Table 1; Table S4), with the middle quintile (5th and 6th deciles) as the reference. Although BC risk positively correlated with the accumulation of risk alleles in both data sets, PRS313 displayed more stably increasing risks and discriminated the risks better between the percentile categories (Figure 2; Table S4). Moreover, in the extremes of the distribution, the difference in calculated ORs was more pronounced in the PRS313 than in the PRS77 data set. For patients in the highest 2.5% of PRS313, the BC risk was calculated as an OR of 3.05 (95% CI, 1.66–5.89; $p = 1.76 \times 10^{-4}$). No such increase was observed in the highest 2.5% of PRS77.

To calculate hazard ratios (HRs) per SD for both SNP sets, we analyzed the association of the standardized PRS with BC risk via Cox regression. Consistent with the results above, the association with BC risk per SD was lower for PRS77 ($HR_{per\ SD}$, 1.40; 95% CI, 1.28–1.53; $p = 3.9 \times 10^{-15}$) than for PRS313 ($HR_{per\ SD}$, 1.64; 95% CI, 1.49–1.81; $p < 2.0 \times 10^{-16}$).

Age-specific HR estimates were used to calculate the absolute cumulative BC risk per PRS percentile with BC incidence data from the Czech National Cancer Registry.

PRS313 outperformed PRS77 because it assessed the risk of disease with significantly better consistency within a wider range of age of disease onset categories. This was also reflected in the global p values obtained (PRS77, $p = .15$; PRS313, $p = .01$; Table S5).
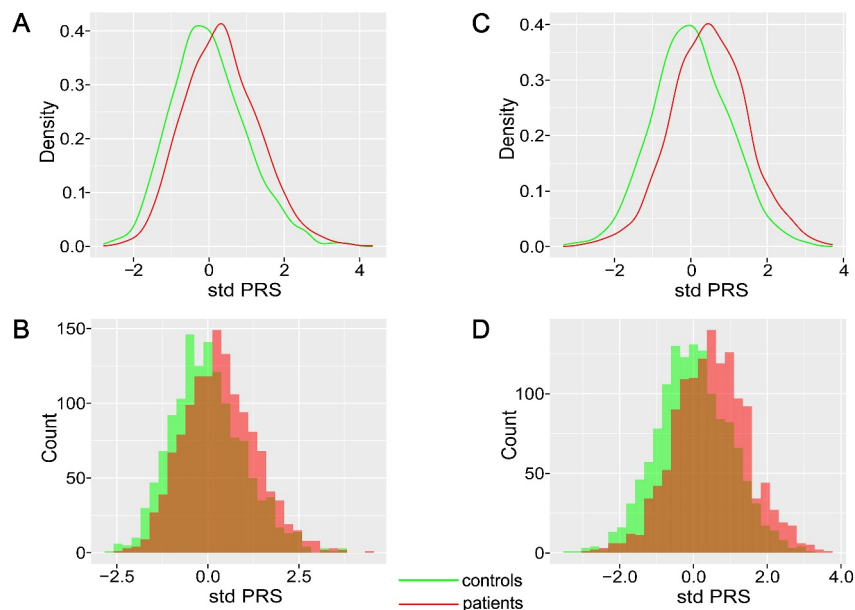

FIGURE 1 Empirical distributions of the standardized PRS of control (green) and patient samples (red). Both PRS sets PRS77 (A,B) and PRS313 (C,D) present statistically significant differences in mean standardized PRS values between the groups. PRS indicates polygenic risk score; std, standardized.

TABLE 1 Association between BC risk and deciles of standardized PRS77 and PRS313.

Decile	PRS77		PRS313	
	OR (95% CI)	p	OR (95% CI)	p
1st	0.51 (0.37–0.70)	1.91×10^{-5}	0.38 (0.28–0.53)	2.59×10^{-9}
2nd	0.72 (0.53–0.98)	.03	0.55 (0.40–0.75)	1.07×10^{-4}
3rd	0.68 (0.50–0.92)	.01	0.66 (0.49–0.90)	.01
4th	0.89 (0.65–1.21)	.48	0.88 (0.65–1.20)	.45
5th and 6th	1	Reference	1	Reference
7th	1.34 (0.99–1.83)	.06	1.23 (0.91–1.68)	.19
8th	1.17 (0.86–1.59)	.34	1.46 (1.07–2.00)	.02
9th	1.59 (1.17–2.18)	2.97×10^{-3}	1.61 (1.18–2.20)	2.48×10^{-3}
10th	1.55 (1.14–2.12)	4.93×10^{-3}	1.87 (1.37–2.58)	6.81×10^{-5}

Abbreviations: BC, breast cancer; OR, odds ratio; PRS, polygenic risk score.
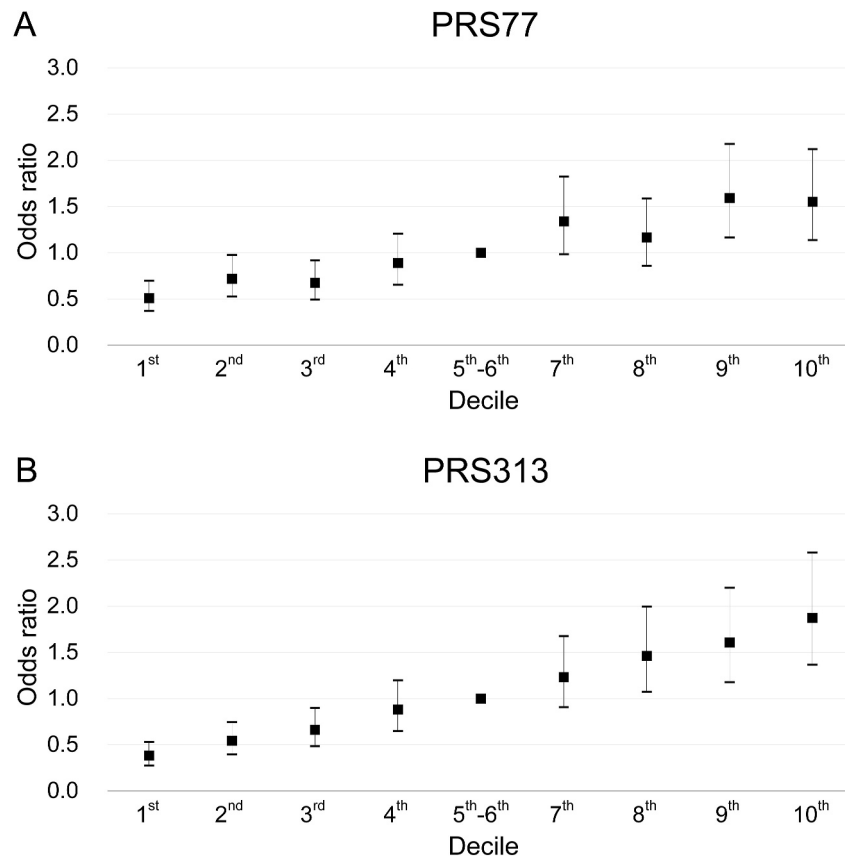

FIGURE 2 Association between PRS77 (A) and PRS313 (B) deciles and the occurrence of primary breast cancer. Odds ratios are calculated for each decile of the PRS relative to the reference (5th and 6th deciles) of the PRS. Ranges correspond to 95% CI. PRS indicates polygenic risk score.

PRS313 better discriminates the risks between the 5th and 95th percentiles (Table 2; Figure 3), which improved cancer risk estimates over PRS77 in both the age categories of 50 years (1.46 vs. 4.90 for PRS77; 1.23 vs. 4.85 for PRS313) and 80 years (5.78 vs. 18.93 for PRS77; 4.54 vs. 21.03 for PRS313). In addition, the estimated risk for

individuals at the 95th percentile exceeds 20% at the age of 80 years only for PRS313 but not for PRS77.

In addition, we evaluated the results of both PRS77 and PRS313 on an individual level. We compared decile categorization for all individuals successfully genotyped in both sets (n = 2653). Surprisingly,

TABLE 2 Absolute risks for the 5th, 10th, 50th, 90th, and 95th percentiles of PRS77 and PRS313 by the ages of 50 and 80 years.

	PRS77 BC risk		PRS313 BC risk	
PRS percentile	Age 50 years, %	Age 80 years, %	Age 50 years, %	Age 80 years, %
5th	1.46	5.78	1.23	4.54
10th	1.57	6.48	1.41	5.36
50th	2.22	9.84	2.35	9.73
90th	3.84	15.81	4.08	17.67
95th	4.90	18.93	4.85	21.03

Abbreviations: BC, breast cancer; PRS, polygenic risk score.

both sets identically categorized only 502 individuals (18.9%), and the categorization over five deciles differed for 248 individuals (9.3%) (Figure 4).

DISCUSSION

Prevention is a key strategy to lower BC burden, as has been demonstrated by the reduction of BC-related mortality since the introduction of mammography for population screening programs.[43,44] Although the value of mammography is unquestionable, further BC reduction requires personalized approaches able to categorize females with different nonmodifiable risks. Various risk assessment models, including the Gail/Breast Cancer Risk Assessment Tool, Claus, Tyrer-Cuzick, and BOADICEA (Breast and Ovarian Analysis of Disease Incidence and Carrier Estimation Algorithm), based on the evaluation of family and personal gynecological/cancer history and clinical characteristics, have been used.[45] Nevertheless, they might not predict risk accurately for women who do not fit into the risk groups for whom they were developed.

Polygenic inheritance has been identified as an important genetic factor modifying BC risk. To date, the two most commonly used sets of variants, PRS77 and PRS313,[10,16] have been validated in various populations.[26,31,37,46–52] Because the effect of SNPs on BC risk may vary among different ethnicities, in this study, we tested their predictive performance in a population of Czech women, which has not been analyzed to date. Recently, Yiangou et al. reported a comparison of PRS313 performance in various European populations and found significant differences between means (−0.12 to 0.25), which can influence the estimation of individual risk and suggest using country-specific PRS distributions to calibrate risk categories.[53]

The comparison of our study in the context of previous work is complicated because of the great heterogeneity in the reporting of the resulting risk estimates (OR vs. HR), given the diverse bio-informatical methods used and the varying numbers of participants.

PRS77 was constructed in 2015 on the basis of samples from 33,673 female patients with BC and 33,381 control individuals collected by the Breast Cancer Association Consortium (BCAC).[8,22] The study identified that PRS77 was associated with BC risk with an $OR_{per\ SD}$ of 1.55.[10] Similar results were observed in a subsequent
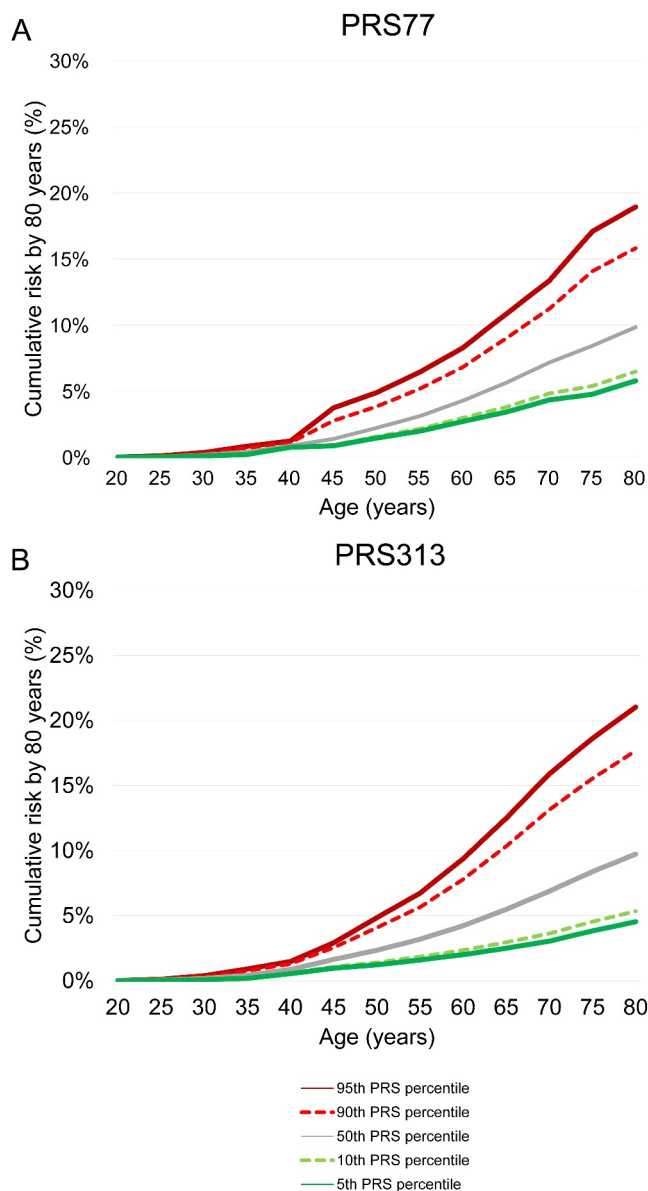

FIGURE 3 Predicted cumulative breast cancer risks according to the percentile of the PRS via sets PRS77 (A) and PRS313 (B). PRS indicates polygenic risk score.

Australian study, which was performed on a much smaller sample set (750 patients with BC and 405 controls), with an $OR_{per\ SD}$ of 1.46.[46] Our results are consistent with these findings ($HR_{per\ SD}$, 1.40).
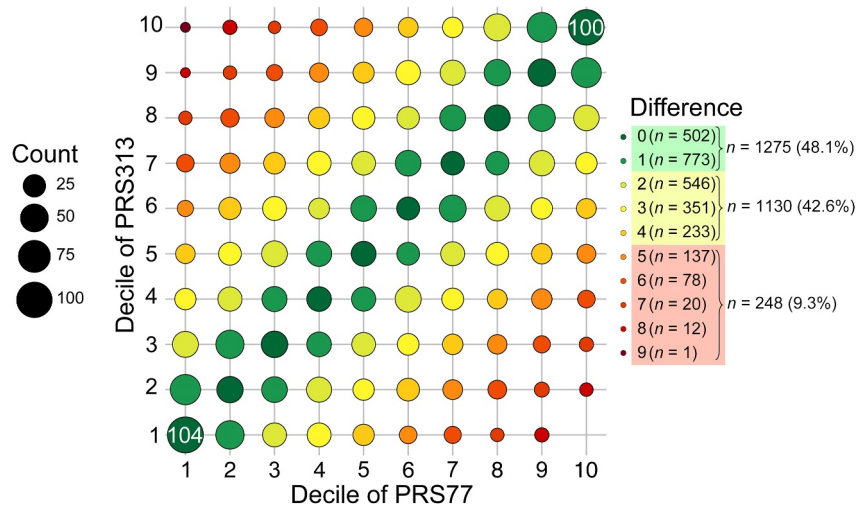
FIGURE 4 Visualization of the discordance in the stratification of PRS values per proband between PRS77 and PRS313. The size of the dots corresponds to the number of probands per category. PRS indicates polygenic risk score.

Regarding PRS77 by percentile, we observed that women in the top PRS decile (90%–100%) were at higher risk (OR, 1.55) when compared to women in the middle quintile (5th and 6th deciles), yet no substantial risk increase was observed for patients in the top 2.5% of PRS77 (OR, 1.55). However, in the original BCAC study, the risk of BC was three times higher for women in the 99th percentile than for women in the middle quintile (OR, 3.36).[10]

PRS313 was constructed in 2019 on the basis of data from 94,075 patients with BC and 75,017 control individuals from expanded BCAC studies.[8,22,23] It states the BC risk as an $OR_{per\ SD}$ of 1.65 in the perspective set and 1.61 in the validation set. In our study, the BC risk for the continuous PRS313 set was assessed as an $HR_{per\ SD}$ of 1.64. Thus, our results correspond to the initial study from 2019 as well as the subsequent Dutch study by Lakeman et al. ($OR_{per\ SD}$, 1.97).[54]

Regarding PRS313 by percentile, we found that women within the PRS top decile (90%–100%) have a higher risk (OR, 1.87) than those in the middle quintile (5th and 6th deciles). Moreover, the BC risk was increased (OR, 3.05) for patients in the highest 2.5% of the PRS. In the original study, the risk was four times higher for women in the 99th percentile in comparison to the middle quintile. A large UK cohort study by Jia et al. described the BC risk for patients in the 5th quintile as double when compared to the middle quintile.[31]

These results suggest that both PRS77 and PRS313 allow the identification of increased BC risk and discriminate between noncancer individuals and patients with BC in the Czech population. However, in our study, PRS313 had a higher discrimination power regarding both when applied in distinct percentile categories and continuously. Two previous studies by Tasa et al. and Jiao et al. also compared both sets in other populations,[48,49] and both studies reported better performance of PRS313 as well.

Mavaddat et al. described that PRSs considering larger numbers of variants discriminate better between patients with BC and noncancer controls.[55] Besides the number of SNPs, the PRS sets differ in the effect sizes of the SNPs included. Therefore, the overlap of only 15 SNPs between PRS77 and PRS313 may lead to a discordant classification of individuals analyzed via different SNP sets, as demonstrated in our results. Such discrepancies could lead to discordant reports for patients with potentially negative effects on their clinical management, which indicates a need for standardization of PRS analysis in clinical settings. The predictive value of PRS77 can be overestimated as a result of using the same patient cohort for development and evaluation[56] and biased because of the design using predominantly later onset patients.[46] The large differences between PRS77 and PRS313 shown in our and other studies call for careful validation of both sets under precise criteria in well-defined case-control data from various populations. This will require the establishment of consensus guidelines for statistical analysis and risk calculation.

Regarding absolute cumulative BC risk, the risk reaches 21.02% for individuals in the highest 5% of PRS313. Similar results were described in the initial study by Mavaddat et al. (19% risk for the 90th–95th PRS percentile; 24% risk for the 95th–99th PRS percentile).[16] An overall risk above 20% exceeds a general threshold for clinical management of individuals at BC risk used for carriers of germline PVs in moderate-penetrance genes in the Czech Republic.[18]

Our data indicate that individuals in the lowest 5% of PRS313 reach the BC risk of the average population at age 55 years. On the other hand, individuals in 95% of PRS313 reach the BC risk of the average population at age 40 years. This is consistent with previously published data suggesting deferral of mammogram screening for women at low risk and earlier screening initiation and shorter time intervals between screening visits for women at high risk.[57,58] However, further studies are needed to evaluate the impact of the PRS on BC onset and the related personalized start of screening.

Currently, the utility of PRS implementation in clinical practice is still a matter of ongoing debate regarding the following issues. The discriminatory power of the PRS should be sufficient to demonstrate its ability to accurately identify individuals at risk of developing the disease. Its performance should be compared with existing predictive methods; even a score with high discriminatory power may be redundant if better predictors are already in clinical use. Appropriate preventive measures must also be available. Well-controlled clinical trials will be needed to fully address these requirements.

A limitation of our study was the lack of information on BC risk factors (i.e., family history) or BC subtypes in the nonindicated group of patients with BC. In order to increase the precision of the risk prediction, the interaction between the PRS and clinical risk factors ought to be considered in future analyses. Further development of a population-specific SNP set validated with extended cohorts of BC cases and controls may improve their discriminatory power.

In conclusion, in this study, we have assessed that the previously designed PRS313 can reliably discriminate groups of patients with BC and noncancer individuals from the Czech population, which stratifies women according to their BC risk. On the other hand, comparison of the two most frequently validated BC sets, PRS77 and PRS313, demonstrated large differences in an individual's classification, which warrants an urgent need for standardization of PRS analysis in routine clinical settings. Moreover, the PRS cannot act as a stand-alone test for BC risk prediction. For the best performance, risk estimates must be combined with the assessment of other genetic (analysis of moderate/high-penetrance cancer predisposition genes) and nongenetic factors (lifestyle, age of onset, and family history). Robust prospective clinical trials that include all risk factors, as well as the PRS, are needed in the future.

AUTHOR CONTRIBUTIONS

Milena Hovhannisyan: Writing–original draft; writing–review and editing; data curation; investigation; validation; and visualization. **Petra Zemankova**: Data curation; formal analysis; investigation; software; visualization; and writing–review and editing. **Petr Nehasil**: Data curation; investigation; software; and writing–review and editing. **Katerina Matejkova**: Visualization; formal analysis; investigation; software; validation; and writing–review and editing. **Marianna Borecka**: Investigation; validation; and writing–review and editing. **Marta Cerna**: Investigation; writing–review and editing; and validation. **Tatana Dolezalova**: Validation and writing–review and editing. **Lenka Dvorakova**: Resources and writing–review and editing. **Lenka Foretova**: Resources and writing–review and editing. **Klara Horackova**: Investigation; writing–review and editing; and validation. **Sandra Jelinkova**: Investigation; validation; and writing–review and editing. **Pavel Just**: Investigation; validation; and writing–review and editing. **Marta Kalousova**: Writing–review and editing and resources. **Jan Kral**: Investigation; validation; and writing–review and editing. **Eva Machackova**: Resources and writing–review and editing. **Barbora Nemcova**: Writing–review and editing and validation. **Marketa Safarikova**: Resources and writing–review and editing. **Drahomira Springer**: Resources and writing–review and editing. **Barbora Stastna**: Investigation; validation; and writing–review and editing. **Spiros Tavandzis**: Writing–review and editing and resources. **Michal Vocka**: Writing–review and editing and resources. **Tomas Zima**: Writing–review and editing and resources. **Jana Soukupova**: Conceptualization; data curation; funding acquisition; methodology; supervision; writing–review and editing; and resources. **Petra Kleiblova**: Conceptualization; funding acquisition; project administration; supervision; writing–review and editing; and resources. **Corinna Ernst**: Formal analysis; methodology; and writing–review and editing. **Zdenek Kleibl**: Conceptualization; funding acquisition; methodology; project administration; supervision; writing–review and editing; and writing–original draft. **Marketa Janatova**: Conceptualization; methodology; writing–original draft; writing–review and editing; data curation; formal analysis; funding acquisition; project administration; supervision; visualization; and resources.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available because of privacy or ethical restrictions.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.