RESEARCH Open Access



Identifying pleiotropic variants and candidate genes for fertility and reproduction traits in Holstein cattle via association studies based on imputed whole-genome sequence genotypes

Shi-Yi Chen^{1,2}, Flavio S. Schenkel³, Ana L. P. Melo⁴, Hinayah R. Oliveira^{1,3}, Victor B. Pedrosa^{1,5}, Andre C. Araujo¹, Melkaye G. Melka⁶ and Luiz F. Brito^{1,3*}

Abstract

Background: Genetic progress for fertility and reproduction traits in dairy cattle has been limited due to the low heritability of most indicator traits. Moreover, most of the quantitative trait loci (QTL) and candidate genes associated with these traits remain unknown. In this study, we used 5.6 million imputed DNA sequence variants (single nucleotide polymorphisms, SNPs) for genome-wide association studies (GWAS) of 18 fertility and reproduction traits in Holstein cattle. Aiming to identify pleiotropic variants and increase detection power, multiple-trait analyses were performed using a method to efficiently combine the estimated SNP effects of single-trait GWAS based on a chisquare statistic.

Results: There were 87, 72, and 84 significant SNPs identified for heifer, cow, and sire traits, respectively, which showed a wide and distinct distribution across the genome, suggesting that they have relatively distinct polygenic nature. The biological functions of immune response and fatty acid metabolism were significantly enriched for the 184 and 124 positional candidate genes identified for heifer and cow traits, respectively. No known biological function was significantly enriched for the 147 positional candidate genes found for sire traits. The most important chromosomes that had three or more significant QTL identified are BTA22 and BTA23 for heifer traits, BTA8 and BTA17 for cow traits, and BTA4, BTA7, BTA17, BTA22, BTA25, and BTA28 for sire traits. Several novel and biologically important positional candidate genes were strongly suggested for heifer (SOD2, WTAP, DLEC1, PFKFB4, TRIM27, HECW1, DNAH17, and ADAM3A), cow (ANXA1, PCSK5, SPESP1, and JMJD1C), and sire (ELMO1, CFAP70, SOX30, DGCR8, SEPTIN14, PAPOLB, JMJD1C, and NELL2) traits.

Conclusions: These findings contribute to better understand the underlying biological mechanisms of fertility and reproduction traits measured in heifers, cows, and sires, which may contribute to improve genomic evaluation for these traits in dairy cattle.

Keywords: Cattle breeding, Genome-wide association study, GWAS, QTL, Whole-genome sequence variants

Full list of author information is available at the end of the article



© The Author(s) 2022. **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 Creative Commons Public Domain Dedication waiver (http://creativecommons.org/publicdomain/zero/1.0/) applies to the data made available in this article, unless otherwise stated in a credit line to the data.

^{*}Correspondence: britol@purdue.edu

¹ Department of Animal Sciences, Purdue University, 270 S. Russell Street, West Lafayette, IN 47907-2041, USA

Chen et al. BMC Genomics (2022) 23:331 Page 2 of 22

Background

Fertility, reproduction, calving, and fertility disorders represent a group of traits that directly impact the economic efficiency and animal welfare in the dairy industry [1, 2]. However, the long-term genetic selection for production traits (especially milk yield) in Holstein cattle has negatively impacted fertility and reproductive performance due to their unfavorable genetic correlations [3-5]. Fertility and reproduction traits were only added to worldwide official genetic evaluations over the past two decades [6, 7]. In this context, the more recent implementation of genomic selection (GS) in North American Holstein cattle has greatly contributed to improving genetic gains for fertility and reproduction traits [8]. The usually low heritability estimates [9] and great complexity of biological mechanisms affecting fertility and reproductive performance impact GS accuracy, which relies, among other factors, on population-specific linkage disequilibrium (LD) between genotype markers and causal variants. Therefore, a promising approach is to genotype and use the causal or tightly linked variants within known quantitative trait loci (QTL) related to fertility and reproduction traits in GS schemes, which is expected to improve the prediction accuracy for such traits [10]. Despite the great efforts that have been made to identify QTL, functional genes, and putative causal variants related to fertility and reproduction traits in dairy cattle, it is expected that many potential candidate variants still remain to be uncovered, especially with the increase in detection power achieved by using whole-genome sequence (WGS) variants.

Genome-wide association studies (GWAS) have been popularly performed as a standard method for QTL mapping and candidate gene discovery in both humans and other species [11]. For instance, Fortes et al. [12] and Ma et al. [3], based on a systematic review, reported that a considerable number of QTL and candidate genes located in the Bos taurus autosomes (BTA) and in the X chromosome are associated with fertility and reproduction traits. However, most of these studies used the low- or medium-density single-nucleotide polymorphism (SNP) panels, which might hinder the discovery of candidate genes and causal variants. Due to the reduced cost of high-throughput sequencing approaches, several largescale genome resequencing initiatives have been undertaken, such as the 1,000 Bull Genomes Project [13] and the Canada's Ten Thousand Cows Genome Project [14]. Based on these large reference populations, WGS variants can be obtained cost-effectively through computational imputation from SNP panels to WGS [15, 16]. The use of WGS variants for GWAS can enhance the discovery of variant-trait associations especially when there is only short-range LD surrounding causal variants [17]. Previous studies have successfully used real or imputed WGS variants for performing GWAS of fertility and reproduction traits in other dairy cattle populations (e.g., [18–20]).

There is a plethora of traditional and novel trait definitions for measuring fertility and reproductive performance in females and males, which are further complicated by alternative definitions across breeding programs [3, 21, 22]. Furthermore, fertility and reproduction traits recorded in heifers and lactating cows have always been treated as different traits, i.e., they have been analyzed separately due to their usually low genetic correlations [9, 23]. Therefore, the detection of pleiotropic variants affecting multiple fertility and reproduction traits is paramount for unraveling their biological background. In this context, Bolormaa et al. [24] proposed an efficient multiple-trait analysis for directly combining the estimated effects of SNPs from single-trait GWAS based on a chi-square statistic, which facilitates the discovery of potential pleiotropic variants. In dairy cattle, this method has been applied to multiple fertility and reproduction traits, which were mainly based on SNP array data (e.g., [25-27]).

In this study, we first performed single-trait GWAS analyses for 18 fertility and reproduction traits in North American Holstein cattle, using imputed WGS genotypes. Following the method proposed by Bolormaa et al. [24], the multiple-trait chi-square statistics were subsequently calculated regarding different trait categories, including heifer traits, cows traits, sire traits, and their combinations. Our main objective was to identify candidate pleiotropic SNPs and genes associated with various fertility and reproduction traits in heifers, cows, and sires, which will contribute to a better understanding of the underlying biological mechanisms of fertility and reproduction traits in North American Holstein cattle.

Results

Deregressed breeding values and imputed SNP variants

The analyzed traits and their phenotypic summaries (i.e., deregressed estimated breeding values, dEBV) are shown in Table 1. The number of included animals that have phenotypes ranged from 3,803 for SCSc (sire calf survival – cow) to 5,986 for CA (calving ability). The average accuracy of dEBV (\pm standard deviation, SD) was 0.55 \pm 0.02. After performing the quality control (QC), about 5.6 million SNPs (ranging from 5,396,362 for CA to 5,880,012 for SCSc) were retained for single-trait GWAS analyses. These SNPs were distributed across all autosomes with a mean (\pm SD) pairwise distance of 445 \pm 1,478 bp and a mean (\pm SD) minor allele frequency (MAF) of 18.7 \pm 15.6% (Table S1).

Chen et al. BMC Genomics (2022) 23:331 Page 3 of 22

Table 1 Traits, summary statistics, and trait categories of multiple-trait analysis

Traits	Full names of traits	dEBV ^a			Accuracy		Trait categories used for multiple- trait analysis ^b					
		N	Mean	Min	Max	Mean	SD	Н	С	S	HC	HCS
AFS	Age at first service	5,123	81	-1,790	1,992	0.56	0.02					
FSTCh	First service to conception heifer	5,451	114	-1,934	2,134	0.55	0.03	\checkmark			\checkmark	$\sqrt{}$
NRRh	Non-return rate heifer	5,374	86	-1,939	2,137	0.55	0.03	\checkmark			\checkmark	$\sqrt{}$
CEh	Calving ease heifer	4,623	122	-1,726	1,925	0.56	0.02	\checkmark			\checkmark	$\sqrt{}$
CSh	Calf survival heifer	5,168	121	-1,887	2,082	0.55	0.03	\checkmark			\checkmark	$\sqrt{}$
CA	Calving ability	5,986	110	-1,881	2,074	0.56	0.02	\checkmark	$\sqrt{}$		\checkmark	$\sqrt{}$
CTFS	Calving to first service	4,800	125	-1,847	2,046	0.56	0.02		$\sqrt{}$		\checkmark	$\sqrt{}$
DO	Days open	5,034	93	-1,773	1,970	0.55	0.02		$\sqrt{}$		\checkmark	$\sqrt{}$
FSTCc	First service to conception cow	5,036	88	-1,835	2,032	0.55	0.02		\checkmark		\checkmark	$\sqrt{}$
NRRc	Non-return rate cow	5,283	105	-1,923	2,118	0.55	0.02		$\sqrt{}$		\checkmark	$\sqrt{}$
CEc	Calving ease cow	4,761	101	-1,814	2,012	0.56	0.02		\checkmark		\checkmark	$\sqrt{}$
CSc	Calf survival cow	5,045	122	-1,956	2,156	0.55	0.03		$\sqrt{}$		\checkmark	$\sqrt{}$
DCA	Daughter calving ability	5,191	116	-1,874	2,072	0.55	0.02		$\sqrt{}$		\checkmark	$\sqrt{}$
DF	Daughter fertility	5,529	106	-1,851	2,048	0.55	0.02		$\sqrt{}$		\checkmark	$\sqrt{}$
SCEh	Sire calving ease heifer	5,782	85	-1,974	2,167	0.56	0.02			\checkmark		$\sqrt{}$
SCEc	Sire calving ease cow	5,133	112	-1,974	2,171	0.56	0.02			$\sqrt{}$		$\sqrt{}$
SCSh	Sire calf survival heifer	4,687	109	-1,897	2,103	0.54	0.02			$\sqrt{}$		$\sqrt{}$
SCSc	Sire calf survival cow	3,803	113	-1,887	2,100	0.53	0.02			\checkmark		$\sqrt{}$

^a dEBV: deregressed estimated breeding values

Summaries of single-trait and multiple-trait GWAS analyses

The single-trait GWAS revealed a total of 1,484 SNPs that were significantly associated with the 18 fertility and reproduction traits with no overlapping SNPs between traits. The highest and lowest numbers of significant SNPs were observed for DO (days open) and NRRh (nonreturn rate heifer), respectively (Fig. 1A). These significant SNPs were broadly distributed across all autosomes (Fig. 1B), with the greatest number of significant SNPs located on BTA3, BTA22, and BTA23. For each trait, the top three chromosomes with the greatest numbers of significant SNPs are shown in Fig. 1C. BTA4, BTA20, and BTA22 were observed in common for four traits [i.e., CSc (calf survival cow), DCA (daughter calving ability), DO, and SCEc (sire calving ease cow) for BTA4, CSh (calf survival heifer), DF (daughter fertility), NRRh, and SCSh (sire calf survival heifer) for BTA20, and CA, CEh (calving ease heifer), FSTCh (first service to conception heifer), and SCEh (sire calving ease heifer) for BTA22]. The detailed distribution of significant SNPs identified across traits and chromosomes is shown in Table S2. The number of QTL identified in the single-trait GWAS ranged from 38 for NRRh to 73 for SCEc. There were three QTL overlapping between CA and CTFS (calving to first service), and three overlapping between CSh and SCEc (Table S3). The highest estimated genome inflation factor was equal to 1.090 (95% CI of 1.075–1.104) for DCA, and its mean \pm SD across all traits was equal to 1.052 ± 0.024 (Fig. S1).

For the multiple-trait analyses, the defined trait categories of heifer, cow, and sire traits, and their combinations are shown in Table 1. There were 425 significant SNPs revealed by multiple-trait analysis, including 87 for heifers, 72 for cows, 84 for sires, 96 for heifers and cows, and 86 for all animals. Of these, only one SNP (BTA9:21,350,462) was shared between heifers and cows, whereas no SNP for sire traits was shared with heifers, cows, or heifers and cows (Fig. S2). When both heifer and cow traits were analyzed together, there were 15 and 25 significant SNPs overlapping with the independent analyses of heifer and cow traits, respectively. In summary, the multiple-trait analyses revealed a total of 328 unique significant SNPs, which are distributed across all autosomes.

Multiple-trait analysis for heifer traits

The multiple-trait analysis of six heifer traits revealed 87 significant SNPs broadly distributed across 22 chromosomes (Fig. 2 and Table 2). Of these, the highest numbers of significant SNPs were observed on BTA20, BTA22, BTA23, and BTA18. The three most significant SNPs were located on BTA18, BTA20, and BTA20. A total of

^b The trait categories are defined with respective to heifers (H), cows (C), sires (S), heifers and cows (HC), and all the animals together (HCS), respectively

Chen et al. BMC Genomics (2022) 23:331 Page 4 of 22

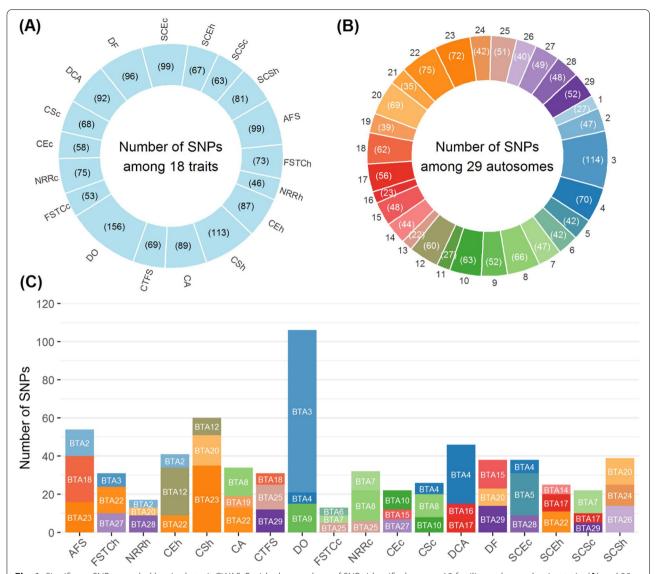


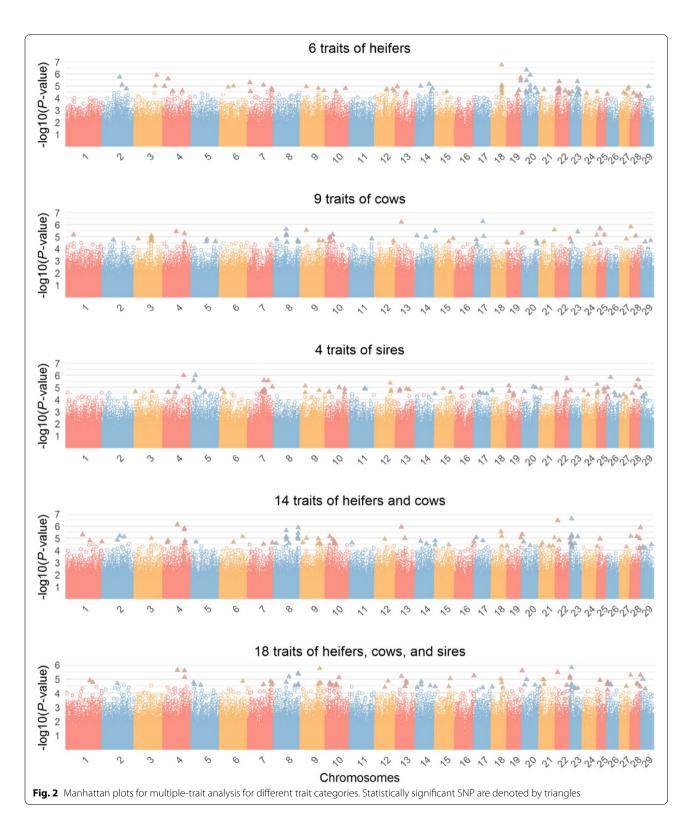
Fig. 1 Significant SNPs revealed by single-trait GWAS. Beside the numbers of SNPs identified among 18 fertility and reproduction traits (**A**) and 29 autosomes (**B**), the top three chromosomes with the largest numbers of significant SNPs were shown for each trait (**C**). AFS = Age at first service; FSTCh = First service to conception heifer; NRRh = Non-return rate heifer; CEh = Calving ease heifer; CSh = Calf survival heifer; CA = Calving ability; CTFS = Calving to first service; DO = Days open; FSTCc = First service to conception cow; NRRc = Non-return rate cow; CEc = Calving ease cow; CSc = Calf survival cow; DCA = Daughter calving ability; DF = Daughter fertility; SCEh = Sire calving ease heifer; SCEc = Sire calving ease cow; SCSh = Sire calf survival heifer; SCSc = Sire calf survival cow

176 protein-encoding and eight long non-coding RNAs (lncRNA) genes were found within±100 Kb regions around the significant SNPs, and 41 SNPs were located in the exonic, intronic, or upstream/downstream regions of 36 genes. All 87 significant SNPs were clustered into 69 QTL and three QTL (BTA18:39.58–40.01 Mb, BTA20:15.57–15.94 Mb, and BTA20:29.77–30.06 Mb) were identified based on three or more SNPs. Furthermore, 21 of these QTL (30.4%) overlapped with 138 previously reported reproduction-related QTL in

cattle (Table S4). Among them, one QTL on BTA3:89.78–89.98 Mb overlapped with 98 previously reported QTL that are associated with luteal activity (LA) and conception rate (CR).

The functional analyses revealed that the identified 184 candidate genes were significantly enriched into 21 Gene Ontology (GO) terms and Kyoto Encyclopedia of Genes and Genomes (KEGG) pathways (Fig. S3). Among them, the immunity-associated biological functions were predominant, such as the antigen processing

Chen et al. BMC Genomics (2022) 23:331 Page 5 of 22



and presentation that was associated with multiple genes within the regions of BTA23:25.72–25.92 Mb and BTA23:28.53–25.73 Mb. These genes included the major

histocompatibility complex (MHC), class II, DR alpha (BOLA-DRA), MHC class I antigen (BOLA-NC1), MHC class I heavy chain (BOLA), and MHC Class I JSP.1

Chen et al. BMC Genomics (2022) 23:331 Page 6 of 22

Table 2 Significant SNPs and candidate genes from multiple-trait analysis for six heifer fertility and reproduction traits

Chr	Position (bp)	P values	Genomic location	Candidate genes (within ± 100 kb) ^a	N of QTL ^b
BTA2	70,633,250	1.7755e-06	Intergenic	EN1	0
	80,773,959	8.2906e-06	Intron	TMEFF2	0
	98,894,327	1.703e-05	Intergenic	_	0
BTA3	83,818,837	9.9389e-06	Exon	PATJ	0
	89,878,033	1.2513e-06	Intergenic	_	98
BTA4	2,476,516	1.0209e-05	Intergenic	_	0
	17,304,670	2.5726e-06	Intergenic	_	0
	36,768,135	2.6301e-05	Intergenic	ENSBTAG00000053333*	0
	77,892,378	2.4934e-05	Intergenic	HECW1	0
BTA6	31,807,526	1.248e-05	Intergenic	_	2
	54,108,303	9.9442e-06	Intergenic	_	1
BTA7	6,177,026	5.1964e-06	Intron	CPAMD8, F2RL3 , SIN3B, NWD1	1
	8,193,333	2.7732e-05	Exon	CASP14, CCDC105, SLC1A6 , ENSBTAG00000053903, <i>OR7C19</i> , <i>OR7A85</i> , ENSBTAG00000051946	0
	62,865,717	8.3985e-06	Intergenic	FAT2, SPARC, ENSBTAG00000054940, ATOX1	0
	97,438,333	1.6934e-05	Intergenic	_	0
	100,189,059	2.344e-05	Intergenic	ST8SIA4	2
BTA9	21,350,462	1.1343e-05	Intergenic	_	0
	71,191,104	1.5112e-05	Intergenic	_	0
	95,975,870	2.4538e-05	Intergenic	ENSBTAG00000052316, SOD2, WTAP, ACAT2, TCP1, MRPL18, PNLDC1	5
TA10	41,323,422	2.7906e-05	Intergenic	_	0
	81,606,975	1.5652e-05	Intron	SLC10A1, SMOC1	1
BTA12	45,686,110	1.8064e-05	Intergenic	_	0
	45,712,972	2.0906e-05	Intergenic		
	69,768,461	1.8444e-05	Intergenic	_	0
	77,682,412	2.495e-05	Intron	NALCN	4
TA13	3,327,860	1.1246e-05	Intergenic	ANKEF1	0
	42,023,779	3.7745e-05	Downstream	NXT1 , <i>GZF1</i> , NAPB , ENSBTAG00000027420, <i>MGC133636</i> , <i>CST8</i> , ENS-	0
	42,049,979	3.7745e-05	Intron	BTAG0000015949	-
BTA14	18,883,604	1.0029e-05	Intergenic	_	3
,,,,,,	54,326,109	7.0163e-06	Intergenic	_	1
	61,221,242	3.2749e-05	Intergenic	CTHRC1, FZD6, BAALC	3
	67,859,596	1.5109e-05	Intergenic	PTDSS1	0
BTA15	45,999,990	2.9729e-05	Intergenic	OR6A2, OR6B18, ENSBTAG00000027525, OR6B17, ENS- BTAG00000037603, OR2D4, OR2D3G, OR2AG1E, OR2AG1G, OR2AG1, OR2AG2	0
3TA18	39,676,071	1.3142e-05	Intron	ZNF19, ZNF23, ENSBTAG00000053994*, CALB2, CMTR2, ENS-	0
	39,750,065	2.1267e-05	Intergenic	BTAG00000051512	
	39,767,356	8.5276e-06	Exon		
	39,797,494	1.8113e-07	Downstream		
	39,854,578	9.5369e-06	Upstream		
	39,905,828	2.4327e-05	Intron		
	41,105,349	4.5111e-05	Intron	ZNF536	2
	41,112,039	2.5866e-05	Intron		
BTA19	39,685,286	4.588e-05	Exon	PLXDC1, CACNB1 , RPL19, ENSBTAG00000050597, STAC2, ENSBTAG00000008368, FBXL20	0
	46,856,509	2.2533e-05	Intron	EFCAB3, METTL2A, TLK2	2
	53,776,030	3.7096e-06	Intron	DNAH17, PGS1, SOCS3	0
	53,779,550	2.1366e-06	Intron		

Chen et al. BMC Genomics (2022) 23:331 Page 7 of 22

Table 2 (continued)

Chr	Position (bp)	P values	Genomic location	Candidate genes (within ± 100 kb) ^a	N of QTL ^b
BTA20	12,849,264	2.7392e-05	Intron	ENSBTAG00000049964	0
	15,673,813	3.5073e-06	Intergenic	HTR1A	0
	15,788,934	4.5398e-07	Intergenic		
			-		
	15,839,035	3.8454e-05	Intergenic		
	29,868,266	8.7288e-06	Intergenic	ENSBTAG00000054476	0
	29,957,655	1.2013e-06	Intergenic		
	29,957,766	3.1125e-05	Intergenic		
	29,959,061	1.8094e-05	Intergenic		
	51,156,345	1.4415e-05	Intron	CDH12	0
	62,043,263	3.4353e-05	Intron	CTNND2	0
BTA21	62,043,442	3.5997e-05 2.0376e-05	Intron Intron	AGBL1	0
BTA21	17,250,280 2,072,527	1.8504e-05	Intron	EOMES	0
DIAZZ		4.422e-05	_	TGFBR2, GADL1	1
	5,159,344 9,601,560	4.422e-05 4.4335e-05	Intron Intergenic	ARPP21	0
	9,634,144	1.8949e-05	Intergenic	ANTZI	O
	11,393,650	1.341e-05	Intron	CTDSPL, VILL, PLCD1, DLEC1	0
	11,701,385	2.9746e-05	Intron	ACAA1, ENSBTAG00000054286, MYD88, OXSR1 , ENS -	0
		4.1052e-06	Downstream	BTAG0000050531*, SLC22A14, XYLB, ACVR2B	U
	11,737,948	2.4904e-05	Intron	MAGI1	0
	35,777,156				2
	51,337,027	3.512e-05	Intron	CELSR3, SLC26A6, TMEM89, UQCRC1, ENSBTAG00000049917*, ENS- BTAG00000052088*, ENSBTAG00000049028*, UCN2, PFKFB4 , SHISA5, ENSBTAG00000048942, TREX1, ATRIP, TMA7, CCDC51	2
	55,900,928	4.9063e-05	Intergenic	TAMM41, TRH, TMCC1	1
BTA23	5,726,221	2.9329e-05	Intergenic	_	0
	25,235,958	5.2155e-05	Intron	GSTA1, GSTA5, GSTA3, GSTA4, CILK1 , FBXO9, GCM1	0
	25,819,703	4.2745e-05	Intergenic	ENSBTAG00000013919, ENSBTAG00000048364, ENS- BTAG00000038397, ENSBTAG0000015565, <i>BOLA-DRA, BTNL2</i> , ENSBTAG00000034945, ENSBTAG00000007618	0
	26,689,257	1.4214e-05	Intergenic	_	0
	28,036,775	4.1923e-06	Intron	ENSBTAG00000051047, ENSBTAG0000007075 , ENS- BTAG00000053433, <i>POU5F1</i> , <i>TCF19</i> , <i>CCHCR1</i> , <i>PSORS1C2</i> , <i>CDSN</i> , <i>C23H6orf15</i>	1
	28,634,425	3.1365e-05	Intergenic	BOLA-NC1, JSP.1, ENSBTAG00000037421, BOLA	0
	30,058,286	2.9988e-05	Intron	ZNF311, ENSBTAG00000052294*, TRIM27 , ENSBTAG00000053198	0
	34,904,897	1.9645e-05	Intergenic	GHE4, PRP2, PRP14 , PRP9	0
	34,928,894	5.2141e-05	Intron		
BTA24	13,978,039	3.8859e-05	Intron	PIK3C3	0
	58,070,140	2.9176e-05	Intron	ZNF532, ENSBTAG00000022829 , SEC11C	0
BTA25	38,933,869	4.7617e-05	Intron	FBXL18, ENSBTAG00000050734*, TNRC18 , SLC29A4, WIPI2	3
BTA27	13,585,281	3.5455e-05	Intron	TENM3	1
	23,857,214	4.66e-05	Intron	DLC1	0
	30,435,395	1.768e-05	Intergenic	_	0
	34,758,502	1.2659e-05	Intron	ADAM2, ADAM3A	3
3TA28	10,602,903	3.7999e-05	Intergenic	RYR2, ZP4	1
	24,802,568	6.4777e-05	Intron	PBLD, HNRNPH3, RUFY2 , DNA2, SLC25A16	0
	39,062,420	5.1602e-05	Intergenic	GHITM, C10orf99, CDHR1	0
	27,630,533	1.1083e-05	Intergenic	OR8G5, OR8G47, OR8D2, OR8B1U, OR8B1S, OR8B1AE, ENS-	0

^a Candidate genes are represented by gene symbol when available, otherwise by the Ensembl gene ID. The long noncoding RNA genes are marked by asterisk (*). The genes directly linked to SNPs are further denoted in bold

 $[^]b \, The \, number \, of \, known \, and \, reproduction-associated \, QTL \, found \, in \, Cattle \, QTL \, Database \, v43 \, (www.animalgenome.org)$

Chen et al. BMC Genomics (2022) 23:331 Page 8 of 22

(*JSP.1*). Another significantly enriched GO term, the "prolactin receptor binding", was found related to three genes, named growth hormone E4 (*GHE4*), prolactin-related protein 14 (*PRP14*), and prolactin-related protein IX (*PRP9*), within the region of BTA23:34.80–35.03 Mb.

Multiple-trait analysis for cow traits

There were 72 SNPs significantly associated with cow traits (Fig. 2 and Table 3). These significant SNPs were distributed across 25 chromosomes, with the highest number of SNPs observed on BTA3, BTA8, and BTA10. The three most significant SNPs were located on BTA17, BTA13, and BTA27, respectively. There were 37 significant SNPs located within the exonic, intronic, or upstream/downstream regions of 23 genes, while 101 candidate genes were found within ± 100 Kb of 35 intergenic SNPs. Fifty-six QTL were found, and two of them (BTA3:67.59-67.79 Mb, BTA8:49.18-49.38 Mb) were supported by three or more significant SNPs. By searching the Cattle QTL Database, 17 QTL (30.4%) overlapped with 31 previously reported QTL that are associated with calving interval (CI), CR, first service conception (FSC), and number of inseminations per conception (IPC) (Table S5).

Eight GO terms and one KEGG pathway were significantly enriched for the 124 identified candidate genes (Fig. S3). Acylglycerol O-acyltransferase activity and diacylglycerol metabolism were the most significantly associated biological functions, which were linked to four genes (Monoacylglycerol O-acyltransferase 2, MOGAT2; 2-acylglycerol O-acyltransferase 2, LOC785379; ENS-BTAG00000017443; ENSBTAG00000015091) within the region of BTA15:54.88-55.08 Mb and to one gene (Membrane bound O-acyltransferase domain containing 7, *MBOAT7*) within the region of BTA18:63.08–63.28 Mb. Three GO terms of "integrin complex", "protein complex involved in cell adhesion", and "plasma membrane signaling receptor complex" were linked to six genes on BTA25 (Glutamate ionotropic receptor NMDA type subunit 2A, GRIN2A; Integrin subunit alpha M, ITGAM; Integrin subunit alpha X, ITGAX; Integrin subunit alpha D, ITGAD), BTA18 (Shisa family member 7, SHISA7), and BTA10 (Integrin subunit alpha 11, ITGA11). The KEGG pathway of "Olfactory transduction" was also associated with 12 genes on BTA5 and BTA10.

Multiple-trait analysis for sire traits

Eighty-four significant SNPs were associated with sire traits, which were broadly distributed across 24 chromosomes (Fig. 2 and Table 4). The three chromosomes that had the highest numbers of significant SNPs were

BTA7, BTA17, and BTA22. The three most significant SNPs were located on BTA4, BTA5, and BTA26. There were one, 32, and one significant SNP located within the exonic, intronic, and upstream/downstream regions of 30 protein-encoding genes, respectively. Other 104 protein-encoding and 13 lncRNA genes were found within \pm 100 Kb regions of 50 intergenic SNPs. Seventythree QTL regions were determined from the 84 significant SNPs, and 31 of them (42.5%) overlapped with 72 previously reported QTL associated with reproduction traits in sires such as scrotal circumference, daughter pregnancy rate (DPR), CR, IPC, and interval to first estrus after calving (IFEC); Table S6. Among all the 147 candidate genes found for sire reproduction traits, only one GO term of "N-acetyl-beta-D-galactosaminidase activity" was shown to be significantly enriched (Fig. S3). Two genes located on BTA20, including HEXB (Hexosaminidase subunit beta) and LOC786974 (Betahexosaminidase subunit beta) were also involved in this biological function.

Multiple-trait analysis for the combined trait categories

When the 14 female fertility and reproduction traits were combined (heifers and cows), 96 significant SNPs were identified across 28 chromosomes (Fig. 2 and Table S7). The three most significant SNPs were located on BTA23, BTA22, and BTA4, respectively. Ninety-six QTL were detected and 25 of them overlapped with 60 previously reported reproduction-associated QTL in cattle (Table S8). There were 171 candidate genes found, in which, nine GO terms and one KEGG, such as Phagosome (KEGG:04,145) and rough endoplasmic reticulum (GO:0,005,791), were significantly enriched for them (Table S9).

The multiple-trait chi-square statistics was also applied to all 18 traits of heifers, cows, and sires combined. Eighty-six significant SNPs and 178 candidate genes were identified across 26 chromosomes (Fig. 2 and Table S10). All significant SNPs were clustered into 77 QTL, and 27 of them (35%) overlapped with previously reported reproduction-associated QTL in cattle for traits, such as CR, calving ease (CE), DPR, and IPC (Table S11). The functional enrichment analyses revealed four GO terms, including "2-acylglycerol O-acyltransferase activity", "Diacylglycerol biosynthetic process", "Acylglycerol O-acyltransferase activity", and "O-acyltransferase activity" (Table S9). For these biologically relevant genes identified for heifer, cow, and sire traits in this study, we also performed a proteinprotein interaction analysis, but no direct functional interactions among them were observed as shown in Fig. S4.

Chen et al. BMC Genomics (2022) 23:331 Page 9 of 22

Table 3 Significant SNPs and candidate genes from multiple-trait analysis for nine cow fertility and reproduction traits

Chr	Position (bp)	P values	Genomic location	Candidate genes $(within \pm 100 \text{ kb})^a$	N of QTL ^b
BTA1	34,156,863	6.8092e-06	Intergenic	CADM2	0
BTA2	44,192,878	1.7484e-05	Intron	CACNB4	0
BTA3	13,060,985	1.5004e-05	Intergenic	ENSBTAG00000053098, ENSBTAG00000052866*, ENSBTAG00000054932, ENSBTAG00000051454	0
	67,686,622	2.6373e-05	Intron	ST6GALNAC5	0
	67,687,557	2.2745e-05	Intron		
	67,687,632	1.0234e-05	Intron		
	67,687,904	1.6141e-05	Intron		
	67,688,010	8.0894e-06	Intron		
	67,688,259	1.4877e-05	Intron		
	67,691,020	1.2185e-05	Intron		
	67,691,132	9.1178e-06	Intron		
	67,691,448	2.7514e-05	Intron		
	67,691,487	1.6939e-05	Intron		
	67,691,717	2.6505e-05	Intron		
	67,693,137	1.9264e-05	Intron		
	67,693,371	2.0276e-05	Intron		
BTA4	52,090,769	3.731e-06	Intergenic	TES, ENSBTAG00000055251	0
	86,337,952	2.7549e-05	Intron	PTPRZ1	0
	86,338,437	5.4702e-06	Intron		
BTA5	59,741,942	2.5619e-05	Downstream	OR9K2 , OR9K15, OR9K1, OR9K2F, OR9K1B	1
	61,923,964	1.5754e-05	Intergenic	None	2
	98,326,111	2.4699e-05	Intergenic	None	0
BTA8	9,613,389	1.6984e-05	-	KIF13B, HMBOX1	0
	48,903,003	2.4027e-06		ENSBTAG00000048940*, <i>TMC1</i> , ENSBTAG00000052698	0
	49,280,626	6.2112e-06	_	ENSBTAG00000052764*, ANXA1	0
	49,282,386	7.11e-06	Intergenic		
	49,282,702	8.1027e-06	-		
	52,344,611	2.7461e-05	9	PCSK5	0
	97,982,105	1.9975e-05		None	0
	98,998,669	2.7653e-05	Intron	PTPN3	0
	100,989,652	2.3223e-05	Intron	ECPAS, ZNF483, PTGR1, DNAJC25, GNG10	0
BTA9	21,350,462	2.972e-06	Intergenic	None	0
	73,443,174	2.0733e-05	_	AHI1 , ENSBTAG00000046495	0
	91,316,160	2.1955e-05		ENSBTAG00000020723, ENSBTAG00000049872, <i>SCAF8</i>	1
RTA10	15,091,095	1.0356e-05		PIAS1, CALML4, CLN6, FEM1B, ITGA11	2
DITTIO	15,499,538	2.5633e-05	_	CORO2B	0
	15,737,285	1.2939e-05		ANP32A, ENSBTAG00000051138*, SPESP1	0
	27,718,962		Downstream	OR4F67B , OR4G18, OR4K36, OR4G8, OR4G9, OR4G2	0
	30,942,681	2.4868e-05		DPH6	0
RTA11	89,383,411	1.5143e-05		None	3
	74,138,771	2.0551e-05	9	HS6ST3, ENSBTAG00000045566, OXGR1	0
אווע	74,136,771	3.4154e-05	-	ENSBTAG00000052185*	2
RTA 12	20,203,933	6.2166e-07	_	ENSBTAG00000032183 ENSBTAG0000002675, ENSBTAG00000052951	0
		8.1819e-06	-	•	1
14 אוט	2,204,649			ENSBTAG0000048964*	
	40,827,215	1.0856e-05	intergenic	ENSBTAG00000039499	0

Chen et al. BMC Genomics (2022) 23:331 Page 10 of 22

Table 3 (continued)

Chr	Position (bp)	P values	Genomic location	Candidate genes $(within \pm 100 \text{ kb})^a$	N of QTL ^b
BTA15	54,978,763	2.5073e-05	Intergenic	<i>MOGAT2</i> , ENSBTAG00000053794, <i>LOC785379</i> , ENSBTAG00000017443, ENSBTAG00000015091, ENSBTAG00000052936	1
	73,049,607	1.3516e-05	Intergenic	None	0
BTA17	4,778,666	1.7939e-05	Intron	FHDC1, ARFIP1	1
	7,455,065	4.1422e-05	Intron	LRBA	0
	32,848,516	5.4123e-07	Intergenic	None	0
	36,481,658	9.3183e-06	Intron	FSTL5	1
BTA18	61,968,892	2.8497e-05	Intergenic	EPN1, U2AF2, CCDC106, ZNF581, ZNF580, ZNF524, ZNF784, FIZ1, ZNF579, SBK2, SSC5D, NAT14, ZNF628, C19orf85, ENSBTAG0000050011, ISOC2, SHISA7	0
	63,182,112	3.3624e-05	Intergenic	ENSBTAG00000049178, RPS9, TSEN34, MBOAT7, TMC4, LENG1, CNOT3, PRPF31, TFPT, NDUFA3	6
BTA19	59,744,349	4.8366e-06	Intergenic	None	0
BTA20	56,959,618	2.3978e-05	Intron	MARCHF11	4
	60,163,003	4.01e-05	Intergenic	None	0
BTA21	16,945,728	2.5982e-05	Intergenic	AGBL1	0
	60,917,828	2.6523e-06	Intron	C21H14orf132	0
BTA22	56,807,677	1.3049e-05	Intron	PPARG , ENSBTAG00000052393*	0
BTA23	2,330,898	2.7799e-05	Intergenic	None	0
	28,726,064	3.9504e-06	Upstream	JSP.1, ENSBTAG00000037421, BOLA , TRIM26, TRIM15, TRIM10	0
BTA24	45,122,975	4.3551e-05	Intergenic	None	0
	57,019,331	7.1833e-06	Intergenic	ATP8B1	1
BTA25	8,675,209	3.4891e-05	Intron	GRIN2A	0
	8,702,138	2.0848e-06	Intergenic		
	27,413,783	6.8667e-06	Exon	ITGAM, ITGAX , ITGAD, COX6A2, ARMC5, TGFB111	1
BTA27	24,754,025	1.5149e-05	Intron	CLDN23, LOC527981	1
	43,998,949	1.466e-06	Intergenic	ZNF385D	1
BTA28	19,657,628	8.5e-06	Intron	JMJD1C, REEP3	0
BTA29	13,752,854	2.5963e-05	Intergenic	None	0
	37,010,381	1.9927e-05	Intergenic	ENSBTAG00000050640*, SNX19, ENSBTAG00000022460, MS4A8, MS4A18	2

^a Candidate genes are represented by gene symbol when available, otherwise by the Ensembl gene ID. The long noncoding RNA genes are marked by asterisk (*). The genes directly linked to SNPs are further denoted in bold

Discussion

Refined studies on fertility and reproduction traits in dairy cattle

Due to the great economic importance of fertility and reproduction traits in cattle industry, GWAS have been frequently carried out especially since genotyping become affordable for large sample sizes. Besides the fact that SNP panels have been used in former GWAS of cattle fertility and reproduction traits [27–39], wholegenome sequence variants recently began to be used to refine QTL boundaries and identify causal genes [18–20]. Therefore, the imputed or real WGS variants is being increasingly used for GWAS, especially for traits with low heritability and that are highly polygenic. Because of intrinsic correlations among various indicator traits of fertility and reproduction, it is preferable

to perform multiple-trait GWAS to detect pleiotropic variants and increase the detection power of important variants. The classical methods of multiple-trait GWAS [40, 41] are difficult to implement in practice, especially on large-scale datasets due to computing requirements. Alternatively, an approximate method was proposed by Bolormaa et al. [24], which efficiently computes a multiple-trait chi-square statistic from estimated SNP effects from single-trait GWAS. In this study, we used imputed WGS variants and this approximate method for multiple-trait GWAS of fertility and reproduction traits in Holstein cattle, aiming to refine the associated pleiotropic variants, candidate genes, and QTLs.

Polygenic nature of fertility and reproduction traits

Most fertility and reproduction traits are lowly heritable in cattle. Berry et al. [21] reported a summary

^b The number of known and reproduction-associated QTL found in Cattle QTL Database v43 (www.animalgenome.org)

Chen et al. BMC Genomics (2022) 23:331 Page 11 of 22

Table 4 Significant SNPs and candidate genes from multiple-trait analysis for four sire fertility traits

Chr	Position (bp)	P values	Genomic location	Candidate genes $(within \pm 100 \text{ kb})^a$	N of QTL ^b
BTA3	147,935	2.2433e-05	Intergenic	ENSBTAG0000000584, TBX19	0
	71,522,570	2.1323e-05	Intergenic	_	0
BTA4	18,040,294	2.4781e-05	Intergenic	_	0
	47,200,188	2.5485e-05	Intergenic	SYPL1	0
	59,888,193	9.0367e-06	Intron	ELMO1	0
	82,878,864	9.7487e-07	Intergenic	LSM8	3
BTA5	6,106,039	2.7083e-06	Intergenic	ZDHHC17	0
	13,310,594	9.9233e-07	Intergenic	_	0
	32,058,789	1.0382e-05	Intergenic	H1-7, ENSBTAG00000032429, ENSBTAG00000032428, CCDC184, ASB8, PFKM	0
	53,516,007	2.3608e-05	Intergenic		6
BTA6	7,494,351	1.3907e-05	Intergenic	ENSBTAG00000051854*	2
	16,046,562	2.6665e-05	Intergenic	_	0
BTA7	56,985,760	2.23e-05	Intron	PRELID2, GRXCR2	0
	64,117,199	1.5768e-05	Intergenic	_	2
	65,880,766	2.3775e-05	Intergenic	ENSBTAG00000053039*, LARP1	0
	65,887,207	2.5969e-06	Intergenic		
	68,359,300	1.6201e-05	Intergenic	ENSBTAG00000030297, <i>TIMD4</i> , ENSBTAG00000050582*, ENSBTAG00000049542*	0
	68,430,783	1.5884e-05	Intergenic		
	69,170,746	2.7112e-05	Intron	CYFIP2, NIPAL4, ADAM19 , SOX30	0
	83,320,343	2.8225e-06	Intron	XRCC4, VCAN	1
	100,056,219	8.7549e-06	Intron	ST8SIA4	2
BTA9	15,828,286	7.3866e-06	Intergenic	_	2
	15,843,031	2.5491e-05	Intergenic		
	74,655,065	1.7472e-05	Intron	MAP3K5	4
BTA10	13,081,096	2.3448e-05	Intron	MEGF11	0
	55,196,388	9.9519e-06	Intergenic	RSL24D1	0
	77,838,554	2.8177e-05	Downstream	FUT8	0
	77,968,781	1.3016e-05	Intergenic		
BTA11	58,988,314	1.1679e-05	Intergenic	_	0
	63,929,970	1.3355e-05	Intergenic	_	0
BTA12	60,487,742	4.3234e-06	Intergenic	_	0
	63,535,854	1.6981e-05	Intergenic	_	0
	63,538,393	2.1305e-05	Intergenic		
BTA13	13,568,203	2.023e-05	Intergenic	_	0
	14,812,273	1.4407e-05	Intergenic	_	0
	41,317,365	1.2933e-05	Intergenic	_	0
	53,595,922	1.5122e-05	Intron	ENSBTAG00000054594, ENSBTAG00000011638, ENSBTAG00000054447, ENSBTAG00000027221, <i>GINS1</i> , <i>PCMTD2</i> , <i>MYT1</i>	2
BTA14	78,863,167	3.3468e-05	Intergenic	_	0
BTA15	30,636,699	1.2166e-05	Intergenic	TRIM29	3
	60,970,873	2.5168e-05	Intergenic	FSHB, ARL14EP	2
BTA16	23,387,972	1.0853e-05	Intergenic	SLC30A10, EPRS1	0
BTA17	18,332,441	2.8154e-05	Intron	RAB33B, NAA15 , NDUFC1, MGARP , ENSBTAG00000015811, <i>ELF</i> 2	3
	18,371,778	2.706e-05	Intron		
	18,408,888	2.8364e-05	Intron		
	18,458,616	2.3968e-05	Intergenic		
	33,971,794	2.9933e-05	Intergenic	ENSBTAG00000052376*	5

Chen et al. BMC Genomics (2022) 23:331 Page 12 of 22

Table 4 (continued)

Chr	Position (bp)	P values	Genomic location	Candidate genes $(within \pm 100 \text{ kb})^a$	N of QTL ^b
	48,501,570	3.3186e-05	Intron	TMEM132C	2
	73,040,719	1.7853e-05	Intergenic	TANGO2, ENSBTAG00000049742*, DGCR8, TRMT2A, ENSBTAG00000049062, RANBP1, ZDHHC8, CCDC188, ENSBTAG00000052630*, RTN4R, PRODH, DGCR6L	8
BTA19	3,507,732	6.9599e-06	Intergenic	_	0
	6,425,261	2.0337e-05	Intron	PCTP, ENSBTAG00000053407, ENSBTAG00000039563	0
	23,803,632	4.6828e-05	Intron	RAP1GAP2 , ENSBTAG00000049401, <i>OR1D3B</i> , <i>OR1D3</i>	2
	23,811,867	3.2146e-05	Intron		
BTA20	6,792,445	2.1451e-05	Intron	FAM169A, NSA2, GFM2 , HEXB, LOC786974	0
	44,069,982	8.8349e-06	Intergenic	_	0
	53,664,202	1.0238e-05	Intron	CDH18	0
BTA21	3,550,200	1.2359e-05	Intergenic	_	0
BTA22	529,021	3.8026e-05	Intron	VOPP1, LANCL2	0
	756,892	2.5524e-05	Intron		
	37,660,216	4.9522e-05	Intergenic	THOC7, C22H3orf49, ENSBTAG00000051113*, SNTN	3
	42,471,770	2.3695e-05	Intron	CFAP20DC	3
	44,200,445	1.8137e-06	Intron	ARHGEF3	0
	59,781,347	1.759e-05	Intron	MGLL, ABTB1, PODXL2	0
BTA24	1,516,807	1.8306e-05	Intergenic	_	0
	20,595,336	4.1116e-05	Intron	FHOD3	1
	57,446,121	5.5515e-06	Intron	NEDD4L , ENSBTAG00000051924*	0
	57,476,264	2.8706e-05	Exon		
	61,476,879	2.1094e-05	Intron	BCL2	1
BTA25	26,121,115	1.2696e-05	Intron	EIF3CL, CLN3, ENSBTAG00000050361, IL27, NUPR1, SGF29, SULT1A1 , SLX1A, ENSBTAG00000008632, CORO1A, MAPK3, GDPD3, YPEL3, TBX6, PPP4C, ALDOA, ENSBTAG00000050743	1
	27,554,453	2.3765e-05	Intergenic	ITGAD, COX6A2, ARMC5, TGFB1I1, SLC5A2, RUSF1, AHSP, OR7A53, OR7A153, SEP- TIN14, ZNF713, MRPS17	1
	39,147,647	6.6288e-05	Intron	<i>MMD2</i> , ENSBTAG00000051446, <i>RADIL</i> , <i>PAPOLB</i> , <i>AP5Z1</i> , ENSBTAG00000050145*, <i>FOXK1</i>	1
	40,290,599	1.0271e-05	Intergenic	CARD11	0
	40,356,262	5.4215e-05	Intergenic		
BTA26	10,927,671	1.4324e-06	Intergenic	ENSBTAG00000054811*, <i>LIPA</i>	1
	27,142,712	2.691e-05	Intergenic	ENSBTAG00000055185*	0
	30,565,345	4.8874e-05	Intergenic	XPNPEP1, ENSBTAG00000054944, ADD3	0
	48,212,324	5.1946e-05	Intergenic	ENSBTAG00000053738*	5
BTA27	13,351,474	3.8108e-05	Intron	ENSBTAG00000047749	1
	25,506,261	6.2859e-05	Intron	TNKS	1
BTA28	5,066,852	2.9294e-05	Intergenic	_	1
	19,499,175	7.0726e-06	-	JMJD1C	0
	29,298,316	2.2431e-06	Intron	NUDT13, ECD, FAM149B1, DNAJC9, MRPS16 , CFAP70, ANXA7	0
	37,896,374	1.0502e-05	Intron	NRG3	1
BTA29	4,807,970	5.4737e-05	Intergenic	_	1
	14,612,904	3.5086e-05	Intergenic	_	1

^a Candidate genes are represented by gene symbol when available, otherwise by the Ensembl gene ID. The long noncoding RNA genes are marked by asterisk (*). The genes directly linked to SNPs are further denoted in bold

 $^{^{\}rm b}$ The number of known and reproduction-associated QTL found in Cattle QTL Database v43 (www.animalgenome.org)

Chen et al. BMC Genomics (2022) 23:331 Page 13 of 22

of heritability estimates below 0.05 for most female traits and 0.05-0.22 for most male traits. Similarly, the reported QTL and candidate genes in literature have been found to be extensively distributed across genome, and few of them could be repeated across studies [3, 12]. In this study, a similar genetic landscape was observed, as all autosomes harbored significant SNPs for one or more traits analyzed, being consistent with the polygenic nature of these traits. Numerous fertility and reproduction indicator traits have been defined for measuring reproductive performance at different reproductive stages in female cattle [3, 21]. However, some of these traits are by definition related with each other, such as CI is greatly determined by the interval from calving to conception. Therefore, pleiotropic variants are expected for these traits [10, 42]. Overall, we found that the number of significant SNPs from multiple-trait analysis was less than the cumulative sum of separate single-trait analysis; and similar results were found in previous GWAS studies on fertility and reproduction [e.g., 27].

Differences between heifer and cow traits

It is well known that the genetic basis and physiological processes underlying reproduction differ between heifers and lactating cows. In general, heifer traits have higher heritability, but lower genetic correlations with each other compared to cow traits [43, 44]. There are also only moderate genetic correlations between heifer and cow traits, which are lower than between cow traits in different parities [23, 44–46]. Likewise, both ovarian structures and circulating steroids (such as serum concentrations of progesterone and estradiol) were observed to act differently between heifers and cows. In addition, lactating cows have lower circulating steroid concentrations, but larger ovulatory follicles and luteal structures than heifers [47, 48].

In previous GWAS for fertility and reproduction traits, different variants, candidate genes, and QTL were found significantly associated with heifers and cows [20, 26, 27, 37]. For instance, Fang et al. [26] found a significant QTL on BTA17 associated with interval from first to last insemination (IFLI) and non-return rate (NRR) in heifers, but not in cows. For NRR, distinct significant QTL regions on BTA17 were also suggested for heifers and cows [20]. Liu et al. [27] analyzed four fertility traits (IFLI, FSC, IPC, and NRR) measured on both heifers and cows, and found that none of the significant QTL overlapped and most of these QTL were located on distinct chromosomes. In this study, our multiple-trait analysis found that there were only two candidate QTL (around at BTA9:21.35 Mb and BTA23:28.63 Mb) overlapping between heifers and cows. Furthermore, our functional analyses of candidate genes also suggested differences between heifer and cow traits. The candidate genes found for heifers were significantly involved in immunity-associated biological functions, whereas candidate genes found for cows were associated with acylglycerol O-acyltransferase activity and diacylglycerol metabolism.

QTL and candidate genes found for heifer traits

The mean CR of Holstein heifers was estimated to be 56.3% in the United States, which is influenced by the age at breeding, month of breeding, age of service sire, and other factors [45]. Accordingly, our multiple-trait analysis for heifer traits suggested dozens of associated QTL that are broadly distributed across three quarters of all included chromosomes. Notably, one-third of these QTL overlapped with previously identified reproductionrelated QTL in cattle. For example, the QTL located on BTA3:89.78-89.98 Mb was supported by a QTL previously reported to be associated with the commencement of LA and proportion of cows in LA between 25 and 60 days in milk [19], and with CR [49]. There were five QTL previously reported to be associated with DPR, CR, and IFEC [50-52], overlapping with one QTL on BTA9:95.88-96.08 Mb found in this study. The QTL located on BTA12:77.58-77.78 Mb overlapped with four previously reported QTL associated with CE, DPR, and stillbirth [31, 53]. Furthermore, we identified many novel QTL in this study, such as BTA13:41.92-42.15 Mb, BTA18:39.57-40.01 Mb, BTA19:53.68-53.88 Mb, and BTA22:11.29-11.84 Mb, which showed strong association with heifer traits.

For the CR at first service and the number of times bred in Holstein heifers, Galliou et al. [54] found that three out of the five most significant pathways were involved in immune system regulation, which was consistent with our results. More importantly, the non-classical MHC I gene of BoLA-NC1, found in this study and involved in the KEGG pathway of allograft rejection, was suggested to increase maternal immunity against the fetus [55]. Another non-classical MHC I gene (JSP.1) was found to play a crucial role during early pregnancy in heifers in a previous study [56]. Similarly, Melo et al. [57] found that the MHC class II genes were significantly associated with pregnancy success in Nellore cows. As the link between autophagy and reproduction has been acknowledged [58], another autophagy-related gene of phosphatidylinositol 3-kinase catalytic subunit type 3 (PIK3C3) was identified in this study. These findings suggest the importance of immunological tolerance of dam to fetus and other immune responses in establishing successful pregnancy.

Notably, a QTL, that was located on BTA9:95.88–96.08 Mb and supported by five previously reported QTL, contained four candidate genes having biological implications in reproduction, including the superoxide

Chen et al. BMC Genomics (2022) 23:331 Page 14 of 22

dismutase 2 (SOD2) for meiotic defects in mouse oocytes [59], WT1 associated protein (WTAP) for spermatogenesis in mice [60], acetyl-CoA acetyltransferase 2 (ACAT2) for DPR in Holstein [52], and t-complex 1 (TCP1) for mediating sperm-oocyte interaction in mice [61]. On BTA22, there were five suggestive candidate genes, including the transforming growth factor beta receptor 2 (TGFBR2) for female fertility in pigs and mice [62, 63], DLEC1 cilia and flagella associated protein (DLEC1) and solute carrier family 22 member 14 (SLC22A14) regulating male fertility in mice [64, 65], activin A receptor type 2B (ACVR2B) associated with premature ovarian failure in human [66], and 6-phosphofructo-2-kinase fructose-2,6-biphosphatase 4 (PFKFB4) involved in spermatogenesis in mice [67]. Two genes, the tripartite motif containing 27 (TRIM27) and PRP14 on BTA23, were suggested to be associated with male and female fertility, respectively [68, 69]. Other positional candidate genes included the transmembrane protein with EGF like and two follistatin like domains 2 (TMEFF2) on BTA2 involved in early oocyte development in human [70] and associated with bull sperm morphometry [71], HECT, C2 and WW domain containing E3 ubiquitin protein ligase 1 (HECW1) on BTA4 required for estrogeninduced degradation of Scribble [72], cystatin 8 (CST8) on BTA13 involved in sperm maturation [73], dynein axonemal heavy chain 17 (DNAH17) on BTA19 associated with human sperm fertility [74, 75], ADAM metallopeptidase domain 3A (ADAM3A) on BTA27 regulating sperm migration in mice [76], and zona pellucida glycoprotein 4 (ZP4) on BTA28 regulating embryo development in rabbits [77]. Taken together of the experimental evidence in literature, these genes have been supported to hold biological roles in reproduction of humans and other species.

QTL and candidate genes found for cow traits

Our multiple-trait analysis for cow traits revealed that all significant QTL were broadly distributed across more than 85% of the chromosomes and one-third of them were supported by previously reported QTL in cattle. For instance, one QTL located on BTA18:63.08–63.28 Mb was previously reported significantly associated with CI and stillbirth [36, 78]; one QTL located on BTA20:56.86–57.06 Mb was supported by two previously reported associations with CR, FSC, and IPC [49, 54]; and one QTL located on BTA5:61.82–62.02 associated with FSC and CR [79]. In addition, many novel QTL identified in this study harbored candidate genes that have biological functions impacting reproduction according to the literature.

Our analyses of candidate genes for cow traits revealed functional implications that are in contrast to those for heifers. Instead of immune system, the most significant functions were associated with fatty acid metabolism, such as the acylglycerol O-acyltransferase activity and diacylglycerol metabolism. Mattos et al. [80] comprehensively reviewed effects of dietary fatty acids on reproduction in ruminants, which include the influences on ovarian follicle and corpus luteum function via improved energy status, and the synthesis of reproductive hormones, such as steroids and prostaglandins. In addition, the maternal lipid metabolism during pregnancy positively influence fetal growth [81, 82]. Many genes involved in fatty acid metabolism were similarly found to be associated with reproductive performance in Nellore cattle [57]. The seasonal changes in Holstein fertility was related to fatty acid composition of follicles [83]. Furthermore, the relationship between dietary fatty acids and ovarian function was experimentally found in Holstein cows [84].

Interestingly, numerous candidate genes identified in this study also have the known biological functions associated with reproduction in literature. Two genes (GRIN2A and ITGAX) located on BTA25 were associated with CTFS in Iranian Holstein cattle [85] and with altered expression in polycystic ovary syndrome in women [86], respectively. There were four candidate genes located on BTA8, including the kinesin family member 13B (KIF13B) involved in oocyte meiosis [87], annexin A1 (ANXA1) with regulatory functions during early pregnancy in mice [88] and differentially expressed between less fertile and normally fertile Holstein [89], proprotein convertase subtilisin/kexin type 5 (PCSK5) that contributed to ovarian follicle development in rats [90], and zinc finger protein 483 (ZNF483), which is associated with age of puberty in Brahman heifers [91]. Two genes, the fem-1 homolog B (FEM1B) and sperm equatorial segment protein 1 (SPESP1) on BTA10, were reported to be involved in polycystic ovary syndrome in humans [92] and required for fully fertile sperm in mice [93], respectively. Four genes were associated with different reproduction traits, including cell adhesion molecule 2 (CADM2) on BTA1 with the number of piglets born dead in pigs [94], calcium voltage-gated channel auxiliary subunit beta 4 (CACNB4) on BTA2 with CTFS in Iranian Holstein Cattle [85], ST6 N-acetylgalactosaminide alpha-2,6-sialyltransferase 5 (ST6GALNAC5) on BTA3 with fertility index in Holstein cattle [95], and ATP/GTP binding protein like 1 (AGBL1) on BTA21 with out of season lambing in sheep [96]. Other suggestive candidate genes included the protein tyrosine phosphatase receptor type Z1 (PTPRZ1) on BTA4 differentially expressed between high- and low-fertility Holstein cows [97], LPS responsive beige-like anchor protein (LRBA) on BTA17 differentially methylated between high- and low-fertility bulls Chen et al. BMC Genomics (2022) 23:331 Page 15 of 22

[98], peroxisome proliferator activated receptor gamma (*PPARG*) on BTA22 involved in the release of oocytes each estrous cycle [99], and jumonji domain containing 1C (*IMJD1C*) on BTA28 required for long-term maintenance of male germ cells in mice [100].

QTL and candidate genes found for sire traits

In dairy cattle, the genetic evaluation of male reproduction has received much less attention in comparison with female traits [101, 102]. Sire CR in Holstein was included in two previous GWAS studies [103, 104], which revealed significant SNPs located on multiple chromosomes. In this study, we included four sire traits and found that the number and genomic distribution of QTL are comparable with or higher than that in females. Interestingly, more than 40% of these QTL identified in this study overlapped with previously reported reproduction-related QTL in cattle. For instance, all four QTL located on BTA17 (BTA17:18.23–18.56 Mb, BTA17:33.87-34.07 BTA17:48.40-48.60 Mb, and BTA17:72.94-73.14 Mb) overlapped with previous reports for DPR, IPC, CE, stillbirth, IFEC, and NRR [31, 34, 49, 50, 54] and three out of four QTL on BTA25 (BTA25:26.02-26.22 Mb, BTA25:27.45-27.65 Mb, and BTA25:39.05-39.25 Mb) overlapped with previous reports for age at first calving (AFC) and CR [105, 106].

Only one GO term (N-acetyl-beta-D-galactosaminidase activity) was significantly enriched among all candidate genes of sire traits. The two involved genes (HEXB and LOC786974) on BTA20 have no functional evidence in literature with respective to reproduction. However, we found many novel candidate genes that have direct functional implications in reproduction. For example, the engulfment and cell motility 1 (ELMO1) gene on BTA4 was found to play crucial roles in clearance of apoptotic germ cells and spermatogenesis in mice [107]. Two genes, JMJD1C and cilia and flagella associated protein 70 (CFAP70) on BTA28, are required for long-term maintenance of germ cells in mice [100] and are associated with multiple morphological abnormalities of sperm flagella in human [108]. Notably, both ELMO1 and JMJD1C genes were suggested by the significant SNPs located in intronic regions. One well-known candidate gene on BTA15 (follicle stimulating hormone subunit beta, FSHB), associated with semen quality and fertility in bulls [109], was also identified in this study.

There were four suggestive candidate genes on BTA7, including the PRELI domain containing 2 (*PRELID2*) associated with fertility traits in pigs [110], ADAM metallopeptidase domain 19 (*ADAM19*) differentially expressed between different quality of bovine blastocysts [111], SRY-box transcription factor 30 (*SOX30*) required for male fertility in mice [112, 113], and versican (*VCAN*)

involved in embryo implantation in rabbits [114]. Three candidate genes were found on BTA17, including RAB33B, member RAS oncogene family (RAB33B), associated with freezability in boar spermatozoa [115], transport and golgi organization 2 homolog (TANGO2) influencing bull fertility [116], and DGCR8 microprocessor complex subunit (DGCR8) involved in human spermatogenesis [117]. On BTA25, the mitogen-activated protein kinase 3 (MAPK3), septin 14 (SEPTIN14), and poly(A) polymerase beta (PAPOLB) were found to regulate ovulation in mice [118], spermatogenesis in humans [119], and spermatogenesis in mice [120], respectively. Other suggestive candidate genes included the synaptophysin like 1 (SYPL1) on BTA4 contributing to sperm maturation in sheep [121], multiple EGF like domains 11 (MEGF11) on BTA10 associated with lifetime productivity in pigs [122], fucosyltransferase 8 (FUT8) on BTA10 differentially expressed between matured oocytes from older and younger women [123], myelin transcription factor 1 (MYT1) on BTA13 involved in reduced fertility of anovular dairy cows [124], Rho guanine nucleotide exchange factor 3 (ARHGEF3) on BTA22 associated with number of piglets weaned [125], monoglyceride lipase (MGLL) on BTA22 influencing metabolism of endocannabinoids in bovine endometrium [126], NEDD4 like E3 ubiquitin protein ligase (NEDD4L) on BTA24 associated with AFC in buffaloes [127], and BCL2 apoptosis regulator (BCL2) on BTA24 influencing oocyte and early embryo survival in humans [128].

Combining multiple trait categories

We combined multiple trait categories for multiple-trait analysis for exploiting potential pleiotropic effects for fertility and reproduction traits. When the 14 female traits were analyzed together, 10 out of the 33 suggestive candidate genes in heifer and cow traits were identified. In addition, 15 out of the 54 suggestive candidate genes in heifers, cows, and sires were identified when also combining the four male traits together. There were five additional identified candidate genes in the combined analysis that have biological implications in reproduction in the literature, including Cbp/p300 interacting transactivator with Glu/Asp rich carboxy-terminal domain 2 (CITED2) on BTA9, cadherin 1 (CDH1) on BTA18, fanconi anemia complementation group M (FANCM) on BTA23, DPY30 domain containing 1 (DYDC1) on BTA28, and neural EGFL like 2 (NELL2) on BTA5 [129-133]. Among them, NELL2 was recently found to be involved in lumicrine system essential for testis-epididymis-spermatozoa signaling and male fertility [133]. Furthermore, three chromosomes (BTA3, BTA11, and BTA24) no longer contained significant regions when all 18 traits were analyzed together. A possible explanation for these findings Chen et al. BMC Genomics (2022) 23:331 Page 16 of 22

is that the increased amount of information might have removed spurious associations.

Implications of the study

The results of this study have three main implications. First, we enhanced compelling evidence that traits measured in heifers, cows, and sires hold relatively distinct polygenic nature, therefore having specific evaluation is needed in breeding programs. Second, the QTL and candidate genes found in this study can be specifically incorporated into genomic prediction models by giving greater weights to the more important markers. Furthermore, SNPs located in the relevant genomic regions identified can also be included in commercial genotyping platforms to increase the accuracy of genomic prediction. Third, we suggested several novel candidate genes associated with fertility and reproduction traits in cattle, which should be further investigated in sequel studies. Additionally, the use of closer to biology phenotypes that better capture the biological mechanisms underlying the fertility and reproduction traits and the use of multi-omic data (e.g., transcriptomics, metabolomics, epigenomics) can further facilitate the mapping of QTL and variants associated with fertility and reproduction. Future studies could further investigate the most promising candidate genes using gene editing or gene knock-out experiments and real WGS data (instead of imputed WGS), which would enable the investigation of rare alleles (usually removed due to low imputation accuracy) and structural variation in the genome (e.g., copy number of variants, insertions, deletions). For the significant intergenic SNPs found in this study, their possible functional roles will be explored when a comprehensive annotation of genomic regulatory elements are available.

Conclusions

The multiple-trait GWAS of 18 fertility and reproduction traits in North American Holstein cattle revealed several QTL and candidate genes associated with heifer, cow, and sire traits. These QTL were broadly distributed across the entire genome, which are consistent with the polygenic nature of fertility and reproduction traits. The biological functions of immune response and fatty acid metabolism were significantly enriched in heifer and cow traits, respectively, whereas no known functional enrichment was found for sire traits. The most important chromosomes, which had three or more significant QTL, were BTA22 and BTA23 for heifer traits, BTA8 and BTA17 for cow traits, and BTA4, BTA7, BTA17, BTA22, BTA25, and BTA28 for sire traits. Several candidate genes that have not been previously reported in cattle and other livestock were strongly suggested for heifer (SOD2, WTAP, DLEC1, PFKFB4, TRIM27, HECW1, DNAH17, and ADAM3A), cow (ANXA1, PCSK5, SPESP1, and JMJD1C), and sire (ELMO1, CFAP70, SOX30, DGCR8, SEPTIN14, PAPOLB, JMJD1C, and NELL2) traits. More than onethird of the QTL identified in this study overlapped with previously reported reproduction-related QTL in cattle, and more than 50 candidate genes were supported by functional implications in reproduction, as found in the literature. In addition, many important candidate genes were identified via significant SNPs located in their intronic regions. These observations indicate high detection power and mapping resolution of this study. Therefore, a comprehensive investigation on underlying genetic basis of fertility and reproduction in heifers, cows, and sires are provided in this study, whose findings can be used for improving genomic evaluation for fertility and reproduction traits in Holstein cattle.

Methods

Animals, phenotypes and genotypes

The phenotypic and genotypic datasets used in this study were provided by the Canadian Dairy Network (CDN), a member of Lactanet Canada (Guelph, ON, Canada). A total of 18 fertility and reproduction traits were analyzed in this study (Table 1). For all traits, dEBV were used as pseudo-phenotypes, which were computed following VanRaden et al. [134] and only dEBV with accuracy greater than 0.50 were kept for further analyses. The details of trait definitions and the effects included in the statistical model used to predict the original estimated breeding values (EBV) for each trait are reported in Oliveira Junior et al. [9].

Imputed WGS datasets containing 29,548,077 SNPs were available for 9,131 animals. The detailed genotype imputation process using the FImpute software [135], including the number of animals per SNP panel, methods, and QC, was described by Chen et al. [136]. In brief, genotype imputation was performed in two steps: (1) imputation from medium density panels (9,131 cows and 56,955 or 60,914 SNP; Illumina, San Diego, CA, USA) to the BovineHD panel [HD, 311,725 SNP after a preliminary quality control; Illumina, San Diego, CA, USA]; and (2) imputation from HD to WGS. The reference population for step 1 had 2,397 animals (from the same herds and Holstein population), whereas for step 2, there were 1,147 animals with WGS data (from the 1,000 Bull Genomes Project, which also included North American Holstein animals) [136]. An additional QC step was applied after imputation, which required the individual and genotype missing rates to be lower than 0.1 (this step was done as some markers were still missing after the imputation process), MAF to be higher than 0.01, and no extreme deviation from Hardy-Weinberg equilibrium (only retained SNPs with $P > 1.0 \times 10^{-8}$). The SNPs Chen et al. BMC Genomics (2022) 23:331 Page 17 of 22

that were poorly imputed were also removed from the analyses. This was done in a previous step where accuracy of imputation was calculated based on genotype concordance rate and allelic R² on a per-SNP basis, where the SNPs retained had a concordance rate and allelic R² greater than 0.95 and 0.85, respectively. All QC were conducted using the PLINK software [137], after which an average of 5,576,878 SNPs were retained for single-trait GWAS using 3,803 to 5,986 animals (depending on the trait, as showed in Table 1).

Single-trait association analyses

As all known fixed effects were fitted when predicting the EBVs used to compute the dEBVs, only SNP and polygenic effects were included in the mixed linear model used for the association analyses, i.e.:

$$\mathbf{v} = 1\mathbf{\mu} + \mathbf{X}\mathbf{b} + \mathbf{Z}\mathbf{u} + \mathbf{e}$$

where \mathbf{y} is the vector of dEBV for each analyzed trait; 1 is a vector of ones; $\boldsymbol{\mu}$ is the overall mean; b is the fixed effect of the SNP tested for association, \mathbf{X} is a vector containing the genotype score for the tested SNP; \mathbf{u} is the random vector of polygenic effect with $\mathbf{u} \sim N(0, \mathbf{G}\sigma_u^2)$, where \mathbf{G} is the genomic-based relationship matrix (GRM), σ_u^2 is the additive genomic variance of polygenic effects; \mathbf{Z} is the incidence matrix for \mathbf{u} ; and \mathbf{e} is a random vector of residual effects with $\mathbf{e} \sim N(0, \mathbf{I}\sigma_e^2)$, where \mathbf{I} is an identity matrix and σ_e^2 is the residual variance. The genetic relationship between individuals j and k in the GRM was computed as [138]:

$$G_{jk} = \frac{1}{N} \sum_{i=1}^{N} \frac{(x_{ij} - 2p_i)(x_{ik} - 2p_i)}{2p_i(1 - p_i)},$$

where p_i is the frequency of the reference allele for the i^{th} SNP; x_{ij} and x_{ik} are the numbers of copies of the reference allele for individuals j and k, respectively; and N is the total number of SNPs used. Instead of using all included SNPs, a total of 29 GRMs were constructed by randomly sampling 50,000 SNPs from the remaining 28 chromosomes (i.e., iterative process including all chromosomes except the one in which the analyzed SNP was located). These analyses were implemented using the GCTA software [138].

The strongly-linked SNPs were clumped out if they had high LD ($r^2 > 0.9$) with another SNP that have a lower P in the GWAS, using the PLINK software [137]. This clumping process avoids overestimating the number of significant SNPs and was suggested to be preferable compared to the pruning method without considering the P values from GWAS [139]. To check if there was potential stratification due to the population structure, the genomic

inflation factor (λ) [140] was evaluated, along with its 95% confidence interval.

Multiple-trait chi-square statistics

Following Bolormaa et al. [24], the multiple-trait analysis was performed using five different trait categories (i.e., heifers, cows, sires, heifers and cows, and all traits), as shown in Table 1. The CA trait was simultaneously included into both heifer and cow categories as it is a sub-index incorporating other traits. For each category of *n* traits, the multiple-trait chi-square statistics of a SNP was obtained as follows [24]:

$$\chi^2 = \boldsymbol{t}_i^{'} \boldsymbol{V}^{-1} \boldsymbol{t}_i$$

where t_i is a $n \times 1$ vector of signed t-values for i^{th} SNP (that is equal to the allele effect divided by its standard error) across the n analyzed traits; t_i' is the transpose of vector t_i ($1 \times n$); and V^{-1} is the inverse of $n \times n$ correlation matrix, in which the pairwise correlations of traits were calculated over the estimated SNP effects. The null hypothesis that the SNP has no significant effect on any of the tested traits was tested based on the χ^2 distribution with n degrees of freedom.

Adjustment for multiple-hypotheses testing

Due to the polygenic architecture of fertility and reproduction traits, a large number of QTL are expect, therefore a Bonferroni correction at 5% chromosome-wise significance level [141] was carried, by dividing 0.05 by the number of independent chromosome segments (M_e) to account for dependency among tests. The M_e was calculated as follow [142]:

$$M_e = \frac{2N_eL}{\ln(N_eL)},$$

where N_e is the effective population size, which was set to 66 according to a recent report in North American Holstein [143]; L is chromosome length expressed in centi-Morgans (cM; one cM was considered to be equivalent to 1 Mb). Thus, SNPs were considered as statistically significant if their $-\log_{10}(P)$ was higher than the chromosome-wide threshold $[-\log_{10}(0.05/M_e)]$, which ranged from 4.15 to 4.65 depending on the chromosome (average \pm SD = 4.39 \pm 0.12).

QTL, positional candidate genes, and functional analyses

The QTL were defined as chromosomal regions of ± 100 Kb around the significant SNPs, therefore, considering a flanking distance where, on average, high LD is expected in North American Holsteins [144]. The identified QTL were compared to previously reported QTL in the Cattle QTL Database – Release

Chen et al. BMC Genomics (2022) 23:331 Page 18 of 22

43 [145]. To most effectively avoid missing the potential causal genes, all positional candidate genes within QTL region, including protein-encoding and lncRNA, were retrieved using the biomaRt R package [146]. The ARS-UCD1.2 assembly (https://ensembl.org/Bos taurus/Info/Index) was used as the reference genome. Functional enrichment analyses of the candidate genes were conducted using the g:GOSt function of the g:Profiler web server [147], including the target datasets of the GO terms [148] and KEGG pathways [149]. The default parameters and methods for adjusting for multiple hypotheses testing were used, targeting an adjusted 5% level of significance. For the biologically suggested candidate genes, we also performed a protein-protein interaction analysis using the STRING software [150].

Abbreviations

AFC: Age at First Calving; BTA: Bos Taurus Autosomes; CE: Calving Ease; CI: Calving Interval; CR: Conception Rate; DPR: Daughter Pregnancy Rate; dEBV: Deregressed Estimated Breeding Values; EBV: Estimated Breeding Values; FSC: First Service Conception; GO: Gene Ontology; GWAS: Genome-wide Association Studies; GS: Genomic Selection; GRM: Genomic-based Relationship Matrix; IFLI: Interval From First to Last Insemination; IFEC: Interval to First Estrus After Calving; KEGG: Kyoto Encyclopedia of Genes and Genomes; LD: Linkage Disequilibrium; IncRNA: Long non-coding RNAs; LA: Luteal Activity; MHC: Major Histocompatibility Complex; MAF: Minor Allele Frequency; NRR: Non-return Rate; IPC: Number of Inseminations Per Conception; QC: Quality Controls; QTL: Quantitative Trait Loci; SD: Standard Deviation; SNP: Single-nucleotide Polymorphism; WGS: Whole-genome Sequence.

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s12864-022-08555-z.

Additional file 1: Table \$1. Position distribution and minor allele frequencies of SNPs that passed thegenotype quality control; Table S2. Distribution of significant SNPs of single-traitGWAS; Table S3. Numbers of quantitative trait loci revealed by single-traitGWAS and their overlapping among traits; Table S4. The previously reported andreproduction-associated QTL for the significant SNPs revealed by multiple-traitanalysis of six heifer traits; Table S5. The previously reported andreproduction-associated QTL for the significant SNPs revealed by multiple-traitanalysis of nine cow traits; Table S6. The previously reported andreproduction-associated QTL for the significant SNPs revealed by multiple-traitanalysis of four sire traits; **Table S7.** Significant SNPs and candidate genesfrom multiple-trait analysis of 14 heifers and cows' traits; Table S8. Thepreviously reported and reproduction-associated QTL for the significant SNPsrevealed by multiple-trait analysis of 14 heifer and cow traits; Table S9. The significantly enriched GO terms and KEGG from multiple-trait analysis of 18heifers, cows, sire traits; **Table S10.** Significant SNPs and candidate genesfrom multiple-trait analysis of 18 heifers, cows, sire traits; Table S11. Thepreviously reported and reproduction-associated QTL for the significant SNPsrevealed by multiple-trait analysis of 18 heifer, cow, and sire traits; Figure S1. Manhattan plots (left) and Quantile-quantile plots (right) of the single-trait GWAS results based on imputed WGS data; Figure S2. Numbers of significant SNPs foreach trait category and their overlaps found by multiple-trait analysis. Figure S3. Significantly enrichedbiological functions of candidate genes revealed by multiple-trait analysis. Figure S4. Potential proteinprotein interaction among biologically relevantgenes that were identified for heifer, cow, and sire traits in this study.

Acknowledgements

The University of Guelph is a partner in the 1,000 Bull Genomes Project and thanks the Project for the use of the full genome sequence genotypes. This research is also part of the activities of Drs. Schenkel and Brito within the Resilient Dairy Genome Project (http://www.resilientdairy.ca). We also thank the financial support in main part by Agriculture and Agri-Food Canada, and by additional contributions from Dairy Farmers of Canada, the Canadian Dairy Network and the Canadian Dairy Commission under the Agri-Science Clusters Initiative. As per the research agreement, aside from providing financial support, the funders have no role in the design and conduct of the studies, data collection and analysis or interpretation of the data. Researchers maintain independence in conducting their studies, own their data, and report the outcomes regardless of the results. The decision to publish the findings rests solely with the researchers.

Authors' contributions

SC and LFB conceived, designed, and coordinated this research. SC performed the data analyses and wrote the initial version of the manuscript. FSS and MGM provided all the datasets. LFB, FSS, ALPM, VBP, MGM, and ACA provided technical assistance and suggestions in the final version of the manuscript. All authors interpreted the results and edited the manuscript. All authors read and approved the final manuscript.

Funding

Not applicable.

Availability of data and materials

All the data supporting the results of this study are included in the article and in the Additional file.

Declarations

Ethics approval and consent to participate

No Animal Care Committee approval was necessary for the purposes of this study, as all information required was obtained from pre-existing databases.

Consent for publication

Not applicable.

Competing interests

The authors declare that they have no competing interests.

Author details

¹Department of Animal Sciences, Purdue University, 270 S. Russell Street, West Lafayette, IN 47907-2041, USA. ²Farm Animal Genetic Resources Exploration and Innovation Key Laboratory of Sichuan Province, Sichuan Agricultural University, Chengdu 611130, Sichuan, China. ³Centre for Genetic Improvement of Livestock, Department of Animal Biosciences, University of Guelph, Guelph, ON N1G 2W1, Canada. ⁴Department of Reproduction and Animal Evaluation, Rural Federal University of Rio de Janeiro, Seropédica, RJ 23897-000, Brazil. ⁵Department of Animal Sciences, State University of Ponta Grossa, Ponta Grossa, PR 84030-900, Brazil. ⁶Department of Animal and Food Science, University of Wisconsin River Falls, River Falls, WI 54022, USA.

Received: 5 August 2021 Accepted: 12 April 2022 Published online: 28 April 2022

References

- Inchaisri C, Jorritsma R, Vos PLAM, van der Weijden GC, Hogeveen H. Economic consequences of reproductive performance in dairy cattle. Theriogenology. 2010;74:835–46.
- 2. Ritter C, Beaver A, von Keyserlingk MAG. The complex relationship between welfare and reproduction in cattle. Reprod Domest Anim. 2019;54:29–37.
- Ma L, Cole JB, Da Y, VanRaden PM. Symposium review: Genetics, genome-wide association study, and genetic improvement of dairy fertility traits. J Dairy Sci. 2019;102:3735–43.

- Brito LF, Bedere N, Douhard F, Oliveira HR, Arnal M, Peñagaricano F, et al. Invited Review: Genetic selection of high-yielding dairy cattle towards sustainable farming systems in a rapidly-changing world. Animal. 2021:100292.
- Miglior F, Fleming A, Malchiodi F, Brito LF, Martin P, Baes CF. A 100-Year Review: Identification and genetic selection of economically important traits in dairy cattle. J Dairy Sci. 2017;100:10251–71.
- VanRaden PM, Sanders AH, Tooker ME, Miller RH, Norman HD, Kuhn MT, et al. Development of a national genetic evaluation for cow fertility. J Dairy Sci. 2004;87:2285–92.
- Van Doormaal BJ, Kistemaker G, Miglior F. Implementation of reproductive performance genetic evaluations in Canada. Interbull Bull. 2007;37:129–33.
- García-Ruiz A, Cole JB, VanRaden PM, Wiggans GR, Ruiz-López FJ, Van Tassell CP. Changes in genetic selection differentials and generation intervals in US Holstein dairy cattle as a result of genomic selection. Proc Natl Acad Sci U S A. 2016;113:E3995–4004.
- Oliveira Junior GA, Schenkel FS, Alcantara L, Houlahan K, Lynch C, Baes CF. Estimated genetic parameters for all genetically evaluated traits in Canadian Holsteins. J Dairy Sci. 2021: 9002–15.
- Xiang R, MacLeod IM, Daetwyler HD, de Jong G, O'Connor E, Schrooten C, et al. Genome-wide fine-mapping identifies pleiotropic and functional variants that predict many traits across global cattle populations. Nat Commun. 2021;12:860.
- Tam V, Patel N, Turcotte M, Bossé Y, Paré G, Meyre D. Benefits and limitations of genome-wide association studies. Nat Rev Genet. 2019;20:467–84.
- Fortes MR, DeAtley KL, Lehnert SA, Burns BM, Reverter A, Hawken RJ, et al. Genomic regions associated with fertility traits in male and female cattle: advances from microsatellites to high-density chips and beyond. Anim Reprod Sci. 2013;141:1–19.
- Hayes BJ, Daetwyler HD. 1000 Bull Genomes Project to map simple and complex genetic traits in cattle: applications and outcomes. Annu Rev Anim Biosci. 2019;7:89–102.
- Stothard P, Liao X, Arantes AS, De Pauw M, Coros C, Plastow GS, et al. A large and diverse collection of bovine genome sequences from the Canadian Cattle Genome Project. Gigascience. 2015;4:49.
- Rubinacci S, Ribeiro DM, Hofmeister RJ, Delaneau O. Efficient phasing and imputation of low-coverage sequencing data using large reference panels. Nat Genet. 2021;53:120–6.
- Larmer SG, Sargolzaei M, Brito LF, Ventura RV, Schenkel FS. Novel methods for genotype imputation to whole-genome sequence and a simple linear model to predict imputation accuracy. BMC Genet. 2017;18:120.
- 17. Wu Y, Zheng Z, Visscher PM, Yang J. Quantifying the mapping precision of genome-wide association studies using whole-genome sequencing data. Genome Biol. 2017;18:86.
- Höglund JK, Sahana G, Brøndum RF, Guldbrandtsen B, Buitenhuis B, Lund MS. Fine mapping QTL for female fertility on BTA04 and BTA13 in dairy cattle using HD SNP and sequence data. BMC Genomics. 2014;15:790.
- Tenghe AMM, Bouwman AC, Berglund B, Strandberg E, de Koning DJ, Veerkamp RF. Genome-wide association study for endocrine fertility traits using single nucleotide polymorphism arrays and sequence variants in dairy cattle. J Dairy Sci. 2016;99:5470–85.
- Frischknecht M, Bapst B, Seefried FR, Signer-Hasler H, Garrick D, Stricker C, et al. Genome-wide association studies of fertility and calving traits in Brown Swiss cattle using imputed whole-genome sequences. BMC Genomics. 2017;18:910.
- Berry DP, Wall E, Pryce JE. Genetics and genomics of reproductive performance in dairy and beef cattle. Animal. 2014;8:105–21.
- Fleming A, Baes CF, Martin AAA, Chud TCS, Malchiodi F, Brito LF, et al. Symposium review: The choice and collection of new relevant pheno-types for fertility selection. J Dairy Sci. 2019;102:3722–34.
- Jamrozik J, Fatehi J, Kistemaker GJ, Schaeffer LR. Estimates of genetic parameters for Canadian Holstein female reproduction traits. J Dairy Sci. 2005;88:2199–208.
- Bolormaa S, Pryce JE, Reverter A, Zhang Y, Barendse W, Kemper K, et al. A multi-trait, meta-analysis for detecting pleiotropic polymorphisms for stature, fatness and reproduction in beef cattle. PLoS Genet. 2014;10: e1004198
- Xiang R, MacLeod IM, Bolormaa S, Goddard ME. Genome-wide comparative analyses of correlated and uncorrelated phenotypes identify major pleiotropic variants in dairy cattle. Sci Rep. 2017;7:9248.

- Fang ZH, Pausch H. Multi-trait meta-analyses reveal 25 quantitative trait loci for economically important traits in Brown Swiss cattle. BMC Genomics. 2019;20:695.
- Liu A, Wang Y, Sahana G, Zhang Q, Liu L, Lund MS, et al. Genome-wide association studies for female fertility traits in Chinese and Nordic Holsteins. Sci Rep. 2017;7:8487.
- Feugang JM, Kaya A, Page GP, Chen L, Mehta T, Hirani K, et al. Two-stage genome-wide association study identifies integrin beta 5 as having potential role in bull fertility. BMC Genomics. 2009;10:176.
- Kim ES, Berger PJ, Kirkpatrick BW. Genome-wide scan for bovine twinning rate QTL using linkage disequilibrium. Anim Genet. 2009;40:300–7.
- Sahana G, Guldbrandtsen B, Bendixen C, Lund MS. Genome-wide association mapping for female fertility traits in Danish and Swedish Holstein cattle. Anim Genet. 2010;41:579–88.
- Cole JB, Wiggans GR, Ma L, Sonstegard TS, Lawlor TJ, Crooker BA, et al. Genome-wide association analysis of thirty one production, health, reproduction and body conformation traits in contemporary US Holstein cows. BMC Genomics. 2011;12:408.
- Sahana G, Guldbrandtsen B, Lund MS. Genome-wide association study for calving traits in Danish and Swedish Holstein cattle. J Dairy Sci. 2011;94:479–86.
- Minozzi G, Nicolazzi EL, Stella A, Biffani S, Negrini R, Lazzari B, et al. Genome wide analysis of fertility and production traits in Italian Holstein cattle. PLoS ONE. 2013;8: e80219.
- Gaddis KP, Null DJ, Cole JB. Explorations in genome-wide association studies and network analyses with dairy cattle fertility traits. J Dairy Sci. 2016;99:6420–35
- Nayeri S, Sargolzaei M, Abo-Ismail MK, May N, Miller SP, Schenkel F, et al. Genome-wide association for milk production and female fertility traits in Canadian dairy Holstein cattle. BMC Genet. 2016;17:75.
- Abo-Ismail MK, Brito LF, Miller SP, Sargolzaei M, Grossi DA, Moore SS, et al. Genome-wide association studies and genomic prediction of breeding values for calving performance and body conformation traits in Holstein cattle. Genet Sel Evol. 2017;49:82.
- Nayeri S, Sargolzaei M, Abo-Ismail MK, Miller S, Schenkel F, Moore SS, et al. Genome-wide association study for lactation persistency, female fertility, longevity, and lifetime profit index traits in Holstein dairy cattle. J Dairy Sci. 2017;100:1246–58.
- Atashi H, Salavati M, De Koster J, Crowe MA, Opsomer G, Hostens M, et al. A genome-wide association study for calving interval in Holstein dairy cows using weighted single-step genomic BLUP approach. Animals (Basel). 2020;10:500.
- Hiltpold M, Kadri NK, Janett F, Witschi U, Schmitz-Hsu F, Pausch H. Autosomal recessive loci contribute significantly to quantitative variation of male fertility in a dairy cattle population. BMC Genomics. 2021;22:225.
- Ferreira MA, Purcell SM. A multivariate test of association. Bioinformatics. 2009;25:132–3.
- Turley P, Walters RK, Maghzian O, Okbay A, Lee JJ, Fontana MA, et al. Multi-trait analysis of genome-wide association summary statistics using MTAG. Nat Genet. 2018;50:229–37.
- 42. Solovieff N, Cotsapas C, Lee PH, Purcell SM, Smoller JW. Pleiotropy in complex traits: challenges and strategies. Nat Rev Genet. 2013;14:483–95.
- Muir BL, Fatehi J, Schaeffer LR. Genetic relationships between persistency and reproductive performance in first-lactation Canadian Holsteins. J Dairy Sci. 2004;87:3029–37.
- 44. Tiezzi F, Maltecca C, Cecchinato A, Penasa M, Bittante G. Genetic parameters for fertility of dairy heifers and cows at different parities and relationships with production traits in first lactation. J Dairy Sci. 2012;95:7355–62.
- Kuhn MT, Hutchison JL, Wiggans GR. Characterization of Holstein heifer fertility in the United States. J Dairy Sci. 2006;89:4907–20.
- Muuttoranta K, Tyrisevä AM, Mäntysaari EA, Pösö J, Aamand GP, Lidauer MH. Genetic parameters for female fertility in Nordic Holstein and Red Cattle dairy breeds. J Dairy Sci. 2019;102:8184–96.
- Sartori R, Rosa GJM, Wiltbank MC. Ovarian structures and circulating steroids in heifers and lactating cows in summer and lactating and dry cows in winter. J Dairy Sci. 2002;85:2813–22.
- 48. Sartori R, Haughian JM, Shaver RD, Rosa GJM, Wiltbank MC. Comparison of ovarian function and circulating steroids in estrous cycles of Holstein heifers and lactating cows. J Dairy Sci. 2004;87:905–20.

- Kiser JN, Clancey E, Moraes JG, Dalton J, Burns GW, Spencer TE, et al. Identification of loci associated with conception rate in primiparous Holstein cows. BMC Genomics. 2019;20:840.
- Hawken RJ, Zhang YD, Fortes MRS, Collis E, Barris WC, Corbet NJ, et al. Genome-wide association studies of female reproduction in tropically adapted beef cattle. J Anim Sci. 2012;90:1398–410.
- Cochran SD, Cole JB, Null DJ, Hansen PJ. Discovery of single nucleotide polymorphisms in candidate genes associated with fertility and production traits in Holstein cattle. BMC Genet. 2013;14:49.
- Ortega MS, Denicol AC, Cole JB, Null DJ, Hansen PJ. Use of single nucleotide polymorphisms in candidate genes associated with daughter pregnancy rate for prediction of genetic merit for reproduction in Holstein cows. Anim Genet. 2016;47:288–97.
- Saatchi M, Schnabel RD, Taylor JF, Garrick DJ. Large-effect pleiotropic or closely linked QTL segregate within and across ten US cattle breeds. BMC Genomics. 2014;15:442.
- 54. Galliou JM, Kiser JN, Oliver KF, Seabury CM, Moraes JG, Burns GW, et al. Identification of loci and pathways associated with heifer conception rate in US Holsteins. Genes (Basel). 2020;11:767.
- Shu L, Peng X, Zhang S, Deng G, Wu Y, He M, et al. Non-classical major histocompatibility complex class makes a crucial contribution to reproduction in the dairy cow. J Reprod Dev. 2012;58:2011–018.
- Mansouri-Attia N, Forde N, Roche JF, Lonergan P, Fair T. Immunological characterization of the bovine endometrial response to the presence of an embryo: is the Th1/Th2 paradigm important? Biol Reprod. 2010:83:97
- Melo TPD, De Camargo GMF, De Albuquerque LG, Carvalheiro R. Genome-wide association study provides strong evidence of genes affecting the reproductive performance of Nellore beef cows. PLoS ONE. 2017;12: e0178551.
- Peters AE, Mihalas BP, Bromfield EG, Roman SD, Nixon B, Sutherland JM. Autophagy in female fertility: a role in oxidative stress and aging. Antioxid Redox Signal. 2020;32:550–68.
- Han L, Wang H, Li L, Li X, Ge J, Reiter RJ, et al. Melatonin protects against maternal obesity-associated oxidative stress and meiotic defects in oocytes via the SIRT3-SOD2-dependent pathway. J Pineal Res. 2017;63: e12431.
- 60. Jia GX, Lin Z, Yan RG, Wang GW, Zhang XN, Li C, et al. WTAP function in sertoli cells is essential for sustaining the spermatogonial stem cell niche. Stem Cell Reports. 2020;15:968–82.
- Dun MD, Smith ND, Baker MA, Lin M, Aitken RJ, Nixon B. The chaperonin containing TCP1 complex (CCT/TRiC) is involved in mediating spermoocyte interaction. J Biol Chem. 2011;286:36875–87.
- 62. Du X, Liu L, Li Q, Zhang L, Pan Z, Li Q. NORFA, long intergenic noncoding RNA, maintains sow fertility by inhibiting granulosa cell death. Commun Biol. 2020;3:131.
- Ni N, Fang X, Li Q. Functional similarity between TGF-beta type 2 and type 1 receptors in the female reproductive tract. Sci Rep. 2021;11:9294.
- 64. Okitsu Y, Nagano M, Yamagata T, Ito C, Toshimori K, Dohra H, et al. *Dlec1* is required for spermatogenesis and male fertility in mice. Sci Rep. 2020;10:18883.
- Kuang W, Zhang J, Lan Z, Deepak RK, Liu C, Ma Z, et al. SLC22A14 is a mitochondrial riboflavin transporter required for sperm oxidative phosphorylation and male fertility. Cell Rep. 2021;35:109025.
- Pyun JA, Kim S, Kwack K. Epistasis between polymorphisms in ACVR2B and ADAMTS19 is associated with premature ovarian failure. Menopause. 2015;27:212–6.
- 67. Gómez M, Manzano A, Figueras A, Viñals F, Ventura F, Rosa JL, et al. Sertoli-secreted FGF-2 induces PFKFB4 isozyme expression in mouse spermatogenic cells by activation of the MEK/ERK/CREB pathway. Am J Physiol Endocrinol Metab. 2012;303:E695–707.
- Zhuang XJ, Tang WH, Feng X, Liu CY, Zhu JL, Yan J, et al. Trim27 interacts with Slx2, is associated with meiotic processes during spermatogenesis. Cell Cycle. 2016;15:2576–84.
- 69. Bouilly J, Sonigo C, Auffret J, Gibori G, Binart N. Prolactin signaling mechanisms in ovary. Mol Cell Endocrinol. 2012;356:80–7.
- Markholt S, Grøndahl ML, Ernst EH, Andersen CY, Ernst E, Lykke-Hartmann K. Global gene analysis of oocytes from early stages in human folliculogenesis shows high expression of novel genes in reproduction. Mol Hum Reprod. 2012;18:96–110.

- 71. Azcona F, Sole M, Dorado J, Ross P, Terán E, Demyda-Peyrás S. Whole genome association analysis suggests an influence of inbreeding on bull sperm morphometry. Reprod Fertil Dev. 2019;31:202–3.
- 72. Jin Z, Liu H, Xu C. Estrogen degrades Scribble in endometrial epithelial cells through E3 ubiquitin ligase HECW1 in the development of diffuse adenomyosis. Biol Reprod. 2020;102:376–87.
- Chau KM, Cornwall GA. Reduced fertility in vitro in mice lacking the cystatin CRES (cystatin-related epididymal spermatogenic): rescue by exposure of spermatozoa to dibutyryl cAMP and isobutylmethylxanthine. Biol Reprod. 2011;84:140–52.
- Whitfield M, Thomas L, Bequignon E, Schmitt A, Stouvenel L, Montantin G, et al. Mutations in *DNAH17*, encoding a sperm-specific axonemal outer dynein arm heavy chain, cause isolated male infertility due to asthenozoospermia. Am J Hum Genet. 2019;105:198–212.
- Zhang B, Khan I, Liu C, Ma A, Khan A, Zhang Y, et al. Novel loss-of-function variants in *DNAH17* cause multiple morphological abnormalities of the sperm flagella in humans and mice. Clin Genet. 2021;99:176–86.
- Tokuhiro K, Ikawa M, Benham AM, Okabe M. Protein disulfide isomerase homolog PDILT is required for quality control of sperm membrane protein ADAM3 and male fertility. Proc Natl Acad Sci U S A. 2012;109:3850–5
- Lamas-Toranzo I, Balvís NF, Querejeta-Fernandez A, Izquierdo-Rico MJ, González-Brusi L, Lorenzo PL, et al. ZP4 confers structural properties to the zona pellucida essential for embryo development. Elife. 2019;8:e48904.
- Moore SG, Pryce JE, Hayes BJ, Chamberlain AJ, Kemper KE, Berry DP, et al. Differentially expressed genes in endometrium and corpus luteum of Holstein cows selected for high and low fertility are enriched for sequence variants associated with fertility. Biol Reprod. 2016;94:19.
- Kiser JN, Keuter EM, Seabury CM, Neupane M, Moraes JG, Dalton J, et al. Validation of 46 loci associated with female fertility traits in cattle. BMC Genomics. 2019;20:576.
- Mattos R, Staples CR, Thatcher WW. Effects of dietary fatty acids on reproduction in ruminants. Rev Reprod. 2000;5:38–45.
- 81. Herrera E, Ortega-Senovilla H. Lipid metabolism during pregnancy and its implications for fetal growth. Curr Pharm Biotechnol. 2014;15:24–31.
- Ribeiro ES. Symposium review: Lipids as regulators of conceptus development: Implications for metabolic regulation of reproduction in dairy cattle. J Dairy Sci. 2018;101:3630–41.
- Zeron Y, Ocheretny A, Kedar O, Borochov A, Sklan D, Arav A. Seasonal changes in bovine fertility: relation to developmental competence of oocytes, membrane properties and fatty acid composition of follicles. Reproduction. 2001;121:447–54.
- 84. Garnsworthy PC, Lock A, Mann GE, Sinclair KD, Webb R. Nutrition, metabolism, and fertility in dairy cows: 2. dietary fatty acids and ovarian function. J Dairy Sci. 2008;91:3824–33.
- Mohammadi A, Alijani S, Rafat SA, Abdollahi-Arpanahi R. Genome-wide association study and pathway analysis for female fertility traits in Iranian Holstein cattle. Ann Anim Sci. 2020;20:825–51.
- Palomba S, Daolio J, La Sala GB. Oocyte competence in women with polycystic ovary syndrome. Trends Endocrinol Metab. 2017;28:186–98.
- Camlin NJ, McLaughlin EA, Holt JE. Motoring through: the role of kinesin superfamily proteins in female meiosis. Hum Reprod Update. 2017;23:409–20.
- Hebeda CB, Machado ID, Reif-Silva I, Moreli JB, Oliani SM, Nadkarni S, et al. Endogenous annexin A1 (AnxA1) modulates early-phase gestation and offspring sex-ratio skewing. J Cell Physiol. 2018;233:6591–603.
- Puglisi R, Cambuli C, Capoferri R, Giannino L, Lukaj A, Duchi R, et al.
 Differential gene expression in cumulus oocyte complexes collected by ovum pick up from repeat breeder and normally fertile Holstein Friesian heifers. Anim Reprod Sci. 2013;141:26–33.
- Bae JA, Park HJ, Seo YM, Roh J, Hsueh AJ, Chun SY. Hormonal regulation of proprotein convertase subtilisin/kexin type 5 expression during ovarian follicle development in the rat. Mol Cell Endocrinol. 2008;289:29–37.
- 91. Nguyen LT, Reverter A, Cánovas A, Venus B, Anderson ST, Islas-Trejo A, et al. *STAT6*, *PBX2*, and *PBRM1* emerge as predicted regulators of 452 differentially expressed genes associated with puberty in Brahman heifers. Front Genet. 2018;9:87.
- Ding CF, Chen WQ, Zhu YT, Bo YL, Hu HM, Zheng RH. Circulating micro-RNAs in patients with polycystic ovary syndrome. Hum Fertil (Camb). 2015;18:22–9.

- 93. Fujihara Y, Murakami M, Inoue N, Satouh Y, Kaseda K, Ikawa M, et al. Sperm equatorial segment protein 1, SPESP1, is required for fully fertile sperm in mouse. J Cell Sci. 2010;123:1531–6.
- 94. Balogh EE, Gábor G, Bodó S, Rózsa L, Rátky J, Zsolnai A, et al. Effect of single-nucleotide polymorphisms on specific reproduction parameters in Hungarian Large White sows. Acta Vet Hung. 2019;67:256–73.
- Mesbah-Uddin MB. Genome-wide association study with imputed whole-genome sequence variants including large deletions for female fertility in three Nordic dairy breeds. PhD Thesis. Aarhus: Aarhus Univ: 2019.
- Posbergh CJ, Thonney ML, Huson HJ. Genomic approaches identify novel gene associations with out of season lambing in sheep. J Hered. 2019:110:577–86.
- 97. Moran B, Butler ST, Moore SG, MacHugh DE, Creevey CJ. Differential gene expression in the endometrium reveals cytoskeletal and immunological genes in lactating dairy cows genetically divergent for fertility traits. Reprod Fertil Dev. 2017;29:274–82.
- Gross N, Peñagaricano F, Khatib H. Integration of whole-genome DNA methylation data with RNA sequencing data to identify markers for bull fertility. Anim Genet. 2020;51:502–10.
- Minge CE, Robker RL, Norman RJ. PPAR gamma: coordinating metabolic and immune contributions to female fertility. PPAR Res. 2008;2008:243791.
- Kuroki S, Akiyoshi M, Tokura M, Miyachi H, Nakai Y, Kimura H, et al. JMJD1C, a JmjC domain-containing protein, is required for long-term maintenance of male germ cells in mice. Biol Reprod. 2013;89:93.
- Taylor JF, Schnabel RD, Sutovsky P. Review: Genomics of bull fertility. Animal. 2018;12:s172–83.
- Nani JP, Rezende FM, Peñagaricano F. Predicting male fertility in dairy cattle using markers with large effect and functional annotation data. BMC Genomics. 2019;20:258.
- Peñagaricano F, Weigel KA, Khatib H. Genome-wide association study identifies candidate markers for bull fertility in Holstein dairy cattle. Anim Genet. 2012;43:65–71.
- Han Y, Peñagaricano F. Unravelling the genomic architecture of bull fertility in Holstein cattle. BMC Genet. 2016;17:143.
- McDaneld TG, Kuehn LA, Thomas MG, Snelling WM, Smith TPL, Pollak EJ, et al. Genomewide association study of reproductive efficiency in female cattle. J Anim Sci. 2014;92:1945–57.
- Akanno EC, Plastow G, Fitzsimmons C, Miller SP, Baron V, Ominski K, et al. Genome-wide association for heifer reproduction and calf performance traits in beef cattle. Genome. 2015;58:549–57.
- Elliott MR, Zheng S, Park D, Woodson RI, Reardon MA, Juncadella IJ, et al. Unexpected requirement for ELMO1 in clearance of apoptotic germ cells in vivo. Nature. 2010;467:333–7.
- Beurois J, Martinez G, Cazin C, Kherraf ZE, Amiri-Yekta A, Thierry-Mieg N, et al. CFAP70 mutations lead to male infertility due to severe asthenoteratozoospermia. A case report Hum Reprod. 2019;34:2071–9.
- 109. Dai L, Zhao Z, Zhao R, Xiao S, Jiang H, Yue X, et al. Effects of novel single nucleotide polymorphisms of the FSH beta-subunit gene on semen quality and fertility in bulls. Anim Reprod Sci. 2009;114:14–22.
- Wang Y, Ding X, Tan Z, Xing K, Yang T, Pan Y, et al. Genome-wide association study for reproductive traits in a Large White pig population. Anim Genet. 2018;49:127–31.
- Georges H, Bishop J, Van Campen H, Barfield J, Hansen T. A delay in maternal zygotic transition may lead to early embryonic loss in poorquality bovine blastocysts. Reprod Fertil Dev. 2020;32:177-.
- 112. Feng CWA, Spiller C, Merriner DJ, O'Bryan MK, Bowles J, Koopman P. SOX30 is required for male fertility in mice. Sci Rep. 2017;7:17619.
- Han F, Jiang X, Li ZM, Zhuang X, Zhang X, Ouyang WM, et al. Epigenetic inactivation of SOX30 is associated with male infertility and offers a therapy target for non-obstructive azoospermia. Mol Ther Nucleic Acids. 2020;19:72–83.
- 114. Gardela J, Jauregi-Miguel A, Martinez CA, Rodriguez-Martinez H, Lopez-Bejar M, Alvarez-Rodriguez M. Semen modulates the expression of NGF, ABHD2, VCAN, and CTEN in the reproductive tract of female rabbits. Genes (Basel). 2020;11:758.
- Brym P, Wasilewska-Sakowska K, Mogielnicka-Brzozowska M, Mańkowska A, Paukszto Ł, Pareek CS, et al. Gene promoter polymorphisms in boar spermatozoa differing in freezability. Theriogenol. 2021;166:112–23.

 Aslam MM, Kumaresan A, Sharma VK, Tajmul M, Chhillar S, Chakravarty AK, et al. Identification of putative fertility markers in seminal plasma of crossbred bulls through differential proteomics. Theriogenol. 2014;82:1254–62.

Page 21 of 22

- 117. Babakhanzadeh E, Khodadadian A, Nazari M, Tezerjani MD, Aghaei SM, Ghasemifar S, et al. Deficient expression of *DGCR8* in human testis is related to spermatogenesis dysfunction, especially in meiosis I. Int J Gen Med. 2020;13:185–92.
- Fan HY, Liu Z, Shimada M, Sterneck E, Johnson PF, Hedrick SM, et al. MAPK3/1 (ERK1/2) in ovarian granulosa cells are essential for female fertility. Sci. 2009;324:938–41.
- Barzi NV, Kakavand K, Sodeifi N, Ghezelayagh Z, Sabbaghian M. Expression and localization of Septin 14 gene and protein in infertile men testis. Reprod Biol. 2020;20:164–8.
- Kashiwabara SI, Tsuruta S, Okada K, Yamaoka Y, Baba T. Adenylation by testis-specific cytoplasmic poly (A) polymerase, PAPOLB/TPAP, is essential for spermatogenesis. J Reprod Dev. 2016;62:607–14.
- 121. Leahy T, Rickard JP, Pini T, Gadella BM, de Graaf SP. Quantitative proteomic analysis of seminal plasma, sperm membrane proteins, and seminal extracellular vesicles suggests vesicular mechanisms aid in the removal and addition of proteins to the ram sperm membrane. Proteomics. 2020;20:e1900289.
- 122. Kang JH, Lee EA, Lee SH, Kim SH, Lee DH, Hong KC, et al. Genomewide association study for sow lifetime productivity related traits in a Landrace purebred population. Livest Sci. 2017;202:21–4.
- Zhang JJ, Liu X, Chen L, Zhang S, Zhang X, Hao C, et al. Advanced maternal age alters expression of maternal effect genes that are essential for human oocyte quality. Aging (Albany NY). 2020;12:3950–61.
- 124. Santos JEP, Bisinotto RS, Ribeiro ES. Mechanisms underlying reduced fertility in anovular dairy cows. Theriogenol. 2016;86:254–62.
- Metodiev S, Thekkoot DM, Young JM, Onteru S, Rothschild MF, Dekkers JCM. A whole-genome association study for litter size and litter weight traits in pigs. Livest Sci. 2018;211:87–97.
- 126. Dirandeh E, haffari J. Effects of feeding a source of omega-3 fatty acid during the early postpartum period on the endocannabinoid system in the bovine endometrium. Theriogenol. 2018;121:141–6.
- 127. de Araujo Neto FR, Takada L, Dos Santos DJA, Aspilcueta-Borquis RR, Cardoso DF, do Nascimento AV. Identification of genomic regions related to age at first calving and first calving interval in water buffalo using single-step GBLUP. Reprod Domest Anim. 2020;55:1565–72.
- 128. Boumela I, Assou S, Aouacheria A, Haouzi D, Dechaud H, De Vos J, et al. Involvement of BCL2 family members in the regulation of human oocyte and early embryo survival and death: gene expression and beyond. Reproduction. 2011;141:549–61.
- 129. Li S, Qiao Y, Di Q, Le X, Zhang L, Zhang X, et al. Interaction of SH3P13 and DYDC1 protein: a germ cell component that regulates acrosome biogenesis during spermiogenesis. Eur J Cell Biol. 2009;88:509–20.
- Fonseca DJ, Ojeda D, Lakhal B, Braham R, Eggers S, Turbitt E, et al. CITED2 mutations potentially cause idiopathic premature ovarian failure. Transl Res. 2012;160:384–8.
- 131. Piprek RP, Kolasa M, Podkowa D, Kloc M, Kubiak JZ. Tissue-specific knockout of E-cadherin (*Cdh1*) in developing mouse gonads causes germ cells loss. Reproduction. 2019;158:147–57.
- 132. Yin H, Ma H, Hussain S, Zhang H, Xie X, Jiang L, et al. A homozygous FANCM frameshift pathogenic variant causes male infertility. Genet Med. 2019;21:62–70.
- Kiyozumi D, Noda T, Yamaguchi R, Tobita T, Matsumura T, Shimada K, et al. NELL2-mediated lumicrine signaling through OVCH2 is required for male fertility. Science. 2020;368:1132–5.
- VanRaden PM, Van Tassell CP, Wiggans GR, Sonstegard TS, Schnabel RD, Taylor JF, et al. *Invited review:* Reliability of genomic predictions for North American Holstein bulls. J Dairy Sci. 2009;92:16–24.
- Sargolzaei M, Chesnais JP, Schenkel FS. A new approach for efficient genotype imputation using information from relatives. BMC Genomics. 2014;15:478.
- 136. Chen SY, Oliveira HR, Schenkel FS, Pedrosa VB, Melka MG, Brito LF. Using imputed whole-genome sequence variants to uncover candidate mutations and genes affecting milking speed and temperament in Holstein cattle. J Dairy Sci. 2020;103:10383–98.

Chen et al. BMC Genomics (2022) 23:331 Page 22 of 22

- Purcell S, Neale B, Todd-Brown K, Thomas L, Ferreira MA, Bender D, et al.
 PLINK: a tool set for whole-genome association and population-based linkage analyses. Am J Hum Genet. 2007;81:559–75.
- 138. Yang J, Lee SH, Goddard ME, Visscher PM. GCTA: a tool for genomewide complex trait analysis. Am J Hum Genet. 2011;88:76–82.
- 139. Privé F, Aschard H, Ziyatdinov A, Blum MG. Efficient analysis of largescale genome-wide data with two R packages: bigstatsr and bigsnpr. Bioinformatics. 2018;34:2781–7.
- 140. van den Berg S, Vandenplas J, van Eeuwijk FA, Lopes MS, Veerkamp RF. Significance testing and genomic inflation factor using high-density genotypes or whole-genome sequence data. J Anim Breed Genet. 2019;136:418–29.
- Li X, Buitenhuis AJ, Lund MS, Li C, Sun D, Zhang Q, et al. Joint genomewide association study for milk fatty acid traits in Chinese and Danish Holstein populations. J Dairy Sci. 2015;98:8152–63.
- 142. Goddard ME, Hayes BJ, Meuwissen TH. Using the genomic relationship matrix to predict the accuracy of genomic selection. J Anim Breed Genet. 2011;128:409–21.
- 143. Makanjuola BO, Miglior F, Abdalla EA, Maltecca C, Schenkel FS, Baes CF. Effect of genomic selection on rate of inbreeding and coancestry and effective population size of Holstein and Jersey cattle populations. J Dairy Sci. 2020;103:5183–99.
- Bohmanova J, Sargolzaei M, Schenkel FS. Characteristics of linkage disequilibrium in North American Holsteins. BMC Genomics. 2010;11:421.
- Hu ZL, Park CA, Reecy JM. Building a livestock genetic and genomic information knowledgebase through integrative developments of Animal QTLdb and CorrDB. Nucleic Acids Res. 2019;47:D701–10.
- 146. Smedley D, Haider S, Durinck S, Pandini L, Provero P, Allen J, et al. The BioMart community portal: an innovative alternative to large, centralized data repositories. Nucleic Acids Res. 2015;43:W589–98.
- 147. Raudvere U, Kolberg L, Kuzmin I, Arak T, Adler P, Peterson H, et al. g:Profiler: a web server for functional enrichment analysis and conversions of gene lists (2019 update). Nucleic Acids Res. 2019;47:W191–8.
- 148. The Gene Ontology Consortium. The gene ontology resource: 20 years and still GOing strong. Nucleic Acids Res. 2019;47:D330–8.
- 149. Kanehisa M, Sato Y, Furumichi M, Morishima K, Tanabe M. New approach for understanding genome variations in KEGG. Nucleic Acids Res. 2019;47:D590–5.
- Szklarczyk D, Gable AL, Lyon D, Junge A, Wyder S, Huerta-Cepas J, et al. STRING v11: protein-protein association networks with increased coverage, supporting functional discovery in genome-wide experimental datasets. Nucleic Acids Res. 2019;47:D607–13.

Publisher's Note

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

Ready to submit your research? Choose BMC and benefit from:

- fast, convenient online submission
- thorough peer review by experienced researchers in your field
- rapid publication on acceptance
- support for research data, including large and complex data types
- gold Open Access which fosters wider collaboration and increased citations
- maximum visibility for your research: over 100M website views per year

At BMC, research is always in progress.

Learn more biomedcentral.com/submissions

