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Divergent evolution and purifying selection of the Type 2 diabetes gene sequences in *Drosophila*: a phylogenomic study

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Abstract

The recently developed phylogenomic approach provides a unique way to identify disease risk or protective allele in any organism. While risk alleles evolve mostly under purifying selection, protective alleles are evolving either under balancing or positive selection. Owing to insufficient information, authors employed the phylogenomic approach to detect the nature of selection acting on type 2 diabetes (T2D) genes in *Drosophila* genus using various models of CODEML utility of PAML. The obtained result revealed that T2D gene sequences are evolving under purifying selection. However, only a few sites in membrane proteins encoded via *CG8051*, *ZnT35C*, and *kar*, are significantly evolving under positive selection under specific scenarios, which might be because of positive or adaptive evolution in response to changing niche, diet or other factors. In the near future, this information will be highly useful in the field of evolutionary medicine and the drug discovery process.

Keywords Type 2 diabetes · Natural selection · Drosophila · Phylogenomics

Introduction

Diabetes mellitus (DM) is a polygenic disease. Clinically it is characterized by hyperglycemia, polyuria (frequent urination), polyphagia (hunger), polydipsia (thirst), and loss of weight. DM is mainly of two types, namely, type 1 diabetes (T1D) & type 2 diabetes (T2D). T1D is clinically characterized via autoimmune destruction of insulin-producing pancreatic β cells; if not treated early results in absolute insulin deficiency. T2D is characterized via resistance towards the action of insulin as well as an incapability to produce adequate levels of insulin for overcoming 'insulin resistance' (Walker and Colledge 2013). While T1D is an autoimmune disease, obesity is a major risk factor for causing T2D along with various other genetics as well as environmental factors (Thirlaway and Davies 2001; Baynest 2015; Skyler et al. 2017). As T2D is a complex disorder, there are

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Ramakrishna Vadde vrkrishna70@gmail.com; vrkbtbi@yogivemanauniversity.ac.in still numerous debates on the actual cause, mechanism, and treatment associated with T2D. Thus, interest to understand the mechanism as well as to find a possible therapeutic for T2D with minimum side effects has revolutionized the field of diabetic research. Researchers are implementing several new technologies, like nanotechnology, statins, and gene therapy, for the treatment of T2D. Nevertheless, these new technologies, along with the traditional medicinal approach, are also reported to have certain side effects. For instance, the consumption of nanoparticles may be toxic or harmful (Tiwari 2015). Thus, there is always an urge to detect key gene(s) and its site(s) that play a significant role in the development of T2D, which in turn may function as a plausible therapeutic target towards the treatment of T2D.

The recently developed phylogenomic approach provides a unique way to understand how natural selection has shaped the genetic diversity of any organism. The phylogenomic approach also provides us a unique way to identify disease risk or protective allele in any organism. While risk alleles evolve mostly under purifying selection, protective alleles are evolving either under balancing or positive selection (Gupta and Vadde 2019a). However, when an individual with protective alleles migrate to the contrasting environment, the protective alleles may turn into risk factor and causes diseases (Gupta and Vadde 2019a). Hence, there is an urgent requirement to identify disease-specific protective or

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risk alleles (Gupta and Vadde 2019a). This can be achieved by employing various principles of evolution (Grunspan et al. 2017). Through natural selection, it's easy to understand the processes associated with the adaptation of an organism to its environment through selectively reproducing changes in its genotype or genetic constitution (König 2001; Gupta and Vadde 2019a). By performing a comparative study of gene(s) sequences of closely related species, we can quickly determine the evolutionary relationship for a particular phenotype (e.g., T2D) (Fischman et al. 2011). Since the protein-coding region of any gene is highly conserved throughout evolution, estimation of evolutionary pressure on the protein-coding region provides more significant results in comparison to the non-coding region (Yang 2006). Evolutionary constraints on proteins across divergent lineages are generally estimated via the ratio of substitution rates at nonsynonymous (dN) and synonymous sites (dS) in the protein-coding regions ($\omega = dN/dS$) (Yang 2006). Using the synonymous polymorphisms as a proxy of neutral diversity, one can easily predict whether nonsynonymous polymorphisms have been favored or hindered by natural selection (Yang 2006). In the case of neutral evolving genes, the rate of fixation of synonymous and nonsynonymous mutations will be the same ($\omega = 1$) (Yang 2006). In the case of negative (purifying) selection, the nonsynonymous mutation is not favored via natural selection. It thus is eliminated, causing the rate of fixation of synonymous mutation to be higher than the nonsynonymous rate ($\omega < 1$) (Yang 2006). In the case of positive (adaptive) selection, the nonsynonymous mutation is favored by positive selection, causing the rate of fixation of nonsynonymous mutation to be higher than the synonymous rate ($\omega > 1$) (Yang 2006). Thus, ω value can be employed extensively to understand evolutionary rates of genes, identify least or most conserved genes and also detect genes that may have undergone periods of adaptive (or positive) evolution (Kosiol et al. 2008). For instance, in parasite genomes, ω value enables us to detect rapidly evolving genes in the "evolutionary arms race" against the host's immune system (Yang et al. 2003; Lefébure and Stanhope 2009).

Earlier phylogenomics approaches were utilized to understand antibiotic resistance and pathogen evolution as well as detecting the origins of emerging diseases, for instance, the origin of HIV1 in chimpanzees in Central Africa (Nesse and Stearns 2008). Phylogenomics approaches have also been employed in cancer treatment and research. Cell lines segregate under the influence of mutations, and the genetic differences make it possible to trace the original wild type sequence. Two tumors with identical histological features may have, unlike proteomic signatures, that, in turn, will help us to understand the degree of cellular differentiation. Whether the tumor has developed from the same line of cell or have different origin can also be detected via phylogenomics approaches (Nesse and Stearns 2008). Recently, Al-Daghri and the team have reported that G6PC2 genes are evolving under positive selection in mammal and play a significant role in causing T2D (Al-Daghri et al. 2017). G6PC2 encodes a glucose-6-phosphatase catalytic subunit isoform that catalyzes the hydrolysis of glucose-6-phosphate for producing glucose as well as inorganic phosphate in the endoplasmic reticulum lumen (Pound et al. 2013). In another study, Klimentidis and the team identified three genes, namely, IGF2BP2, WFS1, and SLC30A8, that are under positive selection and also responsible for increasing the risk of T2D in East Asians and Sub-Saharan Africans human population (Klimentidis et al. 2011). In contrast, few studies reported that high milk consumption in Europe caused a positive selection of protective variants in milk-consuming populations, which might explain the low prevalence of T2D in Europeans (Ségurel et al. 2013). Thus, there is always a quest to understand how the evolutionary process has shaped the genetic makeup of the T2D gene in different organisms/ populations and detect and characterize positively selected genes and their sites that may be responsible for either causing T2D or providing protection against T2D.

Because of high conservation between humans and flies at both physiological and molecular levels, Drosophila has served as the best useful model organism for studying a variety of human traits and diseases, including T2D (Musselman et al. 2011; Alfa and Kim 2016; Graham and Pick 2017). Till date numerous studies have been performed for understanding the influence of natural selection on the genetic diversity of numerous gene families, for example, male reproductive genes (Ahmed-Braimah et al. 2017), olfactory and gustatory receptors (Gardiner Anastasia et al. 2009) and immune genes (Hill et al. 2019) in Drosophila. However, no phylogenetic studies have been undertaken on the T2D gene of Drosophila. Thus, there is always a debate about how evolution has shaped the genetic diversity in the T2D genes of the Drosophila genus. Hence, for the first time, authors have utilized aligned protein-coding sequence files of T2D genes of 12 species of Drosophila available in the FlyBase R6.14 database (https://flybase.org/) for detecting nature of selection acting on T2D gene in Drosophila. In the near future, information obtained from the present study will help us in understanding the mechanism associated with T2D in humans, which in turn may be useful in the field of evolutionary medicine, as well as in the drug discovery process.

Materials and methods

Data retrieval and preprocessing

Aligned coding sequence (CDS) file of the longest isoform of every *D. melanogaster*'s genes that are present in all 12 species of *Drosophila* (*D. melanogaster*, *D. sechellia*, *D.* erecta, D. simulans, D. yakuba, D. ananassae, D. persimilis, D. pseudoobscura, D. willistoni, D. virilis, D. grimshawi and D. mojavensis) were downloaded from FlyBase R6.14 databases (ftp://ftp.flybase.net/genomes/12_species_analy sis/clark_eisen/alignments/). For maintaining consistency, CDS file lacking genes sequence of any of the 12 species were discarded. Further, a stop codon from each aligned sequenced file was discarded via bppsuite (https://githu b.com/BioPP/bppsuite).

Orthologs search

FlyBase' gene IDs present in all 12 species of Drosophila were subjected to the DIOPT ("Drosophila RNAi Screening Center Integrative Ortholog Prediction Tool") Diseases and Traits (https://www.flyrnai.org/diopt-dist). Tool for identifying high-confidence orthologs of human T2D genes in Drosophila melanogaster (Hu et al. 2011). DIOPT-DIST is comprised of zebrafish, human, fly, yeast, mouse, and worm ortholog predictions made by several existing tools, like, HomoloGene, Inparanoid, Ensembl Compara, Isobase, OMA, Phylome, RoundUp, TreeFam, and orthoMCL. Based on this information, DIOPT-DIST estimates simple scores that represent the number of tools that support a given orthologous gene-pair relationship, as well as a weighted score based on functional assessment using high quality GO molecular function annotation of all fly-human orthologous pairs predicted by each tool. These scores are represented as low, moderate, and high, where low denotes "least significant orthologous gene-pair relationship" and high denotes "highly significant orthologous gene-pair relationship" (Hu et al. 2011).

Identification of selection pressure acting on T2D genes in the *Drosophila* genus

Initially, ω value of every gene was calculated individually by using M0 (one ratio or neutral) model implemented in Phylogenetics Analysis by Maximum Likelihood (PAML) package v4.9 (Yang 2007). M0 is the simplest model of PAML and presume identical ω value for all branches in a phylogenetic tree and across all sites (Swanson et al. 2003; Lynn et al. 2005). For estimating ω value, the M0 model utilized the F3xF4 model and gene tree of 12 species generated by the Drosophila Genome Consortium (Fig. 1A) (Drosophila 12 Genomes Consortium 2007). Later, quantile regression analysis was carried out between ω value of T2D and non-T2D genes using the QUANTREG package of R (Koenker et al. 2018; Team 2014) to detect the strength of selective pressure that is responsible for shaping the function of T2D across entire Drosophila genus. Results having a *p*-value < 0.05 was considered significant.

Though significant, the result obtained from the M0 model reveals only the global scenario across any genus. However, earlier several studies have also suggested that the evolution shapes each branch of the phylogeny distinctly because the number of rates of nonsynonymous and synonymous substitutions varies across a sequence (Wong et al. 2008). Thus, in the present study, "Branchsite models" were also employed for detecting selection pressure that acts distinctly on T2D genes of each species of Drosophila (Farfán et al. 2009). "Branch-site models" allow ω value to vary both amongst sites as well as lineages. Subsequently, quantile regression analysis between the ω value of T2D and non-T2D genes of each species was performed separately to detect the strength of selective pressure. Results having p-value < 0.05 is considered significant.

Detecting positively selected sites in T2D genes of *Drosophila* genus

Since genes and their sites that are evolving under positive selection are beneficial, there is always a quest to detect them (Wagner 2007). Earlier studies have also reported that few sites in genes that are evolving under purifying selection may also occasionally experience adaptive change (Yang and Bielawski 2000). Such sites point to functionally important gene's regions. Hence, they are of potential interest to protein engineers who alter proteins to produce new functions. By considering the above information, in the present study, T2D genes and their sites that are evolving under positive selection were detected using "fixed-sites models", namely M7 and M8 (Yang and Swanson 2002). M7 allows 10 sites class following a betadistribution of sites with ω value ranging between 0 and 1. M8 model is similar to M7 models, except there is an additional 11th site class with $\omega > 1$ (positive selection allowed). For estimating significance in terms of a *p*-value, a likelihood-ratio test (LRT) was employed. LRT $(2\Delta \ell)$ is computed as $2(\ell_1 - \ell_0)$, where ℓ_1 is the log-likelihood (LL) of the model representing the alternative hypothesis (M8) and ℓ_0 is the LL of the model representing the null hypothesis (M7). LRT statistic approximately follows a chi-square distribution. p-value obtained was further adjusted via "FDR" (false discovery rate) function in the R package. T2D gene and its sites with FDR value < 0.05were considered to be significantly under positive selection. Later, Bayes empirical Bayes (BEB) methods available in PAML4.9 were employed to detect if any positive selection episodes had affected any specific amino acid sites in the protein encoded via genes (Liu et al. 2013; Teng et al. 2017). These T2D genes having positively selected sites are henceforth known as key genes.



Fig. 1 A Gene tree of 12 *Drosophila* species generated by Drosophila Genome Consortium. **B** Global distribution of ω in entire *Drosophila* genome. **C** Violin plot representation of distribution of ω value for non-T2D (red) and T2D (cyan) genes. Black dot in the center of the

red and cyan violin plot represents the mean ω value. **D** Pairwise assessments of dS and dN substitution rates in T2D genes. **E** Saturation plot in *T2D genes*. **F** ω value of T2D genes were plotted against sequence divergence (*t*)

Gene ontology and pathway enrichment analysis

STRING database (Szklarczyk et al. 2017) was utilized for detecting gene ontology (cellular component, biological process, molecular function) and pathway enrichment analysis associated with key genes. Result having gene count > 2 and FDR < 0.05 were considered significant.

Generation of the three-dimensional structure of proteins

The coding sequence of each key genes was submitted to the EMBOSS Transeq tool (https://www.ebi.ac.uk/Tools/st/ emboss_transeq/) for translating nucleic acid sequences to their corresponding peptide sequences. The protein sequence of each key candidate genes was subject to NCBI's protein BLAST (Altschul et al. 1990), separately, for detecting their nearby homologous structure against Protein Data Bank (PDB). Depending on maximum sequence identity, query coverage, or lower e-value, if their homologous structure were available in Protein Data Bank, they were retrieved manually. If homologous structures are absent in Protein Data Bank, each protein sequence was submitted separately to the GalaxyWEB server (https://galaxy.seoklab.org/) for building their three-dimensional model. Ramachandran plot produced via PROCHECK (Laskowski et al. 1993) and Z scores computed through the ProSA-web tool (Wiederstein and Sippl 2007) were employed to validate the geometry of modeled protein structure.

Molecular dynamics (MD) simulations of proteins

For understanding structural characteristics of the protein encoded via each key genes distinctly, molecular dynamics simulations of each protein for 200 ns were done via Gromos96-43a1 force field of "GROningen MAchine for Chemical Simulations" (GROMACS 5.1) (Abraham et al. 2015), individually. If proteins encoded through key candidate genes are situated in the cytoplasm, cubic boxes bearing SPC216 water molecules employed for solvating protein (Gupta and Vadde 2018; Gouda et al. 2019). If proteins produced via key candidate genes are situated in the cell membrane, three-dimension structure of each protein was implanted into equilibrated bilayer of "dipalmitoyl phosphatidylcholine" employing "g_membed" tool (Wolf et al. 2010) of GROMACS utilizing parameters for "Berger lipids" generated from Berger, Edholm, and Jahnig (Berger et al. 1997). Further, the solvation of the membrane systems was carried out by creating a local copy of vdwradii. dat and modifying C value to 0.375 from 0.15 (Gupta and Vadde 2019b; Gupta et al. 2019). By making these changes, solvate assign carbon atoms sufficiently large van der Waals radius, which in turn makes water augmentation within the lipids less likely (Lemkul 2015). Further, neutralization of the entire system was performed through adding suitable ions employing genion application of GROMACS.

To discard faulty steric conflicts and van der Waals contacts protein, energy-minimization performed at an initial stage through steepest descent of 3,000 steps with 0.01 nm energy step size. The energy minimisation step was designed to halt when the maximum force reaches less than 1000 kJ/ mol/nm. To equilibrize the complete system, solute was subjected to constant "number of particles, volume and temperature" (NVT) conditions for 100 ps at 300 K, subsequently followed through 100 ps under constant "number of particles, pressure, and temperature" (NPT) conditions up to 200 ns. All covalent bonds were moderated through the "Linear Constraint Solver" (LINCS) algorithm. Last step of molecular dynamics of the electrostatic interactions was computed through "Particle Mesh Ewald" (PME) method. For each and every step, dynamics simulation was allotted 100,000,000 steps with an energy step size of 0.02 fs (200 ns). The protein atoms were harmonically constrained during solvent equilibration (Donde et al. 2019). Final MD trajectories, along with the quality of simulations, were estimated through GROMACS5.1. Xmgrace (Turner 2005) program was employed for generating two-dimensional plots and trajectory analysis.

Result

File preprocessing and orthologs search

Initial inspection of each aligned CDS file reveals that there are more than ~ 7304 genes across the phylogeny, but 7304 orthologs are present across all groups in the *Drosophila* genus. However, out of 7304, only 5679 genes are present in all 12 species of *Drosophila*. Further, investigation via the DIOPT-DIST tool suggested that, out of 5679, only 202 orthologs of human protein-coding T2D genes are present in *Drosophila* (Supplementary File 1). Thus, aligned coding

sequence files of only 5679 (202 T2D and 5476 non-T2D) genes were considered for downstream analysis.

Identification of selection pressure acting on T2D genes and it's sites in the *Drosophila genus*

The result obtained from the M0 model suggests that the ω value of all genes is less than 1 (Table 1 and Fig. 1B), which in turn supports that almost the almost entire genome of the Drosophila genus is evolving under purifying selection. However, the mean ω of T2D genes (0.063) is slightly less than non-T2D genes (0.064) (Fig. 1C). In T2D genes, dS (range 0.032–25.827) is greater than dN values (range 0.000-1.431) (Fig. 1D). Saturation plot of T2D genes reveals strong saturation of both transitional as well as transversional substitutions till 0.05 (<=1) (Fig. 1E); thereby suggesting the presence of multiple substitutions as well as plausible homoplasy (Farfán et al. 2009). Figure 1F depicts a negative relationship between ω & sequence divergence. Further quantile regression analysis between ω values of T2D and non-T2D genes suggests that T2D is evolving under strong purifying selection in *Drosophila* genus (p-value = 0.044) (Table 1).

It is pertinent to note that dS across 12 species of is higher than 1 in almost all genes. Hence, to avoid misestimation of ω in each species of *Drosophila*, at first, we split our datasets into four group, namely Group A (*D. melanogaster, D. sechellia* and *D. simulans*), Group B (*D. erecta, D. yakuba*), Group C (*D. persimilis* and *D. pseudoobscura*) and Group D (*D. virilis, D. grimshawi* and *D. mojavensis*). Subsequently, dS and dN value of each genes of every group was estimated using the M0 model. Result obtained from "M0

Table 1 Result obtained from quantile regression analysis between ω values of T2D and non-T2D genes in different species of *Drosophila*

Organism	Value	Std. error	t value	Pr(>ltl)
Drosophila genus	- 0.005	0.003	- 2.015	0.044
Group A				
D. melanogaster	-0.008	0.002	- 3.137	0.002
D. simulans	-0.017	0.008	- 2.251	0.024
D. sechellia	- 0.021	0.007	- 2.911	0.004
Group B				
D. yakuba	-0.005	0.004	- 1.276	0.202
D. erecta	- 0.009	0.010	-0.850	0.396
Group C				
D. pseudoobscura	-0.005	0.005	- 1.130	0.258
D. persimilis	- 0.030	0.036	- 0.839	0.402
Group D				
D. virilis	- 0.005	0.003	- 1.593	0.111
D. mojavensis	-0.007	0.005	- 1.303	0.193
D. grimshawi	- 0.007	0.005	- 1.248	0.212

models" reveals that dS value in each range between 0 and 1.5 (Fig. 2). Later, genes with 0.05 < dS < 1 was only considered for "Branch-site models" analysis to get a better estimation of ω in each group distinctly. It is pertinent to note that dS value of all 202 T2D genes in all four group range between 0.05 and 1.

The result obtained from "Branch-site models" reveals that mean ω of T2D genes is less than non-T2D genes in all species of each four group (Supplementary File II and Table 1). However, quantile regression analysis between ω of T2D and non-T2D genes in each species separately suggests that T2D is evolving significantly under strong purifying selection only in GroupA (p-value < 0.05) (Table 1). Hence, *D. melanogaster*, *D. sechellia*, and *D. simulans* serve as a better model to study T2D in comparison to others. Later, LRT between Model 8 and 7 in all four groups suggests that few sites only in three T2D genes, namely, *CG8051* (ASN7, ALA71, THR323 & HIS330), *ZnT35C* (VAL22, SER174, ALA177, THR227) and *kar* (ASN496 & ALA499), of GroupA experience positive selection (Supplementary file III). No significant result found in GroupB, GroupC and GroupD. Thus, these three genes are key genes and may play an important role in maintaining normal insulin level in the body.



Fig. 2 Pairwise assessments of dS and dN substitution rates in T2D genes of A Group A (*D. melanogaster, D. sechellia* and *D. simulans*), B Group B (*D. erecta, D. yakuba*), C Group C (*D. persimilis* and *D. pseudoobscura*) and D Group D (*D. virilis, D. grimshawi* and *D. mojavensis*)

Gene ontology and pathway enrichment analysis

Analysis of three key genes via the STRING database reveals that the main molecular function associated with them are monocarboxylic acid transmembrane transporter activity, ion transmembrane transporter activity and inorganic molecular entity transmembrane transporter activity (Fig. 3A). All three key genes mainly reside in the integral component of the membrane. The main biological process associated with them is monocarboxylic acid transport, ion transmembrane transport, and carboxylic acid transmembrane transport. The main pathway associated with these key genes is SLCmediated transmembrane transport.

Generation of the three-dimensional structure of proteins

As no homologous structure of proteins encoded via these three key genes was identified in Protein Data Bank, the protein sequence of each key gene was submitted to the GalaxyWEB server separately. Generated structures of *CG805*, *ZnT35C*, and *kar* are made up of only 24, 19, and 36 α -helices and loops, respectively (Fig. 3B, I–III). Further, validation of the three-dimensional structure of each protein via PROCHEK suggests that overall, 99.762%, 98.000% and 99.000%, of *CG8051*, *ZnT35C*, and *kar* residues, respectively, are present in allowed regions (Fig. 4). Z scores of *CG8051* (1.800), *ZnT35C* (0.560) and *kar* (1.540) also range between -10 and 10, thereby proposing that stereo-chemical geometry of the generated models is sensibly good.

MD simulations of proteins

To understand structural characteristics, MD trajectories of three-dimensional structure of all three proteins for 200 ns were performed separately. During energy minimization, the final potential energy of CG8051, ZnT35C, and kar, was - 2,311,545.250 kJ/mol, - 4,860,415.506 kJ/mol, and - 3,469,797.000 kJ/mol, respectively. The temperature of all three proteins varies between 298 and 301 K with mean 299.999 K. Mean pressure of CG8051, ZnT35C, and kar, is -0.175 bar, 1.380 bar, and 0.962 bar, respectively. Mean density of CG8051, ZnT35C, and kar is 978.826, 1014.623, and 998.654, respectively. In CG8051, Rg varies between 10.042 Å and 10.132 Å with a mean Rg of 10.09 Å. In ZnT35C, Rg varies between 5.657 Å and 5.674 Å with mean Rg of 5.665 Å. In kar, Rg varies between 7.362 Å and 7.497 Å with a mean Rg of 7.429 Å. Mean RMSD and RMSF of CG8051 < kar < ZnT35. However, RMSF of amino acids towards the N-terminal is constrained. Amino acid experiencing the highest fluctuation during simulation in CG8051 are PRO257, ARG273, THR323, HIS330,



Fig. 3 A Ontology and B three-dimensional structure of proteins encoded by each of the three key genes

GLU337, and THR372. Amino acid experiencing the highest fluctuation during simulation in *ZnT35* are VAL266, THR277, CY269, and LEU364. Amino acid experiencing the highest fluctuation during simulation in *kar* are ALA236, AGR330, THR359, and ALA499 (Fig. 5). 'Cross-correlation matrix' of the C- α displacement (Fig. 6) and the 'free energy



Fig. 4 Ramachandran plot of modeled proteins encoded via A CG8051, B ZnT35C, and C kar generated via PROCHECK



Fig. 5 The stability parameters for key T2D protein during 200 ns: **A** RMSD of C- α **B** RMSF of C- α and **C** Radius of gyration of C- α . The trajectory projected to the two-dimensional space. Black, light green,

and blue, lines represent proteins encoded via CG8051, ZnT35C, and kar during 200 ns, respectively



Fig. 6 Comparative study of cross-correlation matrices of C- α atoms of modeled proteins encoded via **A** *CG8051*, **B** *ZnT35C*, and **C** *kar* during 200 ns simulation. The range of motion indicated by various

colors in the panel. Red indicates a positive correlation, whereas blue indicates anti-correlation

landscape' analysis (Fig. 7) revealed that all residues present within *CG8051* experience random movement while *ZnT35* experiences constrain movements under wild condition.

Discussion

As both incident of T2D, as well as mortal rate due to T2D, is increasing dramatically every year and imposing huge financial burden on almost every country, there is always an urge to look for new approaches or technology which may enable us to detect key genes and pathway that play key role in the T2D development. For instance, Hu and team (2009) performed GWAS analysis and detected SNPs in PPARG (rs1801282), KCNJ11 (rs5219), CDKAL1 (rs10946398, rs7754840, rs9460546, rs7756992 & rs9465871), CDKN2A-CDKN2B (rs564398 & rs10811161), IDE-KIF11-HHEX (rs10509645, rs1111875 and rs10748582), IGF2BP2 (rs7651090) and SLC30A8 (rs13266634) that are responsible for causing T2D (Hu et al. 2009). Additionally, several authors are also employing evolutionary approaches for unmasking the pathophysiology and molecular mechanism associated with T2D in a more comprehensive way. For instance, in 2017, Little and team tested the hypothesis that "natural selection is associated with type 2 diabetes (T2D)associated mortality and fertility in a rural, isolated Zapotec community in the Valley of Oaxaca, southern Mexico" and reported that frequency of T2D-mortality increases with decrease in natural selection as well as favoured offspring survival of non-T2D descendants (Little et al. 2017). Hence, evolutionary comparative sequence analysis is a powerful way of unraveling the mechanisms that shaped contemporary genetic diversity.

Biochemical pathways involved in growth and metabolism are ancient and well conserved across the animal kingdom. Due to conservation between humans & other organisms at both molecular as well as physiological levels, these organisms may be utilized for understanding the real mechanism associated with T2D development in humans. Numerous T2D associated studies have also been performed in various model organisms, like KK mice and Drosophila melanogaster (King 2012; Murillo-Maldonado and Riesgo-Escovar 2017). Most of the animal models of T2D are obese, mimicking human conditions where obesity is the main cause for developing T2D (King 2012; Murillo-Maldonado and Riesgo-Escovar 2017). The fa/fa rats and ob/ob mice are one of the best examples for the same. Other model organisms, for instance, *Psammomys obesus* (the Israeli sand rat) and db/db mouse, develop hyperglycemia rapidly because their β -cells are incapable of maintaining a high concentration of insulin secretion required throughout life. The study of these animal models may provide significant insight why few humans with severe obesity never develop T2D, while others are more risk at developing hyperglycemic despite modest insulin resistance and obesity (Rees and Alcolado 2005). The zebrafish model also showed a better response to the anti-diabetic drug, namely metformin, and glibenclamide, proposing that zebrafish can also be utilized as a model organism towards understanding the mechanism of T2D in human. However, the organisms, especially mouse, rat, and dog, have strict ethical guidelines for carrying out research (Rees and Alcolado 2005). Additionally, life span of these organisms are also large, and hence, special care is also required for maintaining these organisms.

Owing to smaller genome size and short life span, Drosophila melanogaster serves as one of the best models



Fig. 7 Projections of the free energy landscape of protein encoded via **A** *CG8051*, **B** *ZnT35C*, and **C** *kar* during 200 ns simulation. Various colors in the panel indicate the range of motion, where dark black

indicates the lowest energy configuration, and white shows the highest energy configuration for studying any human diseases. The main advantage of employing Drosophila melanogaster is that, unlike other organisms (e.g., mouse and dog), there are either no or few ethical issues surrounding their use (Jennings 2011). Insulin producing cells (IPCs) of Drosophila is equivalent to mammalian Langerhans' islets ß pancreatic cells (Alfa and Kim 2016; Graham and Pick 2017). However, unlike vertebrates, which have one insulin gene, Drosophila genome encodes seven different insulin-like peptides (ILPs) (Álvarez-Rendón et al. 2018). The ILP2 peptide has the highest homology with insulin gene of the vertebrate and is produced along with ILP1, ILP3 & ILP5 in the IPCs located in the brain (Álvarez-Rendón et al. 2018). ILP2 is also expressed in the imaginal discs and the salivary glands. ILP4, ILP5, and ILP6 are expressed in the midgut, and ILP7 is expressed in the ventral nerve chord. These seven ILPs function together with Drosophila's insulin-like receptor (InR) trigger a cascade of intracellular events facilitated via conserved apparatuses of the insulin/IGF pathway comprising of the insulin receptor substrate (IRS) Chico, the insulin signaling antagonist PTEN, PKB/Akt kinase, PI3K, and dFOXO (the single FOXO orthologs) (Baker and Thummel 2007).

In a normal feeding environment, three ILP genes, namely, ILP2, ILP3 and ILP5, are expressed within median neurosecretory cells of the brain and regulate sugar level in circulating blood. In response to reduced dietary carbohydrate concentration, the expression of ILP3 and ILP5 decreases in IPCs, suggesting that ILP concentration can respond to particular nutritional indications like insulin in humans (Baker and Thummel 2007). Additionally, some studies reported that removal of the insulin-producing cells causes hyperglycemia (Grönke et al. 2010). Like glucagon secretion from pancreatic α -cells in mammals, insect adipokinetic hormone (AKH) counterbalances the actions of insulin via triggering glycogen phosphorylase, enhancing circulating sugars and decreasing fat body glycogen. Akh is expressed in the main endocrine organ of the insects, namely the corpora cardiaca region of the ring gland, which is in direct contacts with the hearts and IPCs. Removal of corpora cardiaca specific cell removes Akh function, which in turn reduces the concentration of circulating trehalose but has no significant effect on the stored concentration of lipid or glucose (Lee and Park 2004; Baker and Thummel 2007). However, ectopic expression of Akh in the fat body, the primary target tissue of Akh, causes hypertrehalosemia and lipolysis, which in turn reduces the amount of stored lipid (Lee and Park 2004). All these earlier studies reported that the central regulatory functions of insulin and glucagon are conserved throughout evolution and supported that *Drosophila* can be utilized as a valid model organisms for functional studies of glucose homeostasis as well as the underlying mechanisms modulating the onset of diabetes. Thus, in present study, authors made an attempt to re-analyzed the publicly

available T2D gene sequences of *Drosophila* for studying evolutionary processes responsible for shaping genetic make-up of T2D genes in genus *Drosophila*.

Result obtained reveals that there are only 202 orthologs of human protein-coding T2D genes in Drosophila genus. Few human T2D genes like ARF5, LIPC, CPA6, CCNQ, KCNJ11, and GALNT14 have more than one orthologs in Drosophila (Supplementary File I). This might be because Drosophila may have underwent an additional round of whole-genome duplication during evolution (Maurer et al. 2015). Further analysis via M0 model of CODEML reveals that all T2D genes present in the Drosophila genus are evolving significantly under purifying selection (p-value < 0.05). Earlier studies have also reported that in comparison to younger proteins, ancient proteins exhibit stronger purifying selection; thereby indicating T2D genes is ancient (Domazet-Loso and Tautz 2003, 2008). The functions of ancient genes, like T2D genes, are highly optimized as well as conserved, and they are likely to have already exhausted all beneficial mutations in recent times. Thus they are expected to evolve under purifying selection and fix only neutral and/or nearly neutral mutations (Vishnoi et al. 2010). Our results is also in accordance with Blekhman and the team, who also demonstrated that genes associated with Mendelian and complex diseases are under purifying selection (Blekhman et al. 2008).

Further, since dS across 12 species of is higher than 1 in almost all genes, dataset was divided into four groups and ω of each species in each group was estimated separately using "Branch-site models". Result obtained revealed that T2D is evolving significantly under strong purifying selection only in GroupA (p-value < 0.05). Hence, D. melanogaster, D. sechellia and D. simulans serve as a better model to study T2D in comparison to other (Table 1). This result is in accordance with earlier studies where authors have reported that evolution shape each branch of the phylogeny distinctly because the number of rates of nonsynonymous and synonymous substitutions varies across a sequence and species (Wong et al. 2008). LRT between Model 8 and 7 in all the four group, separately, suggests that few sites only in three key T2D genes, namely, CG8051, ZnT35C, and kar, of GroupA experience positive selection (Supplementary file II). This is in accordance with earlier studies where authors have reported that few sites in genes that are evolving under purifying selection may also experience adaptive change occasionally (Yang and Bielawski 2000). Earlier studies have also reported that positive selection is the preservation and spread of beneficial mutations throughout the population. Identifying positively selected protein or its site in any branch of a phylogeny suggests that there is a selective advantage of positively selected protein or its site over another branch of a phylogeny. This selective advantage may be in response to change in the various external and internal phenomena, for instance, diet, disease, and adaptation to several ecological niches (Morgan et al. 2012). For instance, the genetic adaptations to the low-salt environment in ancestral populations is a threat to hypertension in present populations residing in a high-salt environment (Balaresque et al. 2007). This salt retention adaptive trait enables ancient humans, consuming low levels of dietary salt to survive in hot and humid areas (Balaresque et al. 2007). Earlier studies have reported that numerous olfactory system genes are positively selected in organisms if odor and pheromone perception is crucial for its reproduction as well as survival (Ngai et al. 1993; Willett 2000; Emes et al. 2004; Krieger and Ross 2002). Such sites point to functionally important gene's regions and, hence, are of potential interest to protein engineers who alter proteins to produce new functions. Information about positively selected protein and their sites are highly required for our understanding of functionally significant amino acids in any protein sequence and their role in protein functional shift (Yang and Bielawski 2000).

Gene ontology and pathway enrichment analysis reveals that these three key genes encode membranes proteins and are mainly involved in the ion transport (Fig. 3A). Earlier studies have also reported that ion channels as well as transporters proteins play key roles in both excitable cells, e.g., skeletal, cardiac, neurons, as well as endocrine cells, and non-excitable cells, e.g., liver (Spires et al. 2019). In human pancreatic β -cells, K_{ATP} channels modulate the membrane potential of the β -cell membrane, which in turn regulates insulin secretion (Spires et al. 2019; Gupta and Vadde 2020a). For instance, several other studies have reported that in humans, ZnT8 transporter protein resides on densecore vesicles in pancreatic β cells and loads Zn^{2+} into these secretory compartments, where it binds with and stabilizes a hexameric form of insulin (O'Halloran et al. 2013). These ZnT8 transporters are mainly responsible for the efflux of zinc from the cytosol to intracellular vesicles, unlike the functions of zinc importers (ZiPs; SLC39), which are responsible for zinc influx into the cytosol as well as zincbinding proteins, like metallothionein. This co-ordination between the function of zinc transporter and importers maintain zinc level in cytosol (Rutter and Chimienti 2015; Gupta and Vadde 2020b). However, mutations in this two protein, namely KATP channels and ZnT8 transporter, is reported to disrupt their normal functions, which in turn cause T2D (Gupta and Vadde, 2020a; b).

Further, molecular dynamics studies suggest that all these three key genes are mainly comprised of α -helices and loops (Fig. 3B). Out of three, *CG8051* experiences more random movement while ZnT35C experience constrains movement under normal conditions. This might be due to less potential energy and higher pressure in ZnT35C. Movement of N-terminal residues of all three key genes is more constrained, thereby supporting that the N-terminal region of all these three proteins is insignificant during protein-ligand interaction. This finding is in accordance with our earlier studies in the human ortholog of ZnT35C, i.e. zinc transporter ZnT8. Movement of ZnT8 protein was also found to be constrained under normal conditions (Gupta and Vadde 2020b). N-terminal region of ZnT8 was also found to be insignificant during protein-ligand interaction (Gupta and Vadde 2020b). RSMF analysis reveals that, out of all positively selected sites, only ARG273 and THR323 in CG805, THR277 in ZnT35C, ALA499 in kar experiences highest fluctuations; thereby supporting their importance during protein-ligand interaction. This, in turn, helps to modulate the normal metabolic function of the body. Thus, in summary, as T2D disease is ancient, they are evolving under purifying selection in the Drosophila genus. Hence, the function of T2D genes is highly conserved throughout evolution. However, few sites in membrane proteins encoded T2D genes, like CG8051, ZnT35C, and kar, are still evolving under positive selection in few species of Drosophila, like, D. melanogaster, D. sechellia and D. simulans; this might be due to adaptive (positive) evolution in response to changes in various external mechanisms, for instance, response to disease & adaptation to several ecological niches, and internal mechanisms (compensatory mutations and co-evolution).

Conclusions

In conclusion, as T2D genes are ancient, they are evolving under purifying selection. Hence, there is almost no or very little scope for new nonsynonymous mutations in T2D genes, and the functions of T2D genes are highly conserved throughout evolution. However, few sites in membrane proteins encoded via few T2D genes, like CG8051, ZnT35C, and kar, are still evolving under positive selection in certain scenarios, which might be due to adaptive (positive) evolution in response to changes in various external mechanisms, for instance, response to disease and adaptation to several ecological niches, and internal mechanisms (compensatory mutations and co-evolution). This study provides a new perspective on an understanding of the evolution of the T2D gene. In the near future, information obtained from the present study will be highly useful in the field of evolutionary medicine, as well as in the drug discovery process.

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Compliance with ethical standards

Conflict of interest The authors of this manuscript declare no conflict of interest.

Ethical approval This article is a computational work and does not contain any studies with human participants or animals.

Informed consent This article is computational work. Hence, this article does not require consent from any individual or organization.

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