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Application of codon usage and context analysis in genes up- or down-regulated in neurodegeneration and cancer to combat comorbidities

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Introduction: Neurodegeneration and cancer present in comorbidities with inverse effects due to the expression of genes and pathways acting in opposition. Identifying and studying the genes simultaneously up or downregulated during morbidities helps curb both ailments together.

Methods: This study examines four genes. Three of these (Amyloid Beta Precursor Protein (*APP*), Cyclin D1 (*CCND1*), and Cyclin E2 (*CCNE2*) are upregulated, and one protein phosphatase 2 phosphatase activator (PTPA) is simultaneously downregulated in both disorders. We investigated molecular patterns, codon usage, codon usage bias, nucleotide bias in the third codon position, preferred codons, preferred codon pairs, rare codons, and codon context.

Results: Parity analysis revealed that T is preferred over A, and G is preferred over C in the third codon position, suggesting composition plays no role in nucleotide bias in both the upregulated and downregulated gene sets and that mutational forces are stronger in upregulated gene sets than in downregulated ones. Transcript length influenced the overall %A composition and codon bias, and the codon AGG exerted the strongest influence on codon usage in both the upregulated and downregulated gene sets. Codons ending in G/C were preferred for 16 amino acids, and glutamic acid-, aspartic acid-, leucine-, valine-, and phenylalanine-initiated codon pairs were preferred in all genes. Codons CTA (Leu), GTA (Val), CAA (Gln), and CGT (Arg) were underrepresented in all examined genes.

Discussion: Using advanced gene editing tools such as CRISPR/Cas or any other gene augmentation technique, these recoded genes may be introduced into the human body to optimize gene expression levels to augment neurodegeneration and cancer therapeutic regimens simultaneously.

KEYWORDS

codon usage, codon pattern, synonymous codons, neurodegeneration, cancer, CRISPR/Cas

1. Introduction

Cancer promotes continuous proliferation, invasion, and metastasis of malignant cells into distal organs. In contrast, neurodegeneration is characterized by neuronal dysfunction and death. These disorders display several opposite features. Where cancer is characterized by abnormal cell

survival and resistance to cell death, cells in neurodegenerative disease are at elevated risk of cell death. Inverse comorbidities have been reported in cancer and neurodegeneration in several reports (Ferreira et al., 2010; Driver et al., 2012; Driver, 2014). Transcriptomic metaanalyses have investigated inverse comorbidities in terms of molecular processes common to CNS disorders and cancers. A significant overlap has been reported between genes that are up-regulated in cancer and down-regulated in neurodegeneration, and vice versa (Ibáñez et al., 2014). Inverse comorbidities are common. Thus, genes and pathways regulated in opposite directions have been thoroughly investigated and understood, and examples of such genes and pathways are available. To date, only a few reports describe pathways operating in same direction in cancer and neurodegeneration. We thus investigated genes implicated in both ailments, to identify ways to simultaneously address cancer and neurodegeneration. We found many genes to be present at the interface of cancer and neurodegeneration, including α -synuclein, PINK1, DJ-1, LRRK2, ATP13A2, PLA2G6, MAPT, and CDK5 (Plun-Favreau et al., 2010) with disease-associated point mutations at various sites (Mavrou et al., 2008; Morris et al., 2010; Veeriah et al., 2010a,b). Specific genes and pathways that simultaneously increased CNS disorder risk while reducing that of cancer were identified. Transcriptomic meta-analyses revealed the simultaneous upregulation of 74 genes, for example PPIAP11, IARS, GGCT, NME2, GAPDHP1, CDC123, PSMD8, MRPS33, FIBP, and OAZ2 in three CNS disorders and downregulation in three cancer types (Ibáñez et al., 2014). Similarly, 19 genes were up-regulated in three cancer types (lung, prostate, and colorectal), and down-regulated in three CNS disorders (Alzheimer's disease, Parkinson's disease and Schizophrenia) and the examples are MT2A, MT1X, NFKBIA, AC009469.1, DHRS3, CDKN1A, and TNFRSF1A (Ibáñez et al., 2014). In cancer, P53 is down-regulated, whereas PIN and Cyclin F are up-regulated. At the same time, P53 is up-regulated, while PIN and Cyclin F are down-regulated in neurodegeneration. Inverse comorbidities make coupled treatment of both diseases difficult.

To find a solution for both diseases, we looked for genes that were up-regulated or down-regulated simultaneously in both disorders, so that they could be handled together. An extensive literature search led us to four genes, amyloid precursor protein (*APP*), Cyclin D, Cyclin E, and protein phosphatase 2A (*PP2A/PTPA*). In cancer and neurodegeneration, *APP*, Cyclin D, and Cyclin E are up-regulated, whereas *PTPA* is down-regulated.

Chromosome 21 trisomy, the presence of *APP* on chromosome 21, and association of *APP* gene upregulation with increased risk of hematologic malignancy in patients with Down syndrome (DS) suggest that *APP* might predispose to cancer. Children with Down syndrome are at 10- to 20-fold higher risk of acute lymphoblastic leukemia and acute myeloid leukemia. In patients with acute myeloid leukemia, *APP* is most overexpressed (Wang et al., 2010), and its overexpression is associated with poor prognosis in oral squamous cell carcinoma (Lin et al., 2020). *APP* overexpression in mouse models leads to neuronal death (Cheng et al., 2016). Overexpression of the human *APP* gene in *Drosophila melanogaster* results in cholinergic and dopaminergic brain neurons that are significantly degenerated later in life compared with controls, accompanied by memory deficits and poor cognitive abilities (Bolshakova et al., 2014).

Cyclins D and E have been reported to be up-regulated, whereas *PTPA* has been reported to be down-regulated in cancer and neurodegenerative disease [reviewed in (Seo and Park, 2020)].

Cyclins control the cell cycle by modulating Cyclin-dependent kinases (CDKs), and their dysregulation underlies several human cancers (Krasniqi et al., 2022; Wu et al., 2022; Sher et al., 2023). In addition to cell cycle regulation, Cyclins participate in cellular processes specific to terminally differentiated neurons (Zhou and Ekström, 2022).

Cyclins play important roles in neuronal physiology and pathology (Cho et al., 2015). Cyclin D1 is a regulatory subunit of CDK4 or CDK6 and is essential for entry into S phase from G1. Mutations leading to aberrant overexpression of Cyclin D alter cell cycle progression and may contribute to tumorigenesis. Thus, CCND1 overexpression correlates with shorter survival and poorly differentiated gastric cancer and other tumors (Shan et al., 2017). Cyclin D1 is associated with apoptosis in post-mitotic neurons (Shupp et al., 2017). In a study of 117 subjects, Cyclin D levels were significantly higher in patients with Alzheimer's disease (AD; Kim et al., 2016). CDK4 induces the re-entry of neurons into the cell cycle, is deleterious to terminally differentiated neurons, and may lead to neuronal degeneration (McShea et al., 1997). Cyclin D1 is involved in breast cancer cell invasion/migration, and its overexpression increases invasion (Gao et al., 2020). Cyclin E is a regulatory subunit of CDK2 that initiates DNA replication during G1/S transition. Its overexpression, resulting in genomic instability, has been reported in triple-negative breast cancer (Chen et al., 2018), non-Hodgkin's lymphoma (Williams and Swerdlow, 1994), lung cancer (Eymin and Gazzeri, 2010), pancreatic cancer (Pang et al., 2020), and liver cancer (Sonntag et al., 2021) and results in genomic instability (Kok et al., 2020). Increased Cyclin D and E levels are evident in degenerating neurons exposed to the neurotoxin 1-methyl-4phenylpyridinium (Höglinger et al., 2007). Elevated Cyclin E levels are observed during spinal cord injury which induce cell cycle activation and neuronal apoptosis (Tian et al., 2006).

Phosphotyrosyl phosphatase activator (*PTPA/PP2A*), a member of the serine/threonine protein phosphatase family, is a tumor suppressor gene product. Its inactivation has been reported in endometrial carcinomas (Remmerie and Janssens, 2019). This inactivation induces cell transformation (Sablina et al., 2010). *PTPA* is decreased in the brains of Alzheimer's disease (AD) mouse models. Additionally, *PTPA* is present in the mitochondrial membrane, and its knockdown induces apoptosis in neuronal cell lines (Luo et al., 2014).

Relative synonymous codon usage (RSCU) explains bias in codon usage within genes or transcripts. This bias can result from various evolutionary (selection, mutation, and GC-biased gene conversion) and compositional factors. Codon usage impacts the level of gene expression through its effect on transcription (Zhou et al., 2016). Preferred codons are commonly present in highly expressed genes, whereas poorly expressed genes contain rare or less common codons. Rare codons in Escherichia coli, including AGG, AGA, CUA, AUA, CGA, and CCC, regulate different endogenous proteins. Expression is limited due to the rarity of their cognate tRNAs (Wang et al., 2016). When RNA polymerase encounters rare codons, transcription generally pauses, resulting in ribosome disassembly (Rosano and Ceccarelli, 2009). Rare codons are generally found in nonrandom clusters (Clarke and Clark, 2008). Codon pair bias is a variant form of codon bias, and is the probability of the presence of two specific adjacent codons. For example, for the adjacent amino acids alanine and glutamate, there are eight possible codon pairs, and all should be equally present; however, the GCC-GAA pair is highly underrepresented despite containing GCC, the most prevalent codon encoding alanine (Coleman et al., 2008).

TABLE 1	List of	transcripts	examined	in this	study	correspon	ding to AP	Р,
CCND1,	CCNE1	, and PTPA	genes.					

S. No.	Name of gene	Accession number of transcript	Length of transcript		
		NM_000484	2,313		
		NM_201413	2,256		
		NM_201414	2088		
		NM_001136016	2,241		
		NM_001136129	1920		
1	APP	NM_001136131	1983		
		NM_001204301	2,259		
		NM_001204302	2,202		
		NM_001385253	2,145		
		NM_001136130	2,145		
		NM_001204303	2034		
2	CCND1	AF511593	888		
		NM_001322262	1,188		
12	CONFI	NM_001322261	1,086		
15	CUNEI	NM_001322259	1,098		
		NM_001238	1,233		
		NM_178001	1,077		
		NM_001193397	867		
17	מ'ד'ם א	NM_001271832	885		
17	FIFA	NM_021131	972		
		NM_178003	846		
		NM_178000	972		

Codon bias may be applied as a tool in synthetic biology to create synthetic gene constructs capable of high level expression (Supek and Šmuc, 2010), to reduce expression when constructing attenuated vaccine candidates (Giménez-Roig et al., 2021), or to create new genomes (Tulloch et al., 2014). In the present study, we envisaged codon bias, its correlation with various molecular features of transcripts, expression profile, preferred and rare codons, codon pairs, and codon context for the genes *APP*, *Cyclin* D, and *Cyclin* E, which are up-regulated, and *PTPA*, which is down-regulated in both cancer and neurodegeneration. The information in this study will help modulate and fine-tune the expression of these genes, contributing to strategies for controlling these ailments concurrently.

2. Materials and methods

2.1. Sequence retrieval

All transcripts corresponding to the genes *APP* (11), *CCND1* (1), *CCNE1* (4), and *PTPA* (06) were retrieved from the National Center for Biotechnology (NCBI) GenBank database.¹ Transcripts containing

a reading frame starting with ATG and ending with a stop codon were included in this study. Accession numbers and transcript lengths are listed in Table 1.

2.2. Principal component analysis

Principal component analysis (PCA) is a multivariate tool used to determine major variation trends. PCA was performed using RSCU values to identify major codon usage trends in up-regulated and down-regulated genes. The up-regulated gene group consisted of transcripts encoded by *APP*, *CCND1*, and *CCNE1*, while the down-regulated gene group consisted of transcripts encoded by *PTPA*. A PCA plot was constructed using the first two axes, which accounted for maximum variation. The figure was made using Origin18 software.

2.3. Protein properties determination

Protein physical properties affect their biological behaviors and influence their codon usage. Various protein properties have been reported to correlate with nucleotide composition and codon bias (Khandia et al., 2021). In this study, we calculated two protein properties: GRAVY and AROMA. GRAVY assesses in combination both hydrophobicity and hydrophilicity, with GRAVY scores ranging between -2 and +2. Positive values suggest hydrophobicity and negative values indicate hydrophilicity. AROMA determines the frequency of aromatic amino acids (Phe, Tyr, and Trp) in a given protein (Alqahtani et al., 2022). These protein indices suggest the action of selective forces (Khandia et al., 2019). Both indices were calculated using COUSIN (COdon Usage Similarity INdex) software developed by Bourret et al. (2019).

2.4. Scaled Chi-square

Shields et al. (1988) suggested a term to quantitate bias based on a Chi-squared (χ^2) value, called the scaled Chi-square (SCS). This SCS value is derived from the equal usage of codons from synonymous codon groups normalized to actual usage, with tryptophan and methionine excluded. SCS values range between 0 and 1, with higher values suggesting a higher bias (Bahiri-Elitzur and Tuller, 2021).

2.5. Codon adaptation index

The Codon Adaptation Index (CAI) was initially developed to determine codon bias in DNA and RNA sequences. It calculates the similarity in codon usage between a given gene and codon usage in highly expressed genes from a reference set (Puigbò et al., 2008). It also predicts gene expression level and is thus frequently used in heterologous gene expression (Raab et al., 2010). CAI is not comprehensive, but is an important measure for determining protein expression, and has been verified using deep learning methods and biological experiments (Fu et al., 2020). In the present study, the CAI values for each transcript were calculated and used for correlation studies.

¹ http://www.ncbi.nlm.nih.gov

2.6. Rare codon analyses

Rare codons occur at low frequencies in genes and transcripts. Rare codons transiently stall ribosomes, helping proteins fold properly (Li et al., 2006). Rare codon frequencies were derived and the frequency of rare codons was adjusted according to transcript length. Codons with a percentage occurrence below 0.5% were considered rare.

2.7. Codon context analysis

Codon context refers to the tendency of codons to be found in pairs. Generally, a few codon pairs are used more than others, and codon pair bias is present in organisms (Kunec and Osterrieder, 2016). Codon pair bias has been implicated in reducing protein expression via codon pair de-optimization while generating attenuated vaccine candidates using a synthetic biology approach (Coleman et al., 2008). Therefore, the codon pair context was derived and analyzed for all four genes in this study.

2.8. Effective number of codons

Effective number of codons (ENc) is a metric in which bias is measured in terms of deviation from random distribution of synonymous codons. ENc values range from 20 to 61. ENc is a nondirectional measure of codon bias. Higher values suggest equal codon usage, whereas lower values suggest more biased codon usage (Li et al., 2022). ENc was calculated for all 22 transcripts, and average values were calculated for individual gene transcripts. ENc-GC3 was plotted to determine the impact of composition, mutation, and selection forces on codon bias. The data points near or along the curve show the impact of mutational force, whereas the points below the GC3 curve show the impact of selection and other forces (Anwar et al., 2021).

2.9. Parity plot analysis

Parity rule 2 (PR2) states that A = T and C = G. Generally, this rule is not precisely followed, thus a deviation is observed. In PR2 bias, the nucleotide skew between A and T and C and G was calculated at the third codon position. A plot was constructed by plotting AT bias (A3/ A3+T3) and GC bias (G3/G3+C3) on the Y- and X-axes, respectively. If all values are near the center of the plot, A, T, C, and G are used equally (Khandia et al., 2019).

2.10. Software used

Scaled Chi-square, CAI, and ENc were calculated using software developed in Bourret et al. (2019). The overall nucleotide composition and the composition at other codon positions were calculated using CAIcal, developed by Puigbò et al. (2008). Graphs and figures were generated, and PCA plots were constructed using Origin18 software. Correlation analysis was performed using Past4.11 software. Despite the low statistical significance, we have to proceed with the available number of transcripts, which is unavoidable because of the inherently low transcript number available for the envisaged genes. Codon frequency and codon pair context were derived using Anaconda 2 software (ANACONDA v.2.0; https://bioinformatics.ua.pt/software/anaconda/).

3. Results

3.1. Nucleotide composition revealed an elevated prevalence of G in the codon third position

Studies of gene composition are critical because composition influences several properties including protein stability over a range of temperatures, pH levels, and metal concentrations (Franzo et al., 2021). Biased codon usage is due to the underlying genomic composition. Therefore, certain types of mutations are favored (Chen et al., 2004). Average compositional analysis (Figure 1A) revealed that in the APP, CCND1, and PTPA gene transcripts, the average composition of %G was the highest (28.11, 29.95, and 27.84%, respectively), followed by %C3 (28.5, 45.58, and 33.58%, respectively). The average %T was the lowest (20.19, 16.66%, and 21.99, respectively). For CCNE1 transcripts, the average composition of nucleotide %A was highest (27.42%), and %C was lowest (22.28%). At the third codon position, for all genes, the average percent composition was highest for %G3 (29.95, 43.91, 32.34, and 35.40% for APP, CCND1, CCNE1, and PTPA gene transcripts, respectively) and lowest for %A3 (19.12, 8.10, 21.08, and 11.98% for APP, CCND1, CCNE1, and PTPA gene transcripts, respectively). Overall GC percentage ranged from 48.72 to 61.14%. For APP, CCND1, and PTPA gene transcripts, average %GC composition (51.98, 61.14, and 54.28%, respectively) was higher than average AT composition (48.01, 38.85, and 45.71%, respectively). For CCNE1 transcripts, the %AT composition (51.29%) was higher than the %GC composition (48.72%). Since the GC composition is high in at least three out of four gene transcripts, there is a high chance of having preferred codons ending with C or G nucleotides.

Percent GC3 composition is an indicator of codon bias, and GC3-rich and GC3-poor gene products may represent distinct subcellular locations in the human genome (Shen et al., 2015). A comparison of the average overall GC composition and the composition at the three codon positions for all genes is depicted in Figure 1B. It is evident from this study that the %GC composition was lowest at the second codon position.

3.2. Gene length correlates with nucleotide %A composition in all genes

For convenience, we divided all transcripts into two sets. One group contained up-regulated transcripts and the other contained down-regulated transcripts. Gene length affects codon bias and gene expression (Duret and Mouchiroud, 1999; Khandia et al., 2022). We performed correlation analysis between gene length and composition (overall composition, and composition at the third codon position), CAI, SCS, GRAVY, AROMA, PC1, and PC2 (Table 2). In both the up-regulated and down-regulated gene transcripts, we found a significant positive correlation between length, %A composition, and SCS. The transcript lengths of the up-regulated genes were significantly correlated with %G3, %GC1, %GC2, GRAVY, AROMA, and PC1. These analyses revealed that length influences the overall %A composition and codon bias in both gene sets. However, in up-regulated gene transcripts, apart from compositional parameters, length also influences protein properties.



TABLE 2 Correlation analysis of transcript length with compositional parameters, codon bias measures, gene expression, and protein properties.

Up-regulated transcript	%A	%C	%Т	%G	%A (3)	%C (3)	%T (3)	%G(3)	%GC (all)
r	0.544	-0.159	-0.397	0.346	0.211	0.071	0.330	-0.717	0.007
р	0.029	0.557	0.128	0.190	0.433	0.793	0.212	0.002	0.978
Significance	*	NS	NS	NS	NS	NS	NS	**	NS
Down-regulated transcript	%A	%C	%T	%G	%A(3)	%C(3)	%T(3)	%G(3)	%GC(all)
r	0.904	-0.215	-0.520	0.294	0.757	-0.610	0.449	-0.363	-0.085
р	0.013	0.683	0.290	0.572	0.081	0.198	0.372	0.480	0.873
Significance	*	NS	NS	NS	NS	NS	NS	NS	NS
Up-regulated transcript	%GC(1)	%GC(2)	%GC(3)	CAI_59	Scaled_Chi	GRAVY	AROMA	PC 1	PC 2
r	0.780	-0.518	-0.284	0.417	0.968	-0.855	-0.579	0.680	0.156
р	0.000	0.040	0.286	0.108	0.000	0.000	0.019	0.004	0.563
Significance	***	*	NS	NS	***	***	*	**	NS
Down-regulated transcript	%GC(1)	%GC(2)	%GC(3)	CAI_59	Scaled_Chi	GRAVY	AROMA	PC 1	PC 2
r	0.414	0.685	-0.760	-0.760	0.995	-0.804	-0.550	0.760	-0.460
р	0.414	0.133	0.079	0.079	0.000	0.054	0.258	0.079	0.359
Significance	NS	NS	NS	NS	***	NS	NS	NS	NS

***p<0.001; **p<0.01; *p<0.05; NS, non-significant.

3.3. Gene expression is highest among all genes for *CCND1*

Codon Adaptation Index analysis was performed for all genes. The average CAI values for *APP*, *CCND1*, *CNE2*, and *PTPA* transcripts were 0.788, 0.861, 0.714, and 0.822, respectively. The highest CAI value is for the *CCND1* gene transcript, followed by *PTPA*. The average CAI value for all genes was high, suggesting high expression of all examined genes.

3.4. Codon bias is highest in the *CCND1* gene transcript and lowest in *CCNE1* gene transcripts

ENc correlates negatively with codon bias, with high ENc values suggesting low codon bias. The highest possible ENc value, 61,

represents equal use of all codons, and the lowest possible value, 20, represents exclusive use of one codon among a set of synonymous codons. Generally, values less than 35 are considered highly biased, whereas values > 50 suggest low bias. The average ENc values for *APP*, *CCND1*, *CCNE1*, and *PTPA* transcripts were 51.55, 33.64, 57.8, and 50., respectively. Hence, overall bias was low, except in *CCND1*, where ENc was below 35 (Wright, 1990; Munjal et al., 2020).

3.5. The codon AGG exhibits the highest loading value in both up-regulated and down-regulated gene sets

Relative synonymous codon usage values were used as descriptor variables in an unsupervised classification method PCA to explore codon usage features. A biplot analysis was performed for both gene sets. The five highest loading values across Axis 1 are listed in



Supplementary Table 1. For up-regulated gene sets, 61.51 and 34.72%, and for down-regulated genes, 42.22 and 39.23% contributions to data inertia were attributed to axes 1 and 2, respectively. These results indicate that codon bias influences codon usage patterns. These results suggest that most can be explained by the first two axes (Yu et al., 2021a). High loading values indicate the most influential codons in shaping codon bias (Alqahtani et al., 2022). This analysis revealed lengthy arrows for AGG and CTG codons in both sets (Figures 2A,B), suggesting a strong influence of these codons on codon usage in both gene sets. All other highly influential codons were dissimilar between gene sets.

3.6. Relative synonymous codon usage analysis revealed a preference for codons ending in G/C

Average RSCU analysis of all four gene transcripts revealed that for 16 of 18 amino acids, G/C ending codons were preferred in at least three genes. For the remaining two amino acids, two genes preferred A/T endings and the other two preferred G/C endings. These results suggest an overall preference for codons ending in C. Codon usage for individual genes is shown in Figure 3. Leucine (CTT) and valine (GTT) are the two most frequently used amino acids in all human coronaviruses (Hou, 2020). In the present study, among the genes simultaneously up-regulated or down-regulated in cancer and neurodegeneration, the CTG codon encoding leucine was the most preferred codon for APP, CCND1, and PTPA, while AGG was the most preferred codon for CCNE1. Nine, 16, 4, and 7 codons were overrepresented in APP, CCND1, CCNE1, and PTPA gene transcripts, respectively. Similarly, 13, 17, 11, and 14 codons were under-represented in APP, CCND1, CCNE1, and PTPA transcripts, respectively. The codons CTA (Leu), GTA (Val), CAA (Gln), and CGT (Arg) were underrepresented in all four genes.

3.7. Parity analysis reveals a preference for T and G in codon third positions

At the center of the parity plot, where the value of both coordinates is 0.5, the numbers of A and T nucleotides will be similar, and reciprocal to G and C nucleotides in codon third positions. This is where no selection or mutational force is applied (Sueoka, 1988). In the present study, the mean values of GC and AT bias were 0.531 ± 0.03 and 0.473 ± 0.04 for up-regulated transcripts, and 0.512 ± 0.01 and 0.386 ± 0.02 for down-regulated transcripts. An average bias value of less than 0.5 suggests a preference for pyrimidine over purine (Zhang et al., 2018). Therefore, for both up-regulated and down-regulated gene transcripts, T was preferred over A, and G was preferred over C (Figure 4).

3.8. Assessment of selectional, mutational, and compositional constraints in shaping codon bias

An ENc-GC3 plot was constructed to investigate the forces influencing codon bias. In the presence of data points on the solid curve, codon bias is considered to result from compositional constraints only (Franzo et al., 2021; Khandia et al., 2021), while if data points are present below the expected Nc curve, other forces, such as natural selection, gene length, and RNA structure also influence codon usage (Yu et al., 2021b). Data points near the solid curve indicate the role of mutational forces (Chen et al., 2017). In the up-regulated gene set, data points were present on the %GC3 curve, near the curve, and below the curve, indicating that composition, mutation, and selection forces shape codon usage. In the down-regulated gene set, data points were present near and below the curve, indicating that selection and mutational forces may shape codon usage (Figure 5). To further ascertain the role of mutational forces, we performed a correlation analysis between nucleotide composition and codon composition (A3s, C3s, G3s, U3s, and GC3s), and ENc and codon composition (Supplementary Table 2). Correlation analysis revealed that for the up-regulated gene set, there was a statistically significant correlation between the overall nucleotide and codon composition at the third codon position, except for T-G3 and G-G3. ENc also exhibited a highly significant correlation with codon composition. In contrast, for the down-regulated gene set, only A-A3, T-A3, and ENc-T3 were significantly correlated. These results suggest the role of mutational forces was stronger in up-regulated gene sets than in down-regulated gene sets.

3.9. CGT codon was rare in all four genes

Rare codons occur less frequently in a given gene or transcript. At open reading frame 5' ends, a small cluster of rare codons is generally present that limits the rate of translation to promote effective



FIGURE 3

Codon usage analysis for APP, CCND1, CCNE1, and PTPA genes. Overexpressed codons (RSCU>1.6) are depicted as dark blue bars, randomly used codons (RSCU between 1.6 and 0.6) are depicted as green bars, and underrepresented codons are depicted as light blue bars.



Parity plot analysis of gene transcripts up- and down-regulated in cancer and neurodegeneration revealed that in bot C is preferred over G.

post-translational folding and prevent ribosome traffic jams (Bentele et al., 2013). Rare codons also influence protein functions (Rosano and Ceccarelli, 2009). Introducing rare codons into a highly expressed gene may reduce the expression levels of that gene and other genes due to reduced availability of the corresponding tRNAs (Frumkin et al., 2018).

Codons with a frequency of < 0.5% in a transcript are considered rare. The adjusted frequencies of the two-, three-, four-, and six-fold

degenerate codons are shown in Figure 6. Codons ACG, ACT, AGC, AGG, ATA, CCG, CTA, CGT, GCG, TCG, TTA and TGT codons for APP, AAT, ACG, ACT, AGA, AGG, AGT, ATA, CAT, CCA, CCT, CGA, CGT, CTA, CTT, GCT, GGA, GGC, GGT, GTA, GTT, TAT, TCA, TCT, TTA, TTG, TTT for CCND1; codons ACT, AGT, CAT, CGC, CGT, CTA for CCNE1 gene and codons AGT, CAA, GCA, CGT, GCG, GTG, GTA, TTA, TTG were rare in the PTPA gene. The CGT codon was rare

in all four genes, whereas ACT, AGT, CTA, and TTA codons were rare in at least three genes. The ATA, CAT, GCG, GTA, TTG, and CAT codons were rare in at least two genes. Information on rare codon frequencies may help to manipulate multiple genes simultaneously.

3.10. High frequency codon pair analysis revealed presence of glutamic acid initiated codon pairs

Three of the four gene transcripts displayed identical codon pairing. Three in the *APP* gene (ACC–ACC, GAA–GAA, and GAG–GAG), two in *CCND1* (GAG–GAG and CTG–CTG), and one in the *PTPA* gene (GCT–GCT). In *APP*, of the 15 highly occurring codon pairs, seven were glutamic acid-initiated, three were aspartic acid-initiated, and two were initiated with valine and alanine codons. In the *CCND1* transcript, alanine and phenylalanine initiate three codon pairs, and leucine and valine initiate two codon pairs. In *CCNE1* transcripts, glutamic acid, leucine, and aspartic acid initiate two codon pairs. In *PTPA*, leucine and glutamic acid initiate three codon pairs, and valine and phenylalanine initiate two codon pairs each. The results suggest that glutamic acid, aspartic acid, leucine, valine, and phenylalanine-initiated codon pairs are abundant in the envisaged genes. The top 15 most frequently occurring codon pairs are listed in Table 3.

Codon context bias reveals a preference for the sequentiality of a pair of codons. In addition to the codon pair bias, codon pair context, specifically, context present at the 3' end has been observed in various organisms, and influences the accuracy and rate of translation. Codon context affects the speed of protein translation and results in translational selection (Tats et al., 2008). Both codon bias and context favor gene expression for a heterologous gene expression (Chung et al., 2013). In the present analysis, in the three transcripts other than *APP*, after the initiating ATG codon, the AAG codon encoding lysine is highly favored (Figure 7).

4. Discussion

Cancer and neurodegeneration are ailments with opposite symptoms: cancer is associated with unchecked cellular proliferation, and neurodegeneration is associated with cell death or degeneration. However, the relationships between cancer and neurodegeneration remain incompletely characterized. Patients with Parkinson's disease, multiple sclerosis, and schizophrenia have lower risk of developing specific cancers (e.g., Parkinson's disease reduces risk of melanoma, multiple sclerosis reduces risk of brain cancers, and schizophrenia reduces risk of breast cancer; Catalá-López et al., 2014). A few epidemiological studies have revealed that subjects with Alzheimer's disease (AD) and Parkinson's disease (PD) have a 35-50% lower risk of cancer. Similarly, cancer patients have lower (35-37%) risk of occurrence of AD and related disorders (Zabłocka et al., 2021). Inverse morbidity results from gene products and genomic pathways being regulated in opposite directions. Many genes and gene products common to both diseases are involved, and mutations in genes such as PINK1, DJ-1, LRRK2, ATP13A2, PLA2G6, MAPT, CDK5, and others (Plun-Favreau et al., 2010) result in disease. Apart from mutations that result in gain or loss of function in these genes, some mutations in disease conditions upregulate or downregulate gene expression. Metagenomic analysis revealed the simultaneous upregulation of 74 genes in CNS disorders and downregulation in cancers, and another 19 genes were reported to be concurrently up-regulated in cancers and down-regulated in CNS disorders (Ibáñez et al., 2014). Comparatively fewer genes are up-regulated or downregulated in both disorders. A literature search revealed four genes that meet this criterion. APP, Cyclin D, and Cyclin E are simultaneously up-regulated in cancer and neurodegeneration, and PTPA tended to be down-regulated. We chose these genes to study codon usage and other analyses because manipulation of these genes will offer possible genetic routes to mitigating both disorders together.

Codon usage analysis reveals molecular patterns within a gene or transcript that can influence gene expression (Quax et al., 2015; Zhou et al., 2016). Codon usage is influenced by gene composition (Alqahtani et al., 2021; Simón et al., 2021). Compositional analysis revealed that in the *APP*, *CCND1*, and *PTPA* gene transcripts, %G and %T displayed maximum and minimum respective prevalences. In contrast, in the *CCNE1* transcripts, %A and %C displayed the highest and lowest respective prevalences. Notably, at the third codon position, both G and T nucleotides were preferred in both up-regulated and down-regulated gene transcripts. Therefore, the nucleotide bias at the third codon position is not dependent on composition.

Gene length has been shown to affect gene composition (Alqahtani et al., 2021), codon bias (Duret and Mouchiroud, 1999; Khandia et al., 2022) and gene expression (Duret and Mouchiroud, 1999). We also investigated whether the neurodegeneration- and





cancer-related gene transcripts displayed a genuine relationship to these diseases. Gene length was found to correlate with the average frequency of A nucleotides in both the up-regulated and downregulated transcripts. Furthermore, the %G3, %GC1, and %GC2 components were significantly correlated with the lengths of the up-regulated transcripts. These analyses indicate that only the composition of the up-regulated transcripts is affected by gene length.

Researchers have reported mixed results on the effects of gene length on codon bias. This correlation is strongly positive for *E. coli* genes; strongly negative for *D. melanogaster* and *S. cerevisiae* genes (Moriyama and Powell, 1998), *Caenorhabditis elegans*, and *Arabidopsis thaliana* (Duret and Mouchiroud, 1999); and weak for sesame (Andargie and Congyi, 2022). Codon bias was significantly positively correlated (p < 0.001) with gene length in both up-regulated and down-regulated gene sets, indicating that with an increase in length, bias also increased. Gene expression in our study did not correlate with transcript length in either up-regulated or down-regulated genes. Our results differ from those of Brown (2021), who demonstrated that gene expression is inversely proportional to gene length (Brown, 2021).

Because CAI is a significant predictor of expression levels (Park et al., 2012), it has been used as a surrogate marker for expression of several human genes, including *HPRT1* (De Mandal et al., 2020), Tlr7, Tlr9 (Newman et al., 2016), *SPANX* (Choudhury and Chakraborty, 2015), *SRY* (Cai et al., 2015), human oncogenes (Mazumder et al., 2014), and human transcriptome data of monocytes, B, and T lymphocytes (Ruzman et al., 2021). Average CAI values for *APP*,

CCND1, *CCNE2*, and *PTPA* transcripts were 0.788, 0.861, 0.714, and 0.822, respectively, suggesting a high level of protein expression for all four genes. The highest CAI among all *E. coli* genes was 0.85 for the most abundant LPP protein in *E. coli* cells (Henry and Sharp, 2007). In the dementia-associated gene set, the maximum CAI value found (0.849) was for *CTSD* (Alqahtani et al., 2022). *APP*, *CCND1*, and *CNE2* are associated with cell cycle progression, whereas *PTPA* negatively regulates cell growth and division. Based on the high CAI values of all genes, it is evident that all genes are required for normal cell functioning, and elevated or suppressed expression may lead to disease.

Relative synonymous codon usage analysis revealed that codons ending in GC are favored over codons ending in AT, and 16 of 18 amino acids preferred codons ending in G/C in at least three genes. Our results are in concordance with the results of Newman et al. (2016) based on a study of 19,105 human and 20,558 mouse genes, which revealed that in both species, most of the preferred codons had high GC content. Codons CTA (Leu), GTA (Val), CAA (Gln), and CGT (Arg) were underrepresented in all four genes. When CTA was assessed in Tlr7 and Tlr9, the frequency in Tlr7 was 14.4%, whereas in Tlr9, similar to our study, the frequency was low (0.5%; Newman et al., 2016). In the present study, we found that CTG, which encodes leucine, was the most preferred codon in APP, CCND1, and PTPA, as well as in genes common to primary immunodeficiency and cancer (Khandia et al., 2021). These results suggest that glutamic acid, aspartic acid, leucine, valine, and phenylalanine-initiated codon pairs are abundant in the studied genes.

No of codons	Adjusted score	CCND1 codon pairs	No of codons	Adjusted score	CCNE1 codon pairs	No of codons	Adjusted score	PTPA codon pairs	No of codons	Adjusted score
77	0.98	GAG-GAG	11	3.72	AGG-GAG	13	0.85	CTG-GAG	18	0.96
66	0.84	GAG-GTC	3	1.01	GAT-GAA	12	0.78	GAC-TAC	17	0.91
55	0.70	CTG-GAG	3	1.01	ATT-GCA	10	0.65	TTC-ATC	16	0.85
44	0.56	CTG-CTG	3	1.01	TTG-GAT	8	0.52	GAT-GAG	16	0.85
44	0.56	TTC-CTG	2	0.68	TTC-TCG	8	0.52	TTC-AAG	12	0.64
44	0.56	TTC-CTC	2	0.68	TTA-ATG	8	0.52	GTG-GAT	12	0.64
44	0.56	TTC-ATT	2	0.68	TGT-GTC	8	0.52	GTC-CCT	12	0.64
44	0.56	TGC-GAG	2	0.68	TCT-GAA	8	0.52	GCT-GCT	12	0.64
39	0.50	TCC-TAC	2	0.68	GGG-AGC	8	0.52	GAT-GAC	12	0.64
33	0.42	TCC-ATG	2	0.68	GCC-ATG	8	0.52	GAG-AAG	12	0.64
33	0.42	GTG-GCC	2	0.68	GAG-GAA	8	0.52	CTG-CCC	12	0.64
33	0.42	GTG-GAC	2	0.68	GAC-AAA	8	0.52	CTC-TGC	12	0.64
33	0.42	GCG-GAG	2	0.68	GAA-GAT	8	0.52	CAG-CTG	12	0.64
33	0.42	GCC-GCA	2	0.68	GAA-ATG	8	0.52	AAG-TTC	12	0.64
33	0.42	GCC-GAG	2	0.68	CTT-CTG	8	0.52	AAG-GCC	12	0.64

TABLE 3 Top 15 high occurr

APP

codon

GAA-GAA

GAG-GAG

GTG-GAA

GCC-AAC

GCA-GAA

GAT-GAG

GAA-GCC

GAA-GAG

GTG-GAG

GAT-GAC

GAG-GAA

GAG-AGA

GAG-ACA

GAC-AAG

pairs ACC-ACC codor



AGG is the most preferred codon in the CCNE1 gene, and an AGG cluster near the ORF 5' end may increase biological activity (Ivanov et al., 1997). This codon is generally rare in E.coli. The advantage of the AGG codon is revealed via protein engineering through reassignment of the AGG sense codon using an orthogonal tRNA CCU and an aminoacyl-tRNA synthetase pair resulting in charging of the tRNA with an unnatural or chemically modified amino acid. The abundance of the AGG codon in CCNE1 could thus be exploited for protein engineering to interrogate other physiological functions (Lee et al., 2015). While recording the genetic sequences of our selected genes to manipulate gene expression profiling, it must be kept in mind that when AGG and TTG codon frequencies increase, the frequencies of other C- or G-ending codons decrease, negatively influencing gene expression in humans. Local compositional biases may not explain this unusual behavior (Kliman and Bernal, 2005).

Rare codons such as AGG, AGA, CUA, AUA, CGA, and CCC have been used to fine tune gene expression in *E. coli* (Wang et al., 2016). A cluster of rare codons present at the 5' end of the transcript ensures proper protein folding and biological activity (Rosano and Ceccarelli, 2009; Bentele et al., 2013). In this study, CGT codons were rare in all four genes, whereas ACT, AGT, CTA, and TTA codons were rare in at least three genes. In humans, the six codons, GCG (Ala),

CCG (Pro), CGT (Arg), CGC (Arg), TCG (Ser), and ACG (Thr) are rare (Kanduc, 2017). It is thus clear that CGT codons are rarely used in the studied transcripts. However, the low occurrence of other codons may be a result of different negative selections for local pauses in translation that can be beneficial for protein biogenesis (Clarke and Clark, 2008). Sequences optimized with codon-pair context exhibited higher protein expression than the native codons.

The extent to which a codon is translated depends on neighboring codons. This is called a context effect, and influences translation kinetics (Chevance et al., 2014). Sequences optimized using a codon-pair context showed better protein expression than those optimized using codon usage (Huang et al., 2021). Removing only two codon pairs that are detrimental to protein expression may increase protein expression levels 30 fold compared to the original sequence (Trinh et al., 2004). Deoptimized codon pairs have been used to generate attenuated vaccine candidates against influenza, polioviruses, and arboviruses (Jack et al., 2017). The same strategy may be adopted to augment the expression profile to the desired level through gene editing. In the present study, an abundance of glutamic acid-, aspartic acid-, leucine-, valine-, and phenylalanineinitiated codon pairs were observed, and disruption of preferred codon pairs can be used to reduce the gene expression level (Jack

et al., 2017). After the ATG codon, a highly positive context was present for the AAG (lysine) codon in all transcripts, except for APP, reflecting a prominent 3' context effect (Tats et al., 2008). With the help of new scientific developments, it is now possible to replace a copy of a defective gene with the desired gene. This strategy may augment expression levels, raising risk of cancer and/or neurodegeneration.

5. Conclusion

From our analysis, it was evident that codons ending in G/C were preferred over codons ending in AT in all genes and such pattern is not the result of nucleotide compositional bias. In the present study, CTA (Leu), GTA (Val), CAA (Gln), and CGT (Arg) were underrepresented in all four genes. In contrast, ACT, AGT, CTA, and TTA codons were rare in at least three genes. This information is helpful for reducing gene expression levels by inserting these codons during gene coding to ameliorate disease symptoms. Negative selection of codons is suggestive of specific requirements for local pauses during protein translation. Glutamic acid-, aspartic acid-, leucine-, valine-, and phenylalanine-initiated codon pairs were abundant. Also, the 3' context of the AAG codon with ATG at the 5' end was evident. Present study has unavoidable limitation of using four genes APP, CCND1, CCNE1, and PTPA only, since so far only four genes have been identified those are commonly implicated in cancer and neurodegeneration. With more number of genes, statistical analyses would be stronger. In the present study, different information gained regarding molecular patterns, codon usage, codon usage bias, nucleotide bias at the third codon position, preferred codons, preferred codon pairs, rare codons, and codon context will guide future studies. Based on this knowledge, these genes may be manipulated to augment their defects through gene editing, CRISPR/Cas, or any other gene augmentation technique.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary material, further inquiries can be directed to the corresponding authors.

References

Alqahtani, T., Khandia, R., Puranik, N., Alqahtani, A. M., Almikhlafi, M. A., and Algahtany, M. A. (2021). Leucine encoding codon TTG shows an inverse relationship with GC content in genes involved in neurodegeneration with iron accumulation. *J. Integr. Neurosci.* 20, 905–918. doi: 10.31083/j.jin2004092

Alqahtani, T., Khandia, R., Puranik, N., Alqahtani, A. M., Chidambaram, K., and Kamal, M. A. (2022). Codon usage is influenced by compositional constraints in genes associated with dementia. *Front. Genet.* 13:884348. doi: 10.3389/fgene.2022.884348

Andargie, M., and Congyi, Z. (2022). Genome-wide analysis of codon usage in sesame (Sesamum Indicum L.). Heliyon 8:e08687. doi: 10.1016/j.heliyon.2021.e08687

Anwar, A. M., Aljabri, M., and El-Soda, M. (2021). Patterns of genome-wide codon usage Bias in tobacco, tomato and potato. *Biotechnol. Biotechnol. Equip.* 35, 657–664. doi: 10.1080/13102818.2021.1911684

Bahiri-Elitzur, S., and Tuller, T. (2021). Codon-based indices for modeling gene expression and transcript evolution. *Comput. Struct. Biotechnol. J.* 19, 2646–2663. doi: 10.1016/j.csbj.2021.04.042

Bentele, K., Saffert, P., Rauscher, R., Ignatova, Z., and Blüthgen, N. (2013). Efficient translation initiation dictates codon usage at gene start. *Mol. Syst. Biol.* 9:675. doi: 10.1038/msb.2013.32

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RK: conceptualization, analysis, software, data curation, writing review and editing, supervision, project administration, and final approval of the version to be published. MP, SA-H, and IB: conceptualization, data analysis, interpretation of data, revision, critical analysis, and editing. MZ: design of work, software, validation, resources, supervision, project administration, funding acquisition, and intellectual content. PG: conceptualization, analysis, software, data curation, writing—review and editing, supervision, and project administration. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Supplementary material

The Supplementary material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fnmol.2023.1200523/ full#supplementary-material

Bolshakova, O. I., Zhuk, A. A., Rodin, D. I., Kislik, G. A., and Sarantseva, S. V. (2014). Effect of human APP gene overexpression on *Drosophila Melanogaster* cholinergic and dopaminergic brain neurons. *Russ J Genet Appl Res* 4, 113–121. doi: 10.1134/S2079059714020026

Bourret, J., Alizon, S., and Bravo, I. G. (2019). COUSIN (COdon usage similarity INdex): a normalized measure of codon usage preferences. *Genome Biol. Evol.* 11, 3523–3528. doi: 10.1093/gbe/evz262

Brown, J. C. (2021). Role of gene length in control of human gene expression: chromosome-specific and tissue-specific effects. *Int. J. Genom.* 2021:8902428. doi: 10.1155/2021/8902428

Cai, J., Guan, W., Tan, X., Chen, C., Li, L., Wang, N., et al. (2015). SRY gene transferred by extracellular vesicles accelerates atherosclerosis by promotion of leucocyte adherence to endothelial cells. *Clin. Sci. (Lond.)* 129, 259–269. doi: 10.1042/CS20140826

Catalá-López, F., Suárez-Pinilla, M., Suárez-Pinilla, P., Valderas, J. M., Gómez-Beneyto, M., Martinez, S., et al. (2014). Inverse and direct Cancer comorbidity in people with central nervous system disorders: a Meta-analysis of Cancer incidence in 577,013 participants of 50 observational studies. *Psychother. Psychosom.* 83, 89–105. doi: 10.1159/000356498

Chen, S. L., Lee, W., Hottes, A. K., Shapiro, L., and McAdams, H. H. (2004). Codon usage between genomes is constrained by genome-wide mutational processes. *Proc. Natl. Acad. Sci. U. S. A.* 101, 3480–3485. doi: 10.1073/pnas.0307827100

Chen, X., Low, K.-H., Alexander, A., Jiang, Y., Karakas, C., Hess, K. R., et al. (2018). Cyclin E overexpression sensitizes triple-negative breast Cancer to Wee1 kinase inhibition. *Clin. Cancer Res.* 24, 6594–6610. doi: 10.1158/1078-0432.CCR-18-1446

Chen, Y., Xu, Q., Yuan, X., Li, X., Zhu, T., Ma, Y., et al. (2017). Analysis of the codon usage pattern in Middle East respiratory syndrome coronavirus. *Oncotarget* 8, 110337–110349. doi: 10.18632/oncotarget.22738

Cheng, N., Jiao, S., Gumaste, A., Bai, L., and Belluscio, L. (2016). APP overexpression causes A β -independent neuronal death through intrinsic apoptosis pathway. *eNeuro* 3. doi: 10.1523/ENEURO.0150-16.2016

Chevance, F. F. V., Le Guyon, S., and Hughes, K. T. (2014). The effects of codon context on in vivo translation speed. *PLoS Genet.* 10:e1004392. doi: 10.1371/journal. pgen.1004392

Cho, E., Kim, D.-H., Hur, Y.-N., Whitcomb, D. J., Regan, P., Hong, J.-H., et al. (2015). Cyclin Y inhibits plasticity-induced AMPA receptor exocytosis and LTP. *Sci. Rep.* 5:12624. doi: 10.1038/srep12624

Choudhury, M. N., and Chakraborty, S. (2015). Codon Usage Pattern in Human SPANX Genes. *Bioinformation* 11, 454–459. doi: 10.6026/97320630011454

Chung, B. K.-S., Yusufi, F. N. K., Mariati, N., Yang, Y., and Lee, D.-Y. (2013). Enhanced expression of codon optimized interferon gamma in CHO cells. *J. Biotechnol.* 167, 326–333. doi: 10.1016/j.jbiotec.2013.07.011

Clarke, T. F., and Clark, P. L. (2008). Rare codons cluster. *PLoS One* 3:e3412. doi: 10.1371/journal.pone.0003412

Coleman, J. R., Papamichail, D., Skiena, S., Futcher, B., Wimmer, E., and Mueller, S. (2008). Virus attenuation by genome-scale changes in codon pair Bias. *Science* 320, 1784–1787. doi: 10.1126/science.1155761

De Mandal, S., Mazumder, T. H., Panda, A. K., Kumar, N. S., and Jin, F. (2020). Analysis of synonymous codon usage patterns of HPRT1 gene across twelve mammalian species. *Genomics* 112, 304–311. doi: 10.1016/j.ygeno.2019.02.010

Driver, J. A. (2014). Inverse association between Cancer and neurodegenerative disease: review of the epidemiologic and biological evidence. *Biogerontology* 15, 547–557. doi: 10.1007/s10522-014-9523-2

Driver, J. A., Beiser, A., Au, R., Kreger, B. E., Splansky, G. L., Kurth, T., et al. (2012). Inverse association between Cancer and Alzheimer's disease: results from the Framingham heart study. *BMJ* 344:e1442. doi: 10.1136/bmj.e1442

Duret, L., and Mouchiroud, D. (1999). Expression pattern and, surprisingly, gene length shape codon usage in Caenorhabditis, Drosophila, and Arabidopsis. *Proc. Natl. Acad. Sci. U. S. A.* 96, 4482–4487. doi: 10.1073/pnas.96.8.4482

Eymin, B., and Gazzeri, S. (2010). Role of cell cycle regulators in lung carcinogenesis. *Cell Adhes. Migr.* 4, 114–123. doi: 10.4161/cam.4.1.10977

Ferreira, J. J., Neutel, D., Mestre, T., Coelho, M., Rosa, M. M., Rascol, O., et al. (2010). Skin Cancer and Parkinson's disease. *Mov. Disord.* 25, 139–148. doi: 10.1002/mds.22855

Franzo, G., Tucciarone, C. M., Legnardi, M., and Cecchinato, M. (2021). Effect of genome composition and codon Bias on infectious bronchitis virus evolution and adaptation to target tissues. *BMC Genom.* 22:244. doi: 10.1186/s12864-021-07559-5

Frumkin, I., Lajoie, M. J., Gregg, C. J., Hornung, G., Church, G. M., and Pilpel, Y. (2018). Codon usage of highly expressed genes affects proteome-wide translation efficiency. *Proc. Natl. Acad. Sci. U. S. A.* 115, E4940–E4949. doi: 10.1073/pnas.1719375115

Fu, H., Liang, Y., Zhong, X., Pan, Z., Huang, L., Zhang, H., et al. (2020). Codon optimization with deep learning to enhance protein expression. *Sci. Rep.* 10:17617. doi: 10.1038/s41598-020-74091-z

Gao, X., Leone, G. W., and Wang, H. (2020). Cyclin D-CDK4/6 functions in Cancer. *Adv. Cancer Res.* 148, 147–169. doi: 10.1016/bs.acr.2020.02.002

Giménez-Roig, J., Núñez-Manchón, E., Alemany, R., Villanueva, E., and Fillat, C. (2021). Codon usage and adenovirus fitness: implications for vaccine development. *Front. Microbiol.* 12:633946. doi: 10.3389/fmicb.2021.633946

Henry, I., and Sharp, P. M. (2007). Predicting gene expression level from codon usage Bias. Mol. Biol. Evol. 24, 10–12. doi: 10.1093/molbev/msl148

Höglinger, G. U., Breunig, J. J., Depboylu, C., Rouaux, C., Michel, P. P., Alvarez-Fischer, D., et al. (2007). The PRb/E2F cell-cycle pathway mediates cell death in Parkinson's disease. *Proc. Natl. Acad. Sci. U. S. A.* 104, 3585–3590. doi: 10.1073/ pnas.0611671104

Hou, W. (2020). Characterization of codon usage pattern in SARS-CoV-2. Virol. J. 17:138. doi: 10.1186/s12985-020-01395-x

Huang, Y., Lin, T., Lu, L., Cai, F., Lin, J., Jiang, Y. E., et al. (2021). Codon pair optimization (CPO): a software tool for synthetic gene design based on codon pair Bias to improve the expression of recombinant proteins in Pichia Pastoris. *Microb. Cell Factories* 20:209. doi: 10.1186/s12934-021-01696-y

Ibáñez, K., Boullosa, C., Tabarés-Seisdedos, R., Baudot, A., and Valencia, A. (2014). Molecular evidence for the inverse comorbidity between central nervous system disorders and cancers detected by transcriptomic Meta-analyses. *PLoS Genet.* 10:e1004173. doi: 10.1371/journal.pgen.1004173 Ivanov, I. G., Saraffova, A. A., and Abouhaidar, M. G. (1997). Unusual effect of clusters of rare arginine (AGG) codons on the expression of human interferon alpha 1 gene in *Escherichia Coli. Int. J. Biochem. Cell Biol.* 29, 659–666. doi: 10.1016/s1357-2725(96)00161-6

Jack, B. R., Boutz, D. R., Paff, M. L., Smith, B. L., Bull, J. J., and Wilke, C. O. (2017). Reduced protein expression in a virus attenuated by codon deoptimization. *G3* (*Bethesda*) 7, 2957–2968. doi: 10.1534/g3.117.041020

Kanduc, D. (2017). Rare human codons and HCMV translational regulation. J. Mol. Microbiol. Biotechnol. 27, 213–216. doi: 10.1159/000478093

Khandia, R., Alqahtani, T., and Alqahtani, A. M. (2021). Genes common in primary Immunodeficiencies and Cancer display overrepresentation of codon CTG and dominant role of selection pressure in shaping codon usage. *Biomedicine* 9:1001. doi: 10.3390/biomedicines9081001

Khandia, R., Saeed, M., Alharbi, A. M., Ashraf, G. M., Greig, N. H., and Kamal, M. A. (2022). Codon usage Bias correlates with gene length in neurodegeneration associated genes. *Front. Neurosci.* 16:895607. doi: 10.3389/fnins.2022.895607

Khandia, R., Singhal, S., Kumar, U., Ansari, A., Tiwari, R., Dhama, K., et al. (2019). Analysis of Nipah virus codon usage and adaptation to hosts. *Front. Microbiol.* 10:886. doi: 10.3389/fmicb.2019.00886

Kim, H., Kwon, Y.-A., Ahn, I. S., Kim, S., Kim, S., Jo, S. A., et al. (2016). Overexpression of cell cycle proteins of peripheral lymphocytes in patients with Alzheimer's disease. *Psychiatry Investig.* 13, 127–134. doi: 10.4306/pi.2016.13.1.127

Kliman, R. M., and Bernal, C. A. (2005). Unusual usage of AGG and TTG codons in humans and their viruses. *Gene* 352, 92–99. doi: 10.1016/j.gene.2005.04.001

Kok, Y. P., Guerrero Llobet, S., Schoonen, P. M., Everts, M., Bhattacharya, A., Fehrmann, R. S. N., et al. (2020). Overexpression of cyclin E1 or Cdc25A leads to replication stress, mitotic aberrancies, and increased sensitivity to replication checkpoint inhibitors. *Oncogenesis* 9:88. doi: 10.1038/s41389-020-00270-2

Krasniqi, E., Goeman, F., Pulito, C., Palcau, A. C., Ciuffreda, L., di Lisa, F. S., et al. (2022). Biomarkers of response and resistance to CDK4/6 inhibitors in breast cancer: hints from liquid biopsy and MicroRNA exploration. *Int. J. Mol. Sci.* 23:14534. doi: 10.3390/ijms232314534

Kunec, D., and Osterrieder, N. (2016). Codon pair Bias is a direct consequence of dinucleotide Bias. *Cell Rep.* 14, 55–67. doi: 10.1016/j.celrep.2015.12.011

Lee, B. S., Shin, S., Jeon, J. Y., Jang, K.-S., Lee, B. Y., Choi, S., et al. (2015). Incorporation of unnatural amino acids in response to the AGG codon. *ACS Chem. Biol.* 10, 1648–1653. doi: 10.1021/acschembio.5b00230

Li, X., Hirano, R., Tagami, H., and Aiba, H. (2006). Protein tagging at rare codons is caused by TmRNA action at the 3' end of nonstop MRNA generated in response to ribosome stalling. *RNA* 12, 248–255. doi: 10.1261/rna.2212606

Li, Y., Khandia, R., Papadakis, M., Alexiou, A., Simonov, A. N., and Khan, A. A. (2022). An investigation of codon usage pattern analysis in pancreatitis associated genes. *BMC Genom. Data* 23:81. doi: 10.1186/s12863-022-01089-z

Lin, Y.-M., Chen, M.-L., Chen, C.-L., Yeh, C.-M., and Sung, W.-W. (2020). Overexpression of EIF5A2 predicts poor prognosis in patients with Oral squamous cell carcinoma. *Diagnostics (Basel)* 10:436. doi: 10.3390/diagnostics10070436

Luo, D.-J., Feng, Q., Wang, Z.-H., Sun, D.-S., Wang, Q., Wang, J.-Z., et al. (2014). Knockdown of Phosphotyrosyl phosphatase activator induces apoptosis via mitochondrial pathway and the attenuation by simultaneous tau hyperphosphorylation. *J. Neurochem.* 130, 816–825. doi: 10.1111/jnc.12761

Mavrou, A., Tsangaris, G. T., Roma, E., and Kolialexi, A. (2008). The ATM gene and Ataxia telangiectasia. *Anticancer Res.* 28, 401–405.

Mazumder, T. H., Chakraborty, S., and Paul, P. (2014). A cross talk between codon usage Bias in human oncogenes. *Bioinformation* 10, 256–262. doi: 10.6026/97320630010256

McShea, A., Harris, P. L., Webster, K. R., Wahl, A. F., and Smith, M. A. (1997). Abnormal expression of the cell cycle regulators P16 and CDK4 in Alzheimer's disease. *Am. J. Pathol.* 150, 1933–1939.

Moriyama, E. N., and Powell, J. R. (1998). Gene length and codon usage Bias in Drosophila Melanogaster, saccharomyces cerevisiae and Escherichia Coli. Nucleic Acids Res. 26, 3188–3193. doi: 10.1093/nar/26.13.3188

Morris, L. G. T., Veeriah, S., and Chan, T. A. (2010). Genetic determinants at the Interface of Cancer and neurodegenerative disease. *Oncogene* 29, 3453–3464. doi: 10.1038/onc.2010.127

Munjal, A., Khandia, R., Shende, K. K., and Das, J. (2020). Mycobacterium Lepromatosis genome exhibits unusually high CpG dinucleotide content and selection is key force in shaping codon usage. *Infect. Genet. Evol.* 84:104399. doi: 10.1016/j. meegid.2020.104399

Newman, Z. R., Young, J. M., Ingolia, N. T., and Barton, G. M. (2016). Differences in codon Bias and GC content contribute to the balanced expression of TLR7 and TLR9. *Proc. Natl. Acad. Sci. U. S. A.* 113, E1362–E1371. doi: 10.1073/ pnas.1518976113

Pang, W., Li, Y., Guo, W., and Shen, H. (2020). Cyclin E: a potential treatment target to reverse Cancer Chemoresistance by regulating the cell cycle. *Am. J. Transl. Res.* 12, 5170–5187.

Park, J., Xu, K., Park, T., and Yi, S. V. (2012). What are the determinants of gene expression levels and breadths in the human genome? *Hum. Mol. Genet.* 21, 46–56. doi: 10.1093/hmg/ddr436

Plun-Favreau, H., Lewis, P. A., Hardy, J., Martins, L. M., and Wood, N. W. (2010). Cancer and neurodegeneration: between the devil and the deep Blue Sea. *PLoS Genet.* 6:e1001257. doi: 10.1371/journal.pgen.1001257

Puigbò, P., Bravo, I. G., and Garcia-Vallve, S. (2008). CAIcal: a combined set of tools to assess codon usage adaptation. *Biol. Direct* 3:38. doi: 10.1186/1745-6150-3-38

Quax, T. E. F., Claassens, N. J., Söll, D., and van der Oost, J. (2015). Codon Bias as a means to fine-tune gene expression. *Mol. Cell* 59, 149–161. doi: 10.1016/j. molcel.2015.05.035

Raab, D., Graf, M., Notka, F., Schödl, T., and Wagner, R. (2010). The GeneOptimizer algorithm: using a sliding window approach to cope with the vast sequence space in multiparameter DNA sequence optimization. *Syst. Synth. Biol.* 4, 215–225. doi: 10.1007/s11693-010-9062-3

Remmerie, M., and Janssens, V. (2019). PP2A: a promising biomarker and therapeutic target in endometrial Cancer. *Front. Oncol.* 9:462. doi: 10.3389/fonc.2019.00462

Rosano, G. L., and Ceccarelli, E. A. (2009). Rare codon content affects the solubility of recombinant proteins in a codon Bias-adjusted *Escherichia Coli* strain. *Microb. Cell Factories* 8:41. doi: 10.1186/1475-2859-8-41

Ruzman, M. A., Ripen, A. M., Mirsafian, H., Ridzwan, N. F. W., Merican, A. F., and Mohamad, S. B. (2021). Analysis of synonymous codon usage Bias in human monocytes, B, and T lymphocytes based on transcriptome data. *Gene Reports* 23:101034. doi: 10.1016/j.genrep.2021.101034

Sablina, A. A., Hector, M., Colpaert, N., and Hahn, W. C. (2010). Identification of PP2A complexes and pathways involved in cell transformation. *Cancer Res.* 70, 10474–10484. doi: 10.1158/0008-5472.CAN-10-2855

Seo, J., and Park, M. (2020). Molecular crosstalk between Cancer and neurodegenerative diseases. *Cell. Mol. Life Sci.* 77, 2659–2680. doi: 10.1007/s00018-019-03428-3

Shan, Y.-S., Hsu, H.-P., Lai, M.-D., Hung, Y.-H., Wang, C.-Y., Yen, M.-C., et al. (2017). Cyclin D1 overexpression correlates with poor tumor differentiation and prognosis in gastric Cancer. *Oncol. Lett.* 14, 4517–4526. doi: 10.3892/ol.2017.6736

Shen, W., Wang, D., Ye, B., Shi, M., Ma, L., Zhang, Y., et al. (2015). GC3-biased gene domains in mammalian genomes. *Bioinformatics* 31, 3081–3084. doi: 10.1093/bioinformatics/btv329

Sher, S., Whipp, E., Walker, J., Zhang, P., Beaver, L., Williams, K., et al. (2023). VIP152 is a selective CDK9 inhibitor with pre-clinical *in vitro* and *in vivo* efficacy in chronic lymphocytic leukemia. *Leukemia* 37, 326–338. doi: 10.1038/s41375-022-01758-z

Shields, D. C., Sharp, P. M., Higgins, D. G., and Wright, F. (1988). "Silent" sites in Drosophila genes are not neutral: evidence of selection among synonymous codons. *Mol. Biol. Evol.* 5, 704–716. doi: 10.1093/oxfordjournals.molbev.a040525

Shupp, A., Casimiro, M. C., and Pestell, R. G. (2017). Biological functions of CDK5 and potential CDK5 targeted clinical treatments. *Oncotarget* 8, 17373–17382. doi: 10.18632/oncotarget.14538

Simón, D., Cristina, J., and Musto, H. (2021). Nucleotide composition and codon usage across viruses and their respective hosts. *Front. Microbiol.* 12:646300. doi: 10.3389/fmicb.2021.646300

Sonntag, R., Penners, C., Kohlhepp, M., Haas, U., Lambertz, D., Kroh, A., et al. (2021). Cyclin E1 in murine and human liver Cancer: a promising target for therapeutic intervention during tumour progression. *Cancers (Basel)* 13:5680. doi: 10.3390/cancers13225680

Sueoka, N. (1988). Directional mutation pressure and neutral molecular evolution. Proc. Natl. Acad. Sci. U. S. A. 85, 2653–2657. doi: 10.1073/pnas.85.8.2653 Supek, F., and Šmuc, T. (2010). On relevance of codon usage to expression of synthetic and natural genes in *Escherichia coli. Genetics* 185, 1129–1134. doi: 10.1534/genetics.110.115477

Tats, A., Tenson, T., and Remm, M. (2008). Preferred and avoided codon pairs in three domains of life. *BMC Genom.* 9:463. doi: 10.1186/1471-2164-9-463

Tian, D.-S., Yu, Z.-Y., Xie, M.-J., Bu, B.-T., Witte, O. W., and Wang, W. (2006). Suppression of Astroglial scar formation and enhanced axonal regeneration associated with functional recovery in a spinal cord injury rat model by the cell cycle inhibitor Olomoucine. *J. Neurosci. Res.* 84, 1053–1063. doi: 10.1002/jnr.20999

Trinh, R., Gurbaxani, B., Morrison, S. L., and Seyfzadeh, M. (2004). Optimization of codon pair use within the (GGGGS)3 linker sequence results in enhanced protein expression. *Mol. Immunol.* 40, 717–722. doi: 10.1016/j.molimm.2003.08.006

Tulloch, F., Atkinson, N. J., Evans, D. J., Ryan, M. D., and Simmonds, P. (2014). RNA virus attenuation by codon pair deoptimisation is an artefact of increases in CpG/UpA dinucleotide frequencies. *elife* 3:e04531. doi: 10.7554/eLife.04531

Veeriah, S., Morris, L., Solit, D., and Chan, T. A. (2010a). The familial Parkinson disease gene PARK2 is a multisite tumor suppressor on chromosome 6q25.2-27 that regulates cyclin E. *Cell Cycle* 9, 1451–1452. doi: 10.4161/cc.9.8.11583

Veeriah, S., Taylor, B. S., Meng, S., Fang, F., Yilmaz, E., Vivanco, I., et al. (2010b). Somatic mutations of the Parkinson's disease-associated gene PARK2 in glioblastoma and other human malignancies. *Nat. Genet.* 42, 77–82. doi: 10.1038/ng.491

Wang, Y., Li, C., Khan, M. R. I., Wang, Y., Ruan, Y., Zhao, B., et al. (2016). An engineered rare codon device for optimization of metabolic pathways. *Sci. Rep.* 6:20608. doi: 10.1038/srep20608

Wang, W., Meng, F.-Y., Huang, Z.-F., Huang, M., and Liu, L.-X. (2010). Expression and role of amyloid precrusor protein gene in acute myeloid leukemia. *Zhonghua Xue Ye Xue Za Zhi* 31, 309–314. doi: 10.3892/ol.2017.7396

Williams, M. E., and Swerdlow, S. H. (1994). Cyclin D1 overexpression in non-Hodgkin's lymphoma with chromosome 11 Bcl-1 rearrangement. *Ann. Oncol.* 5 Suppl 1, 71–73. doi: 10.1093/annonc/5.suppl_1.s71

Wright, F. (1990). The "effective number of codons" used in a gene. *Gene* 87, 23–29. doi: 10.1016/0378-1119(90)90491-9

Wu, W., Yu, S., and Yu, X. (2022). Transcription-associated cyclin-dependent kinase 12 (CDK12) as a potential target for Cancer therapy. *Biochim. Biophys. Acta Rev. Cancer* 1878:188842. doi: 10.1016/j.bbcan.2022.188842

Yu, X., Liu, J., Li, H., Liu, B., Zhao, B., and Ning, Z. (2021a). Comprehensive analysis of synonymous codon usage patterns and influencing factors of porcine epidemic diarrhea virus. *Arch. Virol.* 166, 157–165. doi: 10.1007/s00705-020-04857-3

Yu, X., Liu, J., Li, H., Liu, B., Zhao, B., and Ning, Z. (2021b). Comprehensive analysis of synonymous codon usage Bias for complete genomes and E2 gene of atypical porcine Pestivirus. *Biochem. Genet.* 59, 799–812. doi: 10.1007/s10528-021-10037-y

Zabłocka, A., Kazana, W., Sochocka, M., Stańczykiewicz, B., Janusz, M., Leszek, J., et al. (2021). Inverse correlation between Alzheimer's disease and Cancer: short overview. *Mol. Neurobiol.* 58, 6335–6349. doi: 10.1007/s12035-021-02544-1

Zhang, R., Zhang, L., Wang, W., Zhang, Z., Du, H., Qu, Z., et al. (2018). Differences in codon usage Bias between photosynthesis-related genes and genetic system-related genes of chloroplast genomes in cultivated and wild *Solanum* species. *Int. J. Mol. Sci.* 19:E3142. doi: 10.3390/ijms19103142

Zhou, Z., Dang, Y., Zhou, M., Li, L., Yu, C.-H., Fu, J., et al. (2016). Codon usage is an important determinant of gene expression levels largely through its effects on transcription. *Proc. Natl. Acad. Sci. U. S. A.* 113, E6117–E6125. doi: 10.1073/pnas.1606724113

Zhou, J., and Ekström, P. (2022). A potential role of cyclic dependent kinase 1 (CDK1) in late stage of retinal degeneration. *Cells* 11:2143. doi: 10.3390/ cells11142143