Chapter III:

Materials and Methods

3.1.1. Data collection

We collected data for 24 different cancers, as outlined in Table 3.1, utilizing cBiportal (90-92) an online platform that facilitates the retrieval of extensive cancer data sourced from TCGA and ICGC projects. Additionally, we obtained a list of genes linked to immune responses from ImmPort(93). It is a comprehensive repository that stores and shares immunology-related data, encompassing clinical, experimental, and molecular information. The gene catalogue comprised of 1492 genes associated with different aspects of immune responses.

Sl.	Abbrev	Full name	Dataset	Sample Number		
No	iation			All	Muta tions	RN A seq
1	ACC	Adrenocortic al carcinoma	AdrenocorticalCarcinoma(TCGA, PanCancer Atlas)TCGA PanCancer Atlas, Cell2018	92	91	78
2	BLCA	Bladder Urothelial Carcinoma	Bladder Urothelial Carcinoma (TCGA, PanCancer Atlas) TCGA PanCancer Atlas, Cell 2018	411	410	407
3	BRCA	Breast invasive carcinoma	Breast Invasive Carcinoma (TCGA, Cell 2015) TCGA, Cell 2015	818	817	817
4	CHOL	Cholangiocar cinoma	Cholangiocarcinoma (TCGA, PanCancer Atlas) TCGA PanCancer Atlas, Cell 2018	36	36	36

5	COAD	Colorectal	Colorectal Adenocarcinoma	276	224	274
		adenocarcino	(TCGA, Nature 2012) TCGA,			
		ma	Nature 2012			
6	CESC	Cervical	Cervical Squamous Cell	297	291	294
		squamous	Carcinoma (TCGA, PanCancer			
		cell	Atlas) TCGA PanCancer Atlas,			
		carcinoma	Cell 2018			
7	HCC	Hepatocellula	Harding et al. Clin Cancer Res	127	127	
		r carcinoma	2018			
8	HNSC	Head and	Head and Neck Squamous Cell	523	515	515
		Neck	Carcinoma (TCGA, PanCancer			
		Squamous	Atlas) TCGA PanCancer Atlas,			
		cell	Cell 2018			
		Carcinoma				
9	KICH	Kidney	Kidney Chromophobe (TCGA,	65	65	65
		Chromophob	PanCancer Atlas) TCGA			
		e	PanCancer Atlas, Cell 2018			
10	KIRC	Kidney renal	Kidney Renal Clear Cell	512	402	510
		clear cell	Carcinoma (TCGA, PanCancer			
		carcinoma	Atlas) TCGA PanCancer Atlas,			
			Cell 2018			
11	KIRP	Kidney renal	Kidney Renal Papillary Cell	283	276	283
		papillary cell	Carcinoma (TCGA, PanCancer			
		carcinoma	Atlas) TCGA PanCancer Atlas,			
			Cell 2018			
12	LUAD	Lung	Lung Adenocarcinoma (TCGA,	230	230	230
		adenocarcino	Nature 2014) TCGA, Nature			
		ma	2014			

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13	LUSC	Lung	Lung Squamous Cell	487	484	484
		squamous	Carcinoma (TCGA, PanCancer			
		cell	Atlas) TCGA PanCancer Atlas,			
		carcinoma	Cell 2018			
14	OV	Ovarian	Ovarian Serous	585	523	300
		carcinoma	Cystadenocarcinoma (TCGA,			
			PanCancer Atlas) TCGA			
			PanCancer Atlas, Cell 2018			
15	PRAD	Prostate	Prostate Adenocarcinoma	334	333	290
		adenocarcino	(TCGA, Cell 2015) TCGA,			
		ma	Cell 2015			
16	ESCA	Esophageal	Esophageal Adenocarcinoma	182	182	181
		adenocarcino	(TCGA, PanCancer Atlas)			
		ma	TCGA PanCancer Atlas, Cell			
			2018			
17	THCA	Thyroid	Thyroid Carcinoma (TCGA,	500	498	490
		carcinoma	PanCancer Atlas) TCGA			
			PanCancer Atlas, Cell 2018			
18	UCEC	Uterine	Uterine Corpus Endometrial	373	248	333
		Corpus	Carcinoma (TCGA, Nature			
		Endometrial	2013) TCGA, Nature 2013			
		Carcinoma				
19	GBM	Glioblastoma	Glioblastoma Multiforme	592	397	160
		multiforme	(TCGA, PanCancer Atlas)			
			TCGA PanCancer Atlas, Cell			
			2018			

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20	LGG	Brain Lower	Brain Lower Grade Glioma	514	514	514
		Grade	(TCGA, PanCancer Atlas)			
		Glioma	TCGA PanCancer Atlas, Cell			
			2018			
21	PCPG	Pheochromoc	Pheochromocytoma and	178	178	178
		ytoma and	Paraganglioma (TCGA,			
		Paragangliom	PanCancer Atlas) TCGA			
		a	PanCancer Atlas, Cell 2018			
22	DLBC	Diffuse large	Diffuse Large B-Cell	48	41	48
		B cell	Lymphoma (TCGA, PanCancer			
		lymphoma	Atlas) TCGA PanCancer Atlas,			
			Cell 2018			
23	LAML	Acute	Acute Myeloid Leukemia	200	200	173
		Myeloid	(TCGA, PanCancer Atlas)			
		Leukemia	TCGA PanCancer Atlas, Cell			
			2018			
24	SARC	Sarcoma	Sarcoma (TCGA, PanCancer	255	255	253
	OMA		Atlas) TCGA PanCancer Atlas,			
			Cell 2018			

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Table 3.1: Details of the datasets downloaded from cBioportal

3.1.2. Analysis of alterations in the DNA sequence of the immune related genes

We obtained mutation data for genes listed in the immune-related gene catalogue acquired from the ImmPort database. The mutation data was sourced from the dataset covering 24 different human cancers that we had previously obtained from cBioportal. Using the maftools software, we generated detailed summaries of mutations in each cancer (94). We

conducted a screening for Copy Number Alterations (CNA) in the frequently mutated immune related genes of the particular cancer. This involved analysing available CNA data from the 24 different cancer dataset, using GISTIC 2.0(95). The analysed data (p-value-0.01)was visualised for CNA in frequently mutated immune related genes using maftools (94) in R.

3.1.3. Survival analysis considering mutations

Using mutation data and clinical data available in 9 datasets, Kaplan Meier plots in 5 years survival time were generated for cancers by maftools. Univariate and multivariate cox-proportional hazard analysis considering age for the mutated and non-mutated PIK3CA was performed using the "survminer" and "survival" packages.

3.1.4. Identification of differentially expressed genes (DEGs)

Data was divided into two dataset one mutated and another non-mutated, for malignancies illustrating the influence of gene mutations on survival. The edgeR(96), R package was used for detection of differentially expressed genes (DEGs) among the groups. The statistical cutoff for differential expression was p-value and false discovery rate (FDR) of less than 0.05 and a fold change greater than 1.5.

3.1.5. Identification of over-represented pathways

The DEGs from the analysis were used as input for pathway over-representation analysis using WebGestalt 2019 (97), database used was Kyoto Encyclopaedia of Genes and Genomes (KEGG) pathways database, pathways with FDR < 0.05 were considered in the study.

3.1.6. Estimating infiltration of immune cell to the tumor immune microenvironment

CIBERSORTx was used to estimate the number of immune cells infiltrating the tumor (98). The gene expression profile of both mutated and non-mutated dataset was used as

input. The profile of gene expression from both the mutant and unmutated datasets was utilized as input. The fraction of twenty-two immune cell subtypes was assessed using an LM22 signature. (The LM22 signature is a gene expression profile utilized to deconvolve immune cell populations from bulk tumor gene expression data. It comprises 547 genes representing 22 immune cell subsets) p value calculation was done with 100 permutations. The difference in infiltration was compared.

3.1.7. Statistical analysis and data visualization

The statistical analyses for the study were conducted using the R 4.2.3 statistical framework and the ggplot2 R package was used for generating plots. KEGG pathway plots were generated using SRplots(99).

3.2.1. Expression of 4genes (HLA-A, HLA-B, HLA-DRB1 and CIITA) and survival analysis

The expression profile of 4genes for LGG was analysed by GEPIA (Gene Expression Profiling Interactive Analysis, http:// gepia.cancer-pku.cn/index.html) (100), a platform utilized to analyse RNA sequencing data from TCGA and GTEx projects and generate boxplots for differential expression and Kaplan Meier plots for survival by "Single Gene Analysis" module.

3.2.2. Relationship Between 4genes (HLA-A, HLA-B, HLA-DRB1 and CIITA) and immune infiltration in the tumor microenvironment

The quantity of immunological infiltrates(B cells, CD4+ T cells, CD8+ T cells, NK Cells, Tregs, T follicular helper, macrophages, and dendritic cells) was estimated using TIMER(101). The "Gene module" of the TIMER database was used in this study to assess the relationship between the expression of four genes under investigation and immune cell infiltration.

3.2.3. Correlation between 4genes (HLA-A, HLA-B, HLA-DRB1 and CIITA) and HLA-E

The correlation between 4genes (HLA-A, HLA-B, HLA-DRB1 and CIITA) and HLA-E was analysed using "correlation of expression analysis module" under expression analysis of OncoDB(102).

3.3.1. Identification of putative G-quadruplex in human genome

The study was initiated by acquiring FASTA sequences for the human genome from the National Center for Biotechnology Information-NCBI (GRCh38). These sequences were utilized as input for G4 Hunter (103) to predict locations for putative G-quadruplex (G4) structures along the sequence.

3.3.2. Visualization of overlap between G4 structures and immune-related genes

To visualize the overlap between G4 structures and immune-related genes, we utilized KaryoplotR(104), to generate a karyoplot that could illustrate the intersection.

3.3.3. Annotation of putative G4 locations onto human genome

Putative G4 locations from G4 Hunter were annotated using bedtools intersect (105) on reference human genome GRCh38 from Gencode (106). Thus, the precise location of the putative G4 along genes were determined. The list of proto-oncogenes was sourced from the cancer gene census (107) in the COmmon Software Measurement International Consortium (COSMIC) database. A catalogue of 803 proto-oncogenes from source http://ongene.bioinfo-minzhao.org/ongene_human.txt was downloaded. The list of housekeeping genes was downloaded from https://www.tau.ac.il/~elieis/HKG/, the list had a catalogue of 2832 genes. The list of immune genes and proto-oncogenes had 101 genes in common, these 101 genes were removed from both the list before proceeding with further analysis. There were no such similar genes in list of housekeeping genes to either immune genes or cancer related genes.

3.3.4. Analysing the density of G4

The prevalence of G4 structures in cancer-related genes has been extensively established in prior research(108). G4 are involved in RNA regulation, hence it was expected that the frequency of G4 in housekeeping genes would be low. Therefore, comparative analysis of G4 abundance within immune genes and as opposed to proto-oncogenes and housekeeping genes was done. The density of G4 was considered as putative G4 per 1000 base pairs. Dunnett's test was used for the comparison between the groups.

3.3.5. Examining the frequency of mutations in G4 locations

We overlaid mutations from all 24 different datasets included in our study onto the putative G4 locations along the human genome using bedtools intersect.