



RETRACTED: Identification of an Immunologic Signature of Lung Adenocarcinomas Based on Genome-Wide Immune Expression Profiles

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Background: Lung cancer is one of the most common types of cancer, and it has a poor prognosis. It is urgent to identify prognostic biomarkers to guide therapy.

Methods: The immune gene expression profiles for patients with lung adenocarcinomas (LUADs) were obtained from The Cancer Genome Atlas (TCGA) and the Gene Expression Omnibus (GEO). The relationships between the expression of 45 immune checkpoint genes (ICGs) and prognosis were analyzed. Additionally, the correlations between the expression of 45 biomarkers and immunotherapy biomarkers, including tumor mutation burden (TMB), mismatch repair defects, neoantigens, and others, were identified. Ultimately, prognostic ICGs were combined to determine immune subgroups, and the prognostic differences between these subgroups were identified in LUAD.

Results: A total of 11 and nine ICGs closely related to prognosis were obtained from the GEO and TCGA databases, respectively. *CD200R1* expression had a significant negative correlation with TMB and neoantigens. *CD200R1* showed a significant positive correlation with *CD8A*, *CD68*, and *GZMB*, indicating that it may cause the disordered expression of adaptive immune resistance pathway genes. Multivariable Cox regression was used to construct a signature composed of four prognostic ICGs (*IDO1*, *CD274*, *CTLA4*, and *CD200R1*): Risk Score = $-0.002*IDO1+0.031*CD274-0.069*CTLA4-0.517*CD200R1$. The median Risk Score was used to classify the samples for the high- and low-risk groups. We observed significant differences between groups in the training, testing, and external validation cohorts.

Conclusion: Our research provides a method of integrating ICG expression profiles and clinical prognosis information to predict lung cancer prognosis, which will provide a unique reference for gene immunotherapy for LUAD.

Keywords: lung adenocarcinomas, immune checkpoint genes, immune subtypes, immune gene expression profile, prognosis

BACKGROUND

Lung cancer accounts for more than one-tenth of all cancer cases worldwide and is one of the most common types of cancer (Ferlay et al., 2015), with smoking being a major risk factor. Exposure to high levels of carcinogens in tobacco smoke can induce the accumulation of mutation load in lung cells (Cataldo et al., 2010; Pedersen et al., 2016). Lung cancer prognosis is rather poor, with a 5-year survival rate of 18% (Parascandola and Xiao, 2019). Prognosis is related to patients' clinicopathological characteristics, and the early diagnosis rate is low. Because of this, the formation and pathological grade of lung cancer cannot be accurately judged, thus limiting operation strategies (Ergonul et al., 2017). By the time of diagnosis, most patients already have extensive metastasis. The main therapeutic strategy aims to reduce the malignant phenotype by suppressing the oncogenic pathway. Although the response to chemotherapy and radiotherapy in the early stage is relatively good, this treatment often leads to drug resistance during further treatment. Because of this effect, treatment strategies for lung cancer are relatively limited (Nakaoku and Kohno, 2017; Zhang et al., 2018).

Genome sequencing technologies and data have deepened our understanding of lung cancer development, cellular heterogeneity, and interactions at precise molecular interactions (Xu et al., 2016), and immunotherapy developments have shown great potential in treating various malignant tumors (Turner, 2017). At present, monoclonal antibody-targeted drugs are leading to innovations in the treatment of lung cancer. Most notably, immunotherapy with programmed cell death protein 1 (PD-1) and *CD274* as targets has achieved significant results in clinical trials of lung cancer treatment (Galetta et al., 2017; Choy et al., 2019). Currently, these targeted drugs can be used as first or second-line drugs for lung cancer since more than 50% of tumor cells in patients express programmed death-ligand 1 (PD-L1) (Ru and Zhuang, 2018). However, this therapy does not work for all patients due to dynamic and isomeric expression implications, which suggest that other therapeutic targets are needed for specific patients (Merelli et al., 2014; Kasahara et al., 2019). On the whole, the effect of most targeted monoclonal antibodies is still limited among lung cancer patients. While encouraging responses are observed in some patients, many others do not show the same success (Wang et al., 2017). This indicates that not all patients demonstrate equal sensitivity to therapeutic targets because of tumor heterogeneity. Since established immunotherapy is not effective for all patients, it is necessary to further differentiate tumor immune subtypes to improve clinical trial design and identify patients who may benefit from other types of immunotherapy.

Traditional cancer research usually focuses on the role of a particular target gene in cancer development (Huang et al., 2019). However, each case of cancer is complex and involves the abnormality of multiple genes and signaling pathways. Therefore, studying the role of a single gene has its limitations (Wang and Xia, 2019). At present, biological studies have entered the multi-omics era, which opens the possibility of understanding and studying tumors at the genome level. The establishment of large cancer databases, such as The Cancer Genome Atlas (TCGA)

and the Gene Expression Omnibus (GEO), enables researchers to obtain the gene expression data of multiple immune checkpoints and patients' corresponding clinical data (Tomczak et al., 2015; Zhang et al., 2019). On this basis, integrated analysis can divide different immune subtypes in lung cancer samples in more detail and guide individualized treatment (Yuan et al., 2015; Hanke, 2016). Most existing reports related to lung cancer immunotherapy are drug design studies that use a single immune checkpoint gene (ICG) as a target. There is still a lack of research on gene expression profiles involving multiple immune checkpoints (Sadreddini et al., 2018; Duffy and John, 2019; Long et al., 2019). Therefore, based on the gene expression data of 47 immune checkpoints, such as PD-1 (*PDCD1*), PD-L1 (*CD274*), and *IDO1*, the immune subgroups and prognoses of 761 lung cancer samples from the TCGA and GEO databases were identified.

In our research, the relationships between the expression of 45 ICGs and prognosis were analyzed. Additionally, the relationships between ICGs and immunotherapy biomarkers, such as mismatch repair (MMR) defects and tumor mutation burden (TMB), were studied using integrated cell mutation data. This was done to determine the relationships between the expression of ICGs (PD1, PD-L1, and *CTLA4*) and biomarkers that have not been widely used in immunotherapy. Ultimately, the relationship between ICG expression and immune activation-related signature genes was studied to determine the relationship between immune activation and immunosuppression in the tumor microenvironment, which can provide a reference for individualized gene immunotherapy in patients with lung cancer.

MATERIALS AND METHODS

Data Download and Processing

A total of 47 ICGs from Danilova et al. were downloaded (**Supplementary Table 1**) (Danilova et al., 2019). The RNA sequencing data of lung adenocarcinoma (LUAD) were downloaded from the TCGA Genomic Data Commons (GDC) application programming interface (API), which contained 515 samples. The GSE31210 microarray expression data set was downloaded from the National Center for Biotechnology Information (NCBI), and it contained 226 LUAD samples with clinical features.

The following precursory steps were conducted in the processing of the 515 RNA sequencing samples: (1) samples without clinical information or an overall survival (OS) < 30 days were removed; (2) normal tissue samples were removed; and (3) genes whose fragments per kilobase million (FPKM) value was equal to 0 were removed. Thus, more than half of the samples were removed. Furthermore, GSE31210 data were pre-processed as follows: (1) normal tissue samples were removed, and only primary tumor data were retained; (2) year/month-based OS data were converted into day-based data; (3) the microarray probe was mapped to human gene symbols using the *Bioconductor* package; and (4) only the expression profile of immune-related genes was retained. Statistical clinical information for the two cohorts is shown in **Table 1**.

TABLE 1 | Pre-processed clinical information of the two cohorts in LUAD.

Characteristic	TCGA	Characteristic	GSE31210
Event		Event	
Alive	314	Alive	191
Dead	178	Dead	35
Sex		Sex	
Male	230	Male	105
Female	262	Female	121
Survival times		Survival times	
33~1476	417	221~950	32
1,476~2,919	58	950~1,679	72
2,919~4,362	11	1,679~2,408	86
4,362~5,805	3	2,408~3,137	28
5,805~7,248	2	3,137~3,863	8
Pathologic N			
N0	319	–	–
N1	92	–	–
N2	68	–	–
N3	2	–	–
NX	11	–	–
Pathologic T			
T1	164	–	–
T2	264	–	–
T3	43	–	–
T4	18	–	–
TX	3	–	–
Pathologic M			
M0	362	–	–
M1	24	–	–
MX	142	–	–
TNM stage		Pathological stages	
I	261	I	168
II	114	II	58
III	79	III	0
IV	25	IV	0
Smoke		Smoke	
Non-smoking	68	Non-smoking	115
Smoker	408	Smoker	111

All the LUAD samples collected in our study were from before the first treatment, and all the patients received standard treatment, such as resection. Considering the complexity of clinical treatments, many patients used multiple treatment options during subsequent radiotherapy and chemotherapy. Because the GEO database does not include such treatment information, we made statistics on the TCGA cohort (**Supplementary Table 2**). In the TCGA cohort, 64 samples were collected from the central lung and 127 from the peripheral lung; the GSE31210 cohort did not contain LUAD location records (**Supplementary Table 3**).

Relationship Between ICG Expression and Prognosis

ICGs with gene expression in the TCGA cohort were identified. The patients were divided into different groups based on gene expression. In order to investigate the relation between the expression of ICGs and survival time, we used univariate cox regression analysis to identify prognostic ICGs. The logrank test (logrank $p < 0.05$) was used to compare survival curves between different ICGs expression. The expression and prognostic patterns of the ICGs were analyzed with the same method in the GEO cohorts.

Relationship Between ICGs and Other Immune Checkpoint Biomarkers

Spearman's Rank correlation coefficient is a technique which can be used to summarize the strength and direction (negative or positive) of a relationship between two variables. The Spearman method was used to evaluate the correlation between TMB and ICGs. The relation between neoantigen and ICG expression was further analyzed based on TCGA somatic cell mutation data.

CD200R1 Silencing by Lentiviral-Delivered RNA Interference

The shRNAs targeting the MGAT1 coding sequences are as follows: CD200R1-sh1 (NM_002405), 5'-CCCTTCAGATCAAGCCA-3'; and CD200R1-sh2 (NM_0075606), 5'-CTGTTCAAAAATTATCAAGCT-3'. The control shRNA coding sequences are as follows: RFP, 5'-CTACCATGGCCTACAAGCT-3'. Adherent cells were treated with 0.5 mL of the virus followed by overnight incubation (37 °C, 5% CO₂) without removing the virus. The next day, viral medium was replaced with fresh medium containing puromycin (1 mg/mL) to select a population of resistant cells.

Cell Viability Assay

After knocking down of CD200R1, the tumor cells were seeded in 96-well plates (5×10^3 cells/well), with cell transfected by negative control served as control group. The cells were cultured overnight, the medium was exchanged with 100 μ l of medium supplemented with 10 μ l CCK8. The plates were incubated for 2 h. Afterwards, absorbance at 450 nm was measured to obtain OD value. Similarly, other time points (24, 48, 72, and 96 h) were also assessed according to the procedures.

Flow Cytometry Analysis

Cells were digested with trypsin and then washed with phosphate-buffered saline (PBS). An Annexin V-FITC Apoptosis Detection Kit (Beyotime) was applied to practice cell apoptosis in line with the manufacturer's instructions. The apoptotic cells were dual-stained with propidium iodide (PI) and Annexin V-FITC using an Annexin V-FITC Kit (Thermo Scientific, Shanghai, China). Analysis was carried out via BDTM LSRII flow cytometer (BD Biosciences). Afterward, the data were measured with the Cell Quest software (BD Bioscience, San Jose, CA, USA).

Wound Healing and Transwell Assays

For the wound healing assay, tumor cells were seeded on 6-well plates. When 95% confluence was achieved, the cell monolayer was gently scratched using a 200 μm sterile plastic pipette tip. Then, the wound was photographed. After 24 h, the healing wound was photographed. For Transwell migration or invasion assays, 4×10^4 cells suspended in medium without serum were seeded in the upper chamber membranes coated without/with Matrigel (BD Biosciences). Then, 600 μl of medium with 10% fetal bovine serum (FBS) was added to the lower chamber. After 24 h, the underside of the membrane was fixed for 30 min and stained with 0.1% crystal violet. The inner side of the membrane was wiped with a cotton swab. Then, the cells were quantified under a microscope.

Western Blotting

Western blotting was performed according to standard protocols previously described. We used primary antibodies raised against GAPDH, Snail, E-cadherin, and Vimentin (Santa Cruz Biotechnology, Santa Cruz, CA, USA) and CD200R1 (Proteintech, China). Goat anti-mouse and anti-rabbit antibodies conjugated with horseradish peroxidase were used as secondary antibodies (Jackson ImmunoResearch, West Grove, PA, USA), and we detected the blots using enhanced chemiluminescence (ECL) (Dura, Pierce, NJ, USA).

Statistical Analysis

For comparison between two groups, the statistical significance of the normal distribution variables was estimated with the non-paired student's *t*-test, and the non-normal distribution variables were analyzed using the Mann-Whitney U-test. For comparisons between more than two groups, the Kruskal-Wallis test and one-way analysis of variance (ANOVA) were used as non-parametric and parametric methods, respectively (Yuan et al., 2015). The correlation coefficients were calculated using Spearman correlation analysis. The Kaplan-Meier method was used to generate a survival curve for the subgroups in each cohort, and the logrank test was used to determine the statistical significance at the level of $p < 0.05$. All the analyses were performed using R 3.4.3 using default parameters, unless otherwise specified.

RESULTS

Relationship Between ICGs and Prognosis in the TCGA Cohort

First, a total of 45 ICGs with expression in the TCGA cohort were selected. Depending on their expression, the 45 ICGs were divided into three distinct expression patterns: the high-expression group (red) was represented by *CD44*, *CD40*, *TNFRSF14*, and *NRP1*, with generally high expression levels in all samples; the medium-expression group (green) was represented by *IDO1*, *LAG3*, and *PDCD1*, with notable expression differences between samples; and the low-expression group (blue) was

represented by *KIR3DL1*, *BTNL2*, and the remainder, with lower expression levels in most samples (Figure 1).

Using univariate Cox regression analysis, we calculated the relationships between the 45 ICGs and prognosis in the TCGA cohort and obtained nine genes that were significantly correlated with prognosis: *TNFSF14*, *CD70*, *TNFRSF14*, *CD27*, *LAIR1*, *CTLA4*, *CD28*, *CD40LG*, and *CD200R1* (logrank $p < 0.05$; Figure 2A). These nine genes were mainly positively correlated and showed a significant aggregate effect (Figure 2B) through correlation analysis of ICG expression levels, indicating coordinated expression between the ICGs.

Relationship Between ICGs and Treatment Using Biomarkers for Other Immune Checkpoints

Relationship Between ICGs and TMB

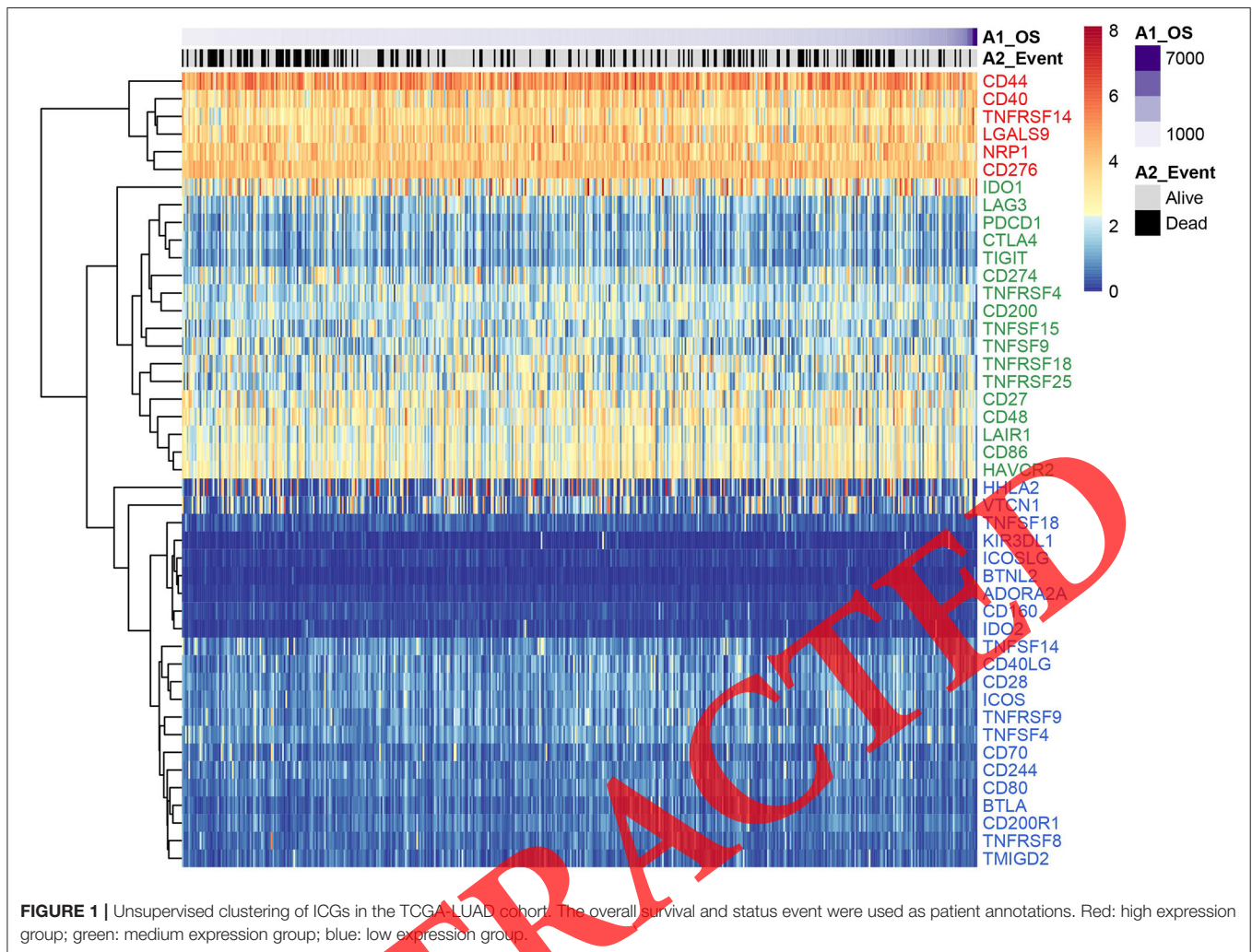
We calculated the TMB of LAUD according to TCGA somatic mutation data, and we removed the intron interval and the mutation annotated as silent. First, we selected nine ICGs with expression quantities strongly correlated with prognosis and used the Spearman method to evaluate the correlation between TMB and the nine ICGs (Shapiro-Wilk test, $p < 2.2e-16$). We observed highly negative correlations between TMB and *CD40LG*, *CD200R1*, *TNFRSF14*, and *TNFSF14* expression ($R < 0$ and false discovery rate [FDR] < 0.005 ; Figure 3). *TNFSF14* was the factor potentially causing unfavorable prognosis. Thus, we speculated that higher *TNFSF14* expression corresponds to lower TMB. Additionally, a low TMB was generally not an indicator of successful immune checkpoint inhibitor treatment.

Relationship Between ICGs and MMRs

MMRs are intracellular mismatch repair mechanisms, and the loss of function of key genes in these mechanisms leads to irreparable DNA replication errors, thereby increasing somatic cell mutations. We used LUAD somatic mutation data from TCGA to evaluate the relationships between five MMR gene mutations (*MLH1*, *MSH2*, *MSH6*, *PMS2*, and *EPCAM*) and ICG expression. It was found that the MMRs mutant gene was mainly positively correlated with the expression level of ICGs, and was highly correlated with *TNFRSF8* and *CD70* genes (Figure 4). *CD70*, a prominent prognosis-correlated gene, could be regarded as a potential predictor of MMR gene mutations.

Relationship Between ICGs and Neoantigens

Tumor somatic mutations in protein-coding genes produce neoantigens, which can be presented by the major histocompatibility class I complex (MHC I). These new peptides induce anti-tumor adaptive immune responses by binding to T-cell receptors (TCR). Based on the TCGA somatic mutation data, we further analyzed the relationship between neoantigens and the expression of the nine ICGs that largely affected prognosis. We found a high negative correlation between four genes (*CD40LG*, *CD200R1*, *TNFSF14*, and *TNFRSF14*) and neoantigen expression ($R < 0$ and FDR < 0.05 ; Figure 5). These results were consistent with the aforementioned results, in which TMB was extremely negatively correlated with the expression of the four genes.



Relationship Between ICGs and Adaptive Immune Resistance Pathway Genes

CD8T cells can produce interferon- γ and lead to upregulated expression of adaptive immune resistance pathway genes (including the PD-1/PD-L1 axis, *IDO1*, etc.). Therefore, we analyzed the correlation between *CD8A*, *GZMB*, *CD68*, and *NOS2* and ICGs. Except for *NOS2*, there were four adaptive immune resistance pathway genes that were positively correlated with ICG expression (Figure 6A). At least half of the correlations between these genes were significant ($p < 1e-3$; Figure 6B).

Relationship Between ICGs and Clinical Features

Univariate Cox analysis identified nine prognostic ICGs. Using the clinical information provided by TCGA, we analyzed the relationship between these nine ICGs and clinical features. Due to the large deviation in the distribution of the samples in the metastasis (M) stage of LUAD (M0/M1:326/24), this study focused on the analysis of the expression patterns of these nine ICGs in the tumor (T), node (N), and clinical stages. In terms of expression level, the ICGs were clearly

divided into three high-expression groups and six low-expression groups (Supplementary Figure 1). The expression level of the nine ICGs in early stage tumor samples was higher than in advanced tumor samples (Figures 7A–C), indicating that *TNFRSF14*, *CD27*, and *CD200R1* show significant differences in the T, N, and clinical stages (Kruskal-Wallis test, $p < 0.05$). No significant relationship was observed between sex, new events, and these ICGs (Supplementary Figure 2).

Validation of ICG Expression and Prognosis in the GEO Cohort

Among the 47 selected ICGs in the GSE31210 cohort, there were 44 ICGs with expression, and their expression patterns were significantly clustered into three categories: high, medium, and low expression (Figure 8A). We downloaded the expression profile of the GSE30219, GSE3141, and GSE81089 cohorts, and analyzed the expression of ICGs with three different expression patterns in these three data sets. As shown in the Supplementary Figure 3, it can be observed that their expression

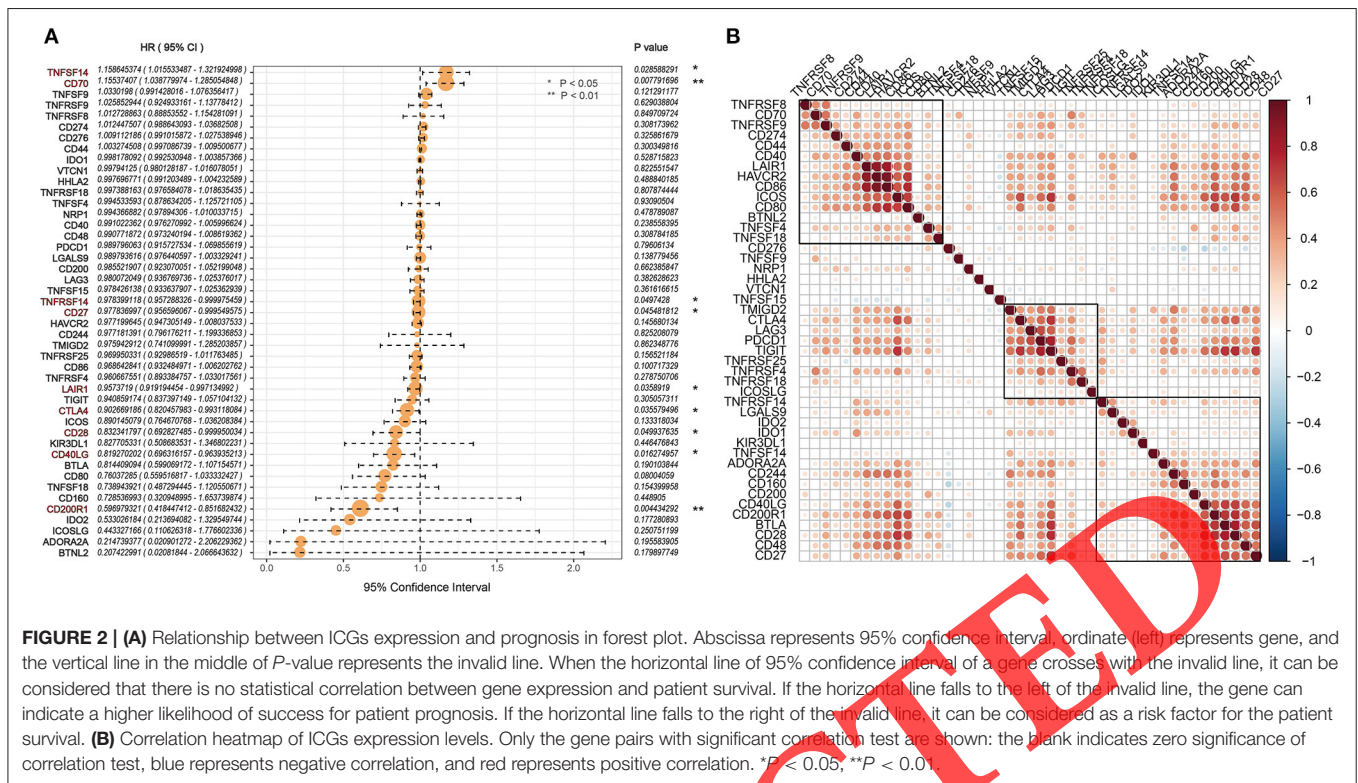


FIGURE 2 | (A) Relationship between ICGs expression and prognosis in forest plot. Abscissa represents 95% confidence interval, ordinate (left) represents gene, and the vertical line in the middle of P -value represents the invalid line. When the horizontal line of 95% confidence interval of a gene crosses with the invalid line, it can be considered that there is no statistical correlation between gene expression and patient survival. If the horizontal line falls to the left of the invalid line, the gene can indicate a higher likelihood of success for patient prognosis. If the horizontal line falls to the right of the invalid line, it can be considered as a risk factor for the patient survival. **(B)** Correlation heatmap of ICGs expression levels. Only the gene pairs with significant correlation test are shown: the blank indicates zero significance of correlation test, blue represents negative correlation, and red represents positive correlation. * $P < 0.05$, ** $P < 0.01$.

patterns were then clustered into three categories: high, medium, and low expression.

Univariate survival analysis of the relationship between the 44 ICGs and OS revealed that 11 ICGs were auspiciously correlated with the prognosis (Figure 8B). Within the GSE31210 cohort, ICG expression levels were largely positively correlated and had a clear aggregation effect (Figure 8C).

Prognostic Signature Construction and Validation

CTLA4, *CD274*, and *IDO1* are important ICGs and biomarkers for immunotherapy. We found that *CTLA4* had a significant prognostic relationship with OS in the TCGA cohort, and *CD274* and *IDO1* had a significant prognostic relationship with OS in the GSE30219 cohort.

CD200R1 was not only significantly correlated with prognosis in the TCGA cohort, but it was also negatively correlated with TMB and neoantigens. In addition, it showed significant positive correlation with *CD8A*, *CD68*, and *GZMB*, indicating that *CD200R1* could cause the imbalanced gene expression in the adaptive immune resistance pathway. Therefore, we combined *CD200R1*, *CD274*, *IDO1*, and *CTLA4* to analyze the relationship with prognosis. We chose the TCGA-LUAD cohort as the training set, the GSE31210 cohort as the testing set, and the GSE30219 cohort as the external validation set. For a unified quantitative analysis, we used multivariable Cox regression to construct a signature with the four ICGs: Risk Score = $-0.002 * IDO1 + 0.031 * CD274 - 0.069 * CTLA4 - 0.517 * CD200R1$.

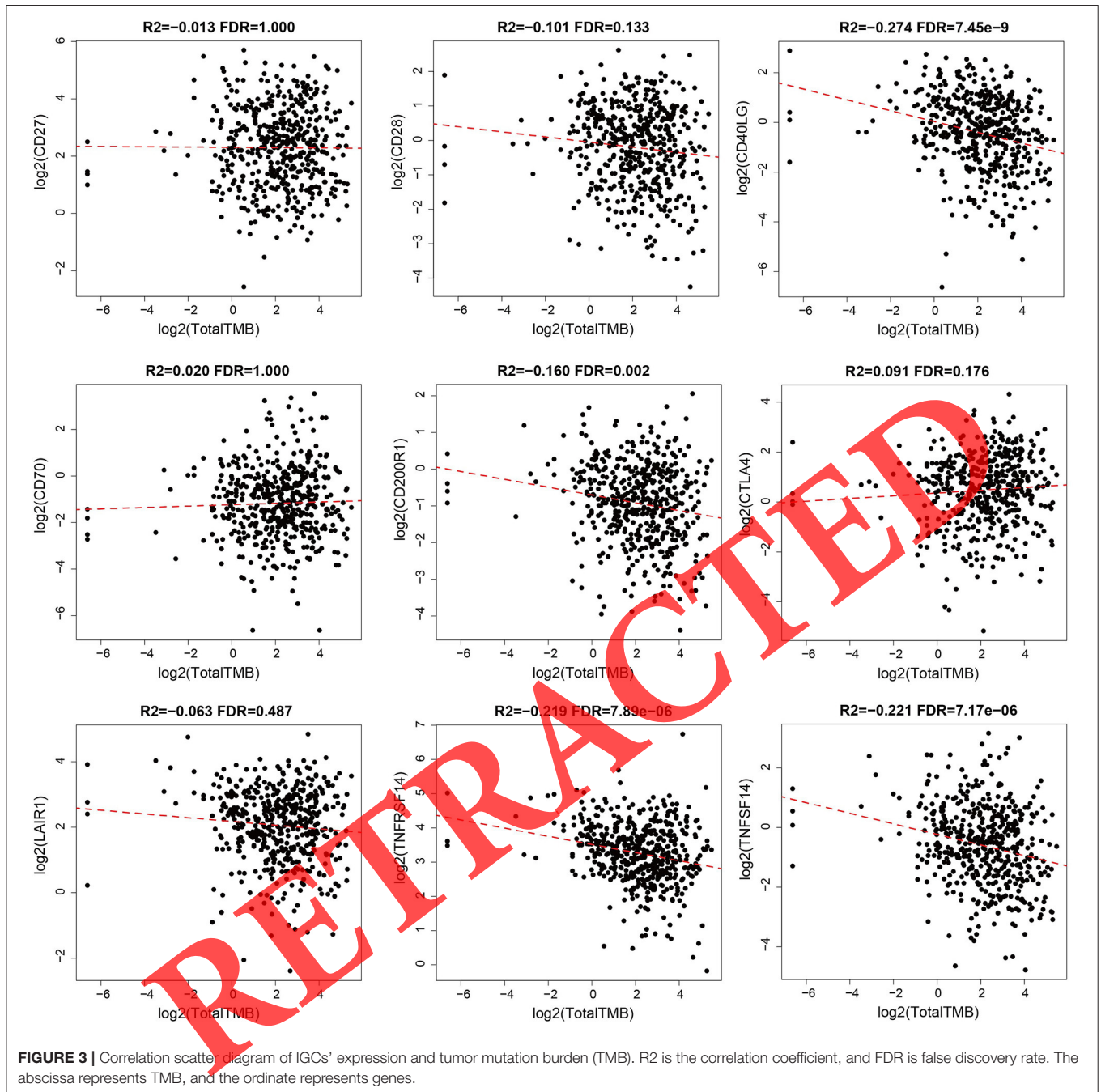
The risk scores of the samples in the three cohorts were calculated by the same method. The median Risk Score was used to classify the high- and low-risk groups, and we observed significant prognostic differences between groups in the training (Figure 9A), testing (Figure 9B), and external validation cohort (Figure 9C).

Biological Behavior of CD200R1 in LUAD

Through the previous analysis, we showed that *CD200R1*, as an important immune checkpoint, has an important relationship with the prognosis and clinical characteristics of patients with cancer. Therefore, this biomarker was further explored.

Baseline expression of *CD200R1* in four kinds of cancer cells was analyzed by western blot, as shown in Figure 10A, the A549 cell line expressed the most *CD200R1* and was therefore used for subsequent study.

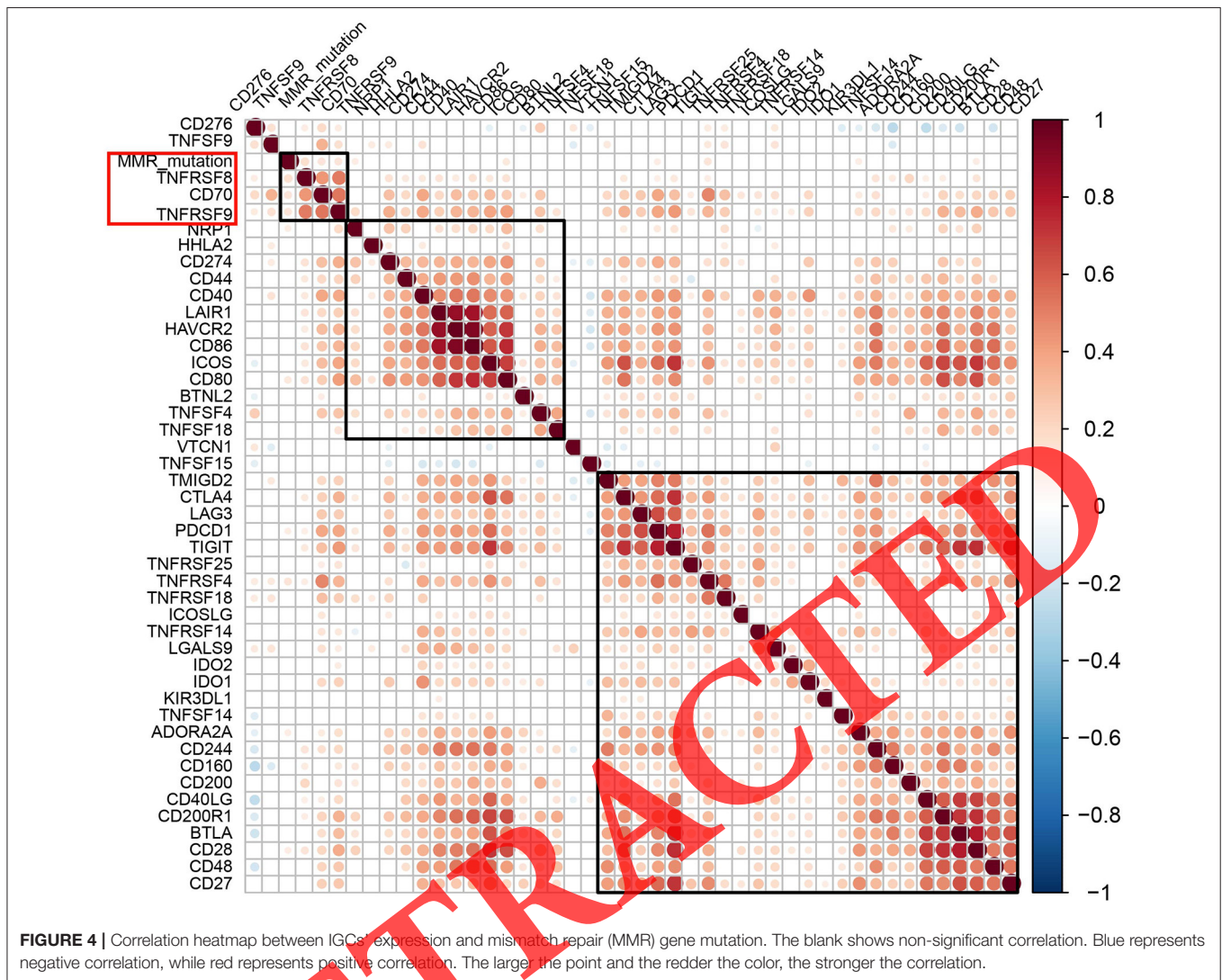
Two shRNAs targeting *CD200R1* were transfected into A549 cell line, and the knockdown effect was confirmed by Western blotting, as shown in Figure 10B. The result shown that shRNA#1 have better knock down effect than shRNA#2, therefore shRNA #1 was selected for subsequently study. CCK8 was used to confirmed effect of *CD200R1* on cancer cell proliferation. As shown in Figure 10C, after *CD200R1* was knocked down, cancer cell growth rate was increased, the conclusion was further confirmed by EdU incorporation assay, as show in Figure 10D, S phase distribution was increased after *CD200R1* was down regulated. Percentage of Ki67 positive was further used to confirm the effect of *CD200R1* on cell



proliferation. As shown in **Figure 10E**, after CD200R1 was knocked down, percentage of Ki67 positive was increased significantly. Apoptosis rate was studied by ANNEXINV stain, as shown in **Figure 10F**, after CD200R1 was knocked down, apoptosis rate of cancer cells was reduced. The effect of CD200R1 on cell migration was studied by transwell and wound healing assay, as shown in **Figures 10G,H**, enhanced migration capacity was observed after CD200R1 was knocked down. To investigated underlying mechanism which result in enhanced

migration capacity, EMT related marker was analyzed, as shown in **Figure 10I**, after CD200R1 was knocked down, expression of Snail and Vimentin was increased and that of E-cadherin was reduced, indicted EMT was occur after CD200R1 was knocked down.

Taken together, our result confirmed that down regulation of CD200R1 promotes cancer cell growth, impaired cancer cell apoptosis, and enhanced migration capacity of cancer cells through EMT mechanism.



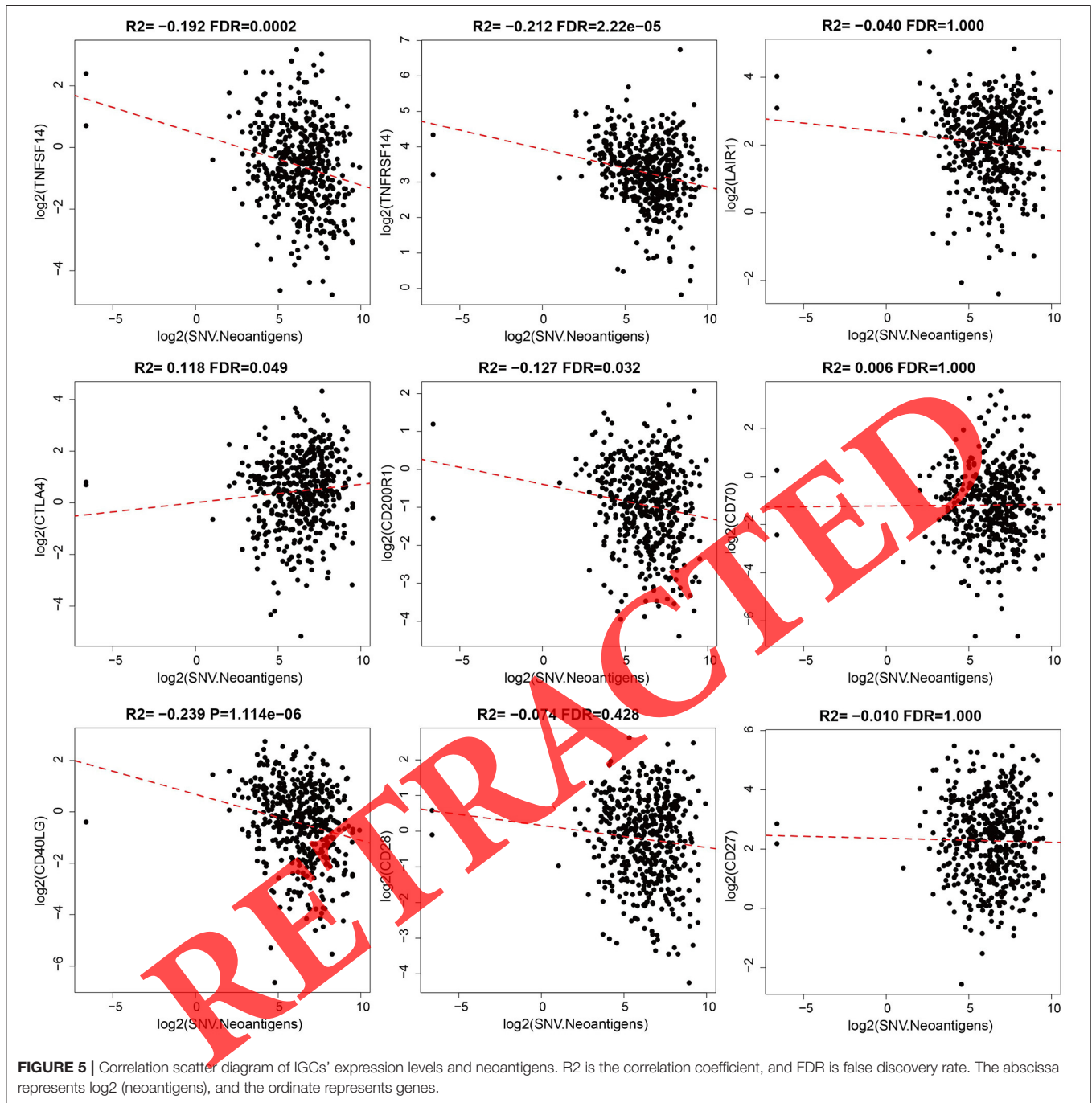
DISCUSSION

In recent years, breakthroughs pertaining to immune checkpoint inhibitors have progressed the treatment of lung cancer (Bai et al., 2020). Atezolizumab for first-line treatment and nivolumab and pembrolizumab for third line treatment have been approved by the U.S. Food and Drug Administration (FDA) (Borghaei et al., 2015; Garon et al., 2015; Socinski et al., 2018). Compared with traditional chemotherapy, immune checkpoint inhibitors have lower toxicity, but only a small proportion of patients in the unselected treatment group can benefit from them (Koster et al., 2015). Therefore, it is crucial to develop methods of identifying lung cancer immune subgroups based on ICG expression profiles, selecting patients more suitable for immunotherapy and thereby enhancing individualized immunotherapy.

This study aimed to identify the relationship between immune subgroups and the prognosis of lung cancer samples based on gene expression data from multiple immune checkpoints. The gene expression profiles from the GEO and TCGA

databases were divided into high-, medium-, and low-expression groups according to the gene expression levels of 47 immune checkpoints. The gene expression of the three expression groups from the two databases were of high consistency. In other words, genes with either high or low expression in the TCGA database were similarly expressed in the GEO database. This indicated a relatively consistent distribution of genes in the collected samples of the two databases. Therefore, the analysis results can be mutually verified in subsequent studies.

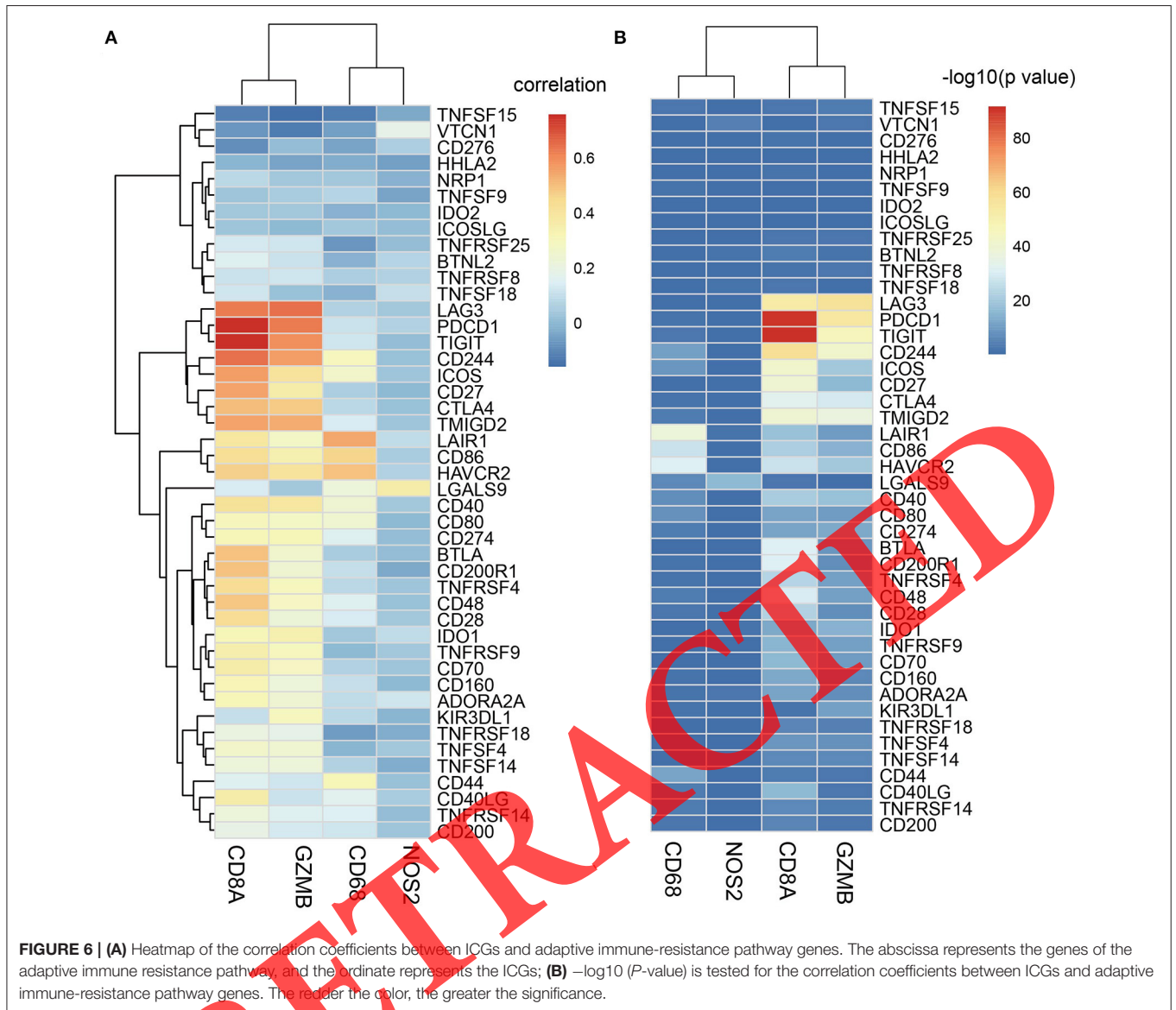
Using univariate Cox regression analysis to identify genes associated with OS, we obtained nine genes significantly related to prognosis from the TCGA database and 11 prognosis-related genes from the GEO database. Among them, *CD40LG*, which is a cluster of differentiation 40 ligand (CD40L), was significantly correlated with better prognosis in both databases (HR < 1, logrank $p < 0.05$) (Takada et al., 2019). CD40L, which is a type II membrane-related glycoprotein and a member of the tumor necrosis factor (TNF) superfamily, is conducive to regulating the immune response and inhibiting tumor growth. It produces



direct growth-inhibiting effects through apoptosis in malignant tumor cells with CD40L overexpression, such as breast cancer (Pan et al., 2013). The correlation of ICG expression levels in both databases was positive and showed a dramatic aggregation effect, indicating the possibility of a coordinated expression relationship between ICGs.

To clarify the relationship between ICGs and other biomarkers for immune checkpoint treatment, we analyzed the relationships between ICGs and TMB, MMRs, and neoantigens.

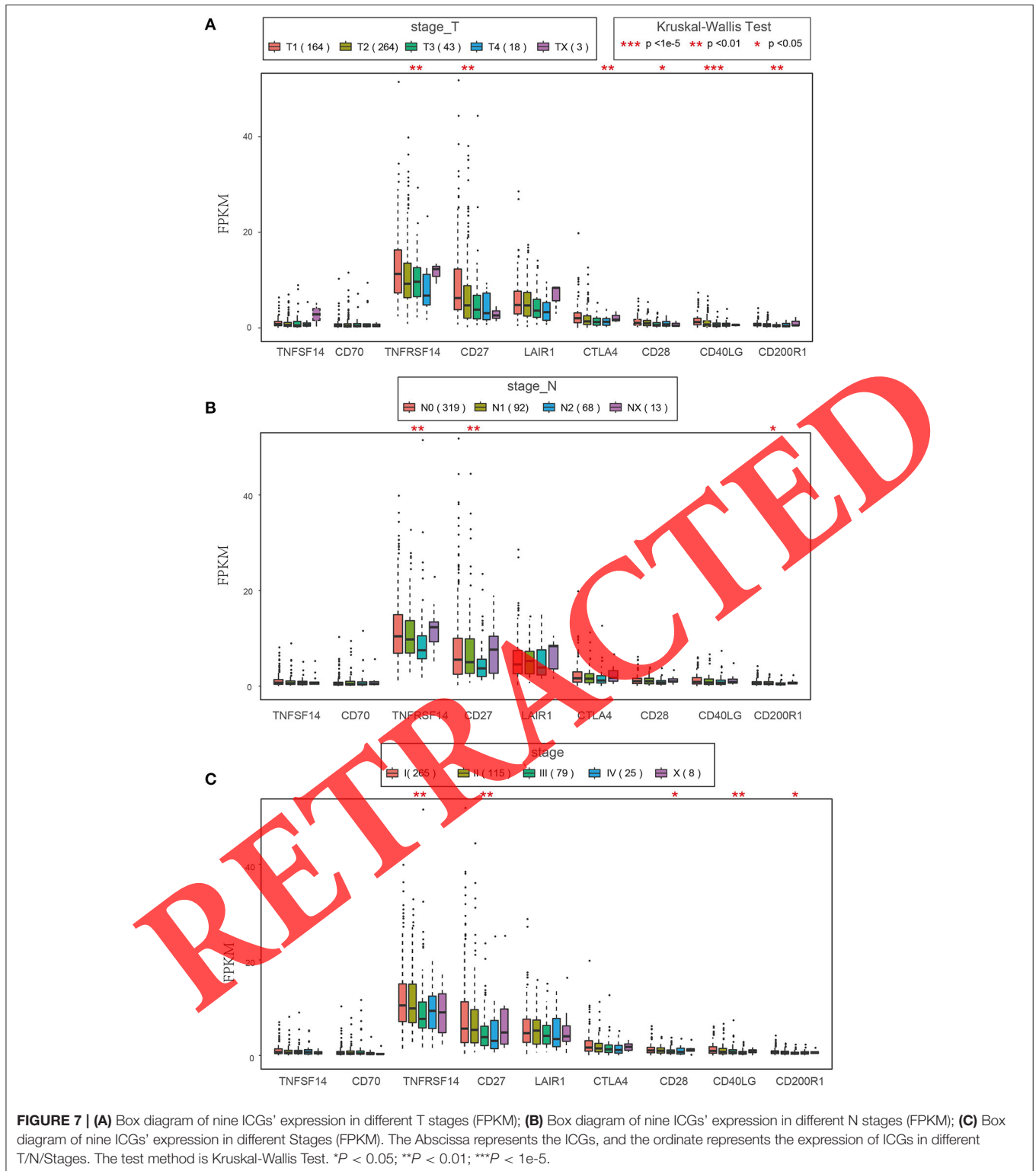
TMB is a reliable indicator of predicted clinical efficacy of the PD-1 inhibitor (Jafarnejad et al., 2019); the more mutant genes in the tumor tissue, the more likely it is that abnormal proteins will be significantly produced. These abnormal proteins can activate the body's anti-tumor immune response, improving the sensitivity of immunotherapy. Therefore, it is more suitable for patients with high TMB levels to continue immunotherapy with PD-1 inhibitors (Penault-Llorca and Radosevic-Robin, 2018).



Some studies have found that TMB can be used as a biomarker for predicting the efficacy of nivolumab monoclonal antibodies. Subsequent phase II and phase III studies have shown that nivolumab combined with ipilimumab produces more significant survival benefits when compared with chemotherapy in patients with high TMB (TMB ≥ 10 mut/Mb) (Hellmann et al., 2018; Ready et al., 2019). Studies have also shown that atezolizumab is more effective in patients with blood TMB ≥ 16 mut/Mb (Gandara et al., 2018). Through analyzing the relationship between ICGs and TMB, we found that the expression of TMB is strongly inversely correlated with *CD40LG*, *CD200R1*, *TNFRSF14*, and *TNFSF14* expression ($R < 0$ and FDR < 0.005). That is, the high expression of *CD40LG*, *CD200R1*, *TNFRSF14*, and *TNFSF14* corresponds to the low expression of TMB. *TNFSF14*, specifically, is a potential cause of unfavorable prognosis. Since high *TNFSF14* expression corresponds to low

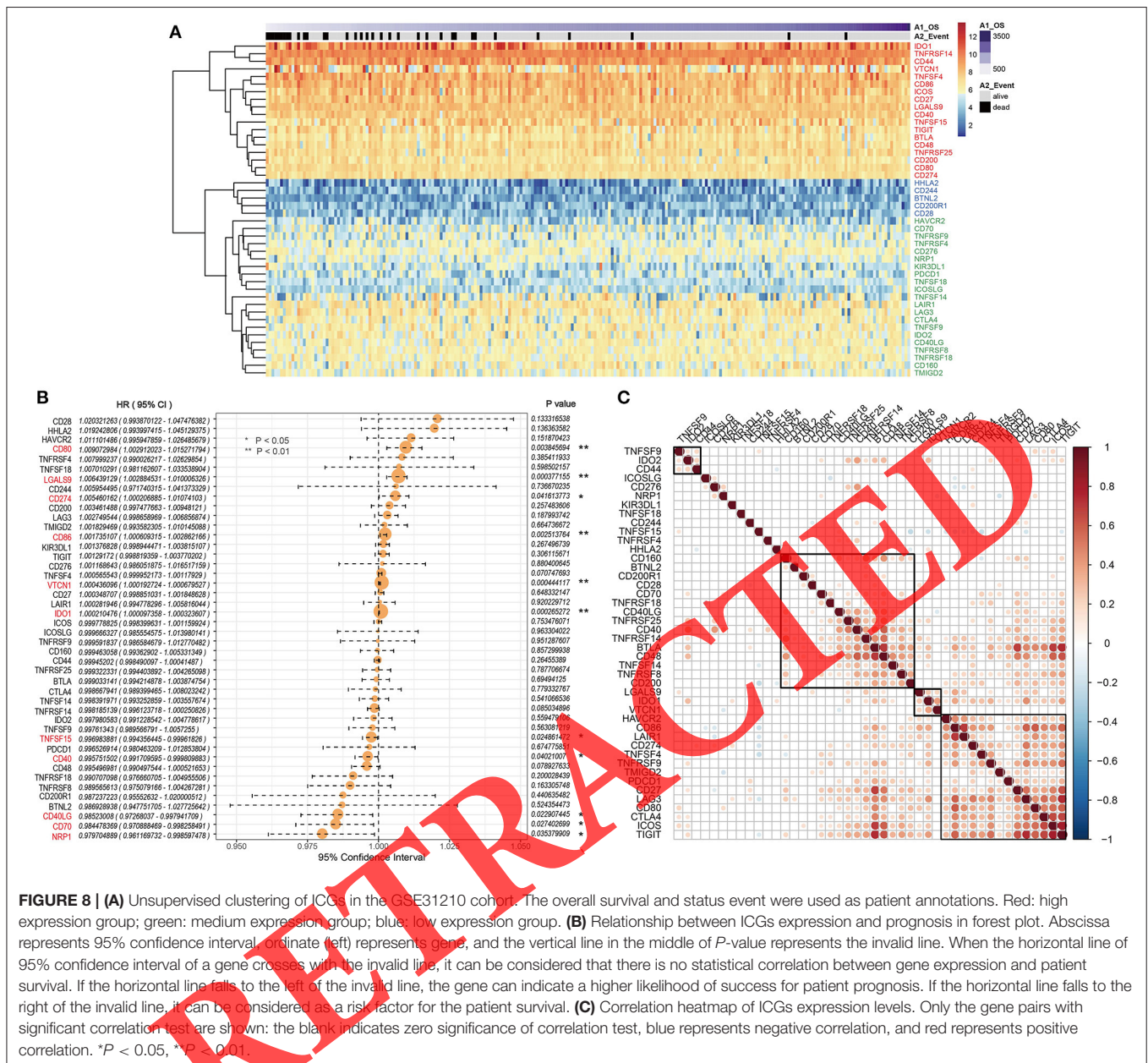
TMB, the high expression of *TNFSF14* may not be suitable for the treatment of immune checkpoint inhibitors.

MMRs are intracellular mismatch repair mechanisms. Their loss of function leads to irreparable DNA replication errors, thus leading to high generation of gene mutations (Chen X. et al., 2019). When tumor cells are mismatch repair-deficient (dMMR) and microsatellite instability is present, many gene mutations will accumulate in tumor cells, and some neoantigens may be recognized and attacked by the immune system, thereby achieving better immunotherapy effects. Recently, the effectiveness of the PD-1 drug pembrolizumab was tested in patients with advanced metastasis in a phase II clinical trial; the objective response rate and non-progressive stage in the MMR colorectal cancer group were as high as 40 and 78%, while in the control group, they were 0 and 11%, respectively (Lee and Le, 2015). Subsequent exon sequencing data indicated that



the MMR tumor group had high TMB, which may translate to more tumor neoantigens and induce more T cells to attack tumor cells, which is conducive to the success of PD-1 immune drugs. MMR is an excellent predictor of the efficacy of PD-1

immune tumor drugs. In 2017, pembrolizumab was approved by the FDA for the treatment of adult and pediatric solid tumor patients with dMMR (Boyadzis et al., 2018). Further, nivolumab combined with ipilimumab has a more significant

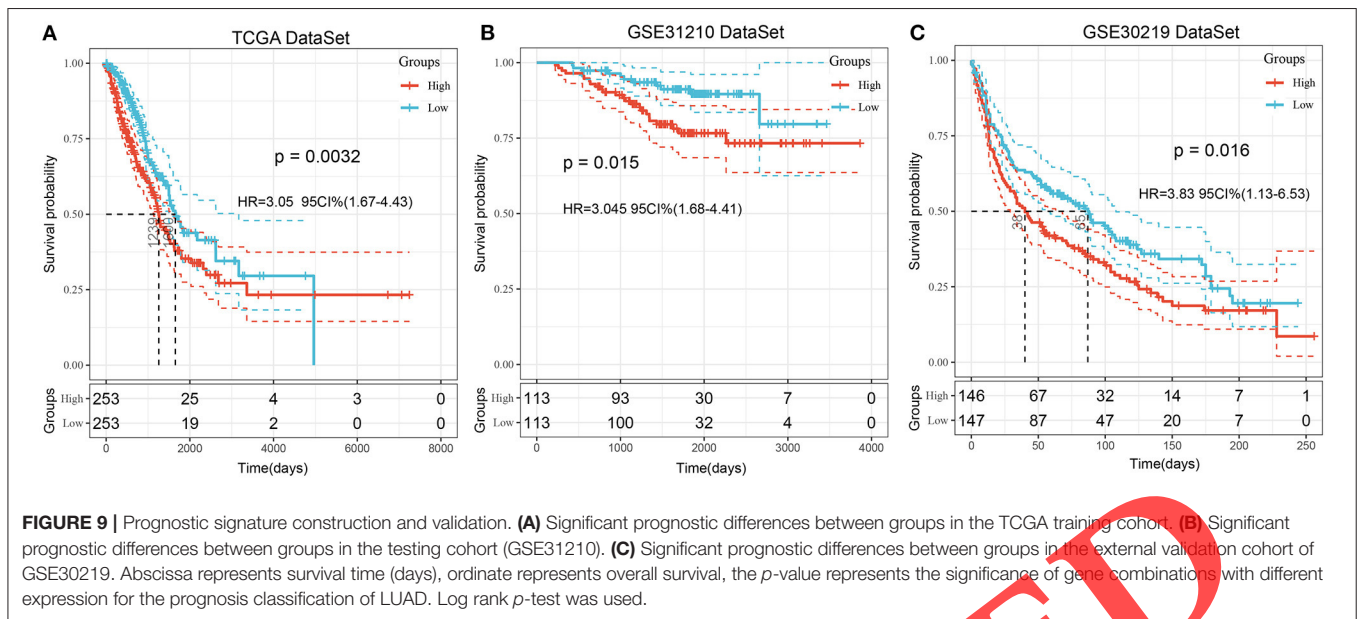


effect on patients with dMMR metastatic colorectal cancer (2018).

The five MMR gene mutations evaluated in this study were positively correlated with ICG expression. Among them, *CD70*, which is also significantly correlated with prognosis, might be a potential predictor of MMR gene mutation. New proteins produced by gene mutation that may activate the immune system and trigger it to attack cancer cells are called neoantigens (Chen F. et al., 2019). Our study found that *CD40LG*, *CD200R1*, *TNFSF14*, and *TNFRSF14* were significantly negatively correlated with neoantigen expression ($R < 0$ and $FDR < 0.05$), which was in line with the extremely high correlation of negative expression between TMB and the four genes mentioned above. Our research showed that *TNFSF14*, the unfavorable prognostic gene, showed

high expression in patients. The high expression of *TNFSF14* corresponds to a low level of neoantigens, so, in this case, it was not appropriate for patients to be treated with personalized neoantigens (Lou et al., 2017). In general, the greater the total number of gene mutations—that is, the higher the TMB—in the tumor tissues of patients, the more neoantigens they carry. According to our results, *CD40LG*, *CD200R1*, *TNFSF14*, and *TNFRSF14* expression was negatively correlated with TMB and neoantigens. This indicated that TMB and neoantigens share the same variation trend, which supports what has been reported in the literature (Jia et al., 2018).

To reveal the relationship between ICGs and adaptive immune resistance pathway genes, we analyzed the correlation between *CD8A*, *GZMB*, *CD68*, and *NOS2* and ICGs. Most were found to



be positively and significantly correlated. We obtained the same results from the GEO and TCGA databases. This indicated that adaptive immune pathway genes might have a certain regulatory effect on ICG expression.

In terms of the relationship between ICGs and clinical features, we found that the expression levels of ICGs in early tumor samples were higher than in advanced tumor samples, *CD200R1* in particular. We also found that *CD200R1* was highly correlated with the OS of patients in the TCGA cohort, but negatively correlated with TMB and neoantigens. In addition, in combination with adaptive immune resistance pathway genes, we found that *CD200R1* was positively correlated with *CD8A*, *CD68*, and *GZMB*, suggesting that *CD200R1* might be the possible cause of the expression dysregulation of adaptive immune resistance pathway genes.

Based on the previous analysis, we found that *CTLA4* had a significant prognostic relationship with OS in the TCGA cohort, and *CD274* and *IDO1* were prognostic genes in the GSE30219 cohort. Therefore, *CD200R1*, *CD274*, *IDO1*, and *CTLA4* were combined to analyze the relationship with prognosis. The TCGA-LUAD cohort was chosen as the training set, the GSE30219 cohort as the testing set, and the GSE31210 cohort as the external validation set. Multivariable Cox regression was used to construct the 4-ICG signature. The risk scores of the samples in the three cohorts were calculated by the same method. There were significant prognostic differences between groups in the training, testing, and external validation sets. *CD200R1*, *CD274*, *IDO1*, and *CTLA4* expression levels can be integrated to evaluate the immune status of patients with LUAD, and together they can provide prognostic information that cannot be obtained by a single ICG.

As an important immune checkpoint, *CD200R1*, is closely related to the prognosis and clinical characteristics of patients with cancer. To further study the relationship between *CD200R1*

and the occurrence and development of lung cancer, we carried out cytological behavior experiments. The results showed that after inhibiting *CD200R1* expression, the proliferation and migration capacity of tumor cells increased, the expression of Snail and Vimentin increased, and the expression of E-cadherin decreased, indicating that EMT occurred after *CD200R1* knockout.

In this genomic era, many genome sequencing technologies have emerged (Wang et al., 2009). Researchers using these tools have made great contributions to tumor diagnosis and prognosis prediction. TCGA, a landmark cancer genomics program, molecularly characterized more than 20,000 primary cancers and matched normal samples spanning 33 cancer types. Although many studies have used bioinformatics methods to find key molecules and potential regulatory pathways related to LUAD prognosis or diagnosis, many others obscure the importance of immune checkpoint-related genes. In this study, we focused on the expression patterns and clinical correlations of ICGs in lung cancer for the first time. We analyzed the potential relationships between ICGs and TMB, MMR defects, neoantigens, and adaptive immune resistance pathway genes, and we combined multiple ICGs to subtype the prognosis of patients with lung cancer. Finally, a gene signature composed of these immune checkpoints was validated by external cohorts.

A gene signature containing 30 immune genes that can predict the prognosis of LUAD patients has been established by Song et al. (2019). He obtained 1534 immune genes from the ImmPort database (<https://immport.niaid.nih.gov>) as the research object, which containing genes related to innate immunity, so the focus of this research is innate immunity genes. In this study, there was no exploration related to immunotherapy. In addition, the number of genes in the signature reported was as many as 30, the clinical application was limited and the detection cost was relatively high.

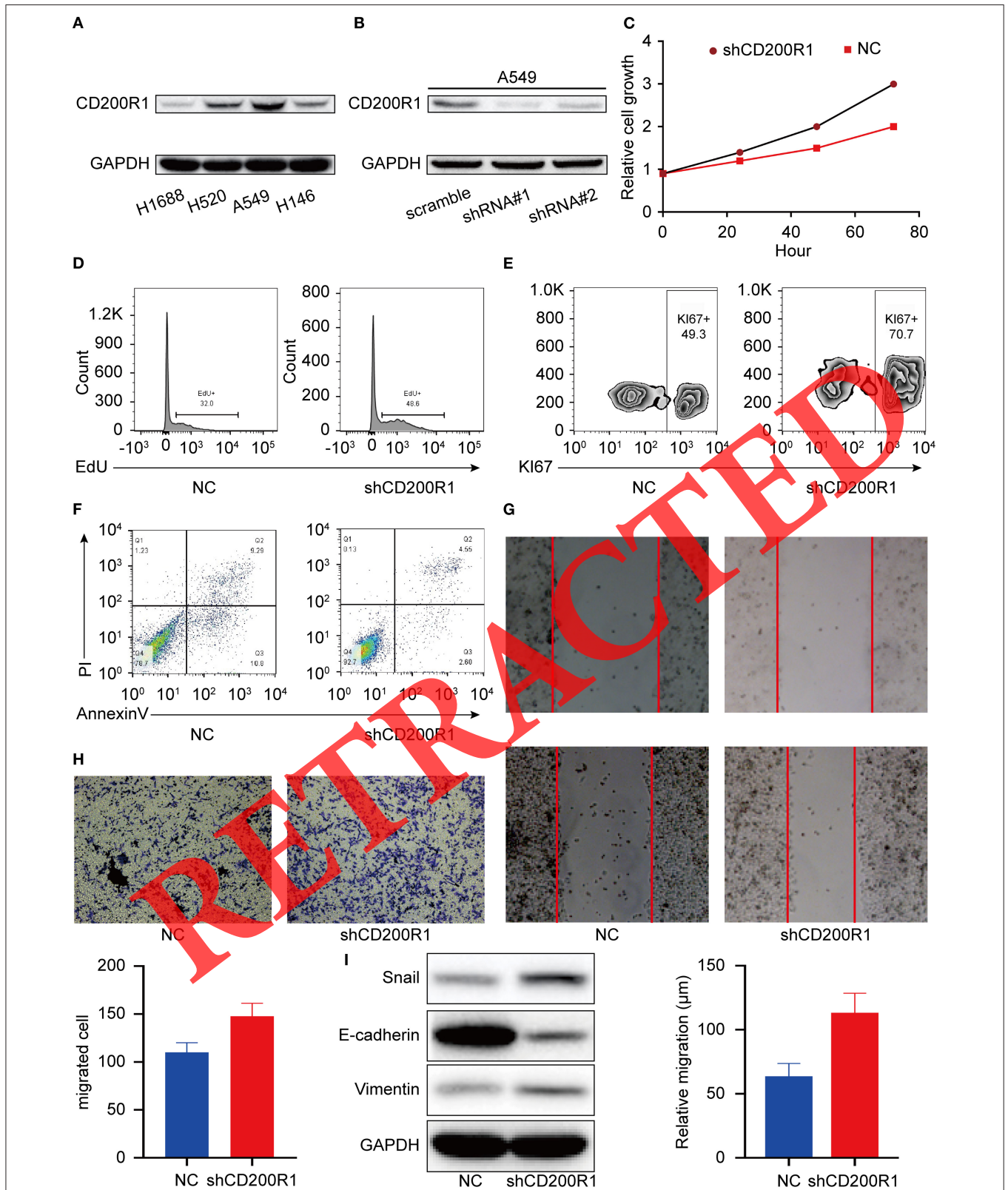


FIGURE 10 | Biological behavior of CD200R1 in lung adenocarcinoma. **(A)** Baseline expression of CD200R1 in four kinds of cancer cells; **(B)** Two shRNA targeting CD200R1 was transfected into A549, effect of knock down was confirmed by western blot; **(C)** Cancer cell growth rate was increased after CD200R1 was knocked down; **(D)** S phase distribution was increased after CD200R1 was down-regulated. **(E)** Percentage of Ki67 positive was used to confirm the effect of CD200R1 on cell proliferation. **(F)** Apoptosis rate was studied by ANNEXIN V stain; **(G,H)** The effect of CD200R1 on cell migration was studied by transwell and wound healing assay; **(I)** The expression of Snail and Vimentin was increased and that of E-cadherin was reduced, indicated EMT was occurred after CD200R1 was knocked down.

Our research mainly used immune checkpoint genes as the research object to determine the subgroups that benefit from immunotherapy and related biomarkers, and finally identified four biomarkers closely related to immunotherapy, so although they are all related to immune markers research, our research is more inclined to clinical application.

Our study also has some limitations. For example, there are insufficient large-scale lung cancer samples for calculation and analysis, and most of the samples are no more than 1000 (Chang et al., 2015). Our results need to be verified by more experiments and clinical observation, and on this basis, with the development and design of potential immune checkpoint inhibitors (Tanoue, 2010). In addition to tumor cell immune-related gene expression, the effects of immune checkpoint inhibitors in tumor treatments are related to the strength of tumor immune stimulation signals, the function of immune effector cells, and the activity of other immune suppression signaling pathways (Zhu et al., 2019). It is not easy to find a single, comprehensive curative effect prediction index. An effective predictive model combining ICG expression profiles would lead to more effective uses of immunotherapy. Researchers are currently working on multiple immune checkpoint inhibitors and targeted therapeutic drugs (Larsen et al., 2019). Based on the ICG expression profiles of lung cancer immune subgroups, we can identify patients more suitable for immunotherapy and thus help develop personalized immunotherapy.

CONCLUSION

In sum, our results showed that the combined gene signature of *IDO1*, *CD274*, *CTLA4*, and *CD200R1* was a reliable tool for predicting prognosis, and it is of great significance to personalized treatment for patients with LUAD in terms of immunotherapy.

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 author/s.

REFERENCES

- (2018). Nivolumab plus ipilimumab achieves responses in dMMR/MSI-H tumors. *Cancer Discov.* 8:263. doi: 10.1158/2159-8290.CD-RW2018-017
- Bai, X., Chen, X., Wu, X., Huang, Y., Zhuang, Y., Chen, Y., et al. (2020). Immune checkpoint inhibitor-associated pituitary adverse events: an observational, retrospective, disproportionality study. *J. Endocrinol. Invest.* 43, 1473–1483. doi: 10.1007/s40618-020-01226-4
- Borghaei, H., Paz-Ares, L., Horn, L., Spigel, D. R., Steins, M., Ready, N. E., et al. (2015). Nivolumab versus docetaxel in advanced nonsquamous non-small-cell lung cancer. *N. Engl. J. Med.* 2015:150927150118000. doi: 10.1056/NEJMoa1507643
- Boyardzisz, M. M., Kirkwood, J. M., Marshall, J. L., Pritchard, C. C., Azad, N.S., and Gulley, J. L. (2018). Significance and implications of FDA approval of

AUTHOR CONTRIBUTIONS

BL designed the current study. GY and QZ analyzed and interpreted the data. BL, YJ, and LL wrote the manuscript. QT supervised the study. All authors read and approved the final version of the manuscript and agreed to be accountable for all aspects of the research in ensuring that the accuracy or integrity of any part of the work are appropriately investigated and resolved.

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SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: <https://www.frontiersin.org/articles/10.3389/fmolb.2020.603701/full#supplementary-material>

Supplementary Figure 1 | (A) Heatmap of the correlation coefficients between ICGs and adaptive immune-resistance pathway genes in the GSE31210 cohort. The abscissa represents the genes of the adaptive immune resistance pathway, and the ordinate represents the ICGs; **(B)** $-\log_{10}$ (*P*-value) is tested for the correlation coefficients between ICGs and adaptive immune-resistance pathway genes. The redder the color, the greater the significance.

Supplementary Figure 2 | (A) The expression patterns of nine ICGs on T stage, N stage and stage. **(B)** Expression heat map of nine ICGs.

Supplementary Figure 3 | The expression distribution of three types of ICG genes in different data sets.

Supplementary Table 1 | Forty seven immune checkpoint genes.

Supplementary Table 2 | Enrollment treatment information of patients in TCGA cohort.

- pembrolizumab for biomarker-defined disease. *J. Immunother. Cancer* 6:35. doi: 10.1186/s40425-018-0342-x
- Cataldo, J. K., Dubey, S., and Prochaska, J. J. (2010). Smoking cessation: an integral part of lung cancer treatment. *Oncology* 78, 289–301. doi: 10.1159/000319937
- Chang, T. H., Lee, Y. M., and Huang, R. S. (2015). The impact of the cancer genome atlas on lung cancer. *Transl. Res.* 166:S1931524415002789. doi: 10.1016/j.trsl.2015.08.001
- Chen, F., Zou, Z., Du, J., Su, S., Shao, J., Meng, F., et al. (2019). Neoantigen identification strategies enable personalized immunotherapy in refractory solid tumors. *J. Clin. Invest.* 5:1295. doi: 10.1172/JCI99538
- Chen, X., Li, X., Liang, H., Wei, L., Cui, Q., Yao, M., et al. (2019). A new *mutL* homolog 1 c.1896+5G>A germline mutation detected in a Lynch syndrome-associated lung and gastric double primary cancer patient. *Mol. Genet. Genom. Med.* 7:e787. doi: 10.1002/mgg3.787

- Choy, J., Chang, Y., and Newsom-Davis, T. (2019). A single centre experience of anti-PDL1 and anti-PDL agents in the treatment of thoracic malignancies[J]. *Lung Cancer*, 127.
- Danilova, L., Ho, W. J., Zhu, Q. F., Vithayathil, T., De Jesus-Acosta, A., Azad, N. S., et al. (2019). Programmed cell death ligand-1 (PD-L1) and CD8 expression profiling identify an immunologic subtype of pancreatic ductal adenocarcinomas with favorable survival. *Cancer Immunol. Res.* 7, 886–895. doi: 10.1158/2326-6066.CIR-18-0822
- Duffy, M. J., and John, C. (2019). Biomarkers for predicting response to immunotherapy with immune checkpoint inhibitors in cancer patients. *Clin. Chem.* 65, 1228–1238. doi: 10.1373/clinchem.2019.303644
- Ergonul, A., Akcam, T., Ozdil, A., Kavurmaci, O., Turhan, K., and Cagirici, U. (2017). PUB126 the retrospective analysis of asymptomatic lung cancer patients diagnosed incidentally. *J. Thoracic Oncol.* 12:S1520. doi: 10.1016/j.jtho.2016.11.2097
- Ferlay, J., Soerjomataram, I., Dikshit, R., Eser, S., Mathers, C., Rebelo, M., et al. (2015). Cancer incidence and mortality worldwide: sources, methods and major patterns in GLOBOCAN 2012. *Int. J. Cancer* 136, E359–E386. doi: 10.1002/ijc.29210
- Galetta, D., Logroschino, A. F., Misino, A., Montagna, E. S., Petrillo, P., Ricci, D., et al. (2017). P3.02c-085 neutrophil/lymphocyte ratio in advanced non-small cell lung cancer: correlation with prognosis and response to anti-PD1 therapy. *J. Thoracic Oncol.* 12, S1329–S1330. doi: 10.1016/j.jtho.2016.11.1881
- Gandara, D. R., Paul, S. M., Kowanetz, M., Schleifman, E., Zou, W., Li, Y., et al. (2018). Blood-based tumor mutational burden as a predictor of clinical benefit in non-small cell lung cancer patients treated with atezolizumab. *Nat. Med.* 24, 1441–1448. doi: 10.1038/s41591-018-0134-3
- Garon, E. B., Rizvi, N. A., Hui, R., Leighl, N., Balmanoukian, A. S., Eder, J. P., et al. (2015). Pembrolizumab for the treatment of non-small-cell lung cancer. *N. Engl. J. Med.* 372, 2018–2028. doi: 10.1056/NEJMoa1501824
- Hanke, M. L. (2016). Lung cancer subtypes generate unique immune responses. *J. Immunol.* 197, 4493–4503. doi: 10.4049/jimmunol.1600576
- Hellmann, M. D., Ciuleanu, T. E., Pluzanski, A., Lee, J. S., Otterson, G. A., Audigier-Valette, C., et al. (2018). Nivolumab plus ipilimumab in lung cancer with a high tumor mutational burden. *N. Engl. J. Med.* 378, 2093–2104. doi: 10.1056/NEJMoa1801946
- Huang, W., Wu, J., Fanucchi, M., Yin, C., and Dimitrova, N. (2019). Using blood-based gene expression profiling to assess responsiveness to immunotherapy of advanced non-small-cell lung cancer. *Cancer Genet.* 233:S8. doi: 10.1016/j.cancergen.2019.04.026
- Jafarnejad, M., Gong, C., Gabrielson, E., Bartelink, I. H., Vicini, P., Wang, B., et al. (2019). A computational model of neoadjuvant PD-1 inhibition in non-small cell lung cancer. *AAPS J.* 21:79. doi: 10.1208/s12248-019-0350-x
- Jia, Q., Wu, W., Wang, Y., Alexander, P. B., Sun, C., Gong, Z., et al. (2018). Local mutational diversity drives intratumoral immune heterogeneity in non-small cell lung cancer. *Nat. Commun.* 9:5361. doi: 10.1038/s41467-018-07767-w
- Kasahara, N., Sunaga, N., Tsukagoshi, Y., Miura, Y., Sakurai, R., Kitahara, S., et al. (2019). Post-treatment glasgow prognostic score predicts efficacy in advanced non-small-cell lung cancer treated with anti-PD1. *Anticancer Res.* 39, 1455–1461. doi: 10.21873/anticancer.13262
- Koster, B. D., Gruijll, T. D. D., and van den Eertwegh, A. J. M. (2015). Recent developments and future challenges in immune checkpoint inhibitory cancer treatme. *Curr. Opin. Oncol.* 27, 482–488. doi: 10.1097/CCO.0000000000000221
- Larsen, B. T., Chae, J. M., Dixit, A. S., Hartman, T., Peikert, T., and Roden, A. (2019). Clinical and histopathologic features of immune checkpoint inhibitor-related pneumonitis. *Am. J. Surg. Pathol.* 43, 1331–1340. doi: 10.1097/PAS.0000000000001298
- Lee, V., and Le, D. T. (2015). Efficacy of PD-1 blockade in tumors with MMR deficiency. *Immunotherapy* 8, 1–3. doi: 10.2217/imt.15.97
- Long, L., Zhao, C., Ozarina, M., Zhao, X., Yang, J., and Chen, H. (2019). Targeting immune checkpoints in lung cancer: current landscape and future prospects. *Clin. Drug Investig.* 39, 341–353. doi: 10.1007/s40261-018-00746-5
- Lou, Y., Asmann, Y., Thomas, M., and Knutson, K. (2017). MA 05.01 integrating INDEL mutations into neoantigen prediction in lung cancer: developing personalized cancer vaccines. *J. Thoracic Oncol.* 12, S1814–S1815. doi: 10.1016/j.jtho.2017.09.478
- Merelli, B., Massi, D., Cattaneo, L., and Mandalà M. (2014). Targeting the PD1/PD-L1 axis in melanoma: biological rationale, clinical challenges and opportunities. *Crit. Rev. Oncol. Hematol.* 89, 140–165. doi: 10.1016/j.critrevonc.2013.08.002
- Nakaoku, T., and Kohno, T. (2017). P3.03-010 identification of mechanisms of drug resistance in RET-rearranged lung cancer. *J. Thoracic Oncol.* 12:S2276. doi: 10.1016/j.jtho.2017.09.1636
- Pan, W., Gong, J., Yang, C., Feng, R., Guo, F., Sun, Y., et al. (2013). Peripheral blood CD40-CD40L expression in human breast cancer. *Ir. J. Med. Sci.* 182, 719–721. doi: 10.1007/s11845-013-0931-0
- Parascandola, M., and Xiao, L. (2019). Tobacco and the lung cancer epidemic in China. *Transl. Lung. Cancer Res.* 8, S21–S30. doi: 10.21037/tlcr.2019.03.012
- Pedersen, J. H., Tønnesen, P., and Ashraf, H. (2016). Smoking cessation and lung cancer screening. *Ann. Transl. Med.* 4:157. doi: 10.21037/atm.2016.03.054
- Penault-Llorca, F., and Radosevic-Robin, N. (2018). Tumor mutational burden in non-small cell lung cancer—the pathologist's point of view. *Transl. Lung Cancer Res.* 7, 716–721. doi: 10.21037/tlcr.2018.09.26
- Ready, N., Hellmann, M. D., Awad, M. M., Otterson, G. A., Gutierrez, M., Gainor, J. F., et al. (2019). First-line nivolumab plus ipilimumab in advanced non-small-cell lung cancer (checkmate 568) : outcomes by programmed death ligand 1 and tumor mutational burden as biomarkers. *J. Clin. Oncol.* 37, 992–1000. doi: 10.1200/JCO.18.01042
- Ru, C. H., and Zhuang, Y. B. (2018). Efficacy and safety of addition of anti-PD1 to chemotherapy in treatment of non-small cell lung cancer. *Comb. Chem. High Throughput Screen* 21, 711–717. doi: 10.2174/1386207322666190125150921
- Sadreddini, S., Baradaran, B., Aghebati-Maleki, A., Sadreddini, S., Shanebandi, D., Fotouhi, A., et al. (2018). Immune checkpoint blockade opens a new way to cancer immunotherapy. *J. Cell. Physiol.* 234, 8541–8549. doi: 10.1002/jcp.27816
- Socinski, M. A., Jotte, R. M., Cappuzzo, F., Orlandi, F., Stroyakovskiy, D., Nogami, N., et al. (2018). Atezolizumab for first-line treatment of metastatic nonsquamous NSCLC. *N. Engl. J. Med.* 378, 2288–2301. doi: 10.1056/NEJMoa1716948
- Song, Q., Shang, J., Yang, Z., Zhang, L., Zhang, C., Chen, J., et al. (2019). Identification of an immune signature predicting prognosis risk of patients in lung adenocarcinoma. *J. Transl. Med.* 3:171. doi: 10.1186/s12967-019-1824-4
- Takada, Y. K., Yu, J., Shimoda, M., and Takada, Y. (2019). Integrin binding to the trimeric interface of CD40L plays a critical role in CD40/CD40L signaling. *J. Immunol.* 203, 1383–1391. doi: 10.4049/jimmunol.1801630
- Tanoue, L. T. (2010). Molecular origins of cancer. Lung cancer. *Yearb. Pulmonary Dis.* 2010, 158–161. doi: 10.1016/S8756-3452(09)79366-1
- Tomczak, K., Czerwińska, P., and Wiznerowicz, M. (2015). Review The Cancer Genome Atlas (TCGA): an immeasurable source of knowledge. *Contemp. Oncol. Współczesna Onkol.* 19, A68–A77. doi: 10.5114/wo.2014.47136
- Turner, M. (2017). NU04.01 management of toxicities associated with immunotherapy in the lung cancer patients. *J. Thoracic Oncol.* 12:S204. doi: 10.1016/j.jtho.2016.11.181
- Wang, C., Sun, W., Wright, G., Wang, A. Z., and Gu, Z. (2017). Inflammation-triggered cancer immunotherapy by programmed delivery of CpG and anti-PD1 antibody. *Adv. Mater.* 28, 8912–8920. doi: 10.1002/adma.201506312
- Wang, X., and Xia, Q. (2019). Identification of four hub genes associated with adrenocortical carcinoma progression by WGCNA. *PeerJ* 7:e6555. doi: 10.7287/peerj.6555v0.2/reviews/5
- Wang, Z., Gerstein, M., and Snyder, M. (2009). RNA-Seq: a revolutionary tool for transcriptomics. *Nat. Rev. Genet.* 10, 57–63. doi: 10.1038/nrg2484
- Xu, M., Wang, D. C., Wang, X., and Zhang, Y. (2016). Correlation between mucin biology and tumor heterogeneity in lung cancer. *Semin. Cell Dev. Biol.* 64, 73–78. doi: 10.1016/j.semcdb.2016.08.027
- Yuan, A., Hsiao, Y. J., Chen, H. Y., Chen, H. W., Ho, C. C., Chen, Y. Y., et al. (2015). Opposite effects of M1 and M2 macrophage subtypes on lung cancer progression. *Sci. Rep* 5:14273. doi: 10.1038/srep14273

- Zhang, G., Wang, H., Zhu, K., Yang, Y., and Liu, Z. (2019). Investigation of candidate molecular biomarkers for expression profile analysis of the gene expression omnibus (GEO) in acute lymphocytic leukemia (ALL). *Biomed. Pharmacother.* 120:109530. doi: 10.1016/j.biopha.2019.109530
- Zhang, Q., Yang, J., Bai, J., and Ren, J. (2018). Reverse of non-small cell lung cancer drug resistance induced by cancer-associated fibroblasts via a paracrine pathway. *Cancer Sci.* 109, 944–955. doi: 10.1111/cas.13520
- Zhu, J., Pabla, S., Labriola, M., Gupta, R., McCall, S., George, D., et al. (2019). Evaluation of tumor microenvironment and biomarkers of immune checkpoint inhibitor (ICI) response in metastatic renal cell carcinoma (mRCC). *J. Clin. Oncol.* 37:607. doi: 10.1200/JCO.2019.37.7_suppl.607

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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