# Smoking alters the evolutionary trajectory of non-small cell lung cancer

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Abstract. Smoking is the biggest risk factor for lung cancer. Smokers have a much higher chance of developing lung tumors with a worse survival rate; however, non-smokers also develop lung tumors. A number of questions remain including the underlying difference between smoker and non-smoker lung cancer patients and the involvement of genetic and epigenetic processes in tumor development. The present study analyzed the mutation data of 100 non-small cell lung cancer (NSCLC) patients, 12 non-smokers, 48 ex-smokers and 40 smokers, from Tracking Non-Small Cell Lung Cancer Evolution through Therapy Consortium. A total of 68 genes exhibited different mutation patterns across non-smokers, ex-smokers and smokers. A number of these 68 genes encode membrane proteins with biological regulation, metabolic process, and response to stimulus functions. For each group of patients, the top 10 most frequently mutated genes were selected and their oncogenetic tree inferred, which reflected how the genes evolve during tumor genesis. By comparing the oncogenetic trees of non-smokers and smokers, it was identified that in non-smokers, the mutation of epidermal growth factor receptor (EGFR) was an early genetic alteration event and EGFR was the key driver, but in smokers, the mutation of titin (TTN) was more important. Based on network analysis, TTN can interact with spectrin  $\alpha$  erythrocytic 1 through calmodulin 2 and troponin C1. These genetic differences during tumorigenesis of non-smoker and smoker lung cancer patients provided novel insights into the effects of smoking on the evolutionary trajectory of non-small cell lung cancer and may prove helpful for targeted therapy of different lung cancer subtypes.

### Introduction

Lung cancer patients make up ~14% of newly diagnosed cancer cases and is the second most widespread cancer worldwide (1). Of those, ~85% are non-small cell lung cancer (NSCLC) (2). Lung cancer not only has high incidence, but also high death rate. It is a huge healthcare and economic burden for both developing and developed countries.

There are many possible factors that may contribute to the genesis of lung cancer (2). Genetics can explain a large proportion of lung cancer occurrence as many single nucleotide polymorphisms have been discovered to be associated with lung cancer susceptibility by genome-wide association studies (3). Environment factors, such as air pollution (4), particulate matter 2.5 (5) and smoking, can facilitate the epigenetic dysfunctions which will interact with genetic changes and trigger tumorgenesis (2,6-9). Cigarette smoke includes over 5,000 compounds (10), such as nicotine, free radicals, benzopyrene, catechols, polonium-210 and heavy metals (11). Many of these compounds are strong carcinogenic chemicals (12), which can interfere with DNA mismatch repair and cause somatic mutations. Cigarette smoking accounts for 87% of lung cancer deaths (13) and is the leading risk factor.

Unfortunately, the genetic mechanisms of smoking leading to lung carcinogenesis are largely unknown and many observations are contradictory (10). For example, benzoapyrene, a carcinogenic chemical from smoke, can induce lung tumors in mice but not in rats (14). On the molecular level, several well-established signaling pathways, such as cyclooxygenase and its derived prostanoids, peroxisome proliferator-activated receptor y and arachidonate 15-lipoxygenase, epidermal growth factor receptor (EGFR) and the P13K/AKT/mTOR and vascular endothelial growth factor-dependent angiogenetic pathway, have been reported to have important roles (10). As a complex systems disease (2), lung cancer dysfunctions are dynamic and the evolution of smoking-induced lung cancer, i.e. the series of genetic events, can elucidate a more realistic picture of tumorigenesis. With the rapid development of next-generation sequencing, the somatic mutations in cancer patients can be more easily identified. Based on somatic mutation data, the evolutionary trajectories of cancer patients can be reconstructed. Caravagna et al (15) developed an algorithm called

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Pipeline for Cancer Inference (PiCnIc) to analyze the colon adenocarcinoma and rectum adenocarcinoma (COAD/READ) somatic mutation data from The Cancer Genome Atlas project. The underlying somatic evolution based on Suppes' probabilistic causation was reconstructed (16) and it was determined that mutations in APC regulator of WNT signaling pathway, KRAS proto-oncogene, and tumor protein p53 were primary events for micro-satellite stable COAD/READ tumors, which was consistent with previous literature. Brown et al (17), performed phylogenetic analysis on whole-exome sequencing and copy number profiling data of primary and metastatic breast cancer samples and inferred the phylogeny of genomic alterations during breast cancer progression. The study utilized the Dollo parsimony method and the branch and bound exhaustive search algorithm described in Felsenstein (18), to reconstruct the phylogenetic tree.

To investigate the genomic alterations triggered by smoking, the present study analyzed the somatic mutations in 100 NSCLC patients. The different genomic alterations amongst non-smokers, ex-smokers and smokers were identified and the most frequent genetic alterations of each smoking subgroup were analyzed to construct oncogenetic trees, which revealed the evolutionary trajectories of smoking NSCLC. The present results provided novel insights into NSCLC development due to smoking and also identified potential intervention targets for treating NSCLC patients.

### Materials and methods

NSCLC somatic mutation dataset. TRAcking Cancer Evolution through therapy (TRACERx) Consortium is a multi-million pound project funded by Cancer Research UK to better understand the genetic risks of lung cancer through exploring the human genome. The present study obtained the somatic mutation data and smoking status data of 100 NSCLC patients from Jamal-Hanjani et al (19). The clinical information of these 100 patients are provided in Table SI. The dataset consists of 12 people who never smoked in their life, 48 people who used to smoke but have quit smoking for >20 years and 40 current smokers or recent ex-smokers. The somatic mutations were annotated to genes. If there were non-synonymous exonic alterations within a gene, this was considered as a mutated gene and it was allocated '1'; otherwise genes were classed as '0'. There were 11,345 genes that were mutated in at least 1 of the 100 NSCLC patients. An 11345x100 matrix was produced where rows denoted genes, the columns were patients and the binary value indicated whether the particular gene was mutated in this patient.

Unlike the TRACERx study by Jamal-Hanjani *et al* (19), which analyzed the intratumor heterogeneity by constructing phylogenetic trees for each patient, the present study was interested in characterizing the general mutation pattern within patient subtypes.

Identifying the mutated genes amongst different smoking status groups. To identify the various mutated genes amongst different smoking status groups, the Fisher's Exact Test (20) was applied for the confusion table of mutation status and smoking status. P<0.05 was considered to indicate statistical significance.

Construction of the evolutionary trajectories for different smoking status groups. How the most frequently mutated genes evolved in different smoking status groups was analyzed using Oncotree (21,22), a widely used method for oncogenetic tree deduction (23).

In an oncogenetic tree model, the evolutionary trajectories of tumor genesis are simplified and the causality between genetic alteration events is assumed to occur sequentially. In addition, the causation of a genetic alteration event by another is independent of other causations.

The Oncotree method involves several steps. First, a set of the most relevant genetic events is selected. For the present study, the top 10 most frequent genetic alterations for each smoking status group were considered as relevant for the progression of the tumor group and therefore were selected to be modeled. Then, each pair of such genetic events was assigned a weight corresponding to the probabilities of joint or individual occurrence. Finally, based on the assigned weights, the optimal oncogenetic tree was inferred as maximum-weight branching (21,22).

The method was applied for the present study using R package Oncotree (http://cran.r-project.org/web/pack-ages/Oncotree/).

Annotation of the biological function of the mutated genes. WebGestalt was used to annotate the biological function of the mutated genes (24). WebGestalt is a widely used online enrichment tool to model organisms including human, mouse, rat, yeast, fruit fly and *Caenorhabditis elegans*. It has many annotation databases integrated, including Kyoto Encyclopedia of Genes and Genomes, Gene Ontology, DrugBank and Online Mendelian Inheritance in Man. The P-value of overrepresentation enrichment analysis was multiple test-adjusted as the false discovery rate (FDR). In the present study, the enriched categories with FDR<0.2 were considered as significant.

#### **Results and Discussion**

A total of 68 genes demonstrate different mutation patterns amongst smoking status groups. Fisher's exact test was used to identify the different mutated genes amongst the various smoking status groups. A total of 68 gene mutations were considered as significant to smoking status (P<0.05; Table I). The OncoPrinter plots of these 68 genes in the three different smoking status groups, non-smoker, ex-smoker and smoker, are displayed in Fig. 1. The genes were ranked based on the mutation frequency in all lung cancer patients. Zinc finger homeobox 4 (ZFHX4), usherin (USH2A), CUB and Sushi multiple domains 1 (CSMD1), CUB and Sushi multiple domains 2 (CSMD2), spectrin α erythrocytic 1 (SPTA1), pappalysin 2 (PAPPA2), dynein axonemal heavy chain 9 (DNAH9), contactin-associated protein like 5 (CNTNAP5), additional sex combs like 3 (ASXL3) were highly mutated in ex-smokers and smokers, but not in non-smokers. The mutation rate was associated the smoking status with the current smokers demonstrating the highest rate of mutated genes. There were several non-smoker specific mutations, such as lysine demethylase 8 (KDM8), zinc finger protein 677 (ZNF677), TEA domain transcription factor 1 (TEAD1) and phosphatidylinositol glycan anchor biosynthesis class M (PIGM). These non-smoker

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Table L A total of 68	genes that demonstrated	different mutation n	hatterns amonost non-sr	nokers ex_smokers and	smokers
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Gene symbol	Gene name	NCBI gene ID	Fisher's exact test P-value
		1056	0.00052
EGFK	Epidermal growin factor receptor	1930	0.00032
	Tituli Zina finaar hamaahay 4	70776	0.00071
	Linc higer homeobox 4	7300	0.00433
USHZA SDTA 1	Spectrin a crythropytic 1	6708	0.00349
SF IAI TDDV6	Transient recenter potential estion channel subfemily V member 6	55503	0.00733
IRPV0	SEC16 homolog A and an learning ration hum ownert factor	0010	0.00988
SECTOA SCN1A	SEC to homolog A, endoptastinc renculum export factor	9919 6222	0.00988
SUNIA ZNE477	Zing finger protein 677	0323	0.01210
	TEA domain transmintion factor 1	342920	0.01333
DICM	TEA domain transcription factor f	7003	0.01333
PIGM EDC5	Fotopia D. groupulas autophagy protain 5 homelas	93183 57724	0.01333
EPG3	Ectopic P-granules autophagy protein 5 nomolog	57724	0.01427
TENM3	Olf the second for the formation of the December 1	55714	0.01482
UKOP1	Diractory receptor family 6 subfamily P member 1	128300	0.01494
PAPPA2	Pappalysin 2 $72$	00070	0.01743
ZNF/83	Zinc finger family member 783	100289678	0.01769
CINNBI CDATA 12	Catenin ß I	1499	0.01769
SPAIA13	Spermatogenesis associated 13	221178	0.01769
HIPI	Huntingtin interacting protein 1	3092	0.01769
SENP/	SUMOI/sentrin specific peptidase /	57337	0.01769
PCDHGA8	Protocadherin γ subfamily A, 8	9708	0.01769
SNPH	Syntaphilin	9751	0.01769
ENPEP	Glutamyl aminopeptidase	2028	0.01819
KCNH2	Potassium voltage-gated channel subfamily H member 2	3757	0.01819
NLGN3	Neuroligin 3	54413	0.01819
MS4A14	Membrane spanning 4-domains A14	84689	0.01819
DEPDC5	DEP domain containing 5	9681	0.01819
SMARCA4	SWI/SNF related, matrix associated, actin dependent regulator of	6597	0.02044
INOT	chromatin, subfamily a, member 4	1120	0.00157
LYSI	Lysosomal trafficking regulator	1130	0.02157
CNTN4	Contactin 4	152330	0.02157
ZNF536	Zinc finger protein 536	9745	0.02420
CNTNAP5	Contactin associated protein like 5	129684	0.02459
ASXL3	Additional sex combs like 3, transcriptional regulator	80816	0.02459
DNAH9	Dynein axonemal heavy chain 9	1770	0.02568
CNGA2	Cyclic nucleotide gated channel $\alpha$ 2	1260	0.02841
KCNH5	Potassium voltage-gated channel subfamily H member 5	27133	0.02841
ZEB2	Zinc finger E-box binding homeobox 2	9839	0.02841
PHLPP2	PH domain and leucine rich repeat protein phosphatase 2	23035	0.02918
GLI2	GLI family zinc finger 2	2736	0.02918
GPR35	G protein-coupled receptor 35	2859	0.02918
ATP13A5	Atpase 13A5	344905	0.02918
MYF5	Myogenic factor 5	4617	0.02918
PCDHGB7	Protocadherin $\gamma$ subfamily B, 7	56099	0.02918
WBSCR17	Williams-Beuren syndrome chromosome region 17	64409	0.02918
BAZ1B	Bromodomain adjacent to zinc finger domain 1B	9031	0.02918
COL6A5	Collagen type VI $\alpha$ 5 chain	256076	0.03141
CSMD1	CUB and Sushi multiple domains 1	64478	0.03183
RYR2	Ryanodine receptor 2	6262	0.03217
TSHZ3	Teashirt zinc finger homeobox 3	57616	0.03459
KDM8	Lysine demethylase 8	79831	0.03728

Gene symbol	Gene name	NCBI gene ID	Fisher's exact test P-value
NALCN	Sodium leak channel, non-selective	259232	0.03732
MALRD1	MAM and LDL receptor class A domain containing 1	340895	0.03732
DOCK10	Dedicator of cytokinesis 10	55619	0.03732
DNAH11	Dynein axonemal heavy chain 11	8701	0.03857
TAF1L	TATA-box binding protein associated factor 1 like	138474	0.04006
PRUNE2	Prune homolog 2	158471	0.04006
PLCH1	Phospholipase C eta 1	23007	0.04006
KIAA1549L	KIAA1549 like	25758	0.04006
RPTOR	Regulatory associated protein of MTOR complex 1	57521	0.04165
CSMD2	CUB and Sushi multiple domains 2	114784	0.04312
CDH23	Cadherin related 23	64072	0.04357
KIAA1324L	KIAA1324 like	222223	0.04374
NUP205	Nucleoporin 205	23165	0.04374
TBC1D4	TBC1 domain family member 4	9882	0.04374
FLNC	Filamin C	2318	0.04717
CHD7	Chromodomain helicase DNA binding protein 7	55636	0.04717
DNAH17	Dynein axonemal heavy chain 17	8632	0.04717

NCBI, National Center for Biotechnology; ID, identification.



Figure 1. OncoPrinter plot of the 68 mutated genes in non-smokers, ex-smokers and smokers. The genes were ranked by the mutation frequency in all lung cancer patients. ZFHX4, USH2A, CSMD1, CSMD2, SPTA1, PAPPA2, DNAH9, CNTNAP5 and ASXL3 were highly mutated in ex-smokers and smokers but not in non-smokers. Smokers had the highest rate of mutated genes, with smoking status directly correlated with number of mutations. KDM8, ZNF677, TEAD1 and PIGM were non-smoker specific mutations. The different mutation patterns suggested the tumor genesis of non-smoker lung cancer patients was different from the tumor genesis of smoking lung cancer patients. ZFHX4, zinc finger homeobox 4; USH2A, usherin; CSMD1, CUB and Sushi multiple domains 1; CSMD2, CUB and Sushi multiple domains 2; SPTA1, spectrin α erythrocytic 1; PAPPA2, pappalysin 2; DNAH9, dynein axonemal heavy chain 9; CNTNAP5, contactin-associated protein like 5; ASXL3, additional sex combs like 3; KDM8, lysine demethylase 8; ZNF677, zinc finger protein 677; TEAD1, TEA domain transcription factor 1; PIGM, phosphatidylinositol glycan anchor biosynthesis class M.



Figure 2. GO analysis for biological process, cellular component and molecular function categories of the 68 mutated genes associated with smoking status. GO, Gene Ontology.

specific mutations suggested that tumorigenesis of lung cancer in non-smoker patients was different from the tumorigenesis of lung cancer in smoking patients.

Biological functions of the 68 gene mutations associated with smoking status. The 68 gene mutations associated with smoking status were annotated using Gene Ontology (GO) and the biological process (BP), cellular component (CC) and molecular function (MF) categories (Fig. 2). Numerous genes were annotated to be membrane proteins with biological regulation, metabolic process, and response to stimulus functions (Fig. 2). These results were expected since smoke is a xenobiotic stimulus to the human body and the chemicals can affect normal metabolic processes, and alter the biological regulations. Rigorous statistical test for the enrichment significance using WebGestalt was performed for deeper investigation into gene function (24) with significantly enriched BP (Table II), CC (Table III) and MF (Table IV) categories. It was demonstrated that the organ development, morphogenesis of an epithelial fold, muscle tissue morphogenesis and the muscle organ morphogenesis categories were enriched (Table II). These genes may serve an important role in tumor initiation and help transform the normal lung tissue to tumor tissue. Proteins associated with the plasma membrane were enriched (Table III), which was consistent with the preliminary biological function analysis (Fig. 2), and indicated that the mutated genes were involved in stimulus response. In addition, enrichment of proteins associated with muscle/fiber functions suggested that the mutated genes may change the lung muscle structure. Significant enrichment of multiple binding functions proved that the mutated genes were key players in signaling transduction and regulation (Table IV), which may amplify the dysfunctions and accelerate tumorigenesis.

Evolutionary trajectories of non-smoker, ex-smoker and smoker lung cancer patients. Cancer is a complex multigene and multiprocess disease. The tumorigenesis of colorectal cancer is well studied (25,26) and can be used as a perfect example to explain the roles of mutations in causing pathway dysfunctions. The process includes several steps (25): i) Mutation of mismatch-repair (MMR) gene; ii) microsatellite instability (MSI) pathway dysfunction caused by MMR mutation; iii) normal epithelium becomes small adenoma; iv) chromosomal instability and mutations in KRAS and BRAF; v) serrated adenoma pathway dysfunction triggered by BRAF mutation; vi) small adenoma becomes large adenoma; and vii) mutations of PIK3CA, PTEN, tumor protein p53 (TP53), BAX, SMAD4 and transforming growth factor  $\beta$  receptor 2 accelerate the progression from large adenoma to cancer.

Similarly, lung cancer must also have several mutational events, which occur sequentially to initiate and accelerate tumorigenesis. Smoking is a major risk factor that can cause genetic and epigenetic changes that alter the tumorigenesis procedures. Research into this process will help explain the mechanism differences between smoker and non-smoker lung cancer patients.

The Oncotree method was used to produce oncogenetic trees of the top 10 most frequent mutated genes in non-smoker, ex-smoker and smoker lung cancer patients (Fig. 3). For non-smokers, the early events were EGFR and titin (TTN) mutation. The late EGFR events were mutations of PIGM and zinc finger protein 677, while TTN was followed by mutations of TEAD1, olfactory receptor family 6 subfamily P member 1, catenin  $\beta$  1, huntingtin interacting protein 1, protocadherin  $\gamma$  subfamily A 8 and SUMO1/sentrin specific peptidase 7. For ex-smokers, TTN was also an early event but more early events were detected compared with non-smokers, including

GO ID	Description	P-value	FDR	Overlap genes
GO:0007423	Sensory organ development	4.48x10 <sup>-5</sup>	0.1801	CTNNB1, EGFR, GLI2, MYF5, CHD7, TENM3, CDH23, SMARCA4, USH2A, ZEB2
GO:0098655	Cation transmembrane transport	0.0001085	0.1801	CNGA2, NALCN, KCNH5, GPR35, ATP13A5, KCNH2, NLGN3, TRPV6, CHD7, RYR2, SCN1A
GO:0034765	Regulation of ion transmembrane transport	0.0001252	0.1801	NALCN, KCNH5, GPR35, KCNH2, NLGN3, CHD7, RYR2, SCN1A
GO:0042391	Regulation of membrane potential	0.0001286	0.1801	CNGA2, NALCN, KCNH5, GPR35, KCNH2, NLGN3, RYR2, SCN1A
GO:0034762	Regulation of transmembrane transport	0.0001394	0.1801	NALCN, KCNH5, GPR35, KCNH2, NLGN3, CHD7, RYR2, SCN1A
GO:0006812	Cation transport	0.0001504	0.1801	CNGA2, CTNNB1, NALCN, KCNH5, GPR35, ATP13A5, KCNH2, NLGN3, TRPV6, CHD7, RYR2, SCN1A, CDH23
GO:0060571	Morphogenesis of an epithelial fold	0.0002124	0.1974	CTNNB1, EGFR, GLI2
GO:0043010	Camera-type eye development	0.0002382	0.1974	CTNNB1, EGFR, MYF5, CHD7, TENM3, SMARCA4, ZEB2
GO:0060415	Muscle tissue morphogenesis	0.0002664	0.1974	MYF5, CHD7, RYR2, TTN
GO:0048644	Muscle organ morphogenesis	0.0002865	0.1974	MYF5, CHD7, RYR2, TTN
GO:0001508	Action potential	0.0003213	0.1974	NALCN, GPR35, KCNH2, RYR2, SCN1A
GO:0030001	Metal ion transport	0.0003543	0.1974	CNGA2, CTNNB1, NALCN, KCNH5, GPR35, KCNH2, TRPV6, CHD7, RYR2, SCN1A, CDH23
GO:0043269	Regulation of ion transport	0.0003573	0.1974	CTNNB1, NALCN, KCNH5, GPR35, KCNH2, NLGN3, CHD7, RYR2, SCN1A
				NLGN3, CHD/, KYK2, SCN1A

Table II. Significantly enriched GO biological process categories of the 68 mutated genes associated with smoking status.

GO, Gene Ontology; ID, identification; FDR, false discovery rate.

mutations of ryanodine receptor 2, ZFHX4 and CSMD1. For smokers, the results revealed the highest number of early events, including mutations of TTN, ryanodine receptor 2, USH2A, SPTA1 and CSMD1. Results demonstrated that smoking increased spontaneous mutations and formed more complex oncogenetic trees. For non-smokers, EGFR was the primary mutation whilst in ex-smokers and smokers, the importance of TTN was increased. Almost all smokers had the TTN mutation.

Oncogenetic differences between non-smoker, ex-smoker and smoker lung cancer patients. Based on the oncogenetic trees of non-smoker, ex-smoker and smoker lung cancer patients (Fig. 3), the key driver gene of non-smoker lung cancer patients was EGFR, whilst the key driver gene of smoker lung cancer patients was TTN.

EGFR is a well-known oncogene that affects the PI3K and RAS pathway and accelerates cell growth and survival (27). EGFR is widely expressed in >60% of NSCLC patients and is a clinically relevant target of tyrosine kinase inhibitors (TKIs). EGFR mutations are more frequent in Asians, females, non-smokers and lung adenocarcinomas (28,29). The present findings determined that EGFR was the key driver gene of non-smoker lung cancer patients which was in agreement with the literature (28,29).

TTN encodes a protein of striated muscle and is the key component for striated muscle assembly and function. TTN mutation is very frequent in the majority of cancer types with the second highest mutation rate behind TP53 in The Cancer Genome Atlas dataset (30). In the present study, 65 patients had the TTN mutation and 35 patients did not. For the 65 patients with TTN mutation, there were 2 adenosquamous carcinoma, 2 carcinosarcoma, 31 invasive adenocarcinoma, 1 large cell carcinoma and 29 squamous cell carcinoma patients. For the 35 patients without TTN mutations, there were 1 adenosquamous carcinoma, 30 invasive adenocarcinoma, 1 large cell neuroendocrine and 3 squamous cell carcinoma patients. Although its mechanisms remain largely unknown, TTN has great potential for investigation due to its roles in tumorigenesis and progression (30). The present study determined that TTN may function through regulating DNAH9, USH2A, SPTA1 or CSMD2 based on the oncogenetic trees (Fig. 3). Although the oncogenetic tree only demonstrated the process of genetic alteration occurrence, it provided hints of functional regulations; however, this needs to be further confirmed. To explore the possible regulation mechanisms of TTN, the

GO ID	Description	P-value	FDR	Overlap genes
GO:0030018	Z disc	4.49x10 <sup>-5</sup>	0.0294	CTNNB1, FLNC, RYR2, SCN1A, TTN
GO:0031674	I band	6.91E-05	0.0294	CTNNB1, FLNC, RYR2, SCN1A, TTN
GO:0044459	Plasma membrane part	0.000105	0.0297	CNGA2, CTNNB1, EGFR, ENPEP, SPATA13, PHLPP2, KCNH5, GPR35, HIP1, ATP13A5, KCNH2, NLGN3, TRPV6, TENM3, PCDHGB7, SCN1A, SPTA1, USH2A, PCDHGA8, SNPH
GO:0030017	Sarcomere	0.00029	0.0572	CTNNB1, FLNC, RYR2, SCN1A, TTN
GO:0042995	Cell projection	0.000359	0.0572	CNGA2, CTNNB1, CNTN4, DNAH9, SPATA13, PHLPP2, GLI2, TENM3, RPTOR, TSHZ3, CDH23, SPTA1, USH2A, DNAH11, SNPH
GO:0044449	Contractile fiber part	0.000456	0.0572	CTNNB1, FLNC, RYR2, SCN1A, TTN
GO:0030016	Myofibril	0.000471	0.0572	CTNNB1, FLNC, RYR2, SCN1A, TTN
GO:0043292	Contractile fiber	0.000588	0.0625	CTNNB1, FLNC, RYR2, SCN1A, TTN
GO:0030122	AP-2 adaptor complex	0.000942	0.0801	EGFR, HIP1
GO:0030128	Clathrin coat of endocytic vesicle	0.000942	0.0801	EGFR, HIP1
GO:0098590	Plasma membrane region	0.001172	0.0906	CNGA2, CTNNB1, EGFR, ENPEP, SPATA13, PHLPP2, HIP1, NLGN3, USH2A, SNPH
GO:0030132	Clathrin coat of coated pit	0.001618	0.1146	EGFR, HIP1
GO:0097458	Neuron part	0.002216	0.1449	CNTN4, PHLPP2, HIP1, TENM3, RPTOR, TSHZ3, CDH23, SMARCA4, SPTA1, USH2A, SNPH
GO:0090575	RNA polymerase II transcription factor complex	0.002476	0.1478	TAF1L, CTNNB1, MYF5
GO:0005929	Cilium	0.003008	0.1478	CNGA2, DNAH9, PHLPP2, GLI2, USH2A, DNAH11
GO:0043234	Protein complex	0.003037	0.1478	TAF1L, CTNNB1, DNAH9, EGFR, NUP205, COL6A5, HIP1, MYF5, RPTOR, RYR2, SMARCA4, TEAD1, TTN, USH2A, DNAH11, DEPDC5
GO:0030125	Clathrin vesicle coat	0.003127	0.1478	EGFR, HIP1
GO:0031226	Intrinsic component of plasma membrane	0.003156	0.1478	CNGA2, ENPEP, KCNH5, GPR35, ATP13A5, KCNH2, NLGN3, TRPV6, TENM3, PCDHGB7, SCN1A, SPTA1, PCDHGA8
GO:0031253	Cell projection membrane	0.003305	0.1478	CNGA2, CTNNB1, SPATA13, PHLPP2, USH2A
GO:0098858	Actin-based cell projection	0.003565	0.1515	CTNNB1, SPATA13, CDH23, USH2A
GO:0030131	Clathrin adaptor complex	0.004254	0.1718	EGFR, HIP1
GO:0031090	Organelle membrane	0.004448	0.1718	CNGA2, EGFR, ENPEP, PHLPP2, NUP205, HIP1, MALRD1, RPTOR, RYR2, WBSCR17, DEPDC5, SNPH, TBC1D4, SEC16A
GO:0044441	Ciliary part	0.004724	0.1746	CNGA2, DNAH9, PHLPP2, GLI2, USH2A
GO:0044798	Nuclear transcription factor complex	0.005127	0.1816	TAF1L, CTNNB1, MYF5

Table III. Significantly enriched GO cellular component categories of the 68 mutated genes associated with smoking status.

GO, Gene Ontology; ID, identification; FDR, false discovery rate.

GO ID	Description	P-value	FDR	Overlap genes
GO:0044877	Macromolecular complex binding	2.18x10 <sup>-5</sup>	0.0308	CTNNB1, EGFR, FLNC, GLI2, HIP1, CHD7, RPTOR, TSHZ3, SMARCA4, SPTA1, TTN, USH2A, KDM8, BAZ1B, DEPDC5
GO:0070577	Lysine-acetylated histone binding	5.57E-05	0.0393	TAF1L, SMARCA4, BAZ1B
GO:0005516	Calmodulin binding	9.33E-05	0.0418	CNGA2, EGFR, KCNH5, TRPV6, RYR2, TTN
GO:0051015	Actin filament binding	0.000118	0.0418	EGFR, FLNC, HIP1, SPTA1, TTN
GO:0005261	Cation channel activity	0.000273	0.0742	CNGA2, NALCN, KCNH5, KCNH2, TRPV6, RYR2, SCN1A
GO:0003682	Chromatin binding	0.0004	0.0742	CTNNB1, EGFR, GLI2, CHD7, TSHZ3, SMARCA4, KDM8, BAZ1B
GO:0000155	Phosphorelay sensor kinase activity	0.000443	0.0742	KCNH5, KCNH2
GO:0004673	Protein histidine kinase activity	0.000443	0.0742	KCNH5, KCNH2
GO:0046982	Protein heterodimerization activity	0.000472	0.0742	CTNNB1, EGFR, KCNH5, HIP1, MYF5, TENM3, SPTA1
GO:0005244	Voltage-gated ion channel activity	0.000918	0.118	CNGA2, NALCN, KCNH5, KCNH2, SCN1A
GO:0022832	Voltage-gated channel activity	0.000918	0.118	CNGA2, NALCN, KCNH5, KCNH2, SCN1A
GO:0016775	Phosphotransferase activity, nitrogenous group as acceptor	0.001053	0.1241	KCNH5, KCNH2
GO:0005216	Ion channel activity	0.001884	0.1874	CNGA2, NALCN, KCNH5, KCNH2, TRPV6, RYR2, SCN1A
GO:0046873	Metal ion transmembrane transporter activity	0.001917	0.1874	CNGA2, NALCN, KCNH5, KCNH2, TRPV6, RYR2, SCN1A
GO:0001159	Core promoter proximal region DNA binding	0.001988	0.1874	GLI2, MYF5, CHD7, SMARCA4, TEAD1, ZNF536
GO:0022838	Substrate-specific channel activity	0.002202	0.1896	CNGA2, NALCN, KCNH5, KCNH2, TRPV6, RYR2, SCN1A
GO:0008324	Cation transmembrane transporter activity	0.002279	0.1896	CNGA2, NALCN, KCNH5, ATP13A5, KCNH2, TRPV6, RYR2, SCN1A
GO:0022836	Gated channel activity	0.002541	0.1903	CNGA2, NALCN, KCNH5, KCNH2, RYR2, SCN1A
GO:0032403	Protein complex binding	0.002557	0.1903	EGFR, FLNC, HIP1, RPTOR, SPTA1, TTN, USH2A, DEPDC5

Table IV. Significantly enriched GO	molecular function catego	ries of the 68 mutated s	genes associated with	smoking status.

GO, Gene Untology; ID, identification; FDR, false discovery rate.

protein functional association network STRING (31,32) was used with medium confidence (>0.4). It was determined that TTN can interact with SPTA1 through calmodulin 2 (CALM2) and troponin C1 (TNNC1; Fig. 4). The STRING confidence scores of each interaction (Table SII) were 0.722 for TTN and CALM2, 0.962 for SPTA1 and CALM2, 0.965 for TTN and TNNC1 and 0.537 for SPTA1 and TNNC1. These results provided insight into how TTN may function in lung cancer of smoking patients, or even other types of cancer.

There were limitations to the oncogenetic tree model. Firstly, the model was based on association rather than causality and the results could not be treated as actual biological regulations, therefore these should be further investigated with experimental methods. Secondly, the oncogenetic tree model cannot handle a large number of genes. The input genes should be carefully picked based on mutation frequency or biological literature with only the highly possible genes analyzed. It is not a general method that can be applied on a genome wide scale. Finally, the sample size should be large enough to capture the association so results generated on small datasets need to be interpreted with caution.

In conclusion, lung cancer is a complex multigene, multiprocess disease with complex genetic and environmental



Figure 3. Oncogenetic trees of the top 10 most frequent mutated genes in non-smoker, ex-smoker and smoker lung cancer patients. (A) Oncogenetic tree for non-smoker lung cancer patients. (C) Oncogenetic tree for smoker lung cancer patients.



Figure 4. STRING network of TTN and SPTA1. TTN can interact with SPTA1 through CALM2 and TNNC1. TTN, titin; SPTA1, spectrin  $\alpha$  erythrocytic 1; CALM2, calmodulin 2; TNNC1, troponin C1; SPTB, spectrin  $\beta$  erythrocyctic; ANK1, ankyrin 1; DES, desmin; TNNI3, troponin I3; ACTN2, actinin  $\alpha$  2; NEB, nebulin; MYL2, myosin light chain 2; TCAP, titin-cap.

risk factors. Smoking is the biggest risk factor that can alter the genetics and epigenetics of lung tissue causing cancer. Smokers have a much greater chance of developing lung cancer. The present study compared the mutation patterns of non-smoker, ex-smoker and smoker lung cancer patients and identified 68 genes that were significantly differentially mutated amongst smoking status groups. Furthermore, oncogenetic trees were constructed of the top 10 most frequently mutated genes in each group and analyzed. It was identified that in non-smoker lung cancer patients, the key driver gene was EGFR, whilst in smoker lung cancer patients the key driver gene was TTN. The EGFR mutation finding in non-smokers is in line with previous literature. A potential mechanism for the high frequency mutated gene TTN in tumorigenesis was suggested. The present study provided novel insights into the effect of smoking on altering the evolutionary trajectory of lung cancer and its progression.

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#### Availability of data and materials

The datasets generated and/or analyzed during the present study are available from the corresponding author on reasonable request.

#### **Authors' contributions**

FMZ designed the experiment and XJY performed the experiment. GC, JY, GCY and PFZ analyzed the data and performed data analysis. ZKJ, KF, YL and BB contributed to the study design. KF and YL wrote the article. ZKJ and BB revised the article. All authors read and approved the final manuscript.

#### Ethics approval and consent to participate

Not applicable.

#### Patient consent for publication

Not applicable.

### **Competing interests**

The authors declare that they have no competing interests.

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