COMPUTATIONAL ONCOLOGY

Circulating cell-free DNA size distribution as a prediction marker for early progression undergoing immune checkpoint inhibitors Linh Nguyen Phuong^{1,2}, Frédéric Fina³, Laurent Greillier^{1,2,4}, Caroline Gaudy-Marqueste^{2,4,5,6}, Jean-Laurent Deville^{2,4}, Audrey

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of circulating cell-free DNA

originating from tumor cells.

BACKGROUND

Despite a significant proportion (20 to 40%)¹ of advanced cancer patients having long-term response to treatment with immune checkpoint inhibitors, many of them do not respond and experience early progression, defined as progression at the first imaging evaluation. Establishing reliable and early predictive biological markers for guiding clinical practice is essential. Analysis of circulating cell-free DNA (cfDNA) fragments size distribution profiles (fragmentome)² offers a promising non-invasive method for assessing treatment response independently of a specific molecular target, cancer type, and treatment.

STUDY

SCHISM (Size CfDNA Immunotherapies Signature Monitoring): clinical study proposing an innovative approach based on patented, standardized cfDNA quantification methods (provided by ID-Solutions and Adelis), providing size profiles fluctuations of plasmatic cfDNA.

OBJECTIVE

To model real-time variations in cfDNA size profile to early predict response and survival following immunotherapy for five cancer types, to early adjust therapeutic strategy and prevent ICI-related progression or toxicity.

DATA



CfDNA size profiles quantified before each immunotherapy infusion, from which 11 cfDNA metrics are extracted



• Clinical and biological data, at baseline and during treatment





METHODS

Classification and survival analyses at baseline		Longitudinal modeling			
 Statistical analysis Boxplots and barplots Logistic regression Student t-test or Chi-2 test 	 Survival analysis Kaplan-Meier estimator Proportional hazard Cox regression Log-rank test 	• Empirical longitudinal Constant	modeling Linear	Hyperbolic e^{l} e^{l}	Double-exponential



RESULTS

Results at baseline

[Classification analysis					Survival analysis					
	AUC	NA	OR uv	Signif UV	OR mv	Signif MV	C Index	HR uv	Signif UV	HR mv	Signif MV
Relative concentration of cfDNA (> 1650 bp)	0.691	0.0%	0.41 (0.25 - 0.67)	***	0.48 (0.28 - 0.83)	**	0.667	0.49 (0.36 - 0.69)	****	0.55 (0.40 - 0.77)	***
Second peak	0.649	0.0%	0.49 (0.32 - 0.76)	**	0.52 (0.31 - 0.87)	*	0.639	0.59 (0.46 - 0.75)	****	0.67 (0.52 - 0.87)	**
Relative concentration of cfDNA (580 - 1650 bp)	0.621	0.0%	0.57 (0.37 - 0.86)	**	0.69 (0.43 - 1.1)	n.s.	0.608	0.61 (0.46 - 0.82)	***	0.70 (0.53 - 0.94)	*
Age	0.512	0.0%	0.93 (0.66 - 1.32)	n.s.	0.78 (0.53 - 1.17)	n.s.	0.505	1 (0.79 - 1.26)	n.s.	0.97 (0.76 - 1.24)	n.s.
LDH	0.359	36.7%	3.3 (1.01 - 10.7)	*	6.34 (1.43 - 28.1)	*	0.593	1.27 (1.04 - 1.54)	*	1.11 (0.91 - 1.35)	n.s.
Ratio neutrophiles/lymphocyte	0.342	18.0%	2.46 (1.47 - 4.1)	***	2.08 (1.16 - 3.72)	*	0.627	1.63 (1.32 - 2)	****	1.23 (0.94 - 1.6)	n.s.





Early progression

Early progression

No early progression

── OVER_1650 = low ── OVER_1650 = high PEAK2 = low 🛨 PEAK2 = high

Longitudinal results

10/11 of the cfDNA metrics showed significant kinetics over time.





1. Sharma P, Hu-Lieskovan S, Wargo JA, Ribas A. Primary, Adaptive, and Acquired Resistance to Cancer Immunotherapy. Cell. 2017;168(4):707-723. doi:10.1016/j.cell.2017.01.017

2. Qi T, Pan M, Shi H, Wang L, Bai Y, Ge Q. Cell-Free DNA Fragmentomics: The Novel Promising Biomarker. Int J Mol Sci. 2023;24(2):1503. doi:10.3390/ijms24021503

FUTURE PERSPECTIVES

Refine population modeling

> Search for clinical covariates associated with model-derived parameters

Mechanistic modeling of the joint tumor kinetics and longitudinal cfDNA

metrics, by integrating biological assumptions on the cfDNA release process

Predict early progression

> From early on-treatment metrics through Bayesian estimation

> Using machine learning to combine multiple metrics into an integrative

algorithm

