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Article

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36 Abstract

Despite the efficacy of natalizumab in Multiple Sclerosis (MS) treatment, approximately 30% 37 of patients do not respond favorably. Individual heterogeneity of T-cell response to VLA-4 38 natalizumab-mediated blockade may underlie disparities in treatment efficacy. Here, a high-39 content cell imaging (HCI) pipeline was implemented to profile the in vitro effects of 40 natalizumab on VLA-4-stimulated leukocytes from MS patients prior to treatment. 41 Unsupervised clustering of image data partially discriminated non-responder MS patients based 42 on morphology, F-actin organization, and signaling-related features in CD8⁺ T cells. Treatment 43 response was assessed through a Random Forest approach with predictive performance of 91% 44 for a discovery cohort and 70% for a validation cohort. Unfavorable treatment response was 45 46 associated with the inefficacy of natalizumab to impair the ability of pretreated CD8⁺ T cells to spread over VCAM-1. Our study unveils that CD8⁺ T cells from individual MS patients display 47 heterogeneous susceptibility to natalizumab in vitro and highlights the potential of HCI-based 48 pretreatment monitoring to assist individualized treatment prescription. 49

50

51 Keywords

- 52 Multiple sclerosis; T cells; VLA-4; natalizumab; high-content cell imaging; pretreatment
- 53 testing of drug efficacy

54 Introduction

Very Late Antigen-4 (VLA-4) is a heterodimeric integrin composed by the α 4 and β 1 subunits 55 ¹. VLA-4 mediates adhesion, transmigration and intra-tissue trafficking of immune cells, 56 including T cells, by interacting with Vascular Cell Adhesion Molecule-1 (VCAM-1) and 57 fibronectin². In addition, this integrin is involved in T-cell immune synapse (IS) assembly³ 58 and activation ^{4,5}. Because of its pivotal role in multiple aspects of T-cell biology, VLA-4 also 59 contributes to mediate dysregulated T-cell responses, such as those underlying inflammatory 60 diseases ⁶. This integrin has been particularly studied in the context of multiple sclerosis (MS), 61 in which lymphocytes overexpress VLA-4 on their surface ⁷ facilitating transmigration to the 62 central nervous system (CNS)^{8–10}. The identification of this mechanism has been the rationale 63 for targeting VLA-4 as a therapeutic approach to treat MS^{11,12}. 64

The humanized anti-α4 monoclonal antibody natalizumab, which blocks VLA-4-VCAM-1 65 interaction, is currently used to treat relapsing-remitting MS (RRMS) patients ^{13,14} This 66 therapeutic antibody acts primarily by reducing the homing of pathogenic lymphocytes and 67 activated monocytes to the CNS¹⁵. The NEDA end point (no evidence of disease activity) is 68 commonly used to define controlled MS¹⁶. Currently, 30% of RRMS patients treated with 69 70 natalizumab present evidence of disease activity ¹⁷, not satisfactorily responding to the 71 treatment according to the NEDA criteria. VLA-4 expression on Peripheral Blood Mononuclear Cells (PBMCs)¹⁸, serum levels of IgM specific for phosphatidylcholine¹⁹, metalloproteinases 72 ²⁰, low percentage of CD5⁺ B cells ²¹, age at prescription and disease duration ²² have been 73 pointed as biological parameters related to natalizumab clinical response, although their 74 robustness as predictive biomarkers remains to be established. To date, we therefore lack a 75 76 pretreatment test to predict whether a given person with MS might benefit from the therapy. This would be particularly relevant to avoid exposing unresponsive patients to potential risks, 77 such as the JC virus-associated Progressive Multifocal Leukoencephalopathy (PML)²³, and to 78 tailor treatment decision toward other available therapeutic lines. In this context, we reasoned 79 that profiling the in vitro response to natalizumab of leukocytes from MS patients might predict 80 81 treatment response and therefore assist treatment decision.

For this purpose, we opted for a high-content cell imaging (HCI) approach to monitor the *in vitro* effect of natalizumab on PBMCs from persons with MS prior to treatment. This approach allows to extract precise morphological and molecular metrics pertaining to leukocyte adhesion ²⁴. Because of its deep phenotyping power, it is also particularly prone to discriminate subtle 86 donor-specific traits that may relate to individual health status ²⁵ and responsiveness to therapies

 26 . We first implemented the approach on healthy donor PBMCs and then applied it to MS

- 88 patients' PBMCs, which pointed to $CD8^+$ T cells as the cellular subset for which the most
- 89 pronounced impact of natalizumab exposure could be captured, based on descriptors related to
- 90 morphology, F-actin and phospho-SLP76. Unsupervised analysis of the HCI data yielded 2 MS
- 91 patient subgroups with distinct CD8⁺ T-cell responses that partially aligned with the subsequent
- 92 treatment response. A machine-learning based approach using the features from the image
- 93 dataset of a discovery cohort and applied to a validation cohort highlighted the predictive power
- 94 of the herein developed pre-treatment morphological profiling approach.

95 **Results**

96 High-content cell imaging captures the *in vitro* sensitivity of primary T cells to 97 natalizumab

Key molecular events underlying the ability of VLA-4 to trigger leukocyte adhesion, spreading 98 and activation are the recruitment of the adaptor protein SLP76 and the remodeling of the actin 99 cytoskeleton ^{4,27,28}. Therefore, to profile the *ex vivo* response of T cells to natalizumab, we 100 implemented an HCI approach, which offered the possibility to collect concomitantly features 101 pertaining to cell morphology, SLP76 phosphorylation and F-actin organization. The HCI 102 pipeline was first optimized on frozen PBMC samples from 10 HD that were or not exposed in 103 vitro to natalizumab and seeded onto VCAM-1-coated 384-well imaging plates for analyzing 104 T-cell subsets based on a staining for the CD4 and CD8 coreceptors. Automated confocal 105 imaging was conducted with a 40X objective by focusing on the ventral side of the cells where 106 107 they were interacting with the VCAM-1-coated surface. A set of 5 descriptors was selected a priori for the analysis, including number of adherent cells, cell area, width-to-length ratio, 108 phosphorylated SLP76 (pSLP76) and F-actin intensity (Figure 1A). Natalizumab exposure led 109 to a reduction in cell spreading and in the intensities of the pSLP76 and F-actin stainings in 110 both CD4⁺ and CD8⁺ T-cell subsets (Figure 1B,C). The combination of the considered 111 descriptors through Principal Component Analysis (PCA) separated the natalizumab-treated 112 from the non-treated samples along component F1 (Figures 1B,C), indicating a robust effect of 113 natalizumab across the samples. The main descriptors that drove the segregation of treated 114 versus non-treated PBMCs along component F1 were pSLP76 intensity and width-to-length 115 ratio for CD4⁺ cells and cell area for CD8⁺ T cells (Table S1). Adhesion over VCAM-1 of both 116 CD4⁺ and CD8⁺ T-cell subsets was severely reduced upon natalizumab exposure in a consistent 117 way across the tested samples (Figures 1D, E). Natalizumab-induced reduction of cell area was 118 more frequent across the donors in CD8⁺ than CD4⁺ T cells. In contrast, the effects of 119 natalizumab on width-to-length ratio and F-actin intensity were more consistent across the 120 donors in CD4⁺ than CD8⁺ T cells, while pSLP76 intensity was decreased in both T-cell subsets. 121 Combined analysis of cell morphology, F-actin and pSLP76 intensities by automated confocal 122 microscopy is therefore an adapted approach to capture the sensitivity of T cells to in vitro 123 natalizumab exposure. 124

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- 126

127 CD8⁺ T cells from MS patients are highly sensitive to natalizumab exposure

We next applied the HCI pipeline to PBMC samples from 40 persons with MS who had received 128 129 at least one first line of treatment but had not yet been treated with natalizumab at the time of sample collection (BIONAT cohort ²⁹, see Table S2). In addition to CD4⁺ and CD8⁺ T-cell 130 131 subsets, we extended the evaluation of the *in vitro* effects of natalizumab on CD14⁺ monocytes and CD19⁺ B cells due to the contribution of these leukocyte subsets to MS pathogenesis ³⁰. 132 Our analysis aimed at defining which subsets within MS PBMCs would be most affected by 133 natalizumab exposure (Figure 2A). A prominent effect of natalizumab exposure was the global 134 reduction of the spreading of MS PBMCs (Figure 2B), as observed with the HD T cells. When 135 considering the monocyte subset by gating on the CD14⁺ cells, our method was however not 136 137 able to clearly distinguish the natalizumab-exposed from the unexposed samples, as shown on the PCA analysis (Figure 2C). A wide dispersion of the samples was observed when considering 138 CD19⁺ B cell and CD4⁺ T-cell subsets, with only a partial discrimination of the natalizumab-139 exposed and unexposed samples (Figures 2D,E). Such discrimination occurred along the F1 140 141 component and was mainly driven by pSLP76 intensity (Table S3). The HCI pipeline separated natalizumab-exposed and unexposed samples when considering the CD8⁺ T-cell subset, as 142 shown by the distribution along the F1 component of the PCA plot, also mainly driven by 143 pSLP76 intensity (Figure 2F and Table S3). Therefore, within the tested MS PBMC samples, 144 CD8⁺ T cells appeared to be the most sensitive cell subset to the effects of natalizumab exposure 145 as captured by our image-based approach. By analyzing the effect of natalizumab on the CD8⁺ 146 T cells of the 40 patients, we observed a decrease in the number of adherent cells, in cell 147 spreading and in cell elongation, as well as a modest decrease in pSLP76 intensity (Figure 2G). 148 As previously observed with the HD PBMCs, F-actin intensity was not reduced in CD8⁺ T cells 149 150 from MS patients upon natalizumab exposure. These findings demonstrate the robustness of the HCI method to capture sensitivity of MS patients' PBMCs to natalizumab. Furthermore, it 151 points to CD8⁺ T cells as the cellular subset exhibiting the most pronounced response to *in vitro* 152 natalizumab exposure. 153

154

155 Unsupervised clustering of HCI data discriminates non-responder MS patients

Based on the reasoning that *in vitro* natalizumab effects on T cells prior to treatment might mirror the *in vivo* treatment efficacy, we next tested whether our HCI pipeline could detect differences in pretreatment PBMC samples from patients that had responded favorably or not

to natalizumab treatment. For that purpose, we selected 40 patients from the BIONAT cohort, 159 corresponding to 20 responders and 20 non-responders to natalizumab therapy, based on the 160 NEDA-3 criteria (Table S2). Comparable levels of CD49d were expressed on the different 161 PBMC subsets from the 2 groups of patients, implying that VLA-4 expression does not by itself 162 determine the response to therapy (Figure S1). We applied our HCI pipeline to the pretreatment 163 PBMC samples, focusing on CD8⁺ T cells since they were identified in the optimization step 164 165 as the most responsive subset. We increased the sensitivity of the HCI pipeline by imaging the 166 samples with a 63X objective and harvesting an enriched set of 407 features based on intensity, 167 cell morphology (symmetry, threshold compactness, axial and radial distributions) and texture elements (spots, edges, and ridges) of F-actin and pSLP76. We calculated, for each feature, the 168 169 difference in absolute value between the natalizumab-exposed and the natalizumab-unexposed 170 samples (mean across cells and wells), which was normalized (relative delta) to investigate the effect of natalizumab on multiple features on the same scale (Figure S2). The unsupervised 171 PCA analysis segregated partially the non-responders' samples along the F1 component, with 172 173 18 of the 20 samples associated with negative F1 values (Figure 3B). T cells from a typical nonresponder patient displayed a reduced spreading upon natalizumab exposure while maintaining 174 a partially polarized shape (Figure 3B, top left image). T cells from the most divergent non-175 responder patient exhibited increased cell width upon natalizumab exposure (Figure 3B, bottom 176 left image). Samples from responder patients occupied a rather dispersed distribution on the 177 PCA plot. Representative T cells from responder patients displayed a pronounced reduction of 178 cell spreading and an apparent loss of cell polarity upon natalizumab exposure (Figure 3B, top 179 right and bottom right). This analysis suggests that CD8⁺ T cells from the non-responder 180 patients were less sensible to *in vitro* natalizumab exposure in terms of cell morphology 181 alterations. The discrimination of non-responder samples was further confirmed by a 182 complementary unsupervised K-means clustering analysis built from the 407 features that 183 identified 2 clusters, including one that gathered 18 of the 20 samples from the non-responder 184 patients (Figure 3C). In agreement with the PCA analysis, the samples from the responder 185 186 patients distributed among the two clusters. Parallel PCA and K-means analysis on the CD4⁺ T-cell compartment failed to indicate segregation (Figures S4A, B). We further applied a Ward 187 clustering approach, built from the 50 most important features from the PCA (Table S4), which 188 segregated the samples in two main branches, with one gathering 15 of the 20 samples from the 189 190 non-responder patients (Figure 3D). This branch was characterized by a majority of features, which values were poorly impacted by natalizumab exposure, as opposed to the branch 191 192 composed of a majority of responder samples. These features included Axial small length, Cell

and Nucleus area, Cell width and multiple F-actin and p-SLP76 texture related descriptors 193 (Figure 3D, Table S4). On the other hand, a minority of discriminative features had values that 194 were highly reduced by natalizumab exposure in the non-responder branch, as Actin symmetry 195 03 SER-spot, that can be interpreted as actin dots uniformly distributed in three parts of the 196 considered cells. Analysis of Actin axial small length (Figure 3E), which was reduced by 197 natalizumab in cells from responders, and Actin profile 1/5 SER-saddles (Figure 3F), which 198 was impacted by natalizumab in cells from non-responders, illustrates how the cells from the 199 200 two patient groups may distinctly remodel their F-actin cytoskeleton upon natalizumab 201 exposure. Together, this unsupervised morphological analysis indicates that CD8⁺ T cells from 202 non-responder patients tend to display reduced loss of cell spreading and polarity upon in vitro 203 exposure to natalizumab.

204

Prediction of natalizumab treatment outcome with a machine learning model

206 As the unsupervised analysis indicated a partial discrimination of responder and non-responder patients based on how natalizumab impacted CD8⁺ T-cell features, we implemented a machine 207 208 learning approach to investigate whether samples from responder and non-responder patients 209 could be distinguished. We opted for a Random Forest (RF)-based approach that trained 210 individual models with the features from the image dataset generated from the 40 MS patient 211 samples, labeled as discovery cohort (Figure 4A). Redundant features displaying >90% correlation were first removed, reducing the number of features to 133. Based on 1024 different 212 combinations used to train the estimators, the RF-based approach generated 33 combinations 213 of features that could distinguish responders from non-responders with F1-score and accuracy 214 higher than 90% (Figure 4B). Surpassing the threshold of 70% performance in each of these 215 scores is indicative of an efficient discrimination. Among the ten most important features, five 216 217 were related to actin segmentation, symmetry and texture, one to pSLP76 distribution symmetry and texture and one to cell morphology (Figures 4C, S4, S5). In addition to the importance, we 218 219 also analyzed how often each feature appeared in decision tree combinations that lead to a F1 220 score higher than 90%. Except for Actin profile 5/5 SER-hole and pSLP76 symmetry 05 SER-221 dark, all features had frequencies above 50% (Figure 4C), suggesting that their combined integration was key for discriminating samples. To challenge the robustness of the HCI 222 223 approach to predict treatment response, it was applied to a validation group of 28 patients, 224 denominated validation cohort, composed of 14 responders and 14 non-responders (Table S5).

We tested the same 1024 combinations of features to evaluate their performance on the 225 226 validation cohort using the 10 most important features as identified through the analysis of the discovery cohort. The most accurate combinations were associated with a F1 score of 77% and 227 an accuracy of 66% (Figure 4D). The two features with low frequencies in combinations in the 228 discovery cohort (Actin profile 5/5 SER-hole and pSLP76 symmetry 05 SER-dark) also 229 displayed low frequencies in the validation cohort (Figure 4E). To further investigate how those 230 ten features were discriminating the two groups of patients, we combined the two cohorts and 231 232 evaluated, for each feature, the p value pertaining to the comparison of the effect of natalizumab on cells from responders and non-responders (Figure 4F). Actin profile 2/5 SER-saddle and 233 234 Nucleus area were the two features with p<0.05 that also had consistent importance and 235 frequency among the two cohorts, suggesting that those two features were the most discriminative ones. The impact of natalizumab on the reduction of nucleus area was barely 236 237 detected in most of the non-responder patients (Figure 4G). This may reflect the propensity of natalizumab to impair T-cell spreading on VCAM-1. On the other hand, natalizumab exposure 238 239 resulted in a decrease of the Actin profile 2/5 SER-saddle feature in most of the non-responder 240 samples but not in the responder samples (Figure 4H). This is suggestive of a specific remodeling of the actin cytoskeleton (smoother distribution of F-actin in the cellular 241 compartment corresponding to the cytoplasm, see Figure S5), upon natalizumab exposure in 242 the CD8⁺ T cells from the non-responders. The combination of our HCI-based analysis with a 243 supervised model therefore provides a proof-of-concept that patient-specific responses to 244 245 natalizumab can be captured in vitro prior to treatment in a way to predict the in vivo treatment 246 response.

247

CD8⁺ T cells from non-responder patients tend to resist the impact of VLA-4 blockade on cell spreading

To gain insight into the biological underpinnings of the diverging therapeutic responses, we sought to further explore the meaning of the individual discriminative features. We combined the data from the two cohorts, ranked features according to the p value of the responder/nonresponder comparison and completed our analysis of T-cell response to natalizumab by live cell imaging (Figure 5A). Among the 407 features, 29 presented a p value<0.05 (Table S6). For each feature, we calculated and normalized the effect of natalizumab for the responder and nonresponder subgroups (relative Δ) and then computed the difference of relative Δ between the 2

subgroups (Figure 5B, X axis). This analysis clearly segregated features into those associated 257 with a more pronounced effect of natalizumab on T cells from responder patients (Figure 5B, 258 259 right side of the chart) and those associated with a more pronounced effect of natalizumab on T cells from non-responder patients (Figure 5B, left side of the chart). Morphology features 260 (cell and nucleus area, cell width) were exclusively found in the first set of features, confirming 261 the notion that T cells from non-responder patients are more resistant to natalizumab-induced 262 reduction of cell spreading and elongation (see Figure 5C-D for individual patient values for 263 264 cell area and cell width). On the other hand, features related to actin texture and distribution 265 were almost exclusively found in the second set of features. This highlights that CD8⁺ T cells from non-responder patients tend to be less susceptible to natalizumab by resisting the impact 266 267 of VLA-4 blockade on cell spreading and polarity, but also by adopting a specific actin cytoskeleton organization. The nature of the actin-related features (e.g. actin ridges and valleys) 268 269 implies that natalizumab evoked a more homogenous distribution of F-actin in T cells from non-responder patients, both at the cell periphery and towards the center of the adhesion plane 270 271 (Figure 5E,F). The biased organization of F-actin in T cells from non-responders was not associated to a difference in F-actin levels (Figure S6). We next asked how the morphological 272 273 and actin remodeling effects of natalizumab on T cells from responder and non-responder patients may translate into their ability to migrate over VCAM-1. For that purpose, we evaluated 274 morphology, velocity, and straightness of CD8⁺ T cells from four patients from each treatment 275 response subgroup, upon interaction with VCAM-1 in an under-agarose setting to prevent non-276 specific cell displacements. T cells tended to form homotopic aggregates upon natalizumab 277 exposure (Figure 5G), as previously reported for other anti-VLA-4 antibodies ^{19,30}, but this 278 phenomenon appeared to impact comparably T cells from both subgroups (Figure 5H). Analysis 279 of cell area confirmed that T cells from non-responders tend to be resistant to the reduction of 280 cell spreading evoked by natalizumab (Figure 5I). Interestingly, tracking analysis indicated that 281 intrinsic velocity and ability to migrate along straight paths, rather that response to natalizumab 282 per se, were the parameters that distinguished T cells from the considered responders and non-283 284 responders (Figures 5J, K). This complementary live microscopy assay therefore suggests that intrinsic differences in the propensity to migrate over VCAM-1 might differentially predispose 285 286 T cells to the activity of natalizumab. Collectively, our analysis points to a multi-parametric 287 origin of the variable sensitivity of MS patient CD8⁺ T cells to natalizumab, including intrinsic 288 determinants related to cell motility, resistance to natalizumab in terms of cell spreading inhibition and actin remodeling upon natalizumab exposure. 289

290 **Discussion**

291 Although natalizumab has revolutionized the treatment of relapsing-remitting MS, a substantial proportion of treated patients experience disease relapse. The incomplete response rate (30%) 292 to natalizumab treatment at one year, and even more thereafter ¹⁷, carries a high societal and 293 human burden to health institutions and to the patients and their families. In this context, 294 strategies to predict natalizumab efficacy would allow for the implementation of personalized 295 treatment schemes. Multiple parameters have been proposed to account for treatment failure in 296 297 individual patients. Given the multiplicity of cellular subsets expressing α 4 integrin subunit and 298 the multiplicity of cellular activities that VLA-4 blockade through natalizumab may alter, identifying a biomarker to discriminate and eventually predict individual patient response has 299 300 remained challenging. Herein, we designed a high-content image-based approach applied to human PBMCs to monitor, through multiple morphological and molecular parameters, the 301 302 sensitivity of patient cells to natalizumab upon ex vivo exposure. We further tested whether such ex vivo challenge would capture inter-individual variability that might align with the 303 304 clinical outcomes of individual MS patients treated with natalizumab.

In the context of personalized medicine, HCI is emerging as a unique approach that captures 305 simultaneously molecular information and cellular morphometrics with single cell resolution. 306 307 The application of HCI in drug testing workflows might generate results within a few days ³¹ and deliver treatment efficacy prediction with high prediction accuracy ³². The potential of HCI 308 to provide support for treatment decision has recently been highlighted by its ability to predict 309 drug efficacy in patients with hematological cancers ^{33,34}. Here, we took the challenge of testing 310 whether HCI might be applicable to screen the efficacy of a therapeutic antibody on non-311 neoplastic immune cells in the context of an auto-immune disease. Differently from previous 312 HCI studies that monitored tumor cell viability and global activity of surrounding immune cells, 313 our approach was tailored to assess the specific activity of the VLA-4-targeting antibody 314 natalizumab, by stimulating PBMC from persons with MS on VCAM-1 and exposing them to 315 natalizumab. We opted for high-resolution confocal acquisition, aiming to precisely capture 316 317 individual cell morphological features, as well as parameters related to F-actin organization and SLP76 distribution, given the central position of these molecular activities in the response of 318 leukocytes to VLA-4 engagement. Instead of extracting predefined sets of parameters, we 319 applied clustering and machine learning methods to hundreds of parameters to take full 320 advantage of the rich image datasets. 321

We provide evidence that such approach focused on the mechanism of action of natalizumab 322 presents with several advantages compared to what has been achieved so far in terms of 323 natalizumab response prediction: timing of prediction, cohort size, statistic strength and 324 biological explanation. Several studies have aimed at predicting the efficacy of natalizumab 325 treatment. High anti-phosphatidylcholine IgM levels in the serum were associated to treatment 326 response in a study involving 33 patients ¹⁹. Decreased levels of B cells and intrathecal 327 immunoglobulin synthesis in the cerebrospinal fluid were also associated with optimal response 328 through the evaluation of 23 patients under treatment ²¹. Another study involving 30 patients 329 under natalizumab treatment pointed to a decrease of metalloproteinases serum levels in 330 patients with no relapse episodes ²⁰. Two studies performed with 29 and 49 patients under 331 treatment pointed to CD49d expression in leukocytes as a biomarker for determining optimal 332 dose and predicting treatment efficacy ³⁵ ¹⁸. Our analysis conducted on PBMC samples prior 333 334 to treatment however failed to establish a link between CD49d expression and natalizumab treatment efficacy, potentially reflecting that the profile of CD49d expression might be altered 335 336 during the treatment. Finally, age and disease duration at treatment initiation were identified as parameters affecting treatment response in a study of 48 patients ²². These studies were 337 conducted with classical statistical analysis by evaluating the fitness of individual biological or 338 patient-related parameters. They suffered from not evaluating the robustness of the considered 339 340 parameters in independent cohorts. Most of them were conducted in the course of treatment and did not evaluate the predictive value of the considered parameters before treatment initiation. 341 In this context, our approach proposes a paradigmatic shift in the search for a treatment efficacy 342 predictor. By combining a miniaturized and automatized image-based bioassay and machine 343 344 learning approaches, we extract individual patient signatures directly reflecting the quantitative and qualitative impact of natalizumab on primary cells from the patients. It reached a prediction 345 power above 70% and presents predictive values of accuracy and F1-score comparable or above 346 those of other studies that applied machine learning methods to predict clinical outcome in other 347 disease settings ^{36,37}. We anticipate that our workflow could be generalized to the testing of 348 349 other therapeutic antibodies across multiple clinical indications.

The HCI pipeline identified CD8⁺ T cells as the most prominent subpopulation to predict response to natalizumab. The CD8⁺ T-cell subset was previously suggested as a cell population to predict PML development risk from MS patients ³⁸. We failed to detect substantial effects of natalizumab exposure on monocytes. This finding might agree with the natalizumab-induced upregulation of α 4 on monocytes ³⁹ contrasting with the downregulation of α 4 on lymphocytes

¹⁸. Despite the VLA-4 mediated role of B cells in MS neuroinflammation ⁴⁰, our study did not 355 356 point B cells as a critical population to determine natalizumab effect and predict patient 357 response. The prediction of natalizumab patient clinical outcome by machine learning was 358 mainly driven by a set of actin related features associated to how CD8⁺ T cells adhere, enrich, and distribute actin at the adhesion plane, spread and elongate on VCAM-1. The role of 359 integrins in promoting cell spreading and their implication in many diseases are well established 360 ^{41–43}. The HCI pipeline leads to the identification that non-responder patients are resistant to 361 natalizumab-induced decrease on cell spreading and elongation, which are morphological 362 363 adaptations needed to allow T-cell interstitial migration through the adaptation and formation of motility related structures such as the lamellipodia and the uropod ⁴⁴. Our data point to an 364 increased migratory profile of the CD8⁺ T cells from the non-responder patients. Thus, we 365 hypothesize that by preserving cell spreading ability, non-responder CD8⁺ T cells have an 366 367 increased capacity to transmigrate towards the CNS and to establish IS with target cells leading to cell killing and consequent inflammation in the CNS. 368

369 Our study showcases how HCI combined to machine learning algorithms may serve as a treatment testing platform to guide treatment prescription. The less sophisticated measurement 370 371 of a single key biological marker might sound as a most desirable approach. However, our study clearly indicates that among many considered parameters, none could by itself be discriminative 372 373 enough to predict treatment outcome. Since automated high-content cell imagers are becoming increasingly available in the technological portfolio of biomedical research centers, the 374 375 development of standardized bioassays based on this technology might become feasible in a near future. 376

377

378 Limitations of the study

Despite the potential of our analysis in coupling HCI of patient PBMCs to machine learning 379 380 algorithms and providing biological interpretation, validation in larger cohorts across multiple clinical centers would be necessary before translation in medical practice. In this study we have 381 382 not investigated whether a more precise examination of the effects of natalizumab on various 383 T-cell subsets might have revealed selective effects and increased the prediction power of our 384 approach. We have also not tested whether our pipeline might predict the risk of developing serious side-effects such as PML. Finally, to reinforce the relevance of the HCI approach, it 385 386 will be interesting to study how the distinct morphological and actin remodeling effects of

- natalizumab on T cells from responder and non-responder patients may be sustained by distinct
- 388 molecular responses and translate into distinct motility capacities.

389

390 Methods

391 Materials

Reagent or resource	Source	Identifier
Antibodies		
Natalizumab	Biogen	Tysabri
Recombinant Anti-SLP76 (phospho Y145) antibody [EP2853Y]	Abcam	ab75829
Zombie NIR [™] Fixable Viability Kit	Biolegend	423105
Human CD4 Antibody	R&D Systems	MAB3791
Human CD8 alpha Antibody	R&D Systems	MAB3803
CD14 antibody TÜK4	Biorad	MCA1568T
Human CD19 Antibody	R&D Systems	MAB4867
Goat anti-Rabbit IgG (H+L) Highly Cross- Adsorbed Secondary Antibody, Alexa Fluor [™] 647	ThermoFisher	A21245
Goat anti-Mouse IgG1 Cross-Adsorbed Secondary Antibody, Alexa Fluor TM 546	ThermoFisher	A21123
Goat anti-Mouse IgG2a Cross-Adsorbed Secondary Antibody, Alexa Fluor [™] 546	ThermoFisher	A21133
Recombinant and purified proteins		
Recombinant human IL-2	Peprotech	200-02
Recombinant Human VCAM-1/CD106 Protein	R&D Systems	ADP5
Medium components, buffers, and chemicals		
RPMI 1640 Medium with GlutaMAX	Gibco	21875-034
Human serum (AB)	Institut de Biotechnologies Jacques Boy	201021334
Penicillin/streptomycin	Gibco	15140-122
Sodium pyruvate	Gibco	11360070
MEM Non-Essential Amino Acids Solution	Gibco	11140050
HEPES	Gibco	15630-056
Phytohemagglutinin (PHA-P)	ThermoFisher Scientific	R30852801
Permeabilization Buffer (PB)	eBioscience	00-8333-56
Paraformaldehyde (PF)	ThermoFisher Scientific	50-980-489
Alexa Fluor [™] 546 Phalloidin	ThermoFisher	A21123
Alexa Fluor [™] 488 Phalloidin	ThermoFisher	A12379
DAPI (4',6-Diamidino-2-Phenylindole, Dihydrochloride)	ThermoFisher	D1306
CellTrace [™] Calcein Red-Orange, AM	ThermoFisher	C34851
CellTracker [™] Green CMFDA Dye	ThermoFisher	C2925

CD8 ⁺ T Cell Isolation Kit, human	Miltenyi Biotec	130-096-495
Plates		
384-well plate CellCarrier-384 Ultra	Perkin Elmer	6057302
Equipment		
High-content screening system (Opera Phenix)	Perkin Elmer	N/A
BD LSR Fortessa Cytometer	BD Biosciences	N/A
MACsQuant VYB cytometer	Miltenyi Biotec	N/A
Softwares		
Fiji ImageJ software	NIH	N/A
TrackMate tool in ImageJ	N/A	N/A
Harmony software	Perkin Elmer	N/A
GraphPad Prism v8.0.2	N/A	N/A
XLSTAT Basic 2022.5.1	N/A	N/A
Scikit 1.2.2	N/A	N/A
FlowJo 10.8.1	N/A	N/A

392

393 Experimental model and subjects' details

PBMCs from healthy donors (HD): frozen PBMCs from 10 HD were obtained from The 394 Etablissement Français du Sang. The corresponding blood samples were collected following 395 standard ethical procedures (Helsinki protocol) and as per French Bioethics law. The work on 396 PBMCs conducted in this study was covered by an approval by the local ethics committee 397 398 (Comité de Protection des Personnes Sud-Ouest II et Outre-Mer II). PBMCs were thawed in RPMI-based growth media (RPMI media (Gibco), 5% human serum (heat inactivated, AB 399 positive blood type, Institut de Biotechnologies Jacques Boy), 100 U/ml penicillin/streptomycin 400 (Gibco), 1 mM sodium pyruvate (Gibco), 1X MEM non-essential amino acids (Sigma), 10 mM 401 HEPES (Gibco). Cell culture was maintained at 37°C and 5% CO₂. Cellular composition was 402 analyzed by measuring CD3, CD49d, CD4 and CD8 expression by flow cytometry. 403

PBMCs from persons with MS: frozen PBMCs from 68 MS patients were obtained from the 404 BIONAT cohort [26]. Patient samples were collected in accordance with law n° 2004-806 of 405 August 9, 2004 relating to public health policy. This research received a favorable opinion from 406 407 the Committee for the Protection of Persons (CPP) Sud Ouest et Outre Mer II on 06/02/2009, received authorization from the competent authority on 09/02/2009, and was declared to the 408 409 Commission Nationale Informatique et Libertés (CNIL). The registration number at 410 ClinicalTrials.gov is NCT00942214. The herein studied blood samples were collected prior to natalizumab treatment, from which PBMCs were prepared and frozen. Samples were thawed in 411 RPMI media 5% human serum maintained for 16 h at 37 °C and 5% CO₂ before being processed 412 through the HCI workflow. Details for each patient are available in Tables S2 and S4. Cellular 413 414 composition was analyzed by measuring CD3, CD49d, CD4 and CD8 expression by flow

415 cytometry.

416 NEDA-3 classification: classification into responder or non-responder patients was performed

417 according to the NEDA-3 score 45 . No Evidence of Disease Activity-3 is calculated based on

the absence of clinical relapses, confirmed disability progression, and new or enlarging lesions

419 on brain magnetic resonance imaging. If a person with MS under treatment has experienced no

- 420 clinical relapse, no confirmed disability worsening and no new lesions during 2 years, he/she is
- 421 considered as responder to natalizumab therapy.

422 CD8⁺ T cells from MS patients: From the obtained PBMC, cells were kept in culture for 5 days
423 in the presence of IL-2 and PHA. CD8⁺ T cells were then purified using CD8⁺ T Cell Isolation
424 Kit.

425

426 High-content cell imaging of PBMCs from HD

Staining: A high-content screening 384-well imaging plate (CellCarrier-384 Ultra, Perkin 427 Elmer) was coated overnight at 4°C with VCAM-1 (R&D Systems) at 0.625 µg/mL. The plate 428 was then washed with phosphate-buffered saline (PBS) and cell culture medium. Freshly 429 thawed PBMCs from 10 HD were centrifuged at 430 g for 5 min, split in two and natalizumab 430 (Biogen) was added in part of the cells at the final concentration of 2 µg/mL. Cells were 431 incubated for 30 min at 37°C and 5% CO₂. Next, cells were washed to remove antibody excess. 432 A total of 9000 cells/30 µL were seeded per well of the 384-well precoated plate, followed by 433 a 10 s centrifugation. After stimulation for 10 min at 37°C, non-adherent cells were removed 434 by flipping the plate. Subsequently, the cells were fixed using 3% paraformaldehyde (PFA), 435 washed with PBS and permeabilization buffer (PB, eBioscience), and then stained with Alexa 436 Fluor[™] 488 Phalloidin (ThermoFisher), anti-pSLP76 antibody and anti-CD4 or anti-CD8 437 antibodies (R&D systems) The plate was incubated overnight at 4°C. The plate was then 438 washed with PB and stained with anti-Rabbit Alexa647 (ThermoFisher), anti-mouse IgG2a 439 Alexa 546 antibodies and 4',6-Diamidino-2-Phenylindole, Dihydrochloride (DAPI, 440 ThermoFisher). After 1 h incubation, the plate was washed three times with PBS and subjected 441 to automated confocal imaging. 442

Acquisition: Images were acquired with a high-content screening system (Opera Phenix, 443 PerkinElmer) equipped with a 40x 1.1 NA Plan Apochromat water immersion objective, 4 444 445 sCMOS cameras (2160x2160 pixels, 16 bits, 6.5 µm pixel) and a Yokogawa spinning disk confocal unit. For each well, 49 fields-of-view and 4 Z-planes per field (with step of 0.5 µm, 446 starting at the cell contact plane with the substrate) were acquired. Z-stacks of images were 447 projected along Z-axis using maximum intensity global projection and flatfield correction using 448 Harmony software. Z-projected data were then processed with the same software. First, nuclei 449 were located via DAPI staining using thresholding on the staining intensity. The cell cytoplasms 450 were identified by thresholding on the 488 Phalloidin staining. CD4⁺ and CD8⁺ T cells were 451 identified by thresholding on the CD4 and CD8 stainings. Number of detected cells, cell area, 452 cell width to length, pSLP76 and F-actin mean intensities were extracted separately for the 453 CD4⁺ and CD8⁺ T-cell subsets with Harmony software. 454

455

456 High-content cell imaging of PBMCs from MS patients

Staining: The HCI workflow described above for HD samples was adapted for MS samples 457 with the following modifications. Imaging plates were coated with 1.25 µg/mL VCAM-1. A 458 total of 27000 cells were seeded in each well and stimulated for 10 min at 37°C, before fixation. 459 Cells were stained overnight at 4°C with α-pSLP76 antibody (Rabbit ab75829), Phalloidin 488 460 (A12379) and either α-CD4 antibody (IgG2a MAB3791), or α-CD8 antibody (IgG2a 461 MAB3803), or α-CD14 antibody (IgG2a MCA1568T), or α-CD19 antibody (IgG1 MAB4867). 462 The secondary staining step consisted in α-rabbit Alexa 647 (A21245), DAPI and either α-IgG1 463 Alexa 546 (A21123) or α-IgG2a Alexa 546 (A21133). 464

Acquisition: Plates were subjected to 2 rounds of confocal imaging with a 20x 0.4 NA Plan 465 Apochromat air objective (25 fields-of view covering the entire well) and a 63x 1.15 NA Plan 466 Apochromat water immersion objective (56 fields-of view). The subpopulations of PBMCs 467 were segregated by thresholding for the staining intensity of the relevant staining (CD4 for 468 CD4⁺ T cells, CD8 for CD8⁺ T cells, CD14 for monocytes and CD19 for B cells). 469 Morphological filters (cell and nucleus area) were added to further distinguish lymphocytes 470 from monocytes. Once the populations were defined, basic morphological and intensity 471 parameters were extracted with Harmony software. For the images acquired with the 63x 472 objective, the analysis was enriched by applying the SER and STAR methods of Harmony on 473 the F-actin and pSLP76 stainings. This resulted in library of 407 features per cell. 474

475

476 Under agarose migration of CD8⁺ T cells from MS patients

A 384-well plate was coated with VCAM-1 (0.625 µg/mL) at 4°C overnight, then rinsed with 477 PBS before cell culture medium was added to accommodate the cells. To produce a confined 478 environment, a 50 µL layer of 0.5% agarose in RPMI was placed in each well used for the 479 assay. CD8⁺ T cells from 4 responders patients and 4 non-responders patients were collected, 480 centrifuged (10 min 122g) and resuspended in RPMI. Responders' cells were stained with 481 Calcein Red-Orange and non-responders' cells were stained with CellTracker[™] Green 482 CMFDA. After incubation at 37°C for 30 minutes and centrifugation, cells were resuspended 483 in RPMI medium containing 5% human serum. Pairs of non-responder/responder cells were 484 formed and mixed gently and adjusted for a concentration of 25,000 cells from each patient per 485 10 µL. Natalizumab was added in a final concentration of 2 µg/mL and cells were then injected 486 under the agarose layer. The plate was then incubated for 30 minutes at 37°C with 5% CO₂, and 487 the microscope's (Opera Phenix, PerkinElmer) temperature and CO₂ levels were adjusted 488 accordingly. An 8-hour acquisition phase followed, capturing images of the entire well at 1-489 minute intervals at 10x magnification. The resulting images from the first 2 h were then 490 processed using the cell tracking tool from Harmony software, and validated by TrackMate tool 491 in ImageJ, to extract relevant cell motility parameters, allowing for the accurate quantification 492 of cell migration. 493

494

495 **Statistical information**

496 Unsupervised analysis for sample discrimination based on natalizumab therapy response

The unsupervised analyses were performed using XLSTAT Basic 2022.5.1. The PCA was done 497 using correlation (Pearson) type, with a maximum of 5 calculated components. The chosen 498 component was based on the highest % to explain system variability. The K-mean clustering 499 was calculated using Euclidian distance dissimilarity index, Determinant (W) clustering 500 criterion with a maximum of 10 clusters. The number of clusters selected to explain the results 501 was based on the highest Silhouette score. To validate the number of clusters pointed by the 502 silhouette scores, hierarchical ascendent classification was also performed. The clustering was 503 considered only if both analyses lead to the same result. 504

505

506 Machine Learning-based analysis for feature combination in natalizumab therapy 507 response

A Random Forest Classifier (RFC) was embedded in the Scikit-learn python library v1.2.0⁴⁶. 508 We independently analyzed the 407 features from both the discovery and validation cohorts. 509 The datasets were split into 70:30 training and test samples for the first (n=28:12) and second 510 (n=19:9) cohorts, while ensuring a stratified distribution of the classes. For each unique 511 combination of features, we trained a separate RFC model. The RFC hyperparameters for each 512 model were tuned using the GridSearchCV function with 10-fold cross-validation. The 513 evaluation focused on combinations with the highest F1-Score. To remove redundancies, we 514 removed features having >90% correlation, leading us to retain 133 features in the first cohort. 515 We subseted the second cohort with the most important features selected on the first cohort to 516 train individual models for each combination, subsequently evaluating their performance 517 metrics. 518

519

520 Statistical analysis and graphical representations

For all experiments, except for the supervised and unsupervised analysis and the bubble chart, the resulting data were subjected to quantification and statistical analysis using GraphPad Prism v8.0.2. The heatmap (Figure 3D) was generated by SRPLOT server and the bubble chart (Figure 5B) was generated by Visual Paradigm server. Specific details regarding the statistical tests employed, representation of significance, and number of experimental data points are provided in the corresponding figure legends.

527

528 Data availability

Additional information and requests for resources should be directed to and will be fulfilled by
the lead contact, Loïc Dupré (loic.dupre@inserm.fr)

531

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661

662 Authorship information

B.C. contributed to the design of the research, performed experiments, designed the analytical
pipeline, analyzed data and wrote the paper; J.S.S, H.N. and M.A. supervised analysis and built
the predictive models; F.B contributed to patient sample management and patient data
collection; C.L., G.P. and S.K. performed experiments; A.L.A, M.M. and J.S. participated in
scientific discussions; R.L participated in research design and scientific discussions; V.C.-d.A. and L.D. designed the research, supervised the analysis pipeline and wrote the paper.

669

670 Declaration of Interests

The authors declare no competing interests.

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Figure 1. Automated cell imaging of healthy donor peripheral blood T cells upon in vitro natalizumab exposure

(A) Schematic of the HCI pipeline applied to PBMCs from healthy donors. PBMCs are exposed or not to natalizumab, seeded on VCAM-1 coated plates, stained for CD4 or CD8, F-actin and pSLP76 and imaged with an automated confocal microscope. Parameters pertaining to cell adhesion, cell shape, F-actin and pSLP76 are extracted separately from CD4⁺ and CD8⁺ subpopulations for further analysis.

Α

(B and C) Representative 40x confocal images of CD4⁺ (B) and CD8⁺ (C) T cells, exposed or not to natalizumab, seeded on VCAM-1 and stained for F-actin (green), pSLP76 (red) and nuclei (blue). Scale bar: 5 μ m. PCA plots indicative of the effect of natalizumab on CD4⁺ (B) and CD8⁺ (C) T cells, based on parameters pertaining to adhesion, morphology, actin and pSLP76 intensity. Dots correspond to individual donors with data stemming from two independent experiments, each with 2 replicates.

(D and E) Values for individual parameters are shown for CD4⁺ T cells (D) and CD8⁺ T cells (E) in unexposed and natalizumab exposed samples. Parameters include number of adherent cells, cell area, width to length ratio, pSLP76 mean intensity and F-actin mean intensity. Dots correspond to individual donors with data stemming from two independent experiments, each with 2 replicates. Paired t test was used for statistical evaluation (ns = p > 0.05; * = p ≤ 0.05 ; ** = p ≤ 0.01 and *** = p ≤ 0.001).



Figure 2. CD8⁺ T cells from MS patients display high sensitivity to natalizumab in vitro exposure

(A) Schematic of the HCI pipeline applied to pre-treatment PBMCs from MS patients. PBMCs are exposed or not to natalizumab, seeded on VCAM-1 coated plates, stained for CD4, CD8, CD14 or CD19, F-actin and pSLP76 and imaged with an automated confocal microscope. Parameters pertaining to cell adhesion, cell shape, F-actin and pSLP76 are extracted separately from CD4⁺, CD8⁺, CD14⁺ and CD19⁺ subpopulations for further analysis.

(B) Representative 20x confocal images of PBMCs from MS patients unexposed (top) or exposed to natalizumab (bottom), seeded on VCAM-1 and stained for F-actin (green), pSLP76 (red) and nuclei (blue). Scale bar: 20 μ m. Individual CD4⁺ and CD8⁺ T cells, CD19⁺ B cells and CD14⁺ monocytes are indicated with a white line. Image does not represent cells from a same well.

(C-F) PCA plots indicative of the effect of natalizumab on CD14⁺ monocytes (C), CD19⁺ B cells (D), CD4⁺ T cells (E) and CD8⁺ T cells (F), based on parameters pertaining to adhesion, morphology, actin and pSLP76 intensity. Dots correspond to individual patients with data stemming from three independent experiments, each with 2 replicates.

(G) Values for individual parameters are shown for CD8⁺ T cells in unexposed and natalizumab exposed samples. Parameters include number of adherent cells, cell area, width to length ratio, pSLP76 mean intensity and F-actin mean intensity. Dots correspond to individual patients with data stemming from three independent experiments, each with 2 replicates. Paired t test was used for statistical evaluation (ns = p > 0.05; ** = $p \le 0.01$ and **** = $p \le 0.0001$).

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Figure 3. Automated cell imaging discriminates CD8⁺ T cells according to natalizumab treatment outcome in MS patients

(A) Schematic of the HCI pipeline applied to pre-treatment PBMCs from MS patients and aiming at identifying morphological signatures associated with natalizumab treatment outcome. PBMCs are exposed or not to natalizumab, seeded on VCAM-1 coated plates, stained for CD8, F-actin and pSLP76 and imaged at high resolution with an automated confocal microscope. A total of 407 parameters are extracted from each imaged CD8⁺ T cell for further analysis.

(B) Representative 63x confocal images of CD8⁺ T cells from 4 MS patients exposed or not to natalizumab, seeded on VCAM-1 and stained for F-actin (green), pSLP76 (red) and nuclei (blue). Scale bar (brackets): 45 μ m. PCA plot aggregating the data from 407 features pertaining to cell adhesion, morphology, F-actin and pSLP76 intensity, distribution and texture (Harmony STAR morphology and SER texture features). Each feature was analyzed as a normalized delta value ((untreated sample – natalizumab-treated sample) / natalizumab-treated x 100)) to account for the effect of natalizumab. Each dot represents a single MS patient with data stemming from three independent experiments. Clinical response to natalizumab treatment is indicated by the dot color.

(C) K-means clustering analysis of the entire HCI dataset, yielding two clusters that partially segregate responder (blue) or non-responder patients (green). A Chi-square test was used for statistical evaluation (** = $p \le 0.01$).

(D) Ward clustering analysis of the HCI dataset represented as heatmap with dendrogram. The analysis was restricted to the 50 top features along F1 component of the PCA. The upper dendrogram represents the clustering of the 40 patients, indicating partial segregation of responder (blue) or non-responder patients (green). The left dendrogram represents the clustering of the 50 features, according to the intensity and the direction of the effect of natalizumab exposure (blue: natalizumab exposure increases the value of the considered feature; red: natalizumab exposure reduces the value of the considered feature).

(E-F) Relative delta values are shown for Actin axial small length (E) and Actin profile 1/5 SER-saddle (F), two features exemplifying the distinct *in vitro* effect of natalizumab on CD8⁺ T cells from responder (blue dots) and non-responder patients (green dots). Bars represent the mean of the considered patient subgroup. An unpaired t-test was used for statistical evaluation (* = $p \le 0.05$; *** = $p \le 0.001$). Schematics of Actin axial small length and Actin profile 1/5 SER-saddle are represented on the side of the corresponding graphs.

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Figure 4. Random Forest approach predicts natalizumab treatment outcome in MS patients

(A) Schematic of the machine learning approach build to predict response to natalizumab treatment on the basis of the analysis of pretreatment PBMC with the HCI pipeline. A RF model is trained on the HCI dataset from a discovery cohort composed of 20 responder and 20 non-responder patients. The elaborated model, which runs with 1024 combinations of a restricted set of 10 features, is then challenged with the HCI dataset from a validation cohort composed of 14 responder and 14 non-responder patients.

(B and D) Highest accuracy and F1-score obtained among 1024 combinations of features applied to decision-tree constructions performed in the RF model. (B) represents RF performance with the discovery cohort (40 MS patients), calculated with 133 features. (D) represents RF performance with the validation cohort (28 MS patients), calculated with the 10 most important features identified in the discovery cohort. Dashed line represents wished threshold of 70% for both scores.

(C and E) Importance of each individual feature and feature frequency on RF combinations with F1 score > 91 % in the RF approach for the discovery cohort (C), importance and frequency on RF combinations with F1 score > 70% for the validation cohort (E).

(F) P values of unpaired t-tests calculated for each of the 10 most important features between the group of responder versus non-responder patients from both cohorts merged (n=68, 34 patients in each subgroup).

(G and H) Relative delta values are shown for Nucleus area (G) and Actin Profile 2/5 SER-saddle (H), two prominent features of the RF model. The relative delta values represent the in vitro effect of natalizumab on CD8+ T cells from responder (blue dots) and non-responder patients (green dots). Bars represent the mean of the considered patient subgroup. An unpaired t-test was used for statistical evaluation (* = $p \le 0.05$; ** = $p \le 0.01$).

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Figure 5. CD8+ T cells from non-responder patients are resistant to natalizumab inhibition of cell spreading

(A) Schematic of the identification of discriminatory features to natalizumab clinical outcomes based on HCI Imaging pipeline and RF analyzes.

(B) Combined analysis of the 29 features with distinct behavior for the responder versus non-responder patients (n=68), based on a p value <0.05 (unpaired t-tests). The Y axis of the chart represents the calculated p value. The X-axis of the chart represents the difference of relative delta mean (Δ responder – Δ non-responder). The size of the bubbles represents the delta average of each feature in the responder patient subgroup, as indicated in the legend. The color of the bubbles represents feature categories, as indicated in the legend.

(C-F) Cell area (C), cell width (D), Actin symmetry 05 SER-ridge (E) and Actin profile 2/5 SER-valley (F) based on the average relative delta of CD8⁺T cells from responder and non-responder MS patients exposed or not *in vitro* to natalizumab. Data represent the mean of 3 HCI experiments conducted on 68 MS patients. Bars represent the mean of the considered patient subgroup. Unpaired t-tests were used for statistical evaluation (* = $p \le 0.05$, ** = $p \le$ 0.01).

(G) Representative snap shots of migrating CD8⁺ T cells from one responder and one non-responder MS patient under agarose at the presence or VCAM-1. Blue indicates non-responders' cells and red indicates responders' cells. Scale bars represent 40 μ m. At the right of each image, representative zoom of cells *in vitro* treated or not with natalizumab.

(H) Ratio of responder/non-responder cells per homotypic aggregation cluster. Bar represents the average of 4 responders' cells and 4 non-responders treated with natalizumab cells after 1h of migration.

(I) Cell area of migrating CD8⁺ T cells from 4 responder MS patients and 4 non-responder MS patients *in* vitro treated or not with natalizumab, under agarose and over VCAM-1. Data were obtained from 301 to 3085 cells per condition and are representative of 3 independent experiments. Bar represents the cell area average of 4 responders' cells and 4 non-responders' cells after 1h of migration. Sidak's multiple comparisons test was used for statistical evaluation (* = $p \le 0.05$).

(J and K) Mean speed (J) and cell straightness (K) of migrating CD8⁺ T cells from 4 responders MS patients and 4 non-responders MS patients under agarose over VCAM-1. Data were obtained from 301 to 3085 cells per condition and are representative of 3 independent experiments. Bar represents the cell speed average of 4 responders' cells and 4 non-responders' cells along 2h tracks. Sidak's multiple comparisons test was used for statistical evaluation (** = $p \le 0.01$).

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

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