A model for the integration of conflicting exogenous and endogenous signals by dendritic cells

To cite this article: Quentin Marcou et al 2018 Phys. Biol. 15 056001

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Cells constantly integrate signals to adapt to their environment. In the immune system, activating signals are critical to initiate and sustain an efficient immune response, and co-exist with inhibitory signals in order to avoid excessive and uncontrolled immune responses [1, 2]. Immune cells must often integrate such opposing signals, the outcome being key to decision making between immunity versus tolerance [3–5]. This signal integration process in immune cells involves many checkpoints that can involve kinetic proofreading [6–8] or multiple feedback loops [9, 10]. In general, feedback allows the system to adjust its output in response to monitoring itself. Both positive and negative feedback loops have been found crucial to control the strength and duration of the system’s activation in order to achieve optimal responses. Such loops represent a fundamental feature in cell development and differentiation [11], hormonal homeostasis [12], intracellular signalling [13] and in the immune response [1]. Cells can receive feedback through paracrine signals coming from their neighbours or from their own autocrine signals [14, 15]. Since the adaptation to the environment occurs at the population level, autocrine and paracrine feedback may play a different role in a cell population responding to opposing signals, notably as a function of cell density.

Dendritic cells (DC) are an essential component of the innate immune system. Acting as the body’s sentinels, they are equipped with a diversity of innate receptors, including pattern recognition receptors such as toll-like receptors (TLRs). Engagement of TLRs by TLR ligands leads to DC maturation, a complex process which includes migration to draining lymph nodes, secretion of a diversity of chemokines and cytokines, as well as up-regulation of major histocompatibility class II (MHC-II) and co-stimulatory molecules, such as CD80 and CD86 [16]. The latter represent crucial
molecular checkpoints for orchestrating DC-T cell communication, playing a key role in the activation and expansion of CD4 T cells [17].

A critical question is how the diversity of signals sensed by DC controls the outcome of the DC maturation process. In this process, we can discriminate exogenous signals, i.e. the nature and dose of microbial stimuli, and endogenous signals, such as autocrine factors induced by exogenous stimulation. When DC are activated by the bacterial component LPS (exogenous signal), they respond with an increased secretion of TNF-alpha (TNFα) and interleukin (IL)-10, generally considered as prototypical pro- and anti-inflammatory signals, respectively [18, 19]. As DC are equipped with the corresponding receptors, both TNFα and IL-10 act as endogenous auto-regulatory feedback signals that control the output response of the cell, and influence the final decision to initiate an immune response or not. Current and past studies have mostly studied each of these signals separately. LPS effect on DC has been extensively studied, including at various concentrations revealing dose-dependent effects [20, 21]. Few studies have addressed the role of the IL-10 negative feedback loop, showing that it dampens LPS-induced maturation [22]. TNFα is a DC-activating pro-inflammatory cytokine [19], but its role as a putative positive feedback factor on DC remains elusive. Studies of these DC-targeting regulatory signals suggest strong dependencies and cross-regulatory mechanisms between LPS, IL-10 and TNFα, but the underlying rules remain unexplored. Here we study MoDC (dendritic cells matured from monocytes) that do not express IL-12 receptors and are not strongly affected by TGF-β signaling [23]. In these cells IL-10 has a strong signaling impact, so we consider its role in DC maturation. We also note that the pro- and anti-inflammatory nature of the signals can depend on the cellular context. In the MoDC maturation system TNFα and IL-10 do behave as pro- and anti-inflammatory signals, respectively [18, 19]. Mechanistic understanding requires the integrated analysis of variations in the three signals level, and their consequences on the behaviour of the system.

In this study, motivated by measurements, we propose a minimal theoretical model that explains the experimentally observed effects of LPS, IL-10, and TNFα effects on human DC. Our original model describes the interplay between contradictory exogenous and endogenous signals in the control of DC maturation.

2. Results

2.1. LPS-induced TNFα and IL-10 differentially control DC maturation

Upon activation by the TLR4 ligand LPS, DC undergo a maturation process leading to an upregulation of costimulatory molecules, such as CD86, but also production of pro- and anti-inflammatory cytokines. CD86 is a classical marker for DC maturation [24], and we will use its expression as a surrogate for it. LPS is not toxic when incorporated into the bacterial outer membrane, but is toxic in solution [25]. We designed an in vitro setup to study how it regulates the expression of the downstream cytokines in solution. First, we measured the production of TNFα and IL-10 in response to a standard LPS concentration of 100 ng ml⁻¹ [26, 27]. The secretion of TNFα was more rapid and was significant already after 2 h, while IL-10 was detected only after 4 h following LPS stimulation (figure 1(A)), as previously reported [28]. After 4 h, both cytokines were detected concomitantly in the cellular supernatant (figure 1(A)). TNFα and IL-10 reached concentrations of 3.3 ng ml⁻¹ and 0.18 ng ml⁻¹, respectively after 6 h figure 1(A). In order to address the contribution of these two endogenous cytokines on DC maturation, we monitored CD86 using flow cytometry, in the presence and absence of blocking antibodies (Ab) to TNFα or IL-10 (figure 1(B)). LPS induced significant upregulation of CD86, consistent with an increase in DC maturation (figure 1(B)). Blocking the IL-10 loop induced a significant increase in CD86 expression. This suggested that IL-10 had a dominant negative effect in controlling LPS-induced DC maturation.

2.2. LPS dose determines the endogenous IL-10 and TNFα control of DC maturation

Microbial-derived signals occur at various concentrations in infected tissue, in relationship to the in situ microbial load. This process is also linked to microbial clearance, which induces a local decrease in microbial signals. First, we addressed the impact of various LPS doses on endogenous TNFα and IL-10 production (figure 2(A)). Both cytokines exhibited a similar LPS dose-dependent pattern, reaching maximum levels at a LPS concentration of 100 ng ml⁻¹ (figure 2(A)).

Given that TNFα and IL-10 co-exist at variable LPS concentrations, we asked whether LPS levels impact the way these endogenous signals are being integrated by DC. To address this question, we cultured DC in the presence or absence of blocking Abs to the TNFα and IL-10 receptors (TNFR and IL10R) while stimulating them with different concentrations of LPS achieved by serial dilutions (figure 2(B)). As for the standard LPS dose, DC maturation was quantified by CD86 expression 24 h following LPS activation. When none of the loops were altered (no blocking or IgG control), the level of activation increased with LPS concentration and reached a plateau for sufficiently high LPS doses (∼100 ng ml⁻¹) (blue curve in figure 2(B)). Blocking the pro-inflammatory TNFα loop led to a decreased expression of CD86 (red curve in figure 2(B)), while blocking the anti-inflammatory IL-10 loop led to an increased expression of CD86 (green curve in figure 2(B)). However, TNFα loop-blocking decreased CD86 levels mostly at LPS concentrations lower than
10 ng ml⁻¹ (red curve in figure 2(B)). By contrast, the impact of IL-10 loop-blocking on CD86 expression was constant along a wide spectrum of medium to high LPS doses, but absent at low LPS doses (green curve in figure 2(B)). The impact of the two opposite/contradictory loops differed not only in the directionality of the effect but also in mode of the effect: blocking the TNFα loop shifted the onset of the response towards higher LPS dose, while blocking the IL-10 loop affected mainly the amplitude of the response, which significantly increased in the presence of IL-10 blocking compared to its value in the absence of any blocking.

DC maturation with or without blocking the loops in the different LPS doses was quantified using the expression of a second maturation marker CD83. The expression of this marker also increased with increasing LPS dose (figure S1 (stacks.iop.org/PhysBio/15/056001/mmedia)). Blocking the TNFα loop led to a similar trend as with CD86, with a strong effect at low LPS doses, and weaker effect at high LPS doses (figure S1). Although both maturation markers were significantly upregulated by LPS, their distribution across the DC population was different. While CD86 demonstrated a unimodal distribution, CD83 demonstrated a bi-modal one (figure S2). In addition to surface markers, blocking the loops also had a significant effect on cytokine secretion (figures 2(C) and (D)). Importantly, the TNFα and IL-10 loops reciprocally affected each other, as blocking the IL-10 loop increased TNFα secretion (green curve in figure 2(C) compared to the other curves), and blocking of the TNFα loop strongly decreased IL-10 production (red curve in figure 2(D)). This suggests potential cross-regulation of TNFα and IL-10 through DC.

2.3. Modulated bottleneck model explains DC maturation control by opposing endogenous and exogenous signals

In order to qualitatively understand the mechanism behind microbial-induced signal integration in DC, we used the above experimental observations to build a minimal phenomenological steady state mathematical model of CD86 response to LPS stimulation. Our phenomenological model aims at reproducing all the experimental observations (summarized in this paragraph) and previously known facts about the interactions between the three signaling molecules in...
the simplest way, without assuming additional modes of regulation. From figure 2(B) we see that the CD86 response follows a sigmoidal dependence on LPS concentration, which we denote as \( L \) and saturates at high LPS level. Additionally, both IL-10 (denoted as \( I \)) and TNF\( \alpha \) (denoted as \( T \)) expressions are sigmoidal functions of LPS (figures 2(C) and (D)) and see supplementary material equations (1)–(4)). As we noted above, TNF\( \alpha \) upregulates IL-10 expression [29], while IL-10 downregulates TNF\( \alpha \) secretion [30, 31] (figures 2(C) and (D)). To avoid behavior that is not observed in the data, we assume there is a basal expression level of both TNF\( \alpha \) and IL-10, even in the absence (presence) of the regulator. Results of blocking IL-10 show that
A schematic representation of the effective regulatory pathway described above is shown in figure 3. A central signal integrator combines the two pro-inflammatory signals, TNFα and LPS, in a single common pathway making this integrator the key regulator of DC decision. The integrator acts as a molecular bottleneck for the pro-inflammatory signals (see figure 3): it responds to increases in the pro-inflammatory signal concentrations only until a certain total concentration. This concentration can be reached either purely by TNFα or purely by LPS, or by their combination (see figure 4(B)). Above this total concentration, set by the effective EC50 (dose at which the response is half of the maximum), the response is saturated and increasing pro-inflammatory signals has no effect on the output. Without the bottleneck effect of the central integrator, the TNFα and LPS pathways would independently control the CD86 response. In this case blocking the TNFα loop would not change the EC50 of the response to LPS. Adding more LPS while the TNFα loop was blocked would lead to a lower saturation level at infinite LPS dose than without blocking. LPS and TNFα are known to control common downstream pathways [32], giving for example NF-κB as a possible candidate for the bottleneck, which we discuss below. In turn IL-10 has been shown to inhibit NF-κB activation in human monocytes [33, 34].

The concentration of the integrator molecule controls the amplitude of the response, which is further modulated downstream by the IL-10 anti-inflammatory signal (figures 3 and 4(B)). A plumbing analogy helps illustrate the role of the bottleneck and downstream anti-inflammatory regulation: there is a very high source of water distributed to each house, but the amount of available water is limited by the throughput capacity of the main pipeline (this is the bottleneck that regulates the amount of pro-inflammatory signals—see figure 4(B)). However when you take a shower, you can regulate the waterflow directly at the faucet (this is the inhibitory action of IL-10). In the absence of IL-10, the bottleneck still limits the scale of the inflammatory response. IL-10 can further downregulate it.

The bottleneck model reproduces all the experimentally observed features in figure 2(B). It further predicts the combined effect of blocking both the IL-10 and TNFα loops (figure 4(A)). We graphically represent the predictions of the model for the four blocking conditions at low and high LPS concentrations in figure 4(B). At high LPS dose the bottleneck limits the signaling of the master integrator, regardless of whether both TNFα or LPS are sensed or only LPS, and the IL-10 further reduces the strength of the response. At low LPS concentrations the effect of the bottleneck is reduced but IL-10 further modulates the output. We experimentally validated the bottleneck model by blocking both loops simultaneously in LPS stimulated DC. In agreement with the prediction, the condition in which both loops were blocked affected the CD86 EC50 expression similarly to blocking the TNFα loop (figure 4(C)) (the data from figure 2(B) is replotted in figure 4(C) adding the yellow curve that describes the simultaneous blocking of the two signaling channels). At higher LPS doses the CD86 amplitude increased similarly to blocking IL-10 alone, also in agreement with the model predictions. We also note that the secondary interactions of TNFα activating IL-10 and IL-10 repressing TNFα explain the experimentally observed results presented in figures 2(C) and (D). Since TNFα effectively represses itself (figure 3), blocking the TNFα receptor (red line in figure 2(C)) decreases the response of TNFα directly from LPS signaling, decreasing IL-10 concentrations, and effectively alleviating the IL-10s repression of TNFα, which results in the observed increase of TNFα concentrations in figure 2(C). Similarly, blocking the

Figure 3. Cartoon of the modulated bottleneck model. Arrows represent functional (not necessarily direct) interactions. LPS controls the activation of the bottleneck, as well as IL-10 and TNFα. TNFα and LPS act through a common bottleneck for the activation of DC, while IL-10 modulates the activation level downstream. The model also includes partial mutual regulation of TNFα and IL-10.
IL-10 receptor effectively increases IL-10 concentrations, although the effect is much smaller in magnitude (figure 2(D)). The model proposes a possible mechanism for signal integration. To test whether the features of the model are constrained by the data, and whether even simpler model assumptions would still be compatible with the experimental observations, we fitted all the parameters of the model to the data of figures 2(B) and (C) using Maximum Likelihood. We assumed Gaussian experimental errors, which we estimated from the pooled error over all donors. We compared models with various assumptions and levels of simplicity (see supplementary material): a bottleneck model such as described above; a model without a bottleneck, where the LPS, TNFα and IL-10 signals are all integrated into a single regulation function; a model with just LPS and TNFα activation; and a linear model of activation. To compete the models of different complexities, we used the Akaike Information Criterion, which penalizes the likelihood score of a model with the number of its parameters. The bottleneck model was the best fitting model (table S1), indicating that the bottleneck is a necessary ingredient to explain the data. The model...
prediction for the levels of cytokines as a function of dose (figure 2(A)) resulting from the fitting procedure are shown in figure S6.

We evaluated the robustness of the parameter fit by sampling from the posterior distribution obtained by Bayes’ rule with a flat prior, using a Monte-Carlo algorithm (see supplementary material). The standard errors and confidence intervals for each parameter, reported in table S2, show that all the parameters are constrained by the data within an order of magnitude of their optimal value. This analysis also estimates the effect of varying the parameters on the accuracy of the model: for instance, changing $K_e$ by 50% would make the prediction fall significantly outside the error bars, while changing $K_f$ or $K_T$ by the same amount would have little effect on the output, as these parameters are less constrained by the data.

2.4. Paracrine signalling predominantly controls DC maturation

DC in our experiment, as in the organism, are not isolated and signal integration depends on the diffusion of cytokines: a cytokine produced by a given cell could be picked up by a receptor on the surface of this same cell (autocrine loop) or by a neighboring cell (paracrine loop). Since we cannot directly measure inter-cellular communication with single molecule resolution, we designed and performed cell dilution experiments to get insight into DC communication at a larger spatial scale. At high cellular concentrations, cells can sense signals from nearby cells (figure 5(A)), and at large dilutions, only from themselves (figure 5(C)). Large dilution conditions correspond to pure autocrine signaling. This experiment is based on the assumption that the effect of a purely paracrine loop will decrease as cells are diluted, while a purely autocrine loop will not be sensitive to dilution of the population density. Since the effect of the TNFα feedback loop was observed at low LPS concentrations, whereas the IL-10 feedback was active at high LPS concentrations, we performed dilution experiments at two distinct LPS doses.

To predict the behavior of the DC response in the dilution experiments we combined our phenomenological bottleneck model (figure 3) with diffusion-based estimates for the probabilities of autocrine and paracrine absorption in an effective heterogeneous medium [35] (see supplementary material for details). The model ignores cross-talk across cytokines. Using previously measured kinetic and geometric parameters (see table S3), the theoretical calculation predicts that a large fraction of the signaling is paracrine in nature. In figures 5(E) and (G) we plot the predictions for the mean log CD86 expression at a low and high LPS concentration as a function of the cell concentrations. If most of the signaling is paracrine in nature, as we see that at high LPS concentrations (figure 5(G)), with increasing cell dilutions all the blocking conditions converge to nearly the same activation levels, equal to the levels predicted in the case when all the loops are non-functional (orange curve in figures 5(B) and (G)). For very low cell density we expect the paracrine feedback loops to have no effect on CD86 expression and all feedback takes place by autocrine loops. Measurements of ligand affinity of TNFα and IL-10 to their respective membrane receptors [36–38] show that TNFα has a greater affinity for its receptor than IL-10 does. We thus predict that TNFα autocrine fraction should be greater than IL-10. Since the effect of the TNFα feedback is observed at low LPS concentrations, and the IL-10 feedback at high LPS concentrations, we expect the convergence of the curves corresponding to different conditions at low LPS concentrations to be less pronounced than at high concentrations. Our model predicts (see figure 5(E)) that the curves corresponding to blocking the TNFα loop do not converge to those where the TNFα is active at high dilutions for low LPS concentration.

To experimentally assess the effect of dilutions on the loops we activated DC with either low (1 ng ml$^{-1}$) or high (100 ng ml$^{-1}$) LPS in different cell dilutions with the initial culture concentration being 10⁶ cells ml$^{-1}$ (figures 5(F) and (H)). In agreement with our model we could observe that at both low and high LPS doses all conditions were converging to the same amount of activation. Because of the saturation effect we could not observe a slower convergence for the case of a blocked TNFα loop for high LPS dose, however it was observable for low LPS dose (figure 5(F)). In the case of the lower LPS dose, in which the TNFα loop plays a more specific role, we observed that despite serial dilution, the effect of blocking the loop was maintained, at least to some extent, suggesting the existence of an autocrine signaling. Interestingly, in the higher dose of LPS, the effect of IL-10 loop was rather sensitive to dilutions, suggesting that in a context of high micro-bial load IL-10 acts in a paracrine manner.

3. Discussion

Innate immune recognition is key to promote an efficient anti-microbial immune response, but also needs to be controlled, in order to avoid immunopathology. It is known that immune activating and immune dampening signals are both rapidly produced and co-exist within any inflamed tissue [2]. However, the interplay between exogenous microbial signals, and endogenous pro- and anti-inflammatory signals has not been formalized in an integrated manner. This is critical to the decision making of the immune response, as it is driven by multiple dynamic signals, conveying different types of information to innate immune cells. By combining experiments with modeling, we showed that the final response of the DC population relies on integrating the initial signal with the induced pro- and anti-inflammatory responses using feedback loops. The integration is based on two steps: first the pro-inflammatory signals are integrated
through a bottleneck and then the amplitude of the result is further modulated by the anti-inflammatory signal. The key element of this integration occurs at the signal bottleneck, which controls the effective concentration range (EC50) of the response to LPS and limits the maximum pro-inflammatory response. The anti-inflammatory regulation that follows is mostly paracrine, as opposed to the bottleneck integration that has an autocrine component, suggesting that the final response is modulated based on the population level response.

Bottleneck signal integration in molecular systems have mostly been proposed for the integration of two positive signals. They were suggested as a means for TNFα activation [39]. Here we propose that a bottleneck is the essential component in making the decision to the response in the presence of two opposing signals: IL-10 and TNFα. Since the negative regulation by IL-10 acts after the bottleneck, it regulates the maximum level of activation, while the positive TNFα acts before the bottleneck thereby affecting the activation threshold. The two opposing signals thus control distinct aspects of the dose response. This feature is independent of the fact that the two signals have opposing effects: the possibility of additional pre- or post-bottleneck regulation would have the same effect on two positive signals.

The modulated bottleneck model is purely phenomenological and aims at describing the observed integration in an effective way, by contrast to more detailed mechanistic models such as proposed for TNFα IL-10 interplay in macrophages [40] and microglia [41]. We do not propose a detailed explanation of how the two cytokines are integrated mechanistically. Further experiments are needed to explore this question in more detail, as well as the possible integration of detailed knowledge about signaling mechanisms. The model proposes an integration mode that seems to be dominant in the experimental system we looked at. Of course, real cells function in many environments and other integration modules with behaviors not predicted by the modulated bottleneck could be present in DC. In general, the modulated bottleneck model is consistent with all experimental observations and known forms of interactions. Simple alternatives to the bottleneck hypothesis cannot explain the data. For example, a model with negative feedback acting on any of the signals would give a plateau that would be either sensitive to the activation signals, or insensitive to IL-10 inhibition. Future experiments that block other DC maturation factors with similar regulatory profiles will give more insight into the role of the bottleneck integrator.

A natural candidate for this bottleneck integrator is the widely studied [42] nuclear factor NFκB: several studies demonstrated how LPS and TNFα trigger NFκB nuclear translocation [32], and how IL-10 inhibits NFκB or its target genes in certain cell types [43]. Additionally the saturation effect observed in our data was also seen when looking at NFκB nuclear translocation due to the limited and constant amount of NFκB [10]. It is also known that, while IL-10 is known to signal through Jak-STAT pathway, IL-10 also inhibits NFκB [33, 34] giving experimental support for the modulation interaction. Future experiments that block other DC maturation factors with similar regulatory profiles will give more insight into the role of the bottleneck integrator.

Additionally to the main modes of signal integration based on the bottleneck and IL-10 repression, TNFα activates IL-10 expression, while IL-10 represses TNFα. These secondary interactions do not change the basic flow of signal integration, but are predicted by the model to produce a maximum in the CD86 at intermediate LPS concentrations (figure 4(A)). Since LPS activates both IL-10 and TNFα, repression of TNFα slightly shifts the EC50 of the response to larger LPS concentrations, while activation of IL-10 results in a larger moderation of the response than in the absence of TNFα for high LPS concentrations.

The presented results are population averages over multiple independent measurements. The fluorescence distributions plotted in figure S2 show a large heterogeneity in the population, indicating that particular cells can have very different responses. The error bars indicate the standard error of the mean over multiple experiments. The measurement noise is impossible to distinguish from the natural heterogeneity of the response in the population. Given this heterogeneity, the mean CD86 response in the double blocked mutant is consistent with the theoretical prediction.

Dendritic cells often are surrounded by other dendritic cells and, through secreting signaling molecules, communicate with each other to make a decision at the population level. This collective decision making process can help make the right readout in a noisy environment thus reducing response variability as for wound healing [44]. By sharing their response, cells in a population can confirm initial measurements by sensing the signals that their neighbors secrete. Alternatively, cells could simply use the feedback loops to amplify their own initial signal to accelerate their response.

Previous experiments have highlighted the difference between population and single cell measurements in TNFα responses [32]. The nature of the signal (paracrine or autocrine) controls the spatial range of the responding cells and determines the lengthscale on which the decision is made. Feedback loops are necessary elements for integrating population-level signals. The signalling range controls whether there is population level averaging, or whether each cell only listens to itself. Here, by using a combination of dilution and fluorescence experiments with modelling, we show that the anti-inflammatory IL-10 signal is paracrine and long range, as opposed to the autocrine and short range pro-inflammatory TNFα signal. Cells rely
on local signals to detect bacterial signals, but integrate anti-inflammatory signals from anywhere in the population to modulate their response.

Such a localized pro-inflammatory response can be useful in the case of an infection: cells that are further away from the source of the signal do not need to respond. In view of their signalling ranges, autocrine or parocrine feedback loops have different roles: autocrine signaling modifies the strength of response to LPS of the cell itself, while paracrine signaling is used to transmit information to neighboring cells that may not have been exposed to LPS directly. Such a combination of local, excitatory feedback with global, inhibitory regulation has been suggested as a general way

**Figure 5.** Discriminating autocrine from paracrine loops using dilutions. (A.) and (B.) Cartoon and prediction of our steady state model with diffusion for high cell concentration (the cell concentrations in the cartoons are illustrative and not quantitative). (C.) and (D.) Cartoon and prediction of our steady state model with diffusion for very low cell concentration. (E.) Prediction of our steady state model with diffusion on DC activation for a weak LPS stimuli. Computing the expected activation for a range of cell concentrations gives us a qualitative prediction for serial dilutions experiments. (F.) Corresponding dilution experiment with low dose of LPS (1 ng.ml⁻¹). (G.) Model prediction for high dose of LPS. (H.) Corresponding dilution experiment with high dose of LPS (100 ng.ml⁻¹). LPS concentration values used for the model predictions in (E.) and (G.) are shown with red dashed lines in (B.) and (D.). The parameters of the model are set to the values summarized in table S3.
to sense differences in spatial concentration profiles, and has been proposed as a mechanism for detecting spatial concentration gradients in the slime mold Dictyostelium [45–47], or more recently for wound healing [44] and in the context of morphogenesis of mammary epithelial cells in response to a gradient of the epidermal growth factor [48]. Our results extend this concept to the immune system following innate microbial sensing.

In summary, in this study we quantified how a cell makes decisions about the appropriate response to a given concentration of the bacterial signal LPS in the environment, and as a result whether to initiate an inflammatory response or not. More broadly, the mechanisms described give a way to integrate information and make decisions in the presence of conflicting signals. Furthermore we show how simple biophysical models give us insights into cell-cell communication in cell density regimes that are inaccessible by single-cell microscopy [14, 15].

Acknowledgments

This work was supported by MCCJG grant no. 303561, by the Agence Nationale pour la Recherche (ANR), by the Fondation pour la Recherche Medicale (FRM), by the European Research Council (ERC Starting Grant 306312 and ERC Consolidator Grant 281987), by ANR-10-IDEX-0001-02 PSL, ANR-11-LABX-0043, 306312 and ERC Consolidator Grant 281987), by the European Research Council (ERC Starting Grant 281987, 2013 Controlling T-cell Mediated T Cell Polarization vol 26 (Berlin: Springer) pp 289–307

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