The dual role of dendritic cells in the immune response to human immunodeficiency virus type 1 infection

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Many aspects of the complex interaction between human immunodeficiency virus type 1 (HIV-1) and the human immune system remain elusive. Our objective was to study these interactions, focusing on the specific roles of dendritic cells (DCs). DCs enhance HIV-1 infection processes as well as promote an antiviral immune response. We explored the implications of these dual roles. A mathematical model describing the dynamics of HIV-1, CD4+ and CD8+ T-cells, and DCs interacting in a human lymph node was analysed and is presented here. We have validated the behaviour of our model against non-human primate simian immunodeficiency virus experimental data and published human HIV-1 data. Our model qualitatively and quantitatively recapitulates clinical HIV-1 infection dynamics. We have performed sensitivity analyses on the model to determine which mechanisms strongly affect infection dynamics. Sensitivity analysis identifies system interactions that contribute to infection progression, including DC-related mechanisms. We have compared DC-dependent and -independent routes of CD4+ T-cell infection. The model predicted that simultaneous priming and infection of T cells by DCs drives early infection dynamics when activated T-helper cell numbers are low. Further, our model predicted that, while direct failure of DC function and an indirect failure due to loss of CD4+ T-helper cells are both significant contributors to infection dynamics, the former has a more significant impact on HIV-1 immunopathogenesis.

INTRODUCTION

Despite advances in our understanding of human immunodeficiency virus type 1 (HIV-1) and the human immune response in the last 25 years, much of this complex interaction remains elusive. CD4+ T-cells are targets of HIV-1, and are also important for the establishment and maintenance of an adaptive immune response (Poli et al., 1993). CD8+ T-cells are the primary effector cells in HIV-1 infection, as they kill infected cells and produce non-lytic antiviral factors. In lymph nodes (LNs), myeloid dendritic cells (DCs) serve as antigen presenting cells, activating CD4+ and CD8+ T-cells (Steinman, 1991). Despite the ‘DC’ moniker, follicular DCs are functionally different from myeloid DCs; therefore, we did not consider follicular DCs in our model. Another class that was not considered here was plasmacytoid DCs, which are noted for their high production of interferon, but are less potent antigen presenting cells. DCs are also of particular importance because HIV-1 exploits DCs to enhance infection (Lekkerkerker et al., 2006). Thus, DCs are a critical link between virus, CD4+ and CD8+ T-cells (Fig. 1). Elucidating the mechanisms of DC–virus interactions is crucial in uncovering more details about host–virus dynamics during HIV-1 infection. Toward this goal, we developed a mathematical model of HIV-1 dynamics within a human LN, as it is the major site of viral replication and generation of the antiviral immune response.

The prototypical ‘Langerhans cell paradigm’ behaviour of DCs is that, after encountering antigen in the periphery, DCs mature and travel to the LN (Wilson & Villadangos, 2004). DC maturation includes increasing antigen presentation on major histocompatibility complex (MHC) molecules, and upregulating co-stimulatory molecules (Steinman, 1991). Mature DCs prime CD4+ T-cells to become effector T-helper cells. Additionally, DCs cross-present exogenous antigens on MHC class I to prime

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Supplementary material is available with the online version of this paper.
Fig. 1. Summary of interactions captured in a model. Resting CD4+ T-cells (T4) become active T-helper cells (Th) via DC antigen presentation. T4 and Th cells become infected (I) and produce virus (V). Viral antigen and T-helper cells promote DC function (bottom green arrow). Immature DCs (iDC) become matured (MDC) by viral antigen, and licensed (LDC) by T-helper function (bottom green arrow). Immature DCs (iDC) become matured (MDC) by viral antigen, and licensed (LDC) by T-helper cells. LDC promote immunity (top left green arrow) by priming CD8+ T-cells to become CTL. CTL promote viral control (top right green arrow) by killing infected cells (I) and via non-lytic antiviral factors. This immunogenic cycle (green arrows) is disrupted by the dual role of DCs promoting infection (bottom red arrow).

CD8+ T-cells. Primed CD8+ T-cells differentiate into cytotoxic T lymphocytes (CTLs). This cell-based immunity is essential for fighting intracellular pathogens like HIV-1 (Janeway, 2005; Mellman & Steinman, 2001).

There is currently debate as to whether CD4+ T-helper cells are necessary for primary CTL response (Serre et al., 2006; Smith et al., 2004; Wang & Livingstone, 2003), or are only required for a subsequent memory response (Janssen et al., 2003; Shedlock & Shen, 2003). One possible mechanism by which T-helper cells influence the CTL response relies on DCs becoming ‘licensed’ through interactions with helper T-cells, such as signalling by CD40 ligation (Ridge et al., 1998; Schoenberger et al., 1998). Once licensed, DCs upregulate expression of MHC class I and co-stimulatory molecules (Bukczynski et al., 2005), making them capable of priming a strong and sustained CTL response. Here, we define licensed DCs as those competent to prime CD8+ T-cells.

In HIV-1 infection, DCs play a dual role of promoting immunity while also facilitating infection. C-type lectin receptors on the surface of DCs, such as DC-SIGN, can bind HIV-1 envelope gp120 (Turville et al., 2002). DCs can then internalize and protect virus, extending the typically short infectious half-life of virus to several days (Kwon et al., 2002). Alternatively, it has been shown that DCs can become infected (Blauvelt et al., 1997). In either case, HIV-1 associates with DCs to travel to lymphoid tissue, where 98% of T-cells reside (Haase, 1999; Trepel, 1974). During antigen presentation, DC-associated virus, HIV-1 receptor and co-receptors co-localize at the site of cell contact, facilitating infection of CD4+ T-cells (Arrighi et al., 2004; McDonald et al., 2003). Taken together, these interactions suggest that DC dynamics are particularly important to HIV-1 infection.

After an acute phase of infection, characterized by high viral loads and high immune system activity that lasts on the order of weeks, the viral–host system stabilizes to a long-term chronic infection (i.e. clinical latency) that lasts years. This chronic state of infection is characterized by a lower, stable, ‘set-point’ viral load (Ho, 1996). Eventually, due to unknown mechanisms, this stable state is broken, leading to low CD4+ T-cell counts and high viral loads characteristic of AIDS.

It is difficult to obtain data on the entire time course of HIV-1 infection, as patients are typically not diagnosed until well after establishment of the infection. It is also difficult to obtain data on the lymphoid compartment due to the invasiveness of LN biopsy. Therefore, simian immunodeficiency virus (SIV) infection of non-human primates (NHPs) is currently the best experimental model of HIV-1 infection in humans. SIV infection in NHPs begins with an acute period of high viraemia that lasts approximately 3 weeks (Reimann et al., 2005), as with HIV-1 infection of humans. In contrast, chronic infection in NHPs lasts in the order of months to a year, compared to years in human infection. As with AIDS in humans, simian AIDS is characterized by high viraemia and depletion of CD4+ T-cells (Dioszeghy et al., 2006).

Several mechanisms have been proposed to explain how progression from the chronic phase of infection to AIDS is triggered. Many have hypothesized that progressive alteration of the immune system results in the transition to AIDS (Chougnet & Gessani, 2006; Granelli-Piperno et al., 2004; Krathwohl et al., 2006). Dysfunction of DCs is central to many of these hypotheses. During progression, DCs either fail to prime T-cells or are actively immunosuppressive (Granelli-Piperno et al., 2004; Krathwohl et al., 2006), resulting in failure of immune control; however, the reasons for this dysfunction are unknown. Are DCs directly affected by HIV-1? Or, does virus alter CD4+ T-cells, indirectly, causing DC dysfunction due to a lack of T-helper cells (Chougnet & Gessani, 2006)?

To study the roles of DCs during HIV-1 infection, we present a mathematical model of HIV-1 infection and accompanying immune response. Expanding on previous work (Bajaria & Kirschner, 2005), we developed a next-generation model focused on the dynamics within an LN, we include recent findings regarding the function of DCs, and we address current questions regarding DCs in HIV-1 infection. We validated our model by comparison to data generated in an NHP SIV infection model and published human clinical data. As the equations that constitute our mathematical model describe specific interactions, our analysis allows us to predict the importance of DC mechanisms and their role in triggering progression
towards AIDS. We explored how T-cell infection is enhanced by DCs, showing that the relative importance of this effect changes with respect to infection state. In particular, our model predicts which mechanisms of DC dysfunction are most significant in the transition to AIDS.

METHODS

NHP SIV infection model. Adult cynomolgus macaques (Macaca fascicularis) were infected intrarectally with SIV/DeltaB670 (Murphy-Corb et al., 1986) and sacrificed at 2 weeks post-infection or upon development of AIDS; defined by reduced CD4+ T-cell counts and clinical symptoms. Axillary and hilar LN tissues were processed as described previously (Fallert & Reinhart, 2002; Reinhart et al., 2002). The animal studies were performed under the guidance and approval of the University of Pittsburgh Institutional Animal Care and Use Committee.

Immunofluorescence microscopy and immunohistochemistry. We performed immunofluorescence on 14 μm tissue sections using primary antibodies for Ki67 (clone MM1, 1:100; Novocastra) and CD3 (clone CD3-12, 1:100; Novocastra), secondary antibodies fluorescein isothiocyanate (FITC)-conjugated goat anti-mouse IgG1 (1:100; Jackson ImmunoResearch), biotinylated goat anti-rabbit Ig (1:100; Zymed), AF488-conjugated rabbit anti-fluorescein (1:80; Molecular Probes) and streptavidin–AF647 (1:100; Molecular Probes). Images were captured on an Olympus Fluoview 500 laser scanning confocal microscope. Images were analysed using MetaMorph software (Universal Imaging). CD3 is a marker for T-cells, and Ki67 indicates cells that have divided within the past 3–4 days (Pitcher et al., 2002). Because T-cell division during HIV-1 infection is primarily due to antigen-driven immune activation rather than an antigen-independent homeostatic response (Cohen Stuart et al., 2000; Hazenberg et al., 2000), we considered CD3+Ki67+ cells to be active, effector T-cells.

Immunohistochemical staining (IHC) was performed to detect DC-SIGN+ cells as described previously (Fallert & Reinhart, 2002; Reinhart et al., 2002) using anti-DC-SIGN mAb (clone DCN46; BD Pharmingen). Stained cells were counted at five different sites in the paracortex and the average of the values were taken. Because DC-SIGN is not a completely specific marker for DCs, observing dendritic morphology of most of the stained cells provided confidence that DCs were counted. IHC to detect CD3+ T-cells was performed similarly and counted in five different microscopic fields and the average of the values were taken.

In all cases, cell counts per volume of tissue were calculated by multiplying the cell count mm−2 of tissue by the thickness of the tissue section (14 μm) and scaling to appropriate units (ml−1).

In situ hybridization. In situ hybridization was performed as described previously (Fallert & Reinhart, 2002; Reinhart et al., 2002). The numbers of SIV vRNA+ cells in 10–20 different microscopic fields per region were manually counted and the average of the values were taken.

Mathematical model. Our mathematical model describes cell–virus interactions within the paracortical region of a human LN by using a system of nine non-linear ordinary differential equations. These equations describe the rates of flow as cells arrive, interact, change phenotype and exit. Fig. 1 outlines the key features. Each of the biological interactions described below is captured by a mathematical term in our model. A more detailed description and biological justification of the model is given in Supplementary Material (available in JGV Online).

CD4+ T-cell dynamics. We considered three phenotypic classes of CD4+ T-cells: resting, activated effector and infected. Resting CD4+ T-cells arrive by infection-independent and -dependent mechanisms. Resting cells can become productively infected, or become abortively infected and undergo apoptosis (Jekle et al., 2003). CD4+ T-cells are primed by DCs to become effector T-helper cells. A fraction are infected during priming (Lekkerkerker et al., 2006). Activated T-helper cells undergo clonal expansion. T-helper cells can become infected by virus or virus-loaded DCs. Infection is inhibited by CTLs (Geiben-Lynn, 2002). Infected CD4+ T-cells can be killed by CTLs. All CD4+ classes can exit via efferent lymphatics.

HIV-1 dynamics. Virus is produced by infected CD4+ T-cells. Production is inhibited by CTL-produced factors (Geiben-Lynn, 2002; Kedzierska & Crowe, 2001; Levy, 2003). The vast majority of virus particles are associated with follicular DCs (Haase, 1999), which extend their half-life (Cavert et al., 1997). Follicular DCs are not explicitly considered here, though we account for their effect on virus half-life.

CD8+ T-cell dynamics. We considered two classes of CD8+ T-cells: resting and activated effector. Resting CD8+ T-cells arrive due to infection-independent and -dependent mechanisms. Because CD8+ T-cells require more (or different) co-stimulatory signals to become activated, our system predicts which mechanisms of DC dysfunction are most significant in the transition to AIDS. Infected and mature CD8+ T-cells can exit via efferent lymphatics.

DC dynamics. Immature DCs arrive independently of infection and mature DCs arrive during infection. Within the LN, immature DCs can encounter antigen and undergo maturation. Mature DCs become licensed through interactions with activated T-helper cells (Ridge et al., 1998). Mature and licensed DCs are susceptible to being killed by CTLs (Rochesch & Hermans, 2001; Yang et al., 2006). Any of these DC classes can die, though mature and licensed DCs are short-lived compared with immature DCs (Ruedl et al., 2000).

Parameter estimation. Parameters are estimated from a variety of published sources. For details of parameter estimation, see Supplementary Material. We handled uncertainties in parameter estimation systematically by uncertainty and sensitivity analysis (see below).

Initialization of the simulation. Prior to infection, the LN is assumed to contain only resting/immature cells. We determined the initial numbers from immunohistochemistry measures of uninfected NHPs herein, and from published CD4:CD8 ratios (Biancotto et al., 2007). HIV-1 infection dynamics begin with the arrival of a single infected and undergo apoptosis (Jekle et al., 2003). CD4+ T-cells are killed by CTLs. The solution of the system at any given time point yields the average number of each type of cell/virion within the LN. We solved our system over a time course representing years.

Solving the model system. The system of differential equations is solved using the ode15s algorithm in MATLAB (Shampine & Reichelt, 1997). The solution of the system at any given time point yields the average number of each type of cell/virion within the LN. We solved our system over a time course representing years.

Model validation. To validate the behaviour of our model, we compared data from our model simulations to NHP SIV-infection data. Our model simulates paracortical LN tissue over a longitudinal time course. However, the invasiveness of LN biopsy makes a longitudinal NHP study difficult. Thus, our experimental data are cross-sectional and categorical. Due to variability between outbred animals, categorization by time post-infection is not completely reliable. Instead, we categorized infection state not only by time post-infection but also by plasma viral load, blood CD4+ T-cell counts and clinical symptoms. We mapped our experimental animal study categories to ranges of time in our model simulation, for the purpose of comparison.
We additionally validated our model by comparison to published human HIV-1 infection data. We scaled human total-body cell count estimates by 1/700 to represent 1 ml of lymphoid tissue. This conversion assumes typical human body weight is 70 kg, 1% by weight is lymphoid tissue (Haase, 1999) and tissue density is 1 g ml⁻¹.

Uncertainty and sensitivity analysis. Parameters that govern the rates of interaction in our model are estimated from a variety of published biological data. Because of variability between experimental systems, all estimates have an associated degree of uncertainty. We addressed this uncertainty in a systematic manner by uncertainty and sensitivity analysis. This analysis also determines which parameters are most important in governing the state of the system. Analysis was performed using Latin Hypercube Sampling and Partial Rank Correlation (LHS/PRC) (Blower & Dowlatabadi, 1994; Marino et al., 2008), and the extended Fourier Amplitude Sensitivity Test (eFAST) (Marino et al., 2008; Saltelli et al., 1999). LHS/PRC was performed using 1000 model simulations, and eFAST was performed using 697 simulations per parameter and 6 × parameter resampling for a total of 175,644 model simulations. Briefly, both algorithms sample input parameters independently over a range (see Supplementary Table S1 available in JGV Online). We sampled using a uniform probability distribution function, and sampled on a log scale if the sampling range was two orders of magnitude or greater. The algorithms then performed model simulations with each parameter combination, and measured the sensitivity of the system to changes in each parameter. Like ANOVA, the eFAST method decomposes variance in model output to determine the fraction of variance in model output explained by each input parameter. The eFAST total-order sensitivity index, which we report here, takes into account higher-order interactions between multiple parameters. We determined the limit of detection by allowing the eFAST algorithm to partition variance to a dummy parameter that does not affect model output. To determine statistical significance we perform two-sample Student’s t-test on eFAST values from parameter resampling. LHS/PRC reports sensitivity as a coefficient of correlation between input parameter and model output. Statistical significance of these correlations was determined by Student’s t-test with Bonferroni correction (Curran-Everett, 2000). Statistical comparison between these correlation coefficients was performed using Fisher’s z transformation (Meng et al., 1992). For a complete discussion of uncertainty and sensitivity analysis, see Marino et al. (2008).

In silico interventions. To explore the role of particular interactions or mechanisms, we performed in silico interventions by changing parameter values during the course of a simulation. In silico intervention is analogous to altering particular interactions in vivo using pharmacological treatments. The flexibility of our in silico system allows us to perform an intervention even if there is no analogous experimental treatment.

In addition, we used in silico intervention to induce depletion of CD8⁺ T-cells: we blocked recruitment and proliferation, so that no new cells entered the population. Maturation and exit are left in place so that CD8⁺ T-cells are gradually depleted. This in silico depletion is analogous to experiments where antibodies are used to deplete CD8⁺ T-cells from SIV-infected Rhesus macaques. A number of groups have demonstrated that this treatment causes a dramatic rise in viral load 1–3 orders of magnitude, depletion of CD4⁺ T-cells and disease progression (Fin et al., 1999; Matano et al., 1998; Schmitz et al., 1999). As a positive control, we depleted CD8⁺ T-cells in silico. For the purpose of our model analysis, we defined an ‘AIDS-like state’ based on this immunity-impaired positive control.

RESULTS

To explore the role of DCs during HIV-1 infection, we first captured the homeostatic mechanisms of a healthy LN in the absence of virus. Next, we introduced virus to simulate an acute phase and chronic state of infection, and validated our model by comparing our simulations to SIV-infected NHP data and published human clinical data. Finally, we analysed our model using uncertainty and sensitivity analysis techniques to identify mechanisms involved in HIV-1 infection and pathogenesis.

Simulation of a healthy LN

As a negative control, we simulated a healthy LN in the absence of virus. By construction, all cell types remained constant in number, reflecting an assumption of homeostasis in the absence of antigen (Doherty & Christensen, 2000). These levels observed in our simulation agreed with NHP infection data derived herein and also with published human clinical data (Haase, 1999) (Table 1).

Simulation of acute phase and chronic steady-state match human and NHP infection data

Solving the model simulates the populations of each cell type and virus over time (Fig. 2). From our model, we

<table>
<thead>
<tr>
<th>Infection state/model time point</th>
<th>Count</th>
<th>Model simulation</th>
<th>NHP</th>
<th>Human clinical data (Haase, 1999)</th>
</tr>
</thead>
<tbody>
<tr>
<td>No infection/day 0</td>
<td>Total CD4⁺ T-cell</td>
<td>3.5 × 10⁸</td>
<td>3.7 × 10⁸⁺</td>
<td>2.9 × 10⁸</td>
</tr>
<tr>
<td>Chronic/day 300</td>
<td>Total CD4⁺ T-cell</td>
<td>8.6 × 10⁷</td>
<td>10.7 × 10⁷⁺</td>
<td>6.7 × 10⁷</td>
</tr>
<tr>
<td>Acute/day 6</td>
<td>Infected cell</td>
<td>2.5 × 10⁶</td>
<td>1.7 × 10⁶</td>
<td>7.1 × 10⁵</td>
</tr>
<tr>
<td>Chronic/day 300</td>
<td>Infected cell</td>
<td>8.2 × 10⁶</td>
<td>6.4 × 10⁵</td>
<td>5.7 × 10⁴</td>
</tr>
<tr>
<td>Acute/day 6</td>
<td>Virus</td>
<td>2.0 × 10⁹</td>
<td>&gt;10⁸</td>
<td>&gt;10⁸</td>
</tr>
<tr>
<td>Chronic/day 300</td>
<td>Virus</td>
<td>8.3 × 10⁸</td>
<td>&gt;10⁸</td>
<td>&gt;10⁸</td>
</tr>
</tbody>
</table>

*This value was calculated from total T-cell count and the CD4:CD8 ratio from (Biancotto et al., 2007).
calculated experimentally relevant variables for comparison to our NHP experimental data (Fig. 3a–d). We found that our model quantitatively recapitulates the depletion of DCs and T-cells (Fig. 3a and b), and the increase in infected and activated T-cell populations (Fig. 3c and d) in the paracortical regions of an LN during uninfected, acute and chronic infection.

Other studies have shown that DCs are depleted during simian AIDS (Brown et al., 2007). Similarly, we found that total DCs became depleted during SIV infection, both in our experimental animal studies and our model simulations (Fig. 3a). The model simulation predicted that DC depletion occurred gradually after infection peaks (Fig. 3, compare a and c).

Because our model distinguished CD4+ from CD8+ T-cells, but our experimental data only measured total T-cells, we additionally validated the model simulation CD4:CD8 ratio by comparison to published HIV-1-infected human LN data (Biancotto et al., 2007). Typically in the blood, the CD4:CD8 ratio inverts from 2:1 to 1:2 over the course of infection (Margolick et al., 2006). However, our model recapitulates the 4:1 to 1:2 inversion of the CD4:CD8 ratio that occurs in human lymphoid tissue during chronic HIV-1 infection (Fig. 3e).

To ensure relevance to human disease, we additionally validated our model simulation by comparison to published human HIV-1 infection data (Table 1). Our model agreed with estimated cell counts of human lymphoid tissue.

**Determination of parameters that drive viral load**

Sensitivity and uncertainty analysis revealed how variation in model parameters affected infection dynamics. First, we analysed parameters directly related to CD4+ T-cells, CD8+ T-cells and virus (see Supplementary Material). Next, we found that many of the significant parameters identified by this analysis were DC related (Table 2). These DC-related mechanisms are either positively or negatively correlated with viral load by LHS/PRC, indicating the dual role of DCs in promoting both infection and immunity. We found that the parameter governing the immigration of mature DCs, which have encountered antigen in the periphery ($\phi_{DM}$) has a negative correlation with viral load. Although additional mature DCs promote infection, the net effect is to promote immunity, reducing steady-state viral load. The parameters that control licensing of DCs by T-helper cells ($\lambda$) and priming of CTLs by licensed DCs ($r_{DM}$) are both strongly negatively correlated with viral load as these mechanisms promote immunity. In contrast, parameters that control priming and subsequent infection of T-helper cells by DC-associated virus ($r_{DM}$ and $k_{DM}$, respectively) are correlated with increased viral load.

**Importance of DC-facilitated infection varies during the course of HIV-1 infection**

Our model captures four mechanisms leading to productive infection of CD4+ T-cells (Fig. 4a). Resting CD4+ T-cells become infected cells by all four routes. In the first case, virus infects resting T-cells directly without a need for priming. Of these cells, a small fraction are stimulated to become productively infected and the rest remain abortively infected and undergo apoptosis. This is the only route of infection described that is completely independent of DCs. In the second case, CD4+ T-cells are concurrently primed and infected by DCs. Cases 3 and 4 depend on...
mature or licensed DCs to first prime CD4\(^+\) T-cells. In the third case, virus infects activated T-helper cells independently of DCs. In the fourth case, DC-associated virus infects primed T-helper cells. To gauge the relative importance of each of these infection mechanisms, we performed a focused sensitivity analysis on these nine parameters during establishment of infection/early acute phase and chronic state of infection. During the acute phase of infection, four parameters were significantly correlated with viral load (see asterisks, Fig. 4b): abortive infection of T-cells \((k_{ab})\), which are then stimulated to become productively infected \((z)\), priming of T-helper cells \((r_{DM})\), and concurrent priming and infection by mature DCs \((b_{M})\) were significantly correlated with viral load. During the earliest establishment of infection, there has not been sufficient time to prime many T-helper cells. Thus, mechanisms that require a pool of activated T-helper host cells (such as \(k_V\), \(k_{DM}\) and \(k_{DL}\)) cannot contribute significantly to infection levels. Comparing the relative strength of each of these four infection mechanisms during infection establishment, we found that priming of T-helper cells, and concurrent priming and infection by mature DCs have a significantly greater correlation with viral load than the other infection mechanisms (see daggers, Fig. 4b). Our model predicted that the ability of DCs to concurrently prime and infect resting CD4\(^+\) T-cells is crucial to the establishment of infection.

During the chronic state of infection (Fig. 4c), abortive infection of resting T-cells becomes negatively correlated, and concurrent priming and infection of T-cells by DCs become insignificant. Instead, infection mechanisms 3 and 4, priming followed by infection (controlled by parameters \(k_V\), \(k_{DM}\) and \(k_{DL}\)), were significantly correlated with chronic state viral loads (see asterisks, Fig. 4c). Comparing the relative significance of each of these mechanisms, we found that infection of activated T-helper cells by DC-associated virus has a significantly greater correlation, revealing the importance of DCs enhancing infection during maintenance of infection (see dagger, Fig. 4c).

**Many mechanisms can cause progression to an AIDS-like state**

As a positive control, we depleted CTLs *in silico* (Fig. 5). In the absence of immune effector functions, the system...
Table 2. Sensitivity and uncertainty analysis identifies parameters that drive viral load

max, Maximum; mat, matured; lic, licensed.

<table>
<thead>
<tr>
<th>Parameter definition</th>
<th>Symbol</th>
<th>Sensitivity†</th>
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<tbody>
<tr>
<td>Sensitivity of DC parameters during chronic state</td>
<td></td>
<td></td>
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<tr>
<td>Recruitment</td>
<td></td>
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<tr>
<td>Max. immigration rate of mat. DC due to antigen</td>
<td>$\phi_{DM}$</td>
<td></td>
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<tr>
<td>Licensing</td>
<td></td>
<td></td>
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<tr>
<td>Licensing rate of mat. DCs by T-helper</td>
<td>$\lambda$</td>
<td></td>
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<tr>
<td>Priming</td>
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<tr>
<td>Priming rate of naive CD4&lt;sup&gt;+&lt;/sup&gt; by mat. DC</td>
<td>$r_{DM}$</td>
<td></td>
</tr>
<tr>
<td>Priming rate of naive CD8&lt;sup&gt;+&lt;/sup&gt; by lic. DC</td>
<td>$r_{SL}$</td>
<td></td>
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<tr>
<td>Enhancement of CD4&lt;sup&gt;+&lt;/sup&gt; T-cell infection</td>
<td></td>
<td></td>
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<tr>
<td>Infection rate of T-helper by mat. DC-associated virus</td>
<td>$k_{DM}$</td>
<td></td>
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<tr>
<td>Source and recruitment</td>
<td></td>
<td></td>
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<tr>
<td>Max. recruitment rate of naive CD4&lt;sup&gt;+&lt;/sup&gt; by DC</td>
<td>$\phi_4$</td>
<td>*</td>
</tr>
<tr>
<td>Max. recruitment rate of naive CD8&lt;sup&gt;+&lt;/sup&gt; by DC</td>
<td>$\phi_8$</td>
<td>↓*</td>
</tr>
<tr>
<td>Max. immigration rate of mat. DC due antigen</td>
<td>$\phi_{DM}$</td>
<td>*</td>
</tr>
<tr>
<td>Death/exit to efferent lymph</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Death/exit rate of infected cells</td>
<td>$\mu_1$</td>
<td>↑</td>
</tr>
<tr>
<td>Destruction rate of virus particles</td>
<td>$\mu_V$</td>
<td>↓*</td>
</tr>
<tr>
<td>Death/exit rate of naive CD8&lt;sup&gt;+&lt;/sup&gt;</td>
<td>$\mu_8$</td>
<td>↑</td>
</tr>
<tr>
<td>Death/exit rate of CTL</td>
<td>$\mu_C$</td>
<td>↑</td>
</tr>
<tr>
<td>Proliferation/clonal expansion</td>
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<tr>
<td>Proliferation rate of CTL</td>
<td>$p_C$</td>
<td>↓</td>
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<tr>
<td>Priming</td>
<td></td>
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<tr>
<td>Priming rate of naive CD4&lt;sup&gt;+&lt;/sup&gt; by mat. DC</td>
<td>$r_{DM}$</td>
<td>↑*</td>
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<tr>
<td>Priming rate of naive CD8&lt;sup&gt;+&lt;/sup&gt; by lic. DC</td>
<td>$r_{SL}$</td>
<td>↓*</td>
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<tr>
<td>Infection</td>
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<tr>
<td>Abortive infection and bystander effects of naive CD4&lt;sup&gt;+&lt;/sup&gt;</td>
<td>$k_{ab}$</td>
<td>↓*</td>
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<tr>
<td>Infection rate of T-helper by virus</td>
<td>$k_V$</td>
<td>↑</td>
</tr>
<tr>
<td>Infection rate of T-helper by mat. DC-associated virus</td>
<td>$k_{DM}$</td>
<td>↑</td>
</tr>
<tr>
<td>Virus properties</td>
<td></td>
<td></td>
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<tr>
<td>Average number of virus produced by an infected cell</td>
<td>$n$</td>
<td>↑*</td>
</tr>
<tr>
<td>CTL effector functions</td>
<td></td>
<td></td>
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<tr>
<td>Inhibition of mat. DC-associated virus infection by CTL</td>
<td>$c_2$</td>
<td>↑</td>
</tr>
<tr>
<td>Inhibition of infected cell virus production by CTL</td>
<td>$c_4$</td>
<td>↑*</td>
</tr>
<tr>
<td>Killing rate of infected cells by CTL</td>
<td>$k_I$</td>
<td>↑*</td>
</tr>
<tr>
<td>Killing rate of lic. DC by CTL</td>
<td>$k_L$</td>
<td>↑</td>
</tr>
<tr>
<td>DC maturation and licensing</td>
<td></td>
<td></td>
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<tr>
<td>Licensing rate of mat. DCs by T-helper</td>
<td>$\lambda$</td>
<td>↓*</td>
</tr>
</tbody>
</table>

† Statistically significant positive correlation by LHS/PRC ($P<5.9 \times 10^{-4}$) for DC parameters; $P<2.4 \times 10^{-4}$ for global sensitivity analysis.
↓ Statistically significant negative correlation by LHS/PRC ($P<5.9 \times 10^{-4}$) for DC parameters; $P<2.4 \times 10^{-4}$ for global sensitivity analysis.
* Numerical correlations are given in Supplementary Material (available in JGV Online).
* Significant total-order sensitivity index by eFAST ($P<0.01$).
* Numerical sensitivity indices are given in Supplementary Material (available in JGV Online).

established a new steady-state characterized by a high viral load set-point (Fig. 5a and b, bold solid line) and reduction in CD4<sup>+</sup> T-cell counts (not shown). In subsequent model analysis, we compared the effects of other in silico interventions to this positive control ‘AIDS-like state’.

The parameters we found to be significant in our sensitivity analysis (Table 2) are important in determining viral load. Thus, mechanisms controlled by these parameters are likely involved, singly or in combination, in the transition to AIDS. Specific parameters identified by both LHS/PRC and eFAST methods have a very significant effect on viral load. However, the relative strengths and weaknesses of these algorithms cause them to identify different subsets of marginally sensitive parameters. These statistically significant but weak mechanisms might work in combination with...
each other, or the more significant mechanisms, causing a multi-factorial progression to AIDS. To test which mechanisms could be involved in progression to an AIDS-like state, we performed in silico intervention by varying the mechanisms that were identified in the sensitivity analysis (Fig. 5). We found that parameters that were able to cause an AIDS-like state fell into three functional categories: first, mechanisms related to infection and viral replication (Fig. 5a); second, mechanisms related to maintenance or effector functions of immune response (Fig. 5b); and third, mechanisms related to death or exit of CD8\(^+\) T-cells or virus (Supplementary Fig. S2). As expected, based on DCs dual roles, DC functions are represented in the infection (Fig. 5a) and immune response (Fig. 5b) categories.

The first functional group of parameters identified (\(N, \mu_I, k_{DM}, r_{DM}\), and \(k_V\)) was related to mechanisms of infection and viral replication. Changing these parameters from their baseline values to the extremes of their range of variation (see Supplementary Table S1) can induce a transition to an AIDS-like state. This supports the hypothesis that a progressive adaptation of virus could result in progression to AIDS. Adaptation of virus has been suggested by others: mechanisms include changes in co-receptor usage or affinity (Gorry et al., 2004; Xiao et al., 1998), or increases in replication number (Stilianakis et al., 1997). In addition, it has been shown that the HIV-1 protein Nef causes upregulation of DC-SIGN in infected DCs, possibly increasing DC-enhanced infection (Sol-Foulon et al., 2002).

The second functional group of parameters (\(r_{BL}, k_I, k_L\), and \(\lambda\)) controls maintenance or effector functions of immune response. Three of these mechanisms form a causal pathway: first, DCs become licensed by T-helper cells (\(\lambda\)); next, licensed DCs prime CTLs (\(r_{BL}\)); and finally: CTLs kill infected T-cells (\(k_I\)). We found that reducing any of these mechanisms to the minimum of their range of variation...
(see Supplementary Table S1) results in a failure of the immune response to control infection, leading to an AIDS-like state. This finding lends support to the hypothesis that an impairment of immune response results in an inability to control viral load. Immunologically, reduction in CTL priming or CTL killing of infected cells could result from the acquisition of CTL epitope mutations (Wodarz & Nowak, 2002). Alternatively, as DCs are central to the generation of CTL response, alterations in licensed DC function could impair immunity.

The third functional group identified, parameters related to death or exit of CD8\(^+\) T-cells or virus, represents mechanisms related to lymphoid tissue architecture and regulated traffic of cells through LNs. This finding is not surprising given that alterations in T-cell migration and LN architecture are hallmarks of HIV-1 infection, other chronic infections and immunodeficiency in general (von Andrian & Mempel, 2003). See Supplementary Material for details on these results.

Finally, we found that statistically significant but weakly correlated parameters (\(w_4, w_8, w_D\), \(p_C, c_2\) and \(c_4\)) were unable to independently induce an AIDS-like viral load. Because components of the immune system are highly interactive, progressive HIV-1 infection to AIDS is likely a multi-factorial and multi-step process. Indeed, we find that these parameters in combination can lead to an increase in viral load approximately equal to acute phase viraemia (Supplementary Fig. S2 available in JGV Online).

**DC dysfunction in progression to AIDS**

Two main hypotheses exist for the role of DC dysfunction in progression to AIDS (Fig. 6a). The first suggests that, as T-helper cells become depleted by HIV-1 infection, they are present in insufficient numbers to license DCs, which in turn reduces the ability of DCs to prime CD8\(^+\) T-cells. The second hypothesis suggests that DC dysfunction is the result of a direct viral effect on DC intracellular processes (Chougnet & Gessani, 2006; Cohen et al., 1999). Likely, both mechanisms are at play during infection; however, our model analysis tests if one hypothesis is more significant in the progression to AIDS. To this end, we varied parameters controlling DC licensing by T-helper cells (\(\lambda\)) and licensed DC priming of CTLs (\(r_{8L}\)). When all other confounding factors are held constant at their default parameter values (Supplementary Table S1) we found that decreasing either or both of these mechanisms can cause an AIDS-like viral load. To examine further, we used global sensitivity analysis using the eFAST method to perform thousands of in silico experiments varying all model parameters simultaneously. This analysis identifies overall sensitivities that were apparent despite uncertainty or variability in other mechanisms. We found that licensed DC priming of CTLs (\(r_{8L}\)) was a significantly more sensitive (\(P<0.01\)) control point than DC licensing by T-helper cells (\(\lambda\)). This result indicates that, given biological variability in many other mechanisms affecting both DCs and CTLs, a direct failure of licensed DCs is more likely to contribute to HIV-1 immunopathogenesis than an indirect failure of DCs due to loss of CD4\(^+\) T-helper cells. This finding suggests that therapies targeting DC function will be more successful than therapies targeting a failure of CD4\(^+\) T-helper cells, as this is a stronger control point of the system.

**DISCUSSION**

The immune response to infectious disease is complex: the individual cells of the immune system are highly interactive, and the overall function of the system is a product of this multitude of interactions. The interplay between HIV-1 and the immune system is particularly complicated, as HIV-1 directly interacts with many immune cells, altering their functions, ultimately subverting the system at its core.
Because of this complexity, the immune response and its interaction with HIV-1 are naturally suited to a mathematical modelling approach. Building on previous work (Bajaria & Kirschner, 2005; Bajaria et al., 2002), we present, to our knowledge, the first mechanistic model of the specific roles of DCs during HIV-1 infection. Here, we focus on the dynamics within an LN and the role of different classes of DCs in HIV-1 dynamics. We moved beyond the ‘Langerhan’s cell paradigm’ of DC function by including LN-resident immature DCs and multiple maturation/activation states. We focused on LN, as it is the nexus of viral replication and antiviral immune response, and is historically under studied due to difficulties in observing human lymphoid tissue. Further, the LN has been consistently under appreciated in mathematical models studying HIV-1 infection and immune system dynamics.

Sensitivity and uncertainty analysis reveals which parameters and, by extension, which interactions are most important in determining the function of the virus–host system. Our analysis shows that many of the most important parameters that determine viral load levels relate to DCs. This finding illustrates the role of DCs as a central hub of interaction and information exchange during HIV-1 infection.

Others have suggested that the immune system has evolutionarily optimized ‘bow-tie’ or ‘hour-glass’ structural motifs, in which diverse and redundant input signals converge on a single control point. The signals are integrated and produce diverse and redundant output signals to the rest of the system. They suggest that CD4+ T-cells serve as one control point, and propose that the severity of AIDS results from HIV-1 compromising this vulnerable control point (Kitano & Oda, 2006). Similarly, our results show that DCs serve as a control point: DCs integrate signals from the pathogen and other components of the immune system, then signal other immune system cells by way of MHC molecules, co-stimulation and cytokines.

Given the central position of DCs in immune system interactions, it is not surprising that HIV-1 has adapted to exploit them to enhance infection. We showed that this enhancement is important in maintaining chronic infection viral load levels, and that increasing this effect can induce progression to an AIDS-like state. Others have suggested that the ability of HIV to infect resting CD4+ T-cells is critical for the earliest stage of infection, as resting T-cells predominate in the peripheral tissue where HIV is first encountered (Zhang et al., 2004). Importantly, we found a similar phenomenon when HIV arrives in an LN: in the early stages, when activated T-helper cells are limited, concurrent priming and infection by DCs is crucial in driving acute viraemia.

We also explored the opposing antiviral immunogenic role of DCs. We showed that DC licensing by T-helper cells, priming of CTLs by licensed DCs and CTL killing of infected cells are all critical steps in controlling chronic infection. Impairing any of these steps can cause an AIDS-like state. In particular, our model analysis suggests that the system as a whole is more sensitive to the direct failure of DCs to prime CTLs, rather than by the indirect route of T-helper cells to license DCs. This finding has implications for the design of therapeutic vaccines and adjuvants: modulation of DC numbers and function could improve the outcome of infection, even if other immunological defects cannot be treated.

One limitation of this kind of model is that differential equations consider average rates of interaction between populations. The model cannot capture stochastic effects or spatial heterogeneity. Ongoing work includes agent-based models of immune response in an LN that addresses these issues (Riggs et al., 2008).

Clearly experimental science has made vast advances in the study of the immune response and, in particular, HIV-1 infection dynamics. The systems biology approach presented here lends an additional tool to guide our understanding of the complexities of this biological system. An integrative approach can be most useful for identifying factors that are crucial to infection outcomes, and here we have presented multiple predictions that can now be further explored in an experimental setting.

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