人机神经同步：推动人工智能和虚拟网络发展的海马体机制

Neural Synchrony of Minds and Machines: Hippocampal Mechanisms to Advance AI and Virtual Networks

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摘要

人工智能（AI）通过学习数字界面收集的用户数据，预测用户行为。在线社交网络等虚拟空间将现实世界扩展到虚拟世界，利用人工智能技术模仿大脑的强化网络，将用户行为转化为数字资产。社交媒体平台利用人工智能通过奖励来操纵用户行为，这些奖励可能会使用户偏离其预期目标。这种错位会破坏用户的行为和认知，导致虚拟脱离。本文介绍了一种基于海马体网络的概念机制，用于人工智能和大脑同步，整合用户在虚拟空间中的身心存在。

Abstract

Artificial intelligence (AI) predicts behavior by learning from user data collected through digitally mediated interfaces. Virtual spaces—such as online social networks—extend the physical world into virtual worlds, leveraging AI technologies to transform user behavior into digital assets by mimicking the brain's reinforcement networks. Social media platforms utilize AI to manipulate user behavior through rewards that can diverge from the user's intended goals. This misalignment fragments user behavior and cognition, resulting in virtual disembodiment. This article presents a conceptual mechanism based on the hippocampal networks to synchronize AI and the brain, synthesizing the user's physical and mental presence in virtual spaces.

跟踪物理和虚拟网络连接

Web 2.0 的特点是利用社交媒体平台、搜索引擎和其他基于 Web 的应用程序的虚拟空间，组织和收集用户生成的内容和行为 [1,2]。Web 2.0 的商业实践利用用户提供的数据集，了解用户的内容消费习惯，从而准确地向用户推销广告[3]。例如，当用户在流媒体服务或社交应用程序上做出选择时，他们的数字网络数据库会更新，从而预测用户的消费[4]。人工智能技术促成这些数据的获取和组织——因此也有助于价值生成。这些人工智能技术（此处定义为开发智能机器的机器学习和统计方法）分析连接的网络数据[5]。与人工智能不同的是，虚拟网络是指以技术为媒介的物理空间扩展到

Tracing Physical and Virtual Network Connections

Web 2.0 is characterized by the organization and collection of user-generated content and behavior gathered through the virtual spaces of social media platforms, search engines, and other web-based applications [1,2]. The business practices of Web 2.0 leverage user-provided datasets to accurately market ads back to users by learning their content-consumption habits [3]. For example, when users make selections on streaming services or social apps, their digital networked databases are updated to predict user consumption [4]. Artificial intelligence (AI) technologies mediate the acquisition and organization of this data—and thus, also of value generation. These AI technologies, defined here as machine learning and statistical methods to develop intelligent machines, analyze connected network data [5]. Virtual networks, distinct from

数字环境，用户可以在其进行交互、共享信息和形成社区（图1）[6]。

深度强化学习（DRL）等技术的最新进展[7,8]，让人工智能现在可以通过ChatGPT等应用程序和谷歌DeepMind开发的游戏来模仿或超越人类的能力。DRL是人工智能的一个子集，社交媒体平台利用它来分析和聚合海量网络数据集，根据用户的行为模式学习用户交互并对其进行个性化[9]。通过利用DRL和其他人工智能技术，脸书等社交平台和谷歌等搜索引擎预测用户行为并将其商品化，创建数字资产，然后与数据经纪人交易并出售中给他们[10,11]。DRL系统有力地维持了用户参与度，以最大限度地提高广告收入，并操纵用户和社交媒体平台之间的目标，加剧了个人福祉和社会问题，如传播虚假信息、政治动荡、心理健康恶化、侵犯用户隐私和降低用户自主权[12–15]。社交网络的目标、DRL技术和用户之间的分离形成了错位，这种错位扭曲了现实世界和虚拟社会身份之间的联系。因此，用户的身体和认知统一感可能会恶化，剥夺用户在虚拟网络中的存在感[16-19]。

AI, refer to the technology-mediated extension of physical space to digital environments where users interact, share information, and form communities (Fig. 1) [6].

Through recent advances in technologies like deep reinforcement learning (DRL) [7,8], AI can now mimic or surpass human capabilities through applications like ChatGPT and games developed by Google's DeepMind. DRL is a subset of AI that social media platforms leverage to analyze and aggregate massive network datasets, learning and personalizing user interactions based on their behavioral patterns [9]. By utilizing DRL and other AI technologies, social platforms like Facebook and search engines like Google predict and commodify user behaviors, creating digital assets that are then traded with and sold to data brokers [10,11]. DRL systems powerfully maintain user engagement to maximize ad revenue and manipulate the goals between users and social media platforms, exacerbating individual well-being and social issues such as spreading fake information, political unrest, degraded mental health, invasion of user privacy, and decreasing user autonomy [12–15]. This misalignment—the separation between the goals of social networks, their DRL technologies, and the user—deforms the connection between real-world and virtual social identities. As a result, the user's sense of physical and cognitive unity can deteriorate, disembodying user presence in virtual networks [16–19].

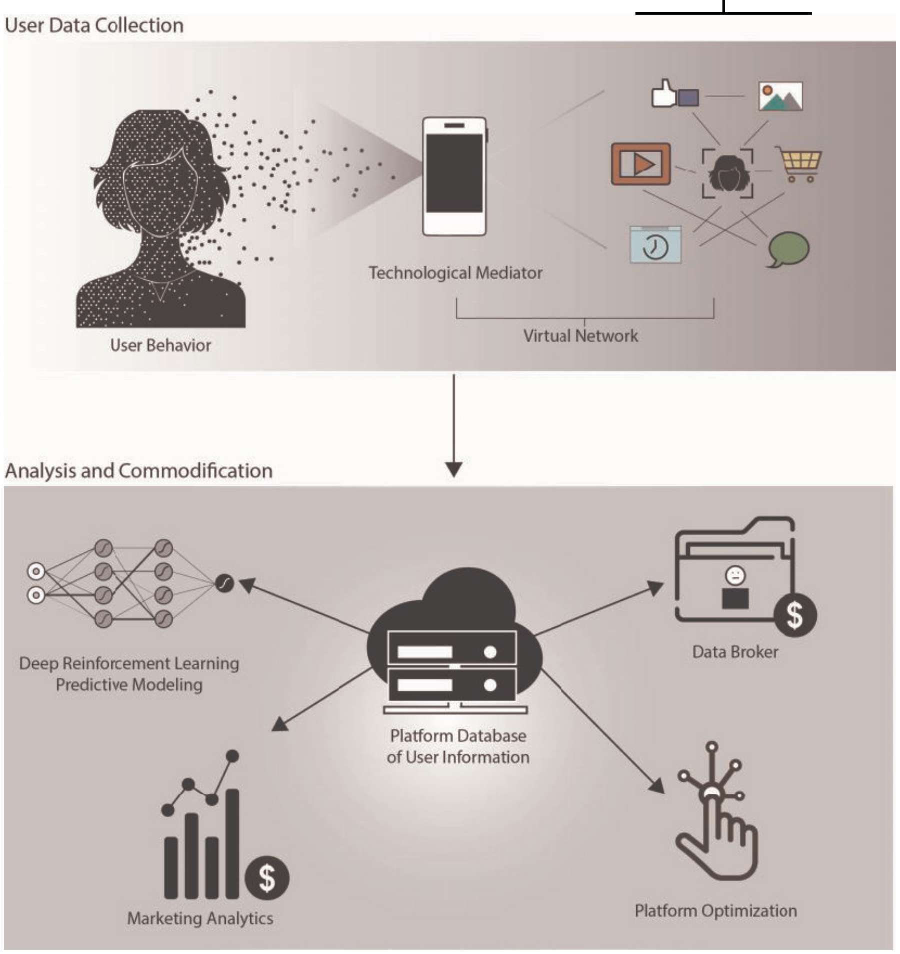

图1. 社交平台使用的DRL功能。这是一个流程图，说明DRL在收集社会数据、预测行为和提高参与度方面的功能。该图表包括通过强化学习将用户交互转换为商品化数据点。

Fig. 1. Social Media Data Collection and Monetization. Networked technologies track user behavior, storing data for deep reinforcement learning analysis. Insights are sold to data brokers and advertisers, while platforms shape user engagement through continuous monitoring. (© Joshua Sariñana)

用户和虚拟网络之间的分歧在于描述社交网络行为的模型、驱动DRL的人工神经网络（ANN）和大脑之间的根本差异。这种不一致源于（1）神经网络和社会网络行为之间的不协调性，以及（2）描述行为和人类认知的人工和有机神经网络模型之间的差异[20,21]。关于第一点，DRL（DNN）背后的ANN模仿了大脑的神经连接和功能；因此，两者共享底层网络计算。大脑和DNN的自适应计算是学习的基础，整合了来自环境的多个信息源。这些功能基于非线性变换，例如网络连接之间的强度变化，从而为复杂问题生成解决方案[22,23]。相比之下，社交网络模型描述了用户之间简化的线性信息流，它只能捕捉到一组浅层的特征和不精确的行为和机械信息[24,25]。社交平台应用了社区之间内容传播的线性模型，但缺乏与用户复杂的非线性行为和新兴社交网络行为相一致的整合过程（图2）[26]。经验数据进一步证实了这种错位，表明虚拟网络之间的信息传输是非线性的，就像强化学习的情况一样[27]。

The divergence between users and virtual networks lies in the fundamental discrepancies between models that describe social network behavior, the artificial neural networks (ANNs) that drive DRL, and the brain. This incompatibility originates from (1) the incongruency between neural network and social network behavior and (2) the differences between artificial and organic neural network models that describe behavior and human cognition [20,21]. Concerning the first point, the ANNs that underlie DRL (DNNs) mimic the activity of neural connections and functions of the brain; hence, the two share underlying network computations. The adaptive computations of the brain and DNNs underlie learning, integrating multiple sources of information from the environment. These functions are based on non-linear transformations—such as changes in the strength between network connections—that generate solutions to complex problems [22,23]. In contrast, social network models describe a simplified linear flow of information between users, which can only capture a shallow set of features and imprecise behavioral and mechanistic information [24,25]. Social platforms apply linear models of content spread between communities but lack an integrative process that aligns with complex non-linear behavior of users and emergent social network behavior (Fig. 2) [26]. This misalignment is further supported by empirical data showing that information transmission across virtual networks is expressed non-linearly, as is the case with reinforcement learning [27].

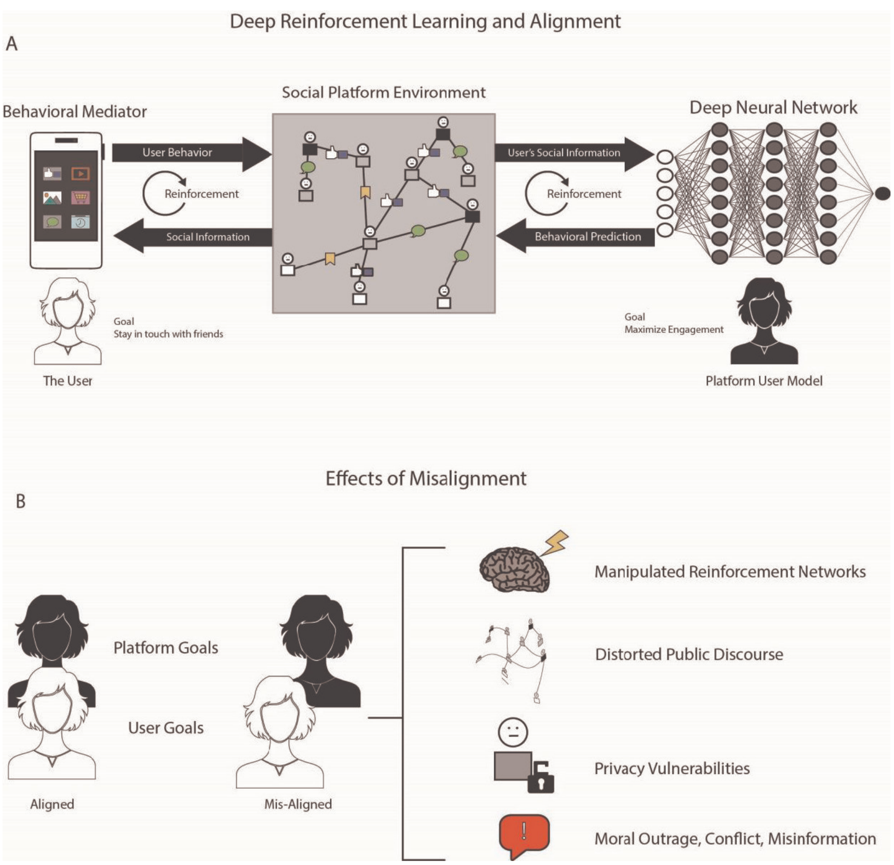

图2. 线性网络与非线性网络。这是一份社交网络模型和神经网络模型之间的比较图。（A）社交网络模型描绘了社交网络中的线性信息流。（B）神经网络的非线性特性强调突触可塑性和自适应计算。（C）大脑的有机神经网络展现了非线性振荡机制，而人工智能网络则没有该机制。

Fig. 2. Deep Reinforcement Learning and User Behavior Alignment. (A) A social platform environment provides user interaction data for DRL models to predict and influence behavior. (B) Misalignment between user and platform goals leads to privacy issues, misinformation, and manipulation of brain-reinforcement pathways. (© Joshua Sariñana)

DNN被社交媒体平台用来训练他们的DRL系统，通过反映和修改大脑的价值体系，间接地模拟用户行为。例如，用户优化他们的行为以提高他们的社会价值（例如，点赞）[28]。平台还利用强化的社会价值来最大限度地提高用户参与度（例如点击率）和广告收入[29,30]。此外，社会强化调节了大脑的价值网络，推动了在线社交网络应用程序的使用[31]。社交网络行为与强化学习难以区别，不能完全用线性机制来解释[32–34]。简单的线性社会模型与用户行为或DRL系统复杂的非线性表达不一致。人工智能无法模拟人类认知，这进一步加重了错位。这导致DRL系统要塑造用户行为以达成平台的目标，通常要以牺牲用户意图和福祉为代价[35]。

错位的第二个来源则是 DNN和构建人类认知的大脑功能之间的差异：更具体地说，是人类生成映射物理、社会和虚拟空间的内部心理表征的能力[36,37]。从功能上讲，大脑利用脑电波来优化直接和间接网络连接之间的协调性[38]。DNN不产生或使用振荡波，而是通过网络结构的直接连接点进行计算，限制了其在网络的间接连接部分捕获重要信息的能力（图2c）[39]；换句话说，用户的间接行为和认知网络无法通过DRL介导的虚拟网络同步，从而导致脱离实体的体验[40-43]。

计算模型表明，振荡波可以解决共享连接，因为它们能在复杂的系统中传播[40,45]。本文这里提出了一种概念模型，该模型利用脑电波（即网络振荡）来同步DRL系统、虚拟社交网络和空间认知的结构和功能。为了解释这些机制，对于基于奖励的强化学习相关的人工神经网络和大脑网络的计算变换，我们有必要首先进行比较。

通过行为强化和多巴胺连接神经科学和人工智能

行为强化学习理论描述了个体与环境之间力量的变化。目前，DRL模型以这些理论为基础，现在已经强大到足以模仿或超越人类的某些能力[46,47,48]。制定强化学习理论的目的是整合行为神经科学的发现，并将其与联想学习的假设神经算法联系起来。其中一个假设是，学习是通过神经元之间的神经活动诱导的变化来实现的：即突触可塑性[49]。然而，当时的技术能力无法测试突触介导的联想学习。由此产生的网络模型产生了ANN，它利用突触可塑性的概念来改变能够学习解决复杂问题的虚拟神经元之间的关联强度（图4）[50]。

随着时间的推移，大脑中的突触可塑性得到了实证验证，证实了人工神经网络的计算与更广泛的联结主义学习方法

Utilized by social media platforms to train their DRL systems, DNNs indirectly model user behavior by reflecting and modifying the brain's value system. For example, users optimize their behavior to enhance their social value (e.g., likes) [28]. Platforms also leverage reinforced social value to maximize user engagement (e.g., click-through rates) and ad revenue [29,30]. Furthermore, social reinforcement modulates the brain's value network, driving online social network app usage [31]. Social network behavior is indistinguishable from reinforcement learning, which is not fully explained by linear mechanisms [32–34]. The simple linear social models do not align with the complex, non-linear expression of user behavior or DRL systems. Misalignment is further compounded by the inability of AI to model human cognition. This results in DRL systems shaping user behavior to meet platform goals, often at the expense of user intentions and well-being [35].

The second source of misalignment stems from the differences between DNNs and the brain functions that construct human cognition: more specifically, the human ability to generate internal mental representations that map physical, social, and virtual spaces [36,37]. Functionally, the brain utilizes brain waves to optimize coordination across direct and indirect network connections [38]. DNNs do not generate or use oscillatory waves but rather compute through the directly connected points of network structures, limiting the ability to capture important information across indirectly connected parts of the network (Fig. 2c) [39]; in other words, the user's indirect behavioral and cognitive networks cannot synchronize through DRL-mediated virtual networks, thus resulting in disembodied experiences [40–43].

Computational models suggest oscillatory waves can resolve shared connections because they propagate across complex systems [40,45]. Proposed here is a conceptual model that utilizes brain waves (i.e., network oscillations) to synchronize the structure and function of DRL systems, virtual social networks, and spatial cognition. To explain these mechanisms, it is necessary to first compare the computational transforms of ANNs and brain networks related to reward-based reinforcement learning.

Connecting Neuroscience and Artificial Intelligence through Behavioral Reinforcement and Dopamine

Theories of behavioral reinforcement learning describe changes in the strength between an individual and the environment. Current DRL models are based on these theories and are now powerful enough to mimic or surpass certain human capabilities [46,47,48]. Reinforcement learning theories were formulated to integrate behavioral neuroscience findings and bridge them to postulated neural algorithms of associational learning. One such postulate is that learning occurs through neural activity-induced changes between neurons: i.e., synaptic plasticity [49]. However, the technolog-

之间的关系[51,52]。强化学习算法提供了一个框架，用于理解奖励体验如何通过代理改变行为与环境之间的关联强度，以及突触权重的变化[53,54]。DNN与大脑价值网络的各个方面相一致，特别是结合中脑多巴胺神经元的计算过程[55]。这些神经元对意外的奖励或惩罚（即强化事件）表现出改变的活动，将多巴胺释放到处理奖励、动机和注意力的大脑中更广泛的价值网络中[256]。多巴胺会改变这些大脑网络内部和他们之间的突触连接[57,58]。随着个体学会预测奖励，多巴胺神经元的活动从接收意外奖励，转变为对预测奖励的环境线索做出反应[59]：例如，咖啡的香味和与增强的注意力和动力相关的感觉，或指示共享或点赞的社交媒体帖子的设备通知（图4）。

多巴胺神经元活动充当大脑价值网络的教学信号，并充当了与人类和DRL系统44中的强化学习过程相匹配的计算桥梁。然而，这种关系也突显了大脑网络中与适应不良状态相关的潜在损伤，例如成瘾、焦虑和抑郁。社交媒体平台为最大限度地提高参与度而部署的DRL系统，会加速此类损伤[60,61]。对强化学习网络（人工智能和有机网络）的重视，突显了设计准确反映健康人类行为和认知的人工智能系统所面临的挑战。

社交网络结构在大脑中以空间表示[62]。然而，DNN无法整合社交导航所需的认知功能，这些功能与社会学、心理学和以用户为中心的设计原则的空间框架相一致[63–65]。社交平台通过DRL调解功能利用用户偏见，创建同质的虚拟空间，阻止用户在社会强化的虚拟空间之外导航，这抑制了用户参与的多样化，并促进了增加道德愤怒的回声室， [66,67]。包括产生现实世界和社交网络内部认知表征的大脑空间过程，可以拓宽用户行为，更好地与虚拟社交网络保持一致，并更有效地导航，而不会陷入助长冲突和错误信息的环境中[68,69]。海马体的振荡网络特性为这种一致性问题提供了一种潜在的解决方案。

空间认知的多维网络映射

海马体在结构和功能上连接着多个大脑区域，提供了一个操作框架，连接强化学习、DNN计算和多维空间网络。多巴胺能神经元活动除了将人类的强化学习与DNN功能联系起来之外，还在海马体的空间编码中发挥着作用[70]。海马体中多巴胺能的投射和释放通过加强突触连接、建立和存储环境空间的实时心理表征，促进空间信息的编码[71–73]。奖励或惩罚的体验（即强化）会导致海马体多巴胺的释放，增强

ical capabilities of the time could not test synaptic-mediated associative learning. The resulting network models gave rise to ANNs that utilized the concepts of synaptic plasticity to alter associational strengths between virtual neurons capable of learning to solve complex problems [50].

Over time, synaptic plasticity was empirically validated in the brain, supporting the relationship between the computations of ANNs and the broader connectionist approach to learning [51,52]. Reinforcement learning algorithms provided a framework for understanding how rewarding experiences alter associative strengths between behavior and the environment and changes in synaptic weights by proxy [53,54]. DNNs (Fig. 3) align with aspects of the brain's value networks, particularly by incorporating computational processes of midbrain dopamine neurons [55]. These neurons exhibit altered activity in response to unexpected rewards or punishment (i.e., a reinforcing event), releasing dopamine to the broader value networks of the brain that process reward, motivation, and attention [56]. Dopamine alters the synaptic connections within and across these brain networks [57,58]. As individuals learn to anticipate rewards, dopamine neuron activity shifts away from receiving an unexpected reward to responding to the environmental cues that predict reward [59]: e.g., the smell of coffee and the rewarding feeling associated with enhanced attention and motivation or device notifications indicating shared or liked social media posts (Fig. 4).

Dopamine neuron activity acts as a teaching signal to the brain's value network and as a computational bridge that matches the processes of reinforcement learning in humans and DRL systems. Yet, this relationship also highlights the potential impairments in the brain's networks related to maladaptive states, such as addiction, anxiety, and depression. Such impairments are precipitated by DRL systems deployed by social media platforms to maximize engagement [60,61]. The emphasis on reinforcement learning networks—artificial and organic—underscores the challenges in designing AI systems that accurately reflect healthy human behavior and cognition.

Social network structures are spatially represented in the brain [62]. However, DNNs cannot incorporate the cognitive functions necessary for social navigation that align with spatial frameworks foundational to sociological, psychological, and user-centered design principles [63–65]. Social platforms exploit user bias through DRL mediation, creating homogenous virtual spaces that discourage users' navigation beyond socially reinforced virtual spaces, which inhibits diverse user participation and promotes echo chambers that increase moral outrage [66,67]. Including the spatial processes of the brain that generate internal cognitive representations of the physical world and social networks may broaden user behavior to better align with and navigate virtual social networks more effectively without getting stuck in contexts that

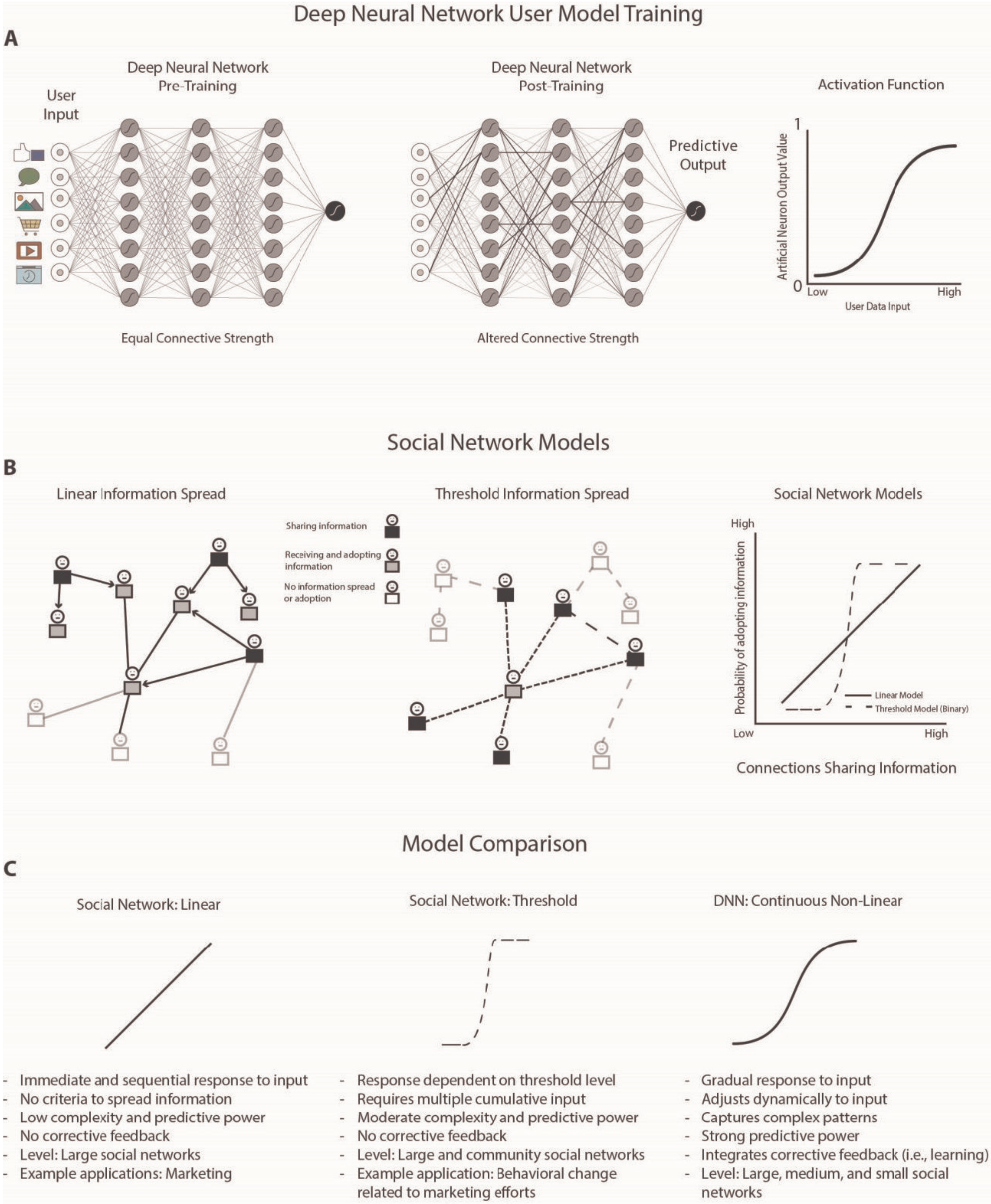

图3. 多巴胺对神经网络和强化学习的影响。(A) 多巴胺能网络及其根据奖励或惩罚释放多巴胺。(B) 多巴胺会改变大脑区域的突触连接，从而实现网络学习和问题的解决。(C) 多巴胺神经元活动的转变从强化事件本身转移到事件的预测因子。

Fig. 3. DNN and Social Network Dynamics. (A) DNN uses user data for connection adjustments via a non-linear activation function. (B) Social networks apply linear and threshold models to analyze information spread. (C) Comparison of properties in social and artificial networks. (© Joshua Sariñana)

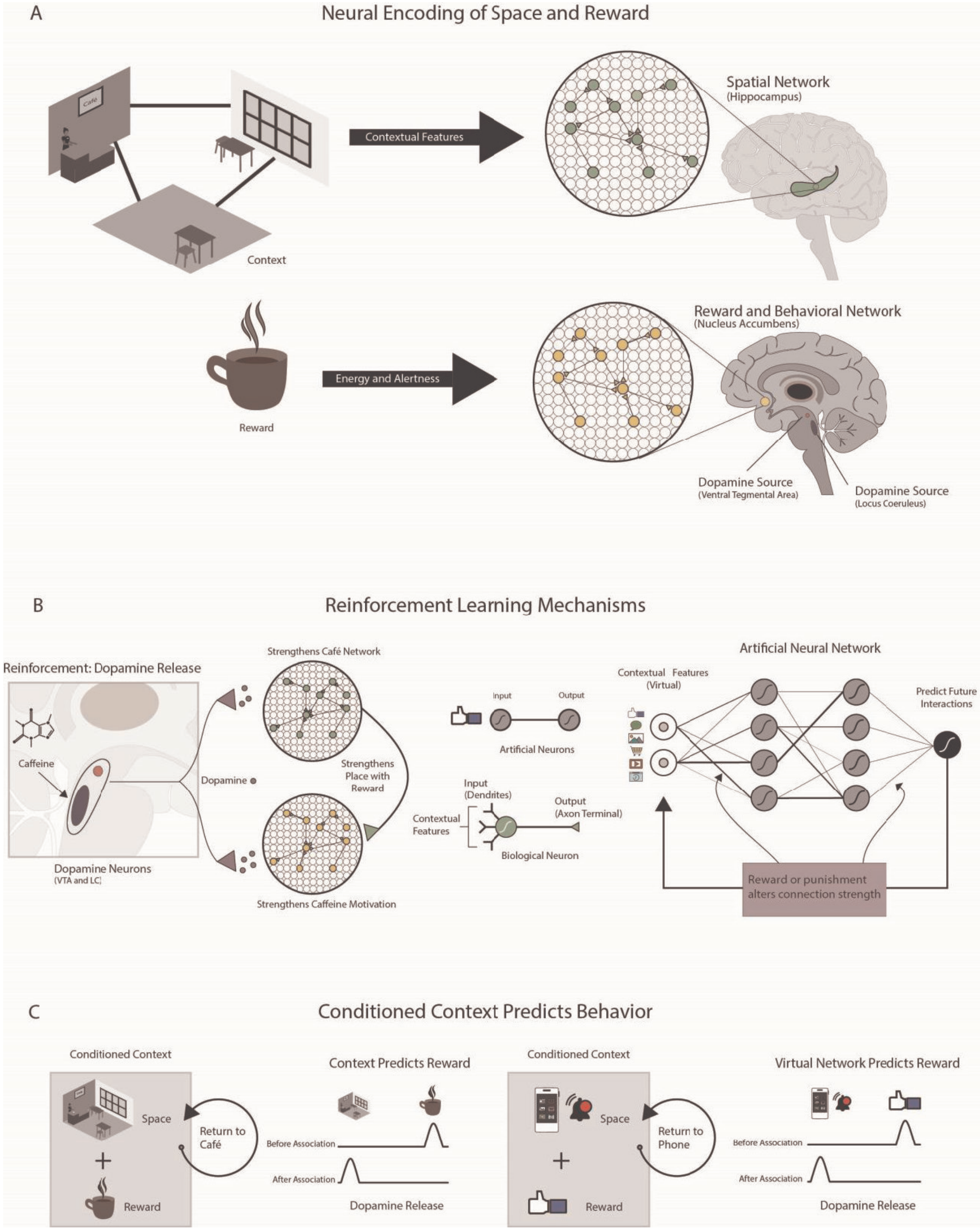

图4. 视觉信息的海马体整合。(A) 该图显示了海马体如何整合感觉信息以创建空间图。(B) 该图表说明了从视觉输入到海马体编码的途径，以及 (C) 振荡波在将这些信息组织成环境空间感知中的作用。

Fig. 4. Brain and Artificial Network Learning in Contextual Encoding. (A) The hippocampus integrates the spatial features of a café, and the nucleus accumbens (NAc) reinforces coffee-seeking by receiving dopamine. (B) Left: Caffeine-induced dopamine release strengthens synapses in the hippocampus and NAc. Center: Hippocampal and artificial neurons compute non-linearly. Right: An ANN models user behavior, where reinforcement signals adjust neuron connections, paralleling brain-based learning. (C) Learning shifts reward prediction from coffee to café; a smartphone-reward pairing conditions behavior, with reward prediction shifting to the smartphone. (© Joshua Sariñana)

周围空间环境与个体行为反应之间的关联[74]。例如，在咖啡店时，海马体会整合周围环境的视觉信息，从而生成该空间的内部表征，这将与咖啡的奖励效果、与好朋友会面或在虚拟工作中取得进步相关联，并促进对咖啡店的持续光顾。

尽管增加突触可塑性的关联机制以多巴胺为基础，也有助于进一步提高环境空间关联与强化学习和DNN的一致性，但这种纯粹的连接主义学习方法无法执行多维空间的认知功能[75-77]。空间认知的出现依赖于海马体产生的振荡，这些振荡组织了海马体局部回路内物理连接的活动，以及大脑中的间接连接网络，如视觉系统和前额叶皮层的注意力系统（图4）[78,79]。更具体地说，感觉输入从眼睛穿过每个突触连接到达海马体所需的时间太长，因此无法实时匹配空间认知[80]。海马体振荡迅速将这些间接连接中的视觉数据组织到海马体内部，构建和协调空间的多维表示：特别是构成空间认知的物理、社会和虚拟空间的表示[81-84]。结构同步和振荡同步的结合，增强了网络功能、效率和个体在环境中的灵活适应性。重要的是，人工智能系统不能结合连接主义和振荡网络模型，这是部署人工智能技术的社交网络与人类认知之间系统性错位的原因（图5）。

简化的社会网络模型无法捕捉神经网络的非线性过程。与这些模型类似，从视觉刺激到认知的转换不能仅由连接主义神经网络执行。视觉感知的神经坐标被转换回视觉空间的感官坐标。更具体地说，眼睛中相邻视网膜细胞对视觉环境中的相邻位置进行编码，这些位置由相邻视觉皮层神经元的活动表示[85]。外部世界、眼睛和视觉皮层之间的神经网络得以保留。随着海马体将视觉感知整合到空间认知的多维表征中，保留的视觉坐标的连续性被破坏[86,87]。由于基于连接主义的视觉系统的计算有局限性，因此不可能直接将空间认知追溯到环境的视觉坐标（图4）[88,89]。空间认知需要整合连接主义和振荡网络，将感官和感知信息转化为物理、社会和虚拟空间的内部表征（图5）。操作这种混合系统的功能可以同步大脑的强化学习网络、DNN过程和空间认知，从而促进用户在虚拟空间中的存在。

虚拟具身的网络同步集成

神经形态计算和振荡神经网络模型可以帮助操作上述概念机制。神经形态计算结合了自适应硬件和算法，模仿大脑将突触计算和记忆存储相集成的能力（图6）[90,91]。因此，与目前用于训练和部署DNN计算的硬件和软件技术相比，神经形态计算在合成多个输入和降低能源成本方面更加高效

promote conflict and misinformation [68,69]. The oscillatory network properties of the hippocampus provide a potential solution for this alignment problem.

Mapping the Multi-Dimensional Networks of Spatial Cognition

The hippocampus structurally and functionally connects multiple brain regions, providing an operational framework that bridges reinforcement learning, DNN computations, and multi-dimensional spatial networks. Dopaminergic neuron activity, in addition to linking reinforcement learning in humans to DNN function, also plays a role in the hippocampal encoding of space [70]. Dopaminergic projection to and release in the hippocampus promotes the encoding of spatial information by strengthening synaptic connections, building and storing real-time mental representations of contextual spaces [71–73]. The experience of a reward or punishment (i.e., reinforcement) results in hippocampal dopamine release, enhancing the association of the surrounding spatial contexts with the behavioral reaction of an individual [74]. For example, when in a coffee shop, the visual information of the environment surrounding a person will be integrated by the hippocampus to generate an internal representation of that space, which will become associated with the rewarding effects of coffee, meeting a good friend, or making progress with virtual work and promote continued patronage of the coffee shop.

Although dopamine-based association mechanisms that increase synaptic plasticity also assist in further aligning spatial associations of contexts with reinforcement learning and DNNs, this purely connectionist approach to learning cannot execute the functions of multi-dimensional spatial cognition [75–77]. The emergence of spatial cognition relies on hippocampal-generated oscillations that organize activity across physical connections within local circuits of the hippocampus and indirectly connected networks across the brain, such as the visual system and the attentional systems of the prefrontal cortex (Fig. 4) [78,79]. More specifically, the time it takes for sensory input to cross each synaptic connection from the eye to the hippocampus is too slow to match spatial cognition in real-time [80]. Hippocampal oscillations quickly organize the visual data across these indirect connections into and within the hippocampus, building and aligning the multi-dimensional representations of space: in particular, the representation of physical, social, and virtual spaces that make up spatial cognition [81–84]. The combination of structural and oscillatory synchrony enhances network functions, efficiency, and flexible adaptation for individuals to navigate the environment. Importantly, AI systems cannot combine connectionist and oscillatory network models, which underlies the systemic misalignment between social networks that deploy AI technologies and human cognition (Fig. 5).

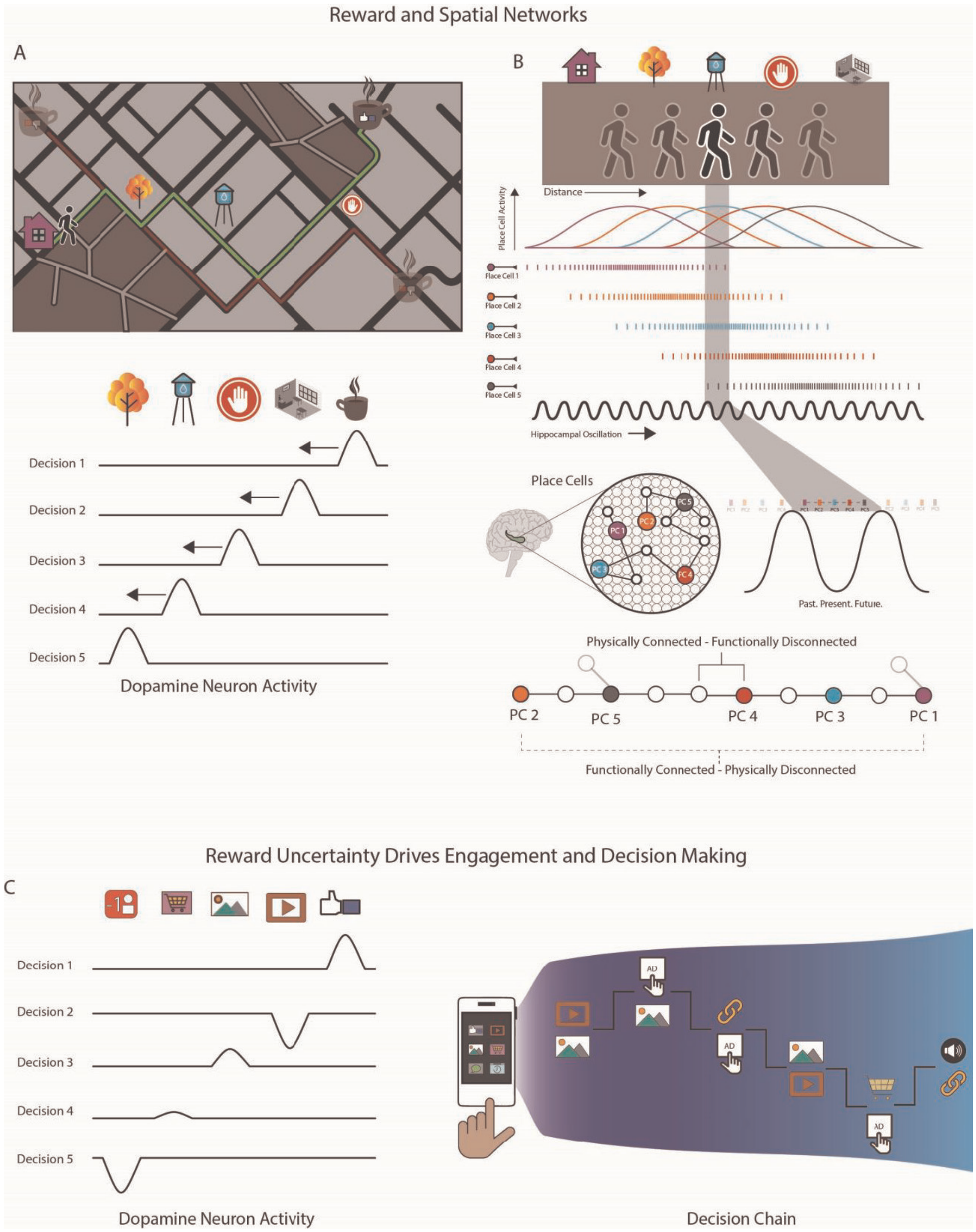

图5. 同步心理表征。(A) 关于物理、社会和虚拟环境的心理表征的海马体生成。箭头表示由振荡波组织的心理图的创建，这些振荡波在功能上连接了这些不同的空间。(B) 人工智能界面显示为调解或破坏这些地图，突出了人工智能在脱离实体中的作用。

Fig. 5. Spatial Cognition and Reward Prediction. (A) Map of an individual's path to a chosen café, with contextual features and related dopamine peaks that shift from coffee to preceding cues, illustrating reward prediction. (B) Top: Linear representation of the path and features, with hippocampal place cell (PC) activity peaking at each position (i.e., curves and related PCs firing as colored tick marks). Middle: Oscillations modulate and align place cell activity along the path. Left: PCs in a hippocampal circuit that are indirectly connected. Right: Expanded oscillation shows sequential activity of PCs, representing past, present, and future locations. Bottom: Linearized PC connections, emphasizing functional vs. structural connectivity. (C) Left: Modeled dopamine prediction activity in a virtual network with variable rewards (upward deflection) and punishments (downward deflection). Right: Virtual network interface shapes user engagement in social networks, illustrating the influence of uncertainty on decision making. (© Joshua Sariñana)

[92]：更具体地说，是最近加速训练和运行DNN的图形处理器（GPU）。由于与相应的存储系统分离，这些特定的图形处理器计算需要更多的能源和财务投资，神经形态计算和大脑能够对其进行有效地集成[93,94]。

振荡神经网络（ONN）模型通过同步来表示和处理信息；它们模拟神经网络振荡，因此成为实时交互式应用的理想选择[95,96]。集成神经形态计算和ONN的混合系统，可以在图像识别和联想学习等任务中结合这两种方法的优势，进一步加速ANN计算，从而节省大量的能源[97,98]。这种混合系统将连接主义和振荡网络功能合并到单个模型中，可以更好地反映行为强化和空间认知背后的神经网络（图6）。

尽管神经形态计算硬件仅限于研究领域，尚未实现在真实世界的应用，但混合系统可用于（1）将混合神经形态和ONN模型的性能与GPU进行比较，以便训练和执行DNN，测量分析社交网络数据的准确性、处理时间和能耗；（2） 测试不同的社会、行为和认知模型如何使用基于社交平台数据的合成数据，修改虚拟代理之间的交互；（3）根据基于自我报告的反馈和与虚拟空间中的认知状态相关的头皮脑电图（EEG）信号，测试混合系统与用户以及用户之间实时保持网络同步的能力；以及（4）观察混合系统如何影响虚拟环境中的用户参与、强化学习、空间认知和导航。这些方法和数据可以提供关键见解，开发支持用户行为和空间认知的系统，从而在虚拟网络中实施[99]。

尽管如此，部署用户行为和认知与虚拟环境的网络同步，会引发严重的隐私问题。私营企业网络和政府对用户内部认知表征的评估，可能会进一步增强他们预测和修改用户行为以及广大公民行为的能力[100]。与此相关的是，可穿戴技术捕获的电子健康记录和个人生物特征数据，可以用于训练预测患者病理状态的ANN[101]。此外，混合现实（MR）头戴式设备似乎即将成为主流，苹果和Meta将物理现实扩展到高维虚拟空间的战略经济投资，表明了这一点，这可能会进一步加剧社会问题，如心理健康、虚假信息的传播（例如深度伪造照片和视频）和社会动荡 [102103104]。随着技术的发展，用户集成的进一步发展，迫切需要制定政策来规范神经技术及其访问分析个人数据，因为这可能进一步侵犯用户隐私（图7）[105]。

总结

本文提出了一种概念机制，使人工智能和大脑同步，以支持用户的身体和精神在虚拟空间中的存在。Web 2.0的力量

Analogous to the simplified social network models that are incapable of capturing the non-linear processes of neural networks, the transformations from visual stimuli to cognition cannot be executed by a purely connectionist neural network. The neural coordinates of visual perception are translated back to sensory coordinates of visual space. More specifically, adjacent retinal cells in the eye encode adjacent locations in the visual environment represented by activity in adjacent visual cortical neurons [85]. The neural network between the external world, the eye, and the visual cortex is preserved. The continuity of conserved visual coordinates is disrupted as the hippocampus integrates visual perception into the multi-dimensional representations of spatial cognition [86,87]. It is impossible to directly trace spatial cognition back to visual coordinates of the environment due to the limitations of the connectionist-based computations of the visual system (Fig. 4) [88,89]. Spatial cognition requires integrated connectionist and oscillatory networks to transform sensory and perceptual information to the internal representations of physical, social, and virtual spaces (Fig. 5). Operationalizing the functions of this hybrid system may synchronize reinforcement learning networks of the brain, DNN processes, and spatial cognition to promote user presence in virtual spaces.

Integrating Network Synchronization for Virtual Embodiment

Neuromorphic computing and oscillatory neural network models can help operationalize the conceptual mechanisms discussed above. Neuromorphic computing combines adaptive hardware and algorithms, mimicking the brain's ability to integrate synaptic computations with memory storage (Fig. 6) [90,91]. As a result, neuromorphic computing is more effective in synthesizing multiple inputs and reducing energy costs than current hardware and software technologies used to train and deploy DNN computations [92]: more specifically, the graphic processing units (GPUs) that have recently accelerated training and running DNNs. These particular GPU computations require more energy and financial investment due to separation from their corresponding memory systems, which neuromorphic computing and the brain are able to effectively integrate [93,94].

Oscillatory neural network (ONN) models represent and process information through synchronization; their emulation of neural network oscillations makes them ideal for real-time, interactive applications [95,96] . Hybrid systems that integrate neuromorphic computing and ONNs can combine the strengths of both approaches in tasks such as image recognition and associative learning, further accelerating ANN computations with exceptional energy savings [97,98]. Such a hybrid system that incorporates both connectionist and oscillatory network functions into a single model could better

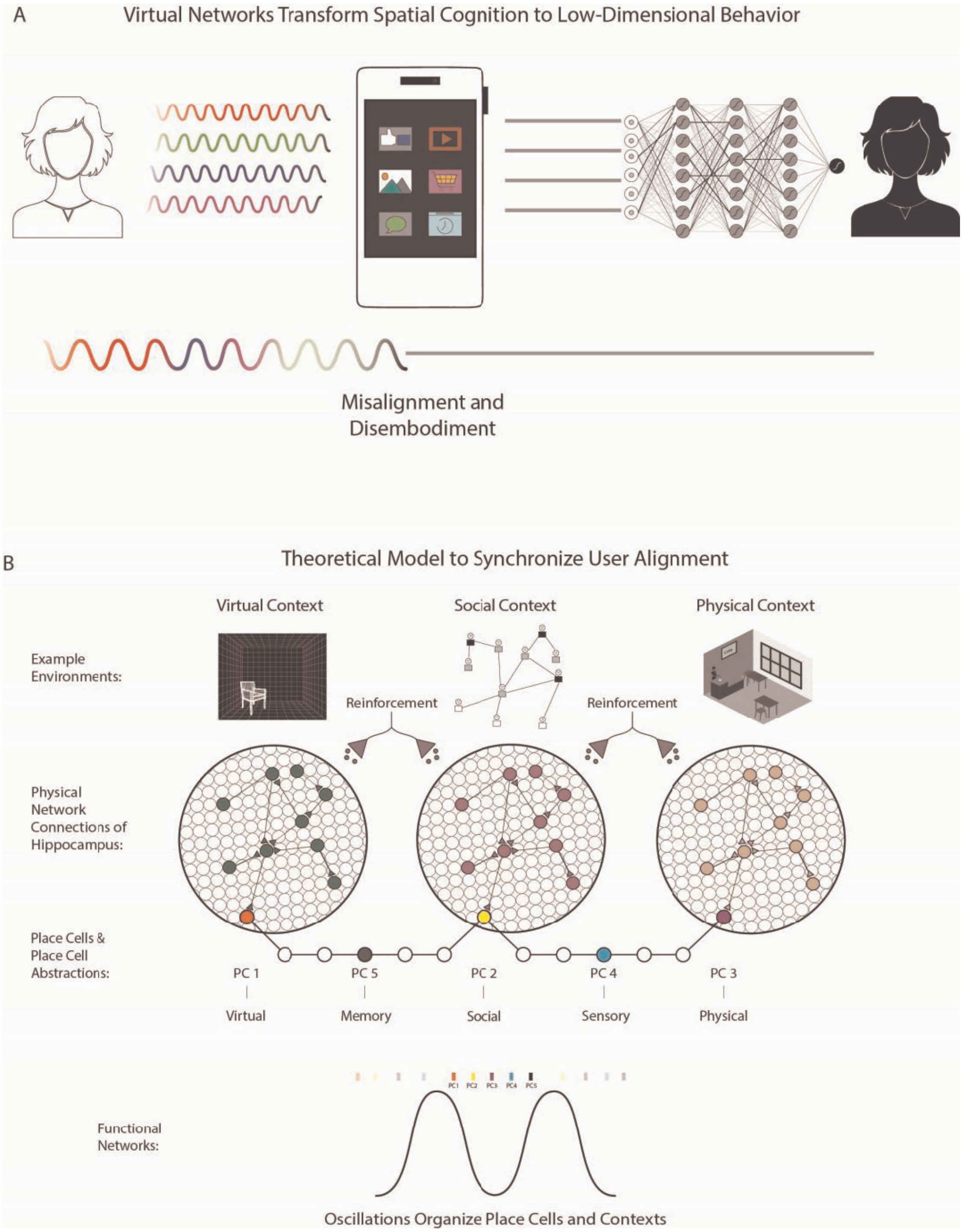

图6. 结合神经形态计算和ONN的混合系统示意图。组件包括自适应硬件、突触、并行处理单元和振荡模块。该图显示了增强的能源效率和图像识别和联想记忆等实时任务表征。

Fig. 6. Spatial Abstractions and Virtual Misalignment. (A) Summary of how reducing high-dimensional cognitive functions (oscillation) to lower-dimensional data (grey lines) desynchronizes user interaction virtual networks underlying misalignment, resulting in disembodiment. (B) Top/Middle: Environments encoded in hippocampal networks form cognitive representations influenced by reinforcement and dopamine signaling. Middle/Bottom: Place cell activity reflects spatial abstractions, with oscillations organizing connectivity across spaces. (© Joshua Sariñana)

源于用户生成的内容以及用户行为和注意力的商品化。脸书等社交平台和谷歌等搜索引擎通过部署DRL来协调和限制用户行为和认知，从而使物理和虚拟环境之间的用户交互不同步。这种错位源于操纵大脑的价值网络增强用户在社会强化空间中的参与度。特别是神经网络和社会网络行为之间的差异，以及神经网络模型和人类认知过程之间的分歧，加剧了心理健康问题、错误信息的传播和用户自主性的降低。计算和理论模型表明，振荡可以连接人工智能和大脑的复杂网络，促进系统协调性。

本文详细论述了利用海马体的振荡功能和机制来拓宽社交网络的能力以及相关的DRL技术。结构功能和振荡功能相结合，有可能使社会、人工和有机神经网络的网络计算保持一致。因此，用户的新兴行为和认知网络可以有效地与扩展的虚拟环境同步，弥合这些系统目标之间的差距。为验证和操作本文讨论的概念机制，神经形态计算和ONN通过进一步整合大脑的复杂和综合计算，提供了一条有前景的途径。利用海马体在同步分布式知识和在网络变量之间创建复杂的非线性关系方面的作用，可以促进反映人类认知的人工内部表征的发展。换句话说，利用海马体功能进一步发展通用人工智能77。其中至关重要的问题是，在开发和部署这种先进的神经技术时，隐私问题必须放在首位。

reflect the neural networks underlying behavioral reinforcement and spatial cognition (Fig. 6).

Although neuromorphic computing hardware is limited to the research community and real-word applications have yet to be realized, a hybrid system could be used to (1) compare the performance of hybrid neuromorphic and ONN models with GPUs to train and execute DNNs, measuring accuracy, processing time, and energy consumption in analyzing social network data; (2) test how different social, behavioral, and cognitive models modify the interactions between virtual agents using synthetic data based on social platform data; (3) test the hybrid systems' ability to maintain network synchronization with and between users in real-time based on self-reported feedback and scalp electroencephalogram (EEG) signals related to cognitive states in virtual spaces; and (4) observe how hybrid systems affect user engagement, reinforcement learning, spatial cognition, and navigation in virtual settings. These methodologies and data can provide key insights to develop systems that support user behavior and spatial cognition for embodiment in virtual networks [99].

Still, deploying network synchronization of user behavior and cognition with virtual environments raises serious privacy concerns. The assessment of internal cognitive representations of users by private enterprise networks and governments may further enhance their capabilities to predict and modify user behavior and that of the larger citizenry [100]. Relatedly, electronic health records and personal biometric data captured by wearable technologies can and are used to train ANNs that predict patients' pathological states [101]. Furthermore, the seemingly imminent mainstream adoption of mixed-reality (MR) headsets, as shown through strategic economic investments by Apple and Meta to extend physical reality into high-dimensional virtual spaces, may further exacerbate social issues such as mental health, the spread of fake information (e.g., deep fake photos and videos), and social unrest [102,103,104]. As user integration advances further with technological development, there is an urgent need for policies that regulate neurotechnologies and their access to analyze personal data that may further breach user privacy (Fig. 7) [105].

Summary

A conceptual mechanism is proposed to synchronize AI and the brain to support the user's physical and mental presence in virtual spaces. The power of Web 2.0 stems from user-generated content and the commodification of user behavior and attention. Social platforms like Facebook and search engines like Google desynchronize user interactions between physical and virtual environments by deploying DRL that mediates and restricts user behavior and cognition. This misalignment stems from manipulating the brain's value networks to enhance user engagement in socially reinforced

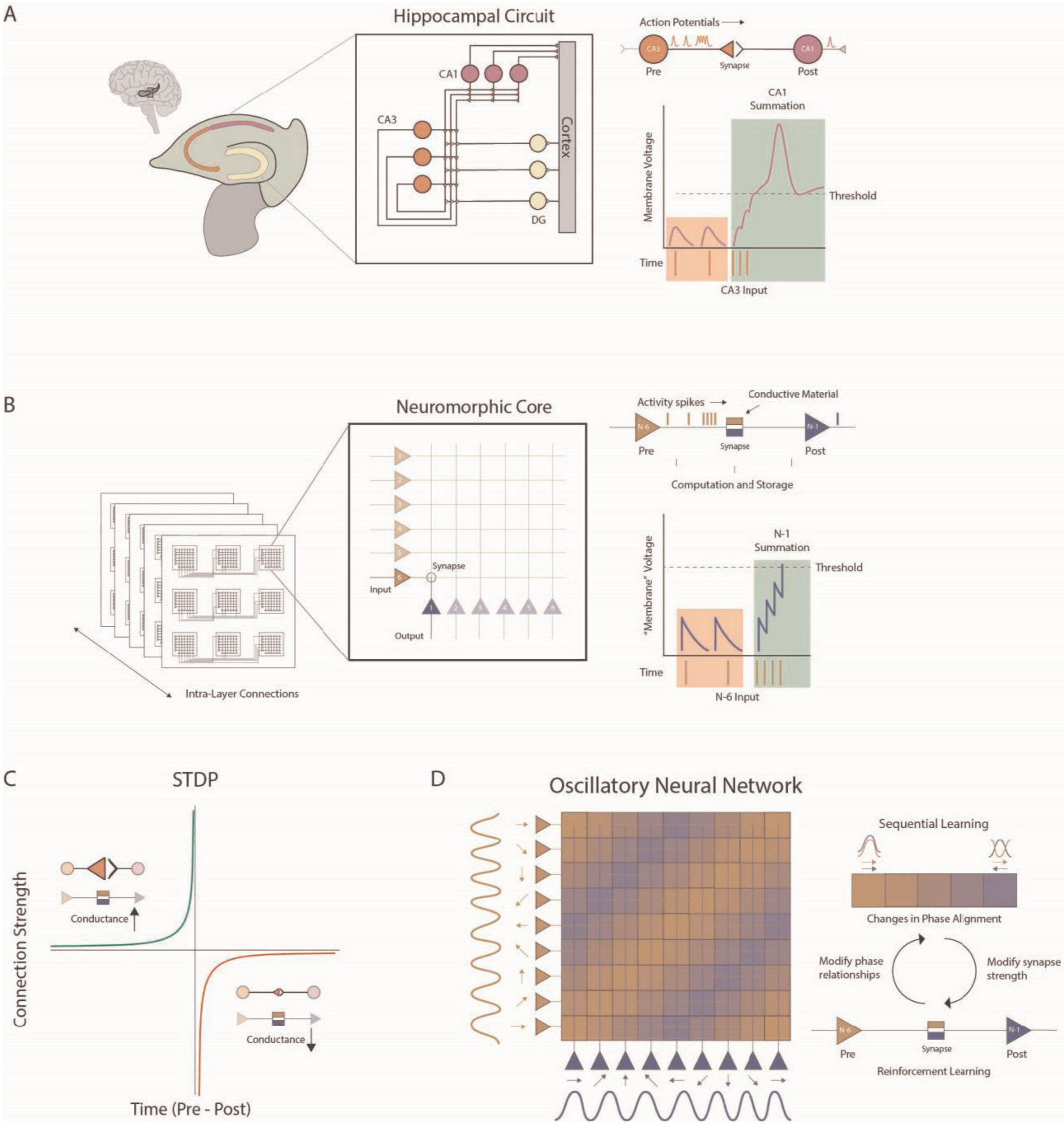

图7. 与神经技术相关的隐私风险。包括混合现实耳机、访问电子健康记录的技术和生物特征数据在内的场景，突显了监控和个人数据的潜在滥用可能性。

Fig. 7. Neuromorphic Computing for Reinforcement and Spatial Learning. (A) An enlarged hippocampal slice with dentate gyrus (DG, yellow), CA3 (orange), and CA1 (purple) sub-circuits. Middle: Tri-synaptic pathway from DG to CA3 (with recurrent collaterals) to CA1. Right: A CA3-CA1 synapse and corresponding voltage response of CA1 from CA3 inputs. Asynchronous inputs cause synaptic weakening (red window), while synchronized inputs reach voltage threshold, promoting synaptic strengthening (green window). (B) Left: Multiple neuromorphic cores process data across layers. Middle: Enlarged 6x6 core with tan input and blue output neurons. Right: Synaptic connection with spike inputs plotted over time. Asynchronous inputs reduce conduction, while synchronized inputs summate and reach voltage threshold, increasing conduction. (C) Spike-timing dependent plasticity (STDP) curve. Upper-left green curve shows potentiation with optimal pre- to post-synaptic timing. Lower-right red curve shows depression with reversed timing. Conductance measures synaptic plasticity. (D) Left: Phase-tuned neuromorphic core. A 9x9 neuron grid with y-axis neurons incrementing clockwise by 45°; and x-axis, counterclockwise. Warm an cooler colors indicate in- (0°) and anti-phase (180°) connections, respectively. Right: Feedback loop illustrates how phase alignment modulates synaptic strength, enabling reinforcement and sequential learning through phase coherence and incremental phase shifts. (© Joshua Sariñana)

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spaces. In particular, the differences between neural and social network behaviors and the divergence between neural network models and human cognitive processes precipitate mental health issues, the spread of misinformation, and decreased user autonomy. Computational and theoretical models suggest that oscillations could bridge the complex networks of AI and the brain, promoting system alignment.

Argued and detailed in this paper is the use of oscillatory functions and mechanisms of the hippocampus to broaden the capacity of social networks and related DRL technologies. Combining structural and oscillatory functions has the potential to align network computations across social, artificial, and organic neural networks. As a result, the user's emergent behavioral and cognitive networks can effectively synchronize with extended virtual environments and bridge the gap between the goals of these systems. Neuromorphic computing and ONNs present a promising avenue to validate and operationalize the conceptual mechanisms discussed in this paper by further synthesizing with the intricate and integrative computations of the brain. Leveraging the hippocampus's role in synchronizing distributed knowledge and creating complex, non-linear relationships across network variables could enhance the development of artificial internal representations that reflect human cognition. In other words, utilizing hippocampal functions to further develop artificial general intelligence. Critically, privacy concerns must be at the forefront when developing and deploying such advanced neurotechnologies.

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