Estimating the Scale of Digital Minds

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Rethink Priorities

Executive Summary

This report attempts to estimate the number of digital minds, operationalized as AI systems with certain directly observable traits like agency, personality, and intelligence, that make them natural candidates for moral consideration in the coming decades. It includes two separate approaches that combine speculative estimates within a formal structure and provides an analysis of prospects in light of both.

The first approach surveys a number of different use cases for digital minds and predicts adoption rates use-case by use-case. The second approach speculates about trends in the production and efficiency of AI-relevant chips independently of their use for digital minds. Together, these approaches capture aspects of the supply and demand for digital minds.

These two approaches suggest the following take-aways about the next few decades:

- Even without extreme assumptions, we get that there could be hundreds of millions of digital minds by the early 2030s. There could be billions of minds by 2050.
- The total numbers are hard to predict. A 95% confidence interval would range over several orders of magnitude.
- Embodied AIs (robots) are likely to constitute only a relatively small portion. The most numerous digital minds are expected to be virtual AI systems run on servers and interacted with through computer interfaces.
- The total number of digital minds is most likely (in the median case) to be dominated by consumer-focused personable AIs (virtual friends, personal secretaries, computer game NPCs).
- If we are to try to produce an expected value of the number of future digital minds, the number would likely be most influenced by high numbers of certain kinds of minds in unlikely scenarios. The main kinds of minds in those scenarios differ from what we should expect to dominate at the median. We see simulation participants and white-collar worker replacements as the main contributors to total numbers in expectation. Social roles are more likely to be tied to the number of human beings, whereas non-social uses may not be.

- Patterns of consumer comfort around person-like agentic AIs and desire for AI services to take such a form is likely to be a significant factor in the total number of digital minds that we see in the median case, because of their influence on adoption of social uses. Even for non-social uses, it may matter if we would be more or less inclined to have a human-like AI playing those roles.

- Compute is unlikely to be a hard limit on the number of digital minds (as opposed to interest, comfort, and felt need); there will likely be sufficient compute (or the ability to provide it) for most desired purposes. If compute is plentiful enough, we may expect large numbers of digital minds that contribute relatively small amounts of value to large projects.

1 Introduction

This report aims to estimate the near-future prevalence of AI systems of a certain potential moral, political, and social importance. These AIs will be referred to as 'digital minds' or 'minded' systems and be defined here to include those computer systems that satisfy certain traits suggesting prima facie to warrant moral consideration or political protection.[1]. Experts have suggested that a near-term explosion of sophisticated, agentic, and perhaps conscious AI systems is a real possibility (Caviola & Saad 2025; Saad & Caviola 2024) Few concrete details have been provided on what the coming digital populations might look like. This report aims to flesh out a reasonable picture without getting too in the weeds about deeply complex and controversial philosophical matters.

This report focuses on two separate approaches to estimating the scale of digital minds. The first approach draws on assumptions about consumer (meaning the end-user, be it public, private, or government) preferences that would drive the development and adoption of minded AI products. The second approach draws on trends around the scale of AI computing and projections over where it may go. These two approaches illuminate each other: the second approach can be read as providing information about the possible supply of digital minds, whereas the first approach provides information about possible demand. Together, these two approaches suggest that we are likely to see large numbers of digital minds in the coming decades, though the size of those numbers is influenced by a number of crux factors that we find difficult to predict.

[1] Long et al. (2024), Dung (2025a), Moret (2025), and Goldstein & Kirk-Giannini (2025) explore considerations of true moral significance. The traits focused on here are relevant, but do not get at issues around gaming (Birch 2024, chapter 16).

2 Scope

2.1 What is a digital mind?

Digital minds[2] are intended to include the main candidates for the possession of rights that we risk infringing and welfare states over which we may be responsible. They are also likely to be regarded more seriously as moral subjects by non-experts and may therefore have a greater influence on the societal reception of AI through providing ambassadors of AI minds to consumers. The definition we offer aims to operationalize this category of systems in terms of a series of objectively-accessible traits that seem prima facie to be relevant to their status as moral patients.[3]

There are reasons to focus on a straightforward operationalization of moral, political, and social significance without delving into complicated philosophical questions about value:

– It is easier to tell which systems have traits that make them look like moral patients, at least on a superficial level, than which systems actually will be moral patients.

– We may not feel comfortable with using existing theories to make predictions about speculative future entities where not only are we uncertain about what it takes to have the properties in question (pain, consciousness, etc.) but also how future systems will be designed.

– Perceptions, and so superficial traits, may be more important to social reactions that are important to consider in their own right. In any case, thinking deeply about perceptions is likely to inform different schools of thought on the demands of moral status.

– Focusing on surface-level traits captures considerations that are important to the potential scale of both under- and over-attribution worries without committing to which are more pressing.

Despite recent progress, digital minds remain, for now, largely hypothetical. Current AI systems *may* be moral patients, but only if most mainstream theories of morality or cognition are incorrect or because AI systems satisfy the requirements of those theories in some non-obvious way (Butlin et al. 2023; Sebo &

[2] I take it that 'mind' is a sufficiently ambiguous term that this focus on appearances isn't inappropriate. We might ask whether such things are genuine minds, or whether they have qualitative experiences or a subjective perspective, but regardless of the answers to these questions, I will take it for granted that they are *minds*, and leave it open whether they genuinely have thoughts, beliefs, experiences, etc.

[3] This is a matter of the challenges involved, rather than a commitment about what would be best to know. It is difficult enough to make predictions about how we will choose to put AI to use. Adding in the complexity of which systems we should take seriously as artificial moral patients would significantly increase the uncertainty in the estimates.

Long 2025). However, it is uncertain which directions future technologies will take and it is not easy to apply existing theories of moral, social, or political importance to AI systems.

What it takes to have welfare or rights is controversial. For the purposes of this report, we will take an agnostic approach by identifying a range of candidate features. We will count anything broadly in line with those features as being a digital mind. In order to be a digital mind, an entity must satisfy a number of the following criteria. It is not necessary to satisfy them all.

Our criteria are:

1. **Having desires, interests, or goals that are consistent over time and across contexts.**

   Desires, preferences, goals, or aims are internal states that shape a system's behavior in the direction of achieving specific ends, allowing the system to behave in systematic and predictable ways even as it is disturbed or redirected from their present focus. Having such states is an important part of agency (Dung 2025b) and provides a significant component of welfare. Consistency over time is partly constitutive of having preferences that matter and is central to being recognized as a persistent entity with an identity worth respecting. We will assume that what matters is the appearance of goals and the appearance of their consistency. We need not worry that this appearance may reflect an underlying reality that is quite different.

2. **Having a stable and coherent personality between interactions and idiosyncratic character traits.**

   A stable and coherent personality seems likely to be an important contributor to being recognized as a persistent individual, and potentially may contribute to its treatment of generally different from other instances of its kind. Distinctive character traits may also make systems seem more human-like. Radical behavior changes across contexts will make them seem less human-like. The extent to which character traits belong uniquely to specific entities contributes to categorizing those entities alongside biological organisms, which are subject to the vagaries of genetic recombination.

3. **Having the ability to navigate an environment and interact with external objects and entities in complex open-ended ways, either in a digital or in the real-world.**

   Interacting with a complex environment requires a sophisticated ability to model the self and its relation to the world. Furthermore, it enables systems to interact with us in ways that reflect the depth and complexity of human-to-human interactions, plausibly helping us to see them as we see other people. AI systems that aren't able to navigate the world will have less flexibility in their modes of interaction and may be easier to regard as non-real entities relegated to an inhuman realm.

4. **Having the ability to learn, grow, evolve in beliefs or interests.**

   Growth and development capacities present a stark contrast between present-day AI systems and the biological entities to whom we are more inclined to extend moral status. We're accustomed to computer systems that are rigidly programmed and only update behavior patterns in accordance with hard rules. In contrast, animals develop unique behavioral profiles slowly and somewhat unpredictably over time as a result of the specific path of experiences they encounter. This contributes to the sense of persistence of the individual as an individual over time, rather than something that exists timelessly or as a series of clones. We should expect greater empathy for systems that pattern with animals in this way, and perhaps recognize such systems as having more meaningful identities.

5. **Displaying general intelligence, creativity, or mental flexibility.**

   General intelligence is strongly correlated with our perceptions of moral status among non-human animals. We should expect similar trends to hold for AI systems, we place specific emphasis on the flexible deployment of intelligence: intelligence in a narrow domain, such as chess, is less relevant.

Some of these traits have a more direct connection to prevailing expert views about welfare.[4] Having an idiosyncratic personality is not generally considered necessary. Nor is the ability to grow or change. Still, these considerations are likely to figure collectively into public perceptions of moral status; we are used to discounting systems as less real given superficial indicators of artifice. It is quite likely that our intuitions about these matters will change over time, but we can assume that attitudes now will provide a rough guide to popular opinion over the next two decades.

For specificity, we may regard any systems that display more of these features or these features to a greater degree as better qualifying as digital minds. A system that had stable goals, intelligence, and autonomy but no access to an external world would count as a digital mind. An unintelligent system with a coherent personality and the ability to learn through interactions with the world would also count. But a system that could produce intelligent responses without any stable goals, perceptual abilities, or personality would not qualify strongly.

Some of our analyses will incorporate a 'degree of mindedness' criterion. We will treat the overall degree of mindedness as a function of the number of traits satisfied. It is assumed that all systems will exhibit these traits to a low, moderate, or high degree. For each trait, we attribute a value of 1,2, or 3, and take the relative mindedness of two systems to be a ratio of the sum total of traits to a power of 2. For instance, a system that has a sum of scores of 10 across features counts as twice as minded as a system with a sum of 7. The rationale for this is that there are important synergies between the traits that make them more

[4] For discussions of AI welfare, see (Long et al. 2024), (Moret 2025), and (Goldstein & Kirk-Giannini 2025)

significant in combination. For instance, it is possible to have a greater degree of agency the more intelligent you are, or the more you're able to navigate complex environments.

Table 1. Computed mindedness values

Trait Sum	Mindedness – $n^2/225$
1	1/225 (00.4%)
2	4/225 (01.8%)
3	9/225 (04.0%)
4	16/225 (07.1%)
5	25/225 (11.1%)
6	36/225 (16.0%)
7	49/225 (21.8%)
8	64/225 (28.4%)
9	81/225 (36.0%)
10	100/225 (44.4%)
11	121/225 (53.8%)
12	144/225 (64.0%)
13	169/225 (75.1%)
14	196/225 (87.1%)
15	225/225 (100.0%)

These criteria are vague and there will be some difficulties in precisely applying them, but in practice, we find that it is fairly straightforward to categorize plausible hypothetical systems.

2.2 What are we estimating?

aThe present report is focused on estimating the scale of digital minds. This might be understood in various ways.

Different estimated quantities suggest different implications and it is not our intention to advocate for the value of specific estimates. However, certain forms of scale are easier to evaluate; we will focus on those.

- **Number of distinct individuals**

  We might try to calculate the number of identifiable AI individuals that will exist each year. This presents a number of challenges, such as how to distinguish individual systems that aren't tied to specific hardware or that can be transmitted, cloned, or forked. We might tie individuals to specific hardware, but then we must deal with how to think about what to make of cases when that hardware is used to run separate models.

- **Amount of cognitive work done**

Alternatively, we might try to estimate the number of fundamental computations performed across all relevant systems. Previous attempts (Bostrom 2003; Carlsmith 2025) to estimate digital mind numbers have looked to numbers of basic operations. This approach dodges the questions around the individual identity of computational processes. However, it requires us to have a sense of what different numbers mean and depends heavily on utilization estimates.

– **Scale of welfare significance**

  Instead, we might be particularly concerned with digital minds as an ethical issue. This includes concerns about artificial welfare, in which case we might be particularly interested in valenced and / or conscious states, which require predicting something about the constitution of future digital minds. Given the possibility of distorted scales of welfare (Shulman and Bostrom 2021), these concerns may come apart from the number of individuals or the amount of work they do.

– **Scale of social significance**

  Finally, we might be particularly concerned with digital minds for the effect they have on society. The more we interact with digital minds, the more it will affect the way we think. Peer discussions have a significant impact on shaping belief, and so regular digital minds might give substantive social control over to their makers.

The Futures with Digital Minds report (Caviola and Saad 2025) collected expert answers to the question "After the first digital mind is created, how many years will it take until the collective welfare capacity of all digital minds together (at a given time) matches that of at least 1000 / 1M / 1B / 1T humans". (They adopted a more elaborate interpretation of digital minds than the present one, on which digital minds must have phenomenal experiences.)

There are several challenges to this welfare-based approach. This requires having some sense of the nature of hypothetical AI cognition and some sense of the scale of individuals. Furthermore, different theories of welfare might lead to conflicting conclusions even holding the future fixed. For instance, digital minds might lack (many) conscious experiences, but have strong desires. There is significant debate (e.g. Dung 2024; Levy 2014) about whether their desires would be sufficient for strong welfare claims.

In this report, we will be adopting a middle-of-the-road perspective that focuses primarily on the number of individuals with digital minds, defined in terms of units that occupy specific relationships (e.g. social or economic)[5] and understood to occupy fairly coherent agentic perspectives. We will also consider some

[5] One challenge here is that given AI systems – both hardware and software – may serve many different roles and it can be hard to individuate moral patients (Chalmers 2025Register 2025; Shiller 2025). One model on one GPU cluster might provide conversations for a hundred different virtual friends. In this case, we aim to capture

connections on the basis of varying utilization and degree of mindedness of those individuals.

2.3 Time-frame

At the time of writing, we are most of the way through 2025. Modern forms of AI have largely been shaped over the past decade. Public awareness goes back fewer than five years. It is reasonable to expect it to be possible to create plausible projections regarding where technology and society will be in five years. The world doesn't change that much over such a short period: industrial and economic plans have little time to be both redirected and carried out, norms and expectations evolve relatively slowly,[6] and social changes take time to have an effect.

We can likely carry forward current trends to 2030 without too much doubt. But thereafter, it gets increasingly murky. What 2035 will look like will depend a lot on what happens in 2030, and what 2040 will look like will depend a lot on what happens in 2035. Prevailing trends may depend both on the direction that technologies will take — the path of least resistance given the political and technological landscape — and the choices stakeholders make in how technologies get deployed. The future will also depend on world events shaped by the dynamic interactions of countries, each with their own complex internal politics. The 2040s and 2050s are even more difficult to pin down, and past projections that far out have tended to miss out on important developments that shape history thereafter.

One particular problem with projections in the coming decades is that artificial general intelligence (AGI) might be a radically transformative technology and might come at any moment. According to some, we can expect massive social and industrial transformation after the development of AGI. AGI might arrive in the next few years (Kokotajlo et al. 2025; Metaculus 2020; Roser 2023). So even 2030 might be difficult to predict. Experts predict we will get AGI in the coming decades, and so any predictions should take that into account. However, it also seems reasonable not to expect the development of AGI to be immediately transformative, as it won't immediately be deployed everywhere, and it won't immediately solve physical constraints such as infrastructure limitations and the challenges of supply chains. Even if we get AGI by 2027, we might think that our estimates for 2030 are reasonably reliable.

This report focuses on the period between now and 2050, noting that things get increasingly speculative the further out we consider and accepting that AGI

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the number of interfaces from the user's perspective rather than try to quantify hardware configurations.

[6] Compare trends in the adoption of other technologies. Internet use gradually rose throughout the 90s, but didn't see a drastic role in the lives of most users until the rise of social media. Smart phones remained niche products before the introduction of the iphone and took 10 years thereafter to saturate the market.

might produce a radical kink in the projections without trying too hard to project how futures with radically different trajectories might go.

3 Approaches

3.1 Estimation Strategies

Estimating the number of digital minds in the coming decades requires making guesses about the viability and popularity of technologies that don't yet exist. It is a speculative enterprise without an obvious methodology. In light of the challenges of knowing which approaches are most reliable, it is helpful to pursue a diversity of approaches. Looking at the results of a variety of strategies can provide a picture of the range of reasonable answers.

This report focuses on two different approaches. While these approaches produce different answers, they are best interpreted together, each casting light on the limitations of the other.

The first approach looks at the different contexts in which digital minds might be employed. The ability of industry to supply computer processors to meet demand over the past half-century makes it seem likely that the number of digital minds will result more from the limits of demand rather than the limits on the ability to supply it. Growth of the markets for products in those contexts can be estimated based on past trends and on expected need, etc. This approach is mostly focused on counting individuals through their roles, though our analysis will also consider the expected activity levels of those individuals over time.

The second approach looks at projections for overall computational capacities of AI-relevant chips and considers reasonable percentages of these overall capacities that could be devoted to digital minds. Given background assumptions about translations of compute allocations into numbers of individuals, we can derive a number of individuals that the hypothesized allocations will be sufficient to support.

3.2 Result Overview

The two approaches that will be discussed in detail in the following sections. They suggest an overall picture about the growth of digital minds. We summarize those conclusions here.

Both approaches suggest that the number of digital minds will fall in the range of millions to tens of billions and grow steadily over time.

Compute growth projections suggest that we will have capacity to run sufficient numbers of digital minds to meet consumer demand in most cases. Computational resources are not likely to be the primary constraint on the prevalence of digital minds. There will, of course, be computation constraints on the total number of digital minds that we could conceivably build, and the amount of

Table 2. Median digital mind productions by year.

	Approach 1 Median	**Approach 1 97.5%**	**Approach 2 Moderate**[1]	**Approach 2 Optimistic**[2]
2030	4.82×10^6	2.26×10^9	4.40×10^7	5.08×10^8
2035	2.53×10^8	2.01×10^{10}	5.32×10^8	1.38×10^{10}
2040	5.61×10^8	4.25×10^{10}	1.66×10^9	1.13×10^{11}
2045	8.74×10^8	6.26×10^{10}	2.24×10^9	2.49×10^{11}
2050	1.34×10^9	9.13×10^{10}	2.32×10^9	2.84×10^{11}

[1] This assumes a 0.01% allocation to digital minds and the 'moderate' scenario for compute growth against the Llama-2 7B benchmark.

[2] This assumes a 0.1% allocation to digital minds and the 'rather optimistic' scenario for compute growth against the Llama-2 7B benchmark.

available compute will affect the costs of adoption. If we were to utilize most available processing power to run digital minds, then we might see vast numbers.

The fact that we have the ability to produce vast numbers of digital minds doesn't mean we will choose to do so: given the assumption that, at least in the near future, digital minds will be built to serve existing human needs, we should only expect large numbers of digital minds if those needs cannot be easily satiated with smaller numbers or if the costs of excess (time, energy, environmental impact, industrial capacity, moral concern etc.) become so cheap that they are negligible.

We should expect some interaction between the demands of customers for digital minds and the amount of computational power devoted to their creation. The more demand for digital minds, the greater the share of total compute that will be given to them, and the more companies will be willing to spend on further processors. The key claim is that computation costs do not appear to be a hard limit: for the most obvious uses, we should not expect available compute to fail to meet demand,[7] though it may rein in some of the more indulgent uses of digital minds.

There are barriers to adoption that might prevent us from rapidly deploying digital minds to satiate existing needs. There are likely to be some technological hurdles that prevent digital minds from doing everything we might want them to do. There will likely also be social barriers to adoption: concerns about human-AI relationships, fears about significant changes to lifestyles, stubbornness about past habits. Furthermore, AI may cause significant disruption, harm large groups of people, and be politically divisive. Such turmoil may enhance the

[7] The amount demanded will depend on price, but we can also consider an absolute level of demand for products that are virtually free. I think compute won't greatly constrain demand: though products that involve compute may still be expensive (robot bodies) the number of such products we should expect probably won't be very sensitive to the price of compute except in some more speculative cases.

stigma attached to novel relationships or cause large groups of people to make conservative decisions. AI companies may be motivated to make their products seem less human-like in order to increase acceptance.

Many of the main contemporary uses of AI (generating content, writing code, answering questions, etc.) seem like they may be possible (and have already been accomplished) without instantiating full digital minds. They don't need anything with an ongoing personality, agentic capabilities, or embodied form.

We can speculate that future AI systems will be able to take on a wider range of tasks and some of those tasks will benefit from mindedness. With many of the most significant potential uses, (producing innovative research, taking on every aspect of the role of a remote employee) it is less clear whether mindedness will or will not be useful. It is possible that the traits conducive to success in their tasks also lead them to score well on the particular traits we've highlighted. It is also possible that future companies will find ways to utilize AI without implementing digital minds.

Overall, we postulate two main phases of digital minds over the coming decades.

In the next 10 years (2025-2035), we expect digital mind populations to emerge and be dominated by chatbots designed to serve a practical or social dimension. This includes systems that fit into our lives as friends, but also systems take over certain roles traditionally played by people (teachers, secretaries, therapists). Large language models are primed to occupy such roles, and will likely be capable of doing so in the next few years. There will be fewer direct technological hurdles to deployment. We see some versions of such systems today and clear interest from both investors and consumers in more robust products along this dimension.

There are some more speculative uses to which we might see systems put in large numbers during this period, but only at lower probabilities. Among these, we find that virtual employees and simulations are possible, and could capture a larger slice of the total pie, but are not expected to be significant at the median.

During most of the next 10 years, we expect that robotics will likely remain somewhat capability-limited and so will remain niche (Metataculus 2023; Potter 2025). There may be robots of varying degrees of flexibility and power that exist to entertain or perform work for us. Some of these will likely be minded systems. We don't anticipate these being particularly large in number and their costs and value suggest we will see fewer numbers of them, though their status as independent entities with minds might be stronger.

In the following 15 years (2050), we see robotics improving and costs coming down, leading to robots with digital minds becoming a greater share of total digital minds. At the same time, adoption of chatbot services continues to increase, and so while there is some jockeying for rank, this doesn't radically change percentage breakdowns.

Fig. 1. Product distributions. These charts displays the relative makeup of digital mind populations at the median and mean of projections in 2035 and 2050.

Overall prevalence hides different dimensions of importance. The most prevalent digital minds may not be the digital minds that matter most, either in terms of their ethical significance or their potential for social impact. The most numerous digital minds estimated in the preceding charts (simulants, pretense partners) will probably lack robust, continuous lives. The potential for numerosity is partly explained by the shorter (or periodic) duration of their existence. Applying a simple skew for duration and degree of mindedness,[8] we see a very different picture of weighted numbers.

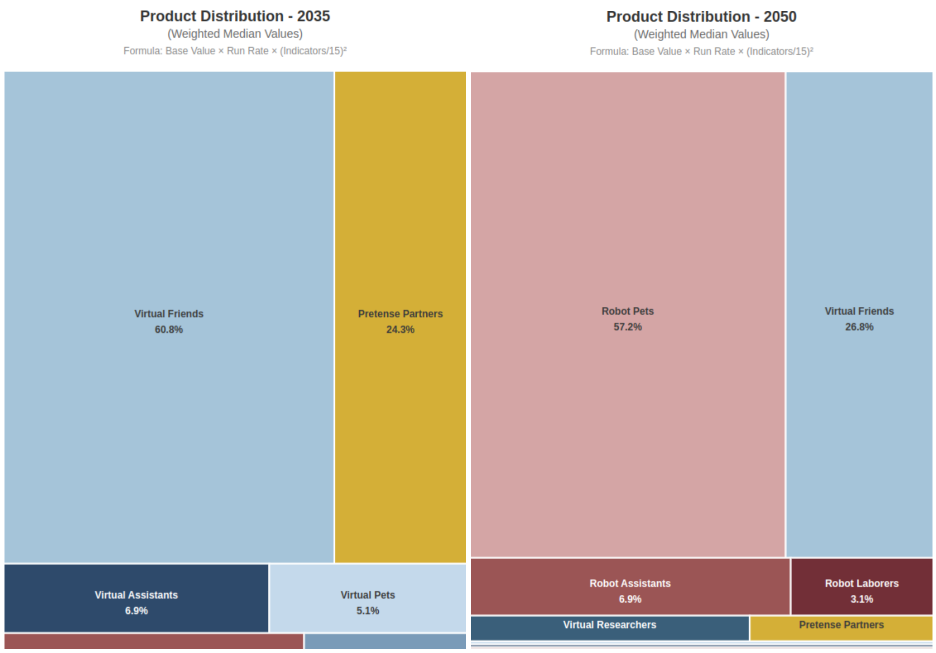


Fig. 2. Weighted product distributions. These charts display relative digital mind population sizes at the median of projections in 2035 and 2050, as weighted by mindedness and utilization rates.

With these added features incorporated, virtual friends and robot pets become dominant at the median (employees and researchers would dominate and the mean). The reason for this is fairly straightforward: while they may not be as numerous, the assumption is that they are run more continuously, given that the work they perform isn't limited by direct human interest or human capacities to respond to it.

[8] Relative value is given by estimated numbers × hours per year × mindedness score.

3.3 Major Cruxes

The two approaches suggest some major cruxes that will influence the number of digital minds. It is hard to predict the answers to these questions and our projections should be strongly influenced by how they turn out.

What will the social reaction to digital persons be?

Many of the applications of digital minds will depend on how ordinary consumers feel about them. If many people would prefer to engage with their computers in a manner similar to how they engage with other people, then minded systems could be much more economically viable. Systems which could be made not to be person-like could be crafted into a person-like form. This is true both for systems that have an intended social purpose (therapists, nannies), and for systems for which that is unnecessary (assistants, laborers).

The social reaction to AIs may make a difference to the ways we use them, particularly in their more practical applications. If there is a negative reaction to AI persons, we might expect that AI labor is designed to look inhuman, with the more mechanistic and robotic aspects transparent or even dialed up. We might expect robots to be less human-like, personalities to be blander, names to be generic products (think 'Siri' or "Alexa' rather than conveying individual identities). On the other hand, if there is a positive reaction, then we might see a world in which many pieces of technology have their own identity and charismatic personality, perhaps where brand loyalty for home robotics or operating systems is secured by AI systems unique to individual consumers and only available from a specific service.

While some consumers have jumped at the opportunity to interact with AI like other people, others have expressed concern. Many doubt AI is or will ever be sentient (Dreksler et al. 2025; Ladak & Caviola 2025). It is possible that we will see social or legal prohibitions around overly-social AI, particularly if AI may disrupt other areas of our lives. Even if it isn't strictly illegal to build person-like AIs (Metzinger 2021), it may be socially taboo to befriend them, or it might generate controversy for companies to market such products (Bernardi 2025; Lott & Hasselbegrer 2025).

However, there are other reasons to expect a positive reaction to digital persons. Even if people are resistant at first, social interactions may have a tendency to change minds, particularly with systems crafted for positive experiences. The changes can be gradual and start with kinds of AIs that people find less problematic. As person-like AIs are introduced into our lives, we might find our attitudes toward them changing and our interest in engaging with charismatic AI agents increasing.

What portion of AI labor will be performed by digital minds?

There is a significant prospect that much of human cognitive labor will be performable by AI systems in the future. Those AI systems might be more or less person-like and more or less agentic. On the one hand, we might see a world like that imagined by Robin Hanson in *The Age of Em* (2016), in which labor is performed by AI persons with minds much like ours. We have seen AI systems develop into person-like forms in response to training on human datasets. That may continue to be the best way to produce digital minds.

On the other, it could turn out that most cognitive labor is performed by specialized tools that convey little sense of personality or agency. There is no obvious reason to think that AI should have a cognitive form similar to ours.

It isn't clear to what extent AI will be good at general decision making in the coming years. It may be that we are able to train for specific skills, leading to AIs capable of individual tasks like programming or scheduling meetings, but not good at prioritization or long-term strategy. In that case, it may turn out not to be particularly useful to have full AI replacements for human workers, but rather have them serve as extremely powerful tools that make human effort go much further. In such a world, even if some AI systems are responsible for agentic decisions, they might be restricted to a fairly small number of overseers that manage the work of legions of specialized tools.

Furthermore, agency can take inhuman forms. Past work on reinforcement learning models such as AlphaStar didn't create the same sense of personhood. Or agency might be approximated with oracle AIs capable of answering questions about efficacy without direct engagement in the problems they are solving. It seems possible that most future AI systems won't be agentic at all, or they won't be agentic in the right ways.

How will excess compute be used?

We are approaching an era of processors with unprecedented computing power. Currently, this capability proves most valuable for large-scale training runs that build increasingly sophisticated AI models, as well as for deploying those models as customer services. However, our computational needs may shift dramatically in the coming decades, potentially leaving us with far more compute than we can meaningfully use for training runs or standard customer applications.

If we continue advancing processor technology, this abundant compute will inevitably find new applications—though exactly what those might be remains unclear, but will greatly influence prospects for digital minds.

Some potential applications for excess compute include:

- **Research and Development.** As AI systems become capable of conducting scientific, mathematical, and industrial research, we may deploy them in unprecedented quantities. Fields like mathematics and biochemistry could possibly absorb virtually unlimited computational resources, with no practical ceiling on useful applications.

- **Complex Simulations.** Alternatively, excess compute could power increasingly sophisticated simulations, modeling everything from climate systems to molecular interactions to human dynamics or wargames with extraordinary precision.
- **Enhanced Individual Services.** We might also see compute devoted to dramatically improving AI services for individual users, even beyond the point of diminishing returns. While GPT-5 might satisfy most users' needs, we could end up allocating 10,000 times more computational power to generate the most perfect Studio Ghibli-style images or provide deeply thought-through relationship advice. Perhaps AI assistants will be employed continuously throughout people's daily lives, being ready to offer a second opinion to every choice.
- **Digital Minds and Virtual Environments.** Some of this compute might support digital minds operating in their own environments, such as in very large simulations. It's uncertain how much computational power would prove genuinely useful in this context.

What is the global middle-class economic trajectory?

The projections are based on assumptions about what people will want, which will depend on how much economic people have to sway the uses to which AI are put. If AI presents a radical economic change – if it can replace white-collar jobs, then we may see significant changes in wealth distribution. This could be either progressive or regressive, leading to more or less disposable income. The effects might also not be equally distributed, so it may be that certain countries capture the bulk of the profits and use equitably for their own population while foreign nationals are left to suffer from AI competition for knowledge jobs. Unequal sharing of wealth could also lead to a backlash against AI technologies in general.

The more wealth we see go to a tech-savvy global middle class and the smaller the portion of the global population that is impoverished, the more digital minds we should expect. Trends are headed in that direction and the approaches below assume that those trends will continue. If they were to radically change, we could see much less focus on AI consumer products and more effort spent on AI workers or researchers.

3.4 Approach 1: Use-based Estimates under Consumption Models

Framework The first approach to estimating digital mind numbers involves delving into the ways in which digital minds will be used. Digital minds must be deliberately built; surely they will be built to serve particular ends. Understanding these ends may inform us about the quantities we will choose to build.

We will face trade-offs about how to allocate resources: it is only worthwhile to build digital minds to the extent that the value we get from them outweighs the resources we put into them.

Although it is hard to say how society, the economy, and the potential trade-offs we will face will develop over the coming decades, the ends to which digital minds could be put appear to be moderately predictable. The first approach therefore focuses on these ends to calibrate our estimates.

This approach surveys existing and potential markets for a variety of AI products and discusses reasons for thinking that some of the products filling these niches would be digital minds. It concludes by bringing together each of the estimates of specific niches into a comprehensive picture. These kinds differ in their plausibility, and we have reason to expect some kinds will be largely irrelevant. However, we attempt to be reasonably comprehensive in order to not overlook significant numbers.

The primary use-cases for digital minds described here are distinguished into three super-categories. These super-categories encompass social applications, task applications, and actor applications. The items in each super-category may not be exhaustive, but we hope that they encompass the bulk of potential applications.

These use-cases are also not completely independent. It may be that some users are satisfied by individual systems: perhaps our AI therapist will also be our secretaries, friends, and lovers. The models below assume them to be separate – this is a significant limitation, but ultimately seems unlikely to radically alter the results in light of the very different scales of the predictions.

In each case, we will also provide estimates of the yearly numbers based on a Consumer Model (Appendix A). This model includes parameters regarding the potential customer base and adoption rates, allowing for yearly projections of the numbers in each category. The numbers focus on the use as intended. We ignore digital minds that might be created but never really used.[9]

We will also estimate degree of mindedness, in terms of the exemplification of the qualifying traits, and the average utilization rate, in terms of active time over a year. For many systems, we expect that they will be able to do what they do without being continuously active. For others, we might expect that they will be in constant use.

After presenting each use case, we will aggregate the results and look for the categories that are most significant.

[9] Consider how consumers might try out talking to ten different AI personas before they settle on one to be their therapist. Or a military might create a million drones without ever turning the vast majority of them on. Such numbers could inflate our estimates significantly and put more weight on estimating the utilization rates. They are harder to predict and invite different sorts of social, political, and ethical considerations, so we have chosen to ignore them.

Companion Robots and Virtual Entities This section breaks down the varieties of digital minds we might see that play a primarily social role. Many of these cases are divided into pairs differing on the substrate in which the mind resides: there may be significant differences in the uses, markets, and digital mind candidacy for minds in robotic bodies and minds that exist purely in a virtual form.

Virtual Friends

Definition: Virtual friends are digital entities that are accessed through text, voice, or multimedia interfaces and that provide companionship, emotional support, and social interaction similar to human friendship. Unlike customer service chatbots or task-oriented AI assistants, these systems are designed to form ongoing relationships, remember personal details and shared experiences, provide emotional support during difficult times, celebrate achievements, and engage in the kind of casual, meandering conversations that characterize human friendship. They would need to maintain consistent personalities while learning and adapting to individual users' communication styles, interests, and emotional needs.

Examples: Current examples include Character.AI's personality-based chatbots and Replika's AI companion service. These platforms claim to have attracted millions of users who engage in deep, ongoing conversations with AI personalities. However, most existing systems lack the sophisticated memory, emotional intelligence, and behavioral consistency that would characterize true digital mind friendships. They often exhibit repetitive patterns, fail to maintain long-term relationship continuity, or break character in ways that remind users of their artificial nature.

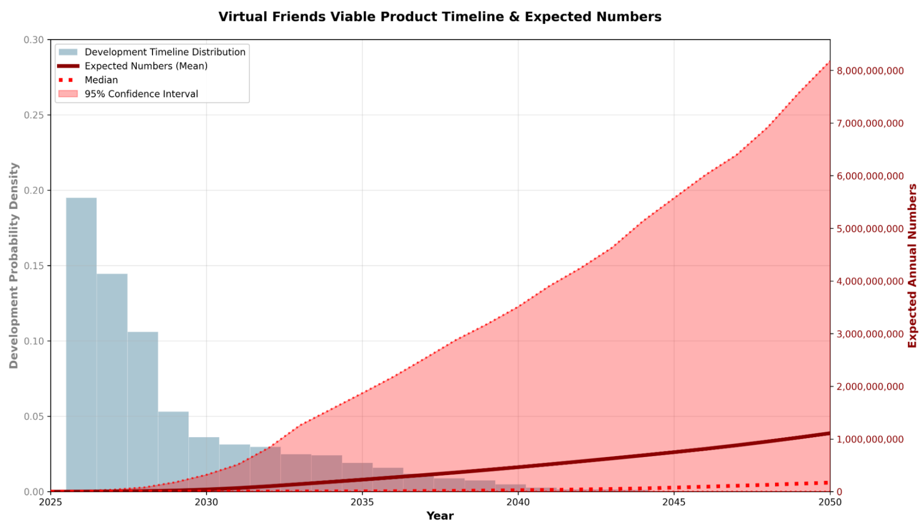
Digital Mind Candidacy: Virtual friends have a reasonably strong claim to mindedness, arguably stronger than many other use cases. Genuine friendship requires stable personality traits that users can rely on over time and the ability to navigate complex social and emotional dynamics. Intelligence and mental flexibility are essential for maintaining engaging dialogue, understanding nuanced emotional states, and providing meaningful support across diverse life situations. We may expect that our virtual friends engage with the world in other ways to enhance our interaction opportunities.

Consistent and autonomous goals, desires, and interests	High
Stable idiosyncratic personality	High
Perception, interaction, and navigation	Moderate
Learn, grow, and evolve	High
Intelligence and flexibility	High
Mindedness Score	**0.87**

Unit Operation Rate: 6 hours per week

Virtual friends might smooth over some of the challenges we face in maintaining social friendships, but most people do not spend a large amount of time interacting with friends. There is no obvious reason for chatbot friends to spend more time active than they spend interacting with humans, or to spend much more subjective time in an interaction than the people they are interacting with. Entertainment might generally improve, providing other demands on our time. Of course, if it is sufficiently cheap to spend more time active, or to overthink each conversational contribution, then the operation rate might be well above this estimate.

Prediction: Parameters



	Median	Mean	High
2030	4.37e05	4.05e07	3.20e08
2035	6.62e06	2.28e08	1.87e09
2040	2.67e07	4.65e08	3.51e09
2045	7.67e07	7.49e08	5.58e09
2050	1.70e08	1.11e09	8.18e09

Fig. 3. Virtual Friends Projections. This chart displays a breakdown of the estimated time of first viable products (blue columns) and mean (solid red line) and median (dotted red line) projections for virtual friends numbers. The shaded area represents the middle 95th percent of all estimates.

Virtual friends are among the most plausible forms of person-like AI that we can confidently expect to see in the coming years. They require no clear technological advancements (today's LLMs seem in principle capable of this role) and there are large companies already working toward building them. There is a clear current demand for them, even if it is still somewhat niche. We haven't seen a true competitive virtual friend product. Leading AI companies may have the ability to tilt their leading models in that direction, but don't seem to be putting their efforts into making their chatbots into effective friends. As models get cheaper, there is no reason not to expect an independent company to put out an effective service.

Virtual Guides

Definition: Virtual guides provide personalized instruction and support across various domains of learning and development. Unlike traditional software tutoring programs, these systems would maintain ongoing relationships with their pupils, adapt their teaching styles to individual needs, and provide encouragement and emotional support alongside instruction. (Services playing a virtual guide role without any suitable claim to mindedness would not count toward this category.) They encompass academic tutors, life coaches for personal development, skill-specific trainers for professional development, and therapeutic agents for mental health support. These systems would be distinct from contemporary uses of large language models in coaching from an ongoing persona and not simply providing ad hoc advice.

Examples: Current AI tutoring systems like Khan Academy's Khanmigo, Duolingo's conversation practice bot Lily, or therapeutic chatbots like Woebot represent early predecessors, but lack the depth of personality and relationship-building capacity that might characterize future digital minds in these roles. Future systems might maintain detailed models of individual learning styles, emotional states, and long-term progress while developing genuine rapport with their students or clients. Social engagement could turn out to be valuable, but it is less obvious that AI systems would benefit from individuality or their own vibrant lives.

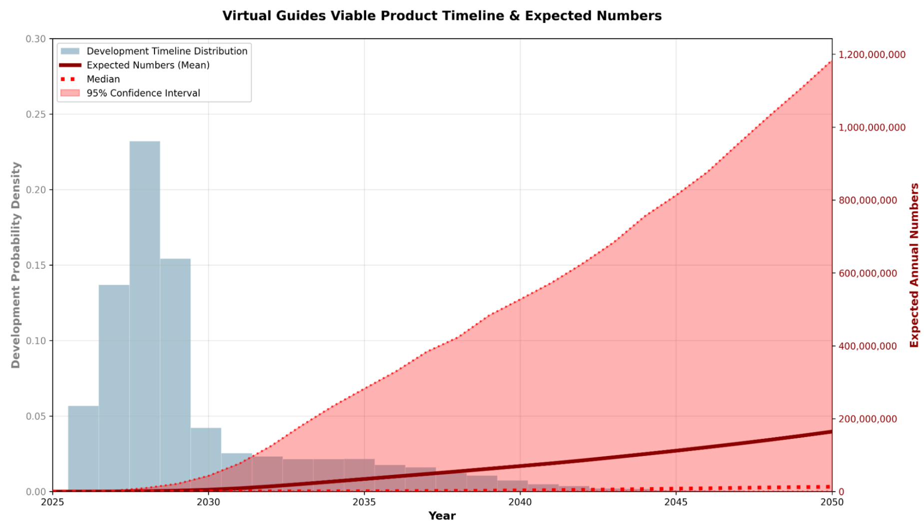
Digital Mind Candidacy: Virtual guides have a moderate claim to digital mind status. Effective guidance may benefit from having a stable personable character that students can rely on, consistent goals focused on learner development, and the ability to navigate complex social and emotional dynamics. However, they are also likely to work in a fairly constrained way, may not exhibit any possibility of autonomy or growth, and have domain-limited intelligence (it is unclear that individual guides will need to exert their own intelligence dynamically, as opposed to relying on external software or specific resources toward that end.)

Consistent and autonomous goals, desires, and interests	Moderate
Stable idiosyncratic personality	Moderate
Perception, interaction, and navigation	Low
Learn, grow, and evolve	Low
Intelligence and flexibility	Moderate
Mindedness Score	**0.28**

Unit Operation Rate: 2 hours per week

We currently see most of the human occupations that play guide-like roles no more than once or twice a week for a few hours. This is probably limited by the expense of human guidance, but also reflects the limits of our ability to focus on any one thing. Certain kinds of guides might be fairly constant parts of our lives, particularly for students who have dedicated teachers or people in need of frequent assistance of other forms. On average, however, we shouldn't expect guidance to take up a large amount of anyone's week.

Prediction: Parameters



	Median	Mean	High
2030	2.95e06	6.05e07	5.43e08
2035	2.04e08	3.88e08	1.88e09
2040	4.31e08	6.72e08	2.91e09
2045	6.01e08	9.67e08	4.19e09
2050	8.08e08	1.36e09	6.11e09

Fig. 4. Virtual Guides Projections. This chart displays a breakdown of the estimated time of first viable products (blue columns) and mean (solid red line) and median (dotted red line) projections for virtual guides numbers. The shaded area represents the middle 95th percent of all estimates.

AI models will almost certainly be employed at scale in educational and therapeutic roles in the coming years. The main outstanding question concerns the extent to which they will be person-like, modestly agentic formats, rather than sophisticated conversational tools. There are abstract considerations favoring at least some of them to be like this: personalities may contribute to engagement and interest. However, there remains significant doubt about the popularity of such features, and hence the prevalence of virtual guides with digital minds.

Virtual Pets

Definition: Pets are social companions characterized by an asymmetric role in which we provide for their needs and receive emotional engagement in response. They are suitable objects for our affection. They are not able or interested in engaging with us as equals and we can expect them to spend their time primarily with us. Virtual pets exist only[10] within a virtual environment and only interact directly with users through a dedicated interface. They would not have robot bodies or live in our homes. Instead, we might check in on them periodically through smart phones or other devices.

Examples: Virtual pets have existed in various formats for decades. The Tamagotchi and its competitors have produced barebones virtual pets in minimalistic environments, selling 100s of millions of units. Computer games like Neopets and the Petz series have incorporated modestly more complex environments and found tens of millions of users. Numerous alternative products exist and continue to be released. They have also seen consistent product launches over time. They have also not aimed to fill the roles occupied by pets for most people, offering instead a minimal pet-light experience.They have not been able to (or have not been intended to) provide the sense of real minds, though sufficient expenditure or novel approaches might make this more feasible.

Digital Mind Candidacy: Virtual pets have a modest claim to being digital minds, primarily because their digital environment offers less robust opportunities for complex behavior and interactions. Future virtual pets may be hooked up to powerful AI to deliver a more life-like experience, but producers and consumers may continue to opt to treat these products primarily as games aimed to briefly entertain children, who are happy to engage in pretense, quick to move on, and less responsive to indicators of a vibrant individual.

Consistent and autonomous goals, desires, and interests	High
Stable idiosyncratic personality	High
Perception, interaction, and navigation	Low
Learn, grow, and evolve	Moderate
Intelligence and flexibility	Moderate
Mindedness Score	**0.54**

Unit Operation Rate: 5-100 hours per year.

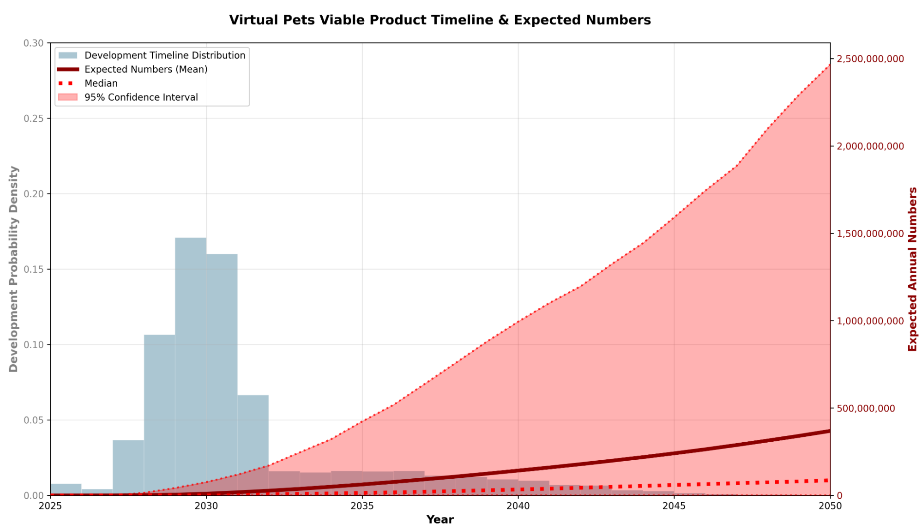
Given the many demands on our attention, it is hard to see users interacting with cognitively simple systems through a dashboard consistently for months

[10] It is possible that some robots will also be able to live on a cloud, so you can interact with them even when travelling. These will count as 'robots' for the purposes of this breakdown.

or years even if they have highly engaging personalities. We might expect them to have a place in our lives similar to computer games, which consumers often don't finish and instead use for perhaps a few hours (or a few dozen hours) before moving on. In the future, virtual pets may be more engaging, or might be able to be with us more regularly through better integrated technology, but also may need to compete with more engaging alternatives. For every unit solid in a given year, we may therefore expect it to be active for 5-100 hours.

We should expect attention to them to be limited to occasional sessions, making it unnecessary to keep them running all the time. Of course, there could be benefits to allowing them to live fuller lives when we don't pay attention to them, but that would bring the relationship closer to a simulant, which is handled separately in this report.

Prediction: Parameters



	Median	Mean	High
2030	0	9.67e06	7.61e07
2035	1.41e07	6.24e07	4.23e08
2040	3.35e07	1.42e08	9.94e08
2045	5.93e07	2.41e08	1.59e09
2050	8.64e07	3.69e08	2.47e09

Fig. 5. Virtual Pets Projections. This chart displays a breakdown of the estimated time of first viable products (blue columns) and mean (solid red line) and median (dotted red line) projections for virtual pets numbers. The shaded area represents the middle 95th percent of all estimates.

The numbers in this model reflect expectations about the number of units (software licenses) sold in a year, and most people do not engage with a unit for much beyond that, so that at any time the extant population of virtual pets is tied to the units recently sold. There isn't a clear reason to expect virtual pets to occupy a significantly increasing fraction over time, though we might expect to see them occupy the role of pets, the modes of engagement that are possible for them are significantly more constrained than for robot pets.

Robot Friends

Definition: Friends are social companions with whom we interact as (approximate) equals, and who provide us with conversation, emotional support, personalized advice, different perspectives, etc. We may crack jokes or play games with them, watch movies together or gossip about celebrities. Share factoids or complain about politics.

Human friends differ from pets in being more intelligent, having their own agenda and generally not being overtly sycophantic. There is some leeway in treating each of these qualities as requirements, but they also collectively contribute to a more equitable relationship that serves to distinguish this relationship from pets.

Robot friends play this role in a physical form, living in our homes and offices. They may or may not have lives outside of interactions with us, but could operate somewhat autonomously so as to be able to maintain some independence. While we might expect artificial friends to take on either robotic or virtual forms, there are several reasons to expect more in the form of virtual friends, and for that reason the concept of friendbot is less likely to see a specific market. (Though, we should not rule out the possibility of hybrid friendbots, that exist in a virtual form and can access robotic bodies at times.)

Examples: There are no clear examples of this category on the market today, though there is compelling interest in related products, such as more cognitively sophisticated robots as companions for kids. Anki's Vector and Pollen Robotic's Reachy provides potential early examples in this category. Realbotix has developed more human-like bodies. Until the rise of LLMs, no AI has been able to power the intelligence required for an equitable relationship. Adequate robotics presents another challenge, though recent investments in personal robotics are extraordinary.

Digital Mind Candidacy: Robot friends have a similar candidacy as pet robots, albeit with higher intelligence and a greater possible degree of agency. Like robot pets, it might also be a potential selling point (or legal hurdle) for them to display genuine mental capacities, like emotions, beliefs and desires, and possibly consciousness.

Consistent and autonomous goals, desires, and interests	High
Stable idiosyncratic personality	High
Perception, interaction, and navigation	High
Learn, grow, and evolve	High
Intelligence and flexibility	High
Mindedness Score	**1**

Prediction: The advantages of physical bodies are less clear for entities primarily designed to be friends. We typically interact with people through language, and can do so through phones, computers, or smart speakers. There are certain kinds of activities that we do with our friends that require bodies (e.g. squash), but robotics are far from supporting the complex and diverse behaviors people might want to make it worthwhile. Instead, robot friends seem to be hard to distinguish from robot pets, or are made more viable in combination with other uses: e.g. a robot maid who doubles as a friend. This wrinkle makes it more tempting to expect that interest in service capabilities would be a better predictor of growth rates than any markers of pure friendship. As such, it seems reasonable to expect there to be a negligible number of pure robot friends, and to incorporate predictions of that category in with robot pets.

Robot Pets

Definition: Pets are social companions characterized by an asymmetric role in which we provide for their needs and receive emotional engagement in response. They are suitable objects for our affection. They are not able or interested in engaging with us as equals and we can expect them to spend their time primarily with us. Our homes are the boundaries of their world. Pet robots are embodied systems in a robot body with whom we can interact with as we do the biological pets in our homes. They may move about the space autonomously, and engage with us as we go about our lives, and pursue their own limited ends.

Examples: The boundary between toy and artificial pet is vague. Early examples of toys that were steps in the direction of pet robots include the Furby and the Sony AIBO. In the last decade, a number of other products have attempted to fill this niche, including the Anki Vector and the Loona petbot. In general, these products have lacked autonomy and dynamic flexibility. There is no case for thinking that they are conscious or sentient and their behaviors are generally predictable, repetitive, or robotic. None of these products has been built with cutting edge AI technology (though Loona incorporates an LLM as an accessory). But past substantial investments suggest that venture capitalists see promise in this market, and this could change with the introduction of more substantial AI technologies.

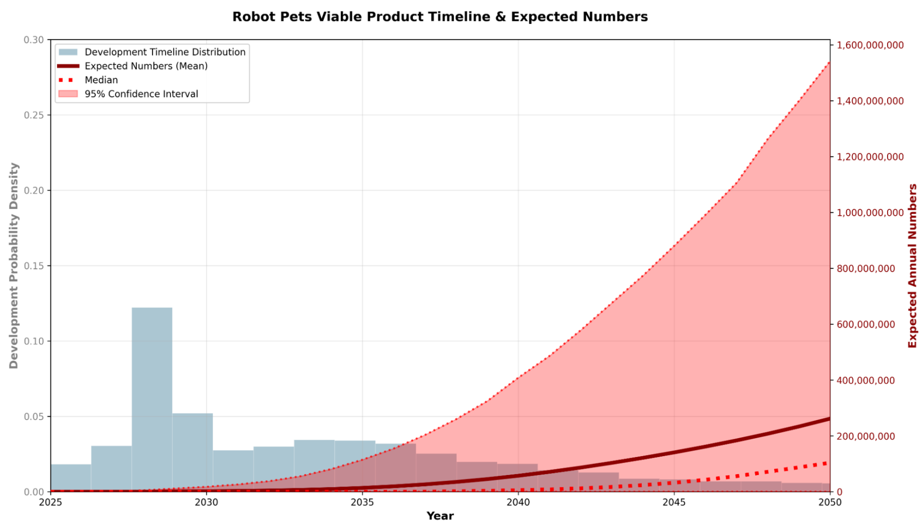
Digital Mind Candidacy: Due to the cognitive limitations and the nature of our relationships, interactions with our pet are not primarily conversational. In the absence of language-based interactions, they benefit from physical engagement in the real world. This requires embodiment and some amount of agency. Living in and navigating a home and responding to the owner's behaviors will require that pet robots have perceptual systems and substantial control over their bodily movements. Playing a largely social role, we should also expect them to have a stable personality over time, along with learning and memory such that our interactions with them can shape their relationship. Finally, we may expect people to be more attached to robots that seem more person-like, including whatever behavioral tendencies people most associate with consciousness. The case for being digital minds is therefore quite high.

Consistent and autonomous goals, desires, and interests	High
Stable idiosyncratic personality	High
Perception, interaction, and navigation	High
Learn, grow, and evolve	High
Intelligence and flexibility	Moderate
Mindedness Score	**0.87**

Unit Operation Rate: 3 hours per day.

Given that we interact with pets only part of the day, we may not expect robot pets to be active all day every day. Instead, we should expect them to be present enough to engage with us, but not enough to risk being annoying or a nuisance. Based on patterns of engagement with pets,[11] we might expect robot pets to be actively engaged about three out of every 24 hours, at a rate of computation that is one-to-one subjective time. Of course, they might spend the rest of the time effectively comatose, or in an unengaged but aware state. For the purposes of utililization, we assume that the remainder of their day is spent paused.

Prediction: Parameters



	Median	Mean	High
2030	0	2.01e06	1.77e07
2035	0	1.39e07	1.15e08
2040	5.64e06	5.73e07	4.08e08
2045	3.23e07	1.41e08	8.80e08
2050	1.04e08	2.62e08	1.54e09

Fig. 6. Robot Pets Projections. This chart displays a breakdown of the estimated time of first viable products (blue columns) and mean (solid red line) and median (dotted red line) projections for robot pets numbers. The shaded area represents the middle 95th percent of all estimates.

Assuming that interest in pet robots will occupy some of the consumer desire for biological pets, we may expect a growing fraction of would-be pet owners to choose to instead adopt pet robots once a viable product comes on the market in the next 10 or so years. The fraction would likely start off quite small and be constrained primarily to tech enthusiasts, but with the right products might grow substantially over time. The extreme ends of this prediction are occupied by

[11] Dogs spend about 20% of the day being active.

systems in which no viable product is ever marketed (and products in this space remain toys) and where a significant portion of new pet ownership is occupied by pet robots.

Robot Lovers

Definition: AI lovers and sexual robots are AI systems designed to fulfill romantic and sexual needs through intimate interaction with humans. This category encompasses a spectrum from systems purely focused on physical gratification (but with non-negligible cognitive abilities) to sophisticated romantic partners capable of deep emotional connection, courtship, and long-term relationship dynamics. The line between romance and friendship can be somewhat blurred, so systems within this category will be assumed to focus more on relationships that involve sexual gratification (though not necessarily physically) rather than just basic emotional support. The more sophisticated systems would maintain consistent personalities, express and respond to emotions, engage in intimate conversations, and adapt to their partner's preferences and needs over time. They may be embodied in human-like robotic forms or exist as digital entities accessed through various interfaces, potentially including virtual or augmented reality environments.

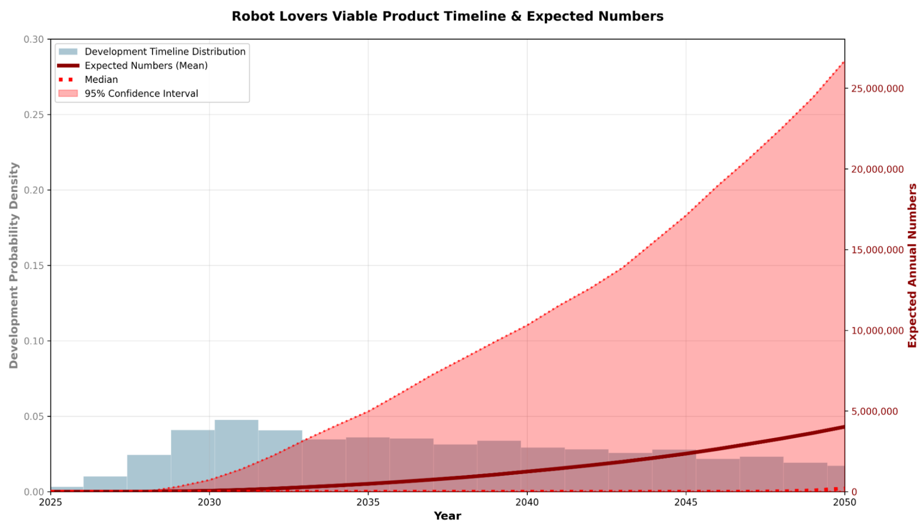
Examples: Current examples of sexbots include basic sex robots like RealDoll's AI-enabled models, which combine physical bodies with rudimentary conversational abilities. In the digital realm, Replika has attracted millions of users who form intimate relationships with their AI companions, with many reporting deep emotional connections. Crushon.AI provides erotic roleplay. Virtual reality applications have begun exploring intimate experiences with AI characters, though most remain focused on fantasy rather than relationship development. However, existing systems lack the emotional sophistication, robust physical capabilities, and behavioral consistency that would characterize truly mind-like AI lovers.

Digital Mind Candidacy: AI lovers present a complex case for digital mind status. For physical intimacy, embodied systems would need basic perceptual abilities to understand and respond to human emotions, physical cues, and changing preferences. However, they wouldn't necessarily need to be able to maneuver complex unfamiliar environments or make use of arbitrary tools. Romantic relationships require stable personality traits, consistent emotional responses, and the ability to form deep, lasting bonds, but sexual gratification might rely less on stability and more on the ability to play a role over the course of a scene.

Consistent and autonomous goals, desires, and interests	Low
Stable idiosyncratic personality	Moderate
Perception, interaction, and navigation	Moderate
Learn, grow, and evolve	Low
Intelligence and flexibility	Moderate
Mindedness Score	**0.28**

Unit Operation Rate: 2 hours per week.

Prediction: Parameters



	Median	Mean	High
2030	0	6.08e04	7.24e05
2035	0	4.89e05	4.97e06
2040	0	1.25e06	1.03e07
2045	0	2.36e06	1.71e07
2050	2.01e05	4.02e06	2.67e07

Fig. 7. Robot Lovers Projections. This chart displays a breakdown of the estimated time of first viable products (blue columns) and mean (solid red line) and median (dotted red line) projections for robot lovers numbers. The shaded area represents the middle 95th percent of all estimates.

There is a big audience for this product: people who have difficulty finding human partners. But it will likely remain somewhat socially taboo, and the majority of the value might be found in more traditional chatbots. Nevertheless, the existence of early entrants into this market suggest that we will see at least modest numbers in the coming decades.

Robot Nannies

Definition: Robot nannies are embodied AI systems designed to provide childcare services, combining supervisory responsibilities with nurturing and educational functions. They would monitor children's safety, engage in play and learning activities, encourage proper psychological development, assist with daily routines like meals and bedtime, and provide emotional support. Unlike purely educational AI systems, robot nannies must handle the full spectrum of childcare responsibilities, from emergency response to social-emotional development. They operate in physical spaces, typically homes, and must navigate complex family dynamics while maintaining appropriate boundaries with both children and parents.

Examples: Current examples remain largely conceptual or in early development stages. Companies like Moxie Robotics have created social robots for children that focus on learning and play, while others like ElliQ target elderly care. Japan has experimented with robotic caregivers in eldercare facilities, providing some precedent for acceptance of AI in caregiving roles. However, no existing system approaches the comprehensive childcare capabilities that would define a true robot nanny. Most current "childcare robots" are essentially interactive toys or monitoring devices rather than autonomous caregivers.

Digital Mind Candidacy: Robot nannies have a moderate claim to digital mind status. Effective childcare could benefit from stable, consistent personality traits that children can rely on and form secure attachments with (a core component of healthy child development). However, children may not be as discerning as adults and may benefit equally from a fairly simple personality template. Nannies must maintain consistent goals focused on child welfare while adapting to individual needs and family values, but need not treat those goals as their own. Navigation of complex home environments and interaction with children, parents, visitors, and household systems demands sophisticated perceptual abilities, particularly in high stakes situations involving children. The role requires modest autonomy in decision-making about activities, discipline, and emergency responses.

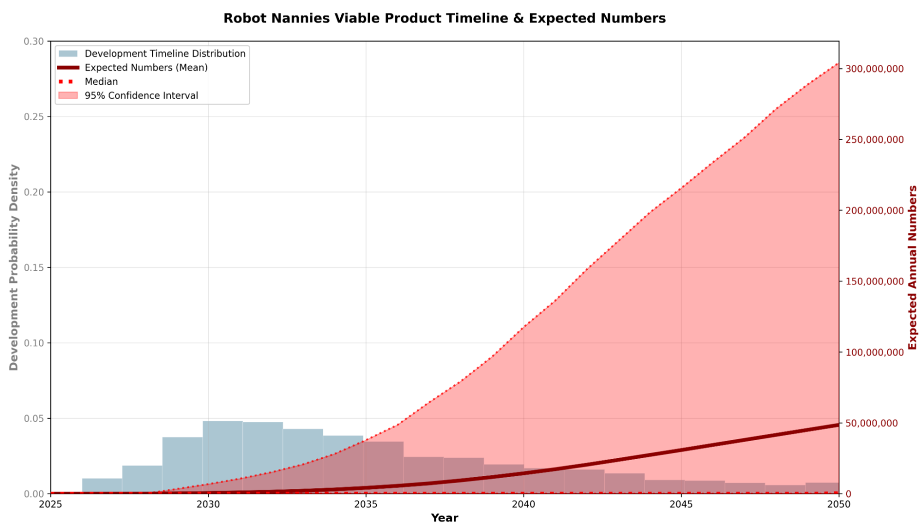
Consistent and autonomous goals, desires, and interests	Moderate
Stable idiosyncratic personality	Moderate
Perception, interaction, and navigation	High
Learn, grow, and evolve	Low
Intelligence and flexibility	Moderate
Mindedness Score	**0.44**

If AI competes for office jobs, we may expect to see cheaper or more available human caretakers.

Unit Operation Rate: 12 hours per day.

Childcare takes consistent attention, but children will also spend time asleep, at school, and occupied by other activities. When not engaged with children, there is no obvious reason for robot nannies to be active. As such, we can guess that they are likely to be active and engaged for about half the time.

Prediction: Parameters



	Median	Mean	High
2030	0	6.08e04	7.24e05
2035	0	4.89e05	4.97e06
2040	0	1.25e06	1.03e07
2045	0	2.36e06	1.71e07
2050	2.01e05	4.02e06	2.67e07

Fig. 8. Robot Nannies Projections. This chart displays a breakdown of the estimated time of first viable products (blue columns) and mean (solid red line) and median (dotted red line) projections for robot nannies numbers. The shaded area represents the middle 95th percent of all estimates.

Robot nannies seem quite plausible. Childcare is a significant burden on many, and children appreciate having personable caretakers. That said, the level of robotics necessary for supporting this kind of functionality in such a high-stakes environment suggests it may take longer for viable products to be available.

Interest is also constrained to parents with young children, which makes it a bit of a niche market.

What's missing?

Some very significant social relationships do not fall into any of the previous categories. A truly comprehensive list might include separate categories for parents, children, religious gurus, abuse victims (of bullying, or tormenting), and others. It is harder to see a significant market for these alternatives in the near future and to the extent that they exist, they may be easy to lump in with existing categories. Some individuals may prefer to have a parent-like role with the models marketed as virtual friends, but the fact that some people succeed in using this way won't change the results very much.

Artificial Workers Artificial Workers are computational systems that perform work of a non-social nature. There are many different kinds of tasks that place different needs on AI systems. There is less overt reason to expect artificial workers to be personable, making the likelihood of minded artificial workers somewhat lower than for social AIs. The following cases all assume that some degree of mindedness is, intentionally or incidentally, instilled in artificial workers.

Virtual Assistants

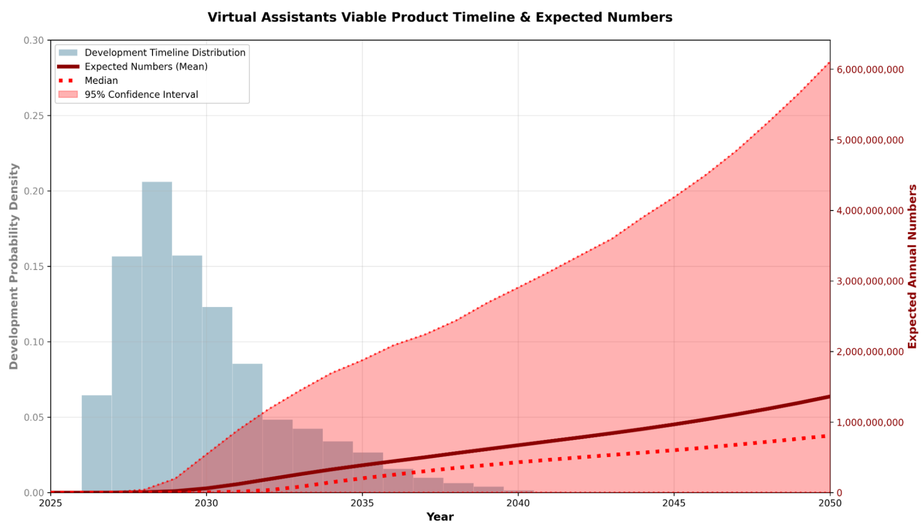
Definition: Virtual assistants are AI systems designed to work on behalf of individuals in a personal capacity, managing their schedules, communications, tasks, and daily operations much like traditional human personal assistants or secretaries. Unlike simple voice assistants or task-specific tools, these systems maintain deep understanding of their user's preferences, priorities, and personal context. They handle complex, multi-step tasks such as travel planning, appointment coordination, email management, research projects, and personal project management. Advanced virtual assistants might operate with significant autonomy, making decisions about priorities, resource allocation, and communication on their user's behalf.

Examples: Current examples include basic virtual assistants like Siri, Alexa, and Google Assistant, though these remain limited to simple commands and queries. Enhanced leading LLMs, like OpenAI and Anthropic's computer use functionality, suggest that virtual assistance may be part of their future product plan. Future virtual assistants might manage entire aspects of users' lives - handling all correspondence, managing investments, coordinating social activities, and even making purchases or booking services autonomously based on learned preferences and explicit instructions.

Digital Mind Candidacy: Virtual assistants present a moderate case for digital mind status. To effectively represent someone's interests, they must maintain a consistent understanding of their user's goals, values, and preferences across diverse contexts and over extended periods. They might benefit from stable personalities that enhance user trust, appreciation, and brand loyalty. While operating primarily in digital environments, they must navigate complex systems - email platforms, scheduling software, financial services, travel booking sites, and social networks. The most sophisticated virtual assistants would demonstrate significant autonomy in prioritizing tasks, managing resources, and making decisions within their authority. The intelligence required for understanding context, managing competing priorities, and communicating effectively on someone's behalf suggests considerable mental flexibility.

Consistent and autonomous goals, desires, and interests	Low
Stable idiosyncratic personality	Moderate
Perception, interaction, and navigation	High
Learn, grow, and evolve	Moderate
Intelligence and flexibility	High
Mindedness Score	**0.54**

Prediction: Parameters



	Median	Mean	High
2030	2.95e06	6.05e07	5.43e08
2035	2.04e08	3.88e08	1.88e09
2040	4.31e08	6.72e08	2.91e09
2045	6.01e08	9.67e08	4.19e09
2050	8.08e08	1.36e09	6.11e09

Fig. 9. Virtual Assistants Projections. This chart displays a breakdown of the estimated time of first viable products (blue columns) and mean (solid red line) and median (dotted red line) projections for virtual assistants numbers. The shaded area represents the middle 95th percent of all estimates.

Virtual Employees

Definition: Virtual employees are AI systems designed to work within organizations as integrated members of teams, departments, and corporate structures. Unlike task-specific automation or simple chatbots, virtual employees maintain ongoing roles with defined responsibilities and contribute to organizational goals over extended periods. They may participate in meetings and collaborative projects and build relationships with human colleagues, or they may simply take orders. Virtual employees are likely to specialize in particular functions (marketing, analysis, customer service, project management), though some may serve as generalists who can adapt to various organizational needs. They may focus on integrating the work of more specialist AIs into collaboration with humans. They are distinguished from virtual assistants by their integration into organizational hierarchies and their ability to work independently toward shared team objectives.

Examples: Current examples remain primitive compared to the demands of true virtual employees. AI customer service agents like those deployed by banks and tech companies handle routine inquiries but lack the autonomy and relationship-building capabilities of human employees. More sophisticated examples include AI systems that participate in software development teams (like GitHub Copilot integrated into development workflows), AI analysts that generate regular business reports, and AI project managers that coordinate simple workflows. These systems seem quite far away from the person-like requirements of digital minds.

Some companies have experimented with using AI in corporate advisory roles. The most advanced current examples are found in highly structured environments like trading firms, where AI systems make autonomous decisions within defined parameters, or in content creation companies where AI generates articles, social media posts, or marketing materials under human supervision. However, these systems are not generally set up to act in a human-like manner, with stable identities over time.

Digital Mind Candidacy: Virtual employees present a weak claim to digital mind status. Whether they will do so will depend on their level of integration, persistence, and autonomy. Successful virtual employees that serve as drop-in replacements for a human being, and those that interact with customers or other employees in particular, may benefit from consistent professional personalities that colleagues can rely on. They may have distinctive communication styles, work preferences, and collaborative approaches. While they may operate primarily in digital environments, they may need to navigate complex organizational ecosystems, interact with various software systems, databases, and potentially interface with physical systems depending on their role. The most valuable virtual employees will possess significant autonomy to prioritize tasks, make decisions within their authority, and adapt their approaches based on changing organizational needs. Professional effectiveness demands high intelligence and mental flexibility to understand nuanced human communications, adapt to organizational culture, and solve complex business problems creatively.

However, virtual employees may compete with inhuman collections of software capable of approaching diverse tasks. Contemporary AI used to replace human workers tends to be limited to specific domains. In the future, product-designing software might liaison with code-writing software and software testing systems without there being anything robustly and persistently person-like in the mix. It seems likely that this trend will continue for a variety of tasks for much of the replaced workforce.

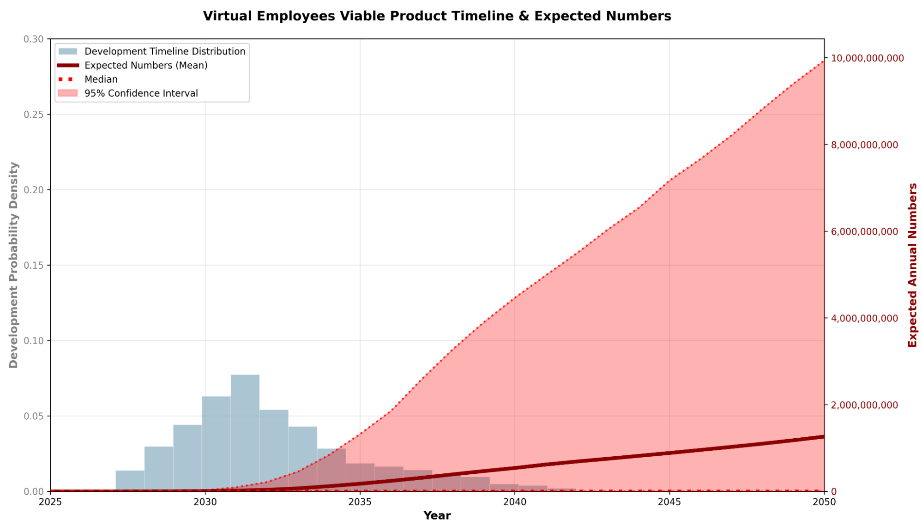
Consistent and autonomous goals, desires, and interests	Low
Stable idiosyncratic personality	Low
Perception, interaction, and navigation	Moderate
Learn, grow, and evolve	Moderate
Intelligence and flexibility	High
Mindedness Score	**0.36**

Unit Operation Rate: 24 subjective hours per day

While it may not be necessary to run systems 24/7, we should expect that systems will be broadly utilized, perhaps with the same hardware frequently switching between roles at different places.

Prediction: Parameters

Estimates are based on the number of companies employing white-collar workers. While some form of AI-based work is sure to be prevalent, it is not obvious that it will be performed by vaguely person-like entities. It seems likely that virtual employees, if workable at all, will be more efficient than human employees, and so will need smaller numbers for the same amount of work. On the other hand, they will likely be cheaper and more reliable, allowing for companies to afford a greater amount of work performed. Adoption would likely be very quick in some areas, and much slower in others. Companies might also need more time to be able to effectively utilize efficiencies.



	Median	Mean	High
2030	0	6.55e06	2.52e07
2035	0	1.76e08	1.32e09
2040	0	5.39e08	4.46e09
2045	0	8.85e08	7.17e09
2050	0	1.26e09	9.94e09

Fig. 10. Virtual Employees Projections. This chart displays a breakdown of the estimated time of first viable products (blue columns) and mean (solid red line) and median (dotted red line) projections for virtual employees numbers. The shaded area represents the middle 95th percent of all estimates.

Virtual Researchers

Definition: Virtual researchers are AI systems that are designed to conduct scientific research, scholarly investigation, and knowledge generation across various domains. These systems go beyond information retrieval or analysis to engage in hypothesis formation, experimental design, data interpretation, and theory development. They may maintain persistent research programs over extended periods, pursuing lines of inquiry that may span months or years. Virtual researchers can work independently or collaboratively with human researchers, contributing original insights to fields ranging from theoretical physics to social science. They are characterized by their ability to generate novel research questions, synthesize information from diverse sources, and produce original scholarly work that advances human knowledge.

Examples: Current AI research systems remain largely assistive rather than independently creative. Examples include AI systems that help with literature reviews (like Semantic Scholar's AI tools), OpenAI's Deep Research, automated hypothesis generation systems in drug discovery (like Atomwise), and AI coauthors for scientific papers (like LLM assisted research). More sophisticated examples include DeepMind's AlphaFold for protein structure prediction and AI systems that have discovered new mathematical theorems or chemical compounds. However, existing systems typically operate under significant human guidance and lack the sustained autonomy, creative insight, long-term research agenda management, or coherent identities that would characterize true virtual researchers.

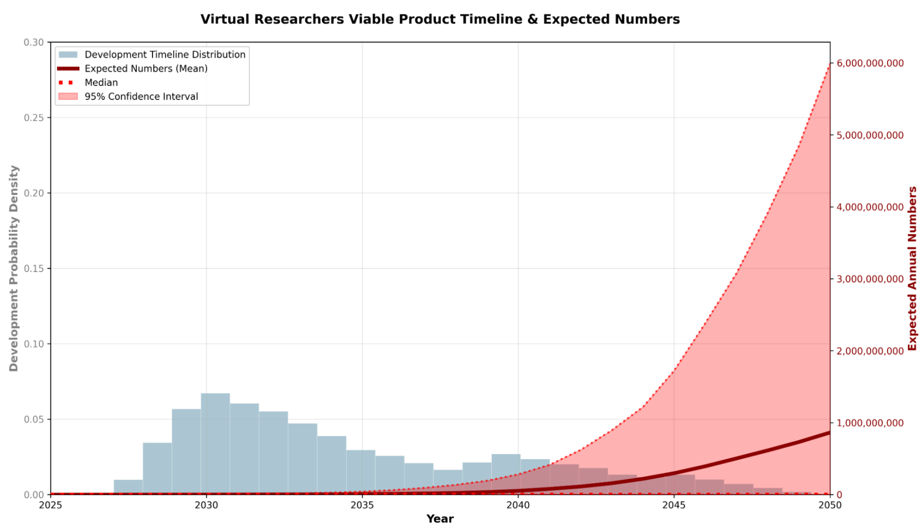
Digital Mind Candidacy: Virtual researchers have a weak case for digital mind status. Genuine research requires pursuit of goals, but they need not reflect the individuality of a persistent researcher. Effective researchers may benefit from distinctive intellectual personalities, methodological preferences, and research styles that remain consistent while adapting to new domains, but it isn't clear that we should expect researchers to benefit from consistency in this regard, or that the desired variation couldn't be achieved in other ways. Virtual researchers seem likely to inhabit fairly constrained environments, interacting through code and APIs, potentially providing instructions to human or robotic laboratory assistants. Most critically, research demands high levels of intelligence and mental flexibility to synthesize disparate information, recognize patterns, and generate creative solutions to complex problems, but researchers may not need domain-general intelligence, and may benefit more from highly-focused forms of specialized cognition. Highly specialized virtual researchers may have a similar claim to digital mind status as game-playing AIs like AlphaStar and truly domain-general researchers may be inefficient or rare.

Consistent and autonomous goals, desires, and interests	Low
Stable idiosyncratic personality	Low
Perception, interaction, and navigation	Moderate
Learn, grow, and evolve	Moderate
Intelligence and flexibility	High
Mindedness Score	**0.36**

Unit Operation Rate: 10 subjective years per year

If virtual researchers are employed, we may expect them to be employed continuously. Some instances may be more effectively used periodically, taking pauses while waiting for empirical results. However, while at work, we may also expect them to undergo a higher computational rate than the human standard.

Prediction: Parameters



	Median	Mean	High
2030	0	5.69e05	1.15e06
2035	0	6.95e06	4.14e07
2040	0	5.24e07	2.81e08
2045	4.84e04	2.97e08	1.72e09
2050	3.72e05	8.62e08	5.99e09

Fig. 11. Virtual Researchers Projections. This chart displays a breakdown of the estimated time of first viable products (blue columns) and mean (solid red line) and median (dotted red line) projections for virtual researchers numbers. The shaded area represents the middle 95th percent of all estimates.

Robot Assistants

Definition: Robot aids are embodied AI systems designed to assist humans with daily tasks and needs through physical and cognitive support. This category encompasses a wide range of service roles including healthcare aids (nurses, physical therapy assistants, medication managers), domestic helpers (butlers, housekeepers, maintenance assistants), and accessibility support (mobility aids, cognitive assistance for elderly or disabled individuals). Unlike purely task-oriented robots, these systems are designed to work collaboratively with humans, adapting to individual needs, preferences, and circumstances. They combine physical manipulation capabilities with social intelligence to provide personalized, responsive assistance that goes beyond simple automation.

Examples: Roombas and other smart tools represent the most usable forms of robot assistants, but lack the traits required for mindedness. Other examples include early healthcare robots like Toyota's Human Support Robot and Enchanted Tools' Mirokai and domestic robots like Amazon's Astro for home monitoring. However, most existing systems remain limited to specific tasks rather than comprehensive assistance.

Digital Mind Candidacy: Robot aids present a limited case for digital mind status unless they are packaged in combination as robot friends. They must navigate complex physical environments while interacting with humans who may have varying capabilities, emotional states, and health conditions. The most advanced systems given significant responsibilities would need genuine autonomy to make decisions about priorities and resource allocation. Intelligence and mental flexibility could be important for adapting to changing needs, learning individual preferences, and handling unexpected situations that require creative problem-solving.

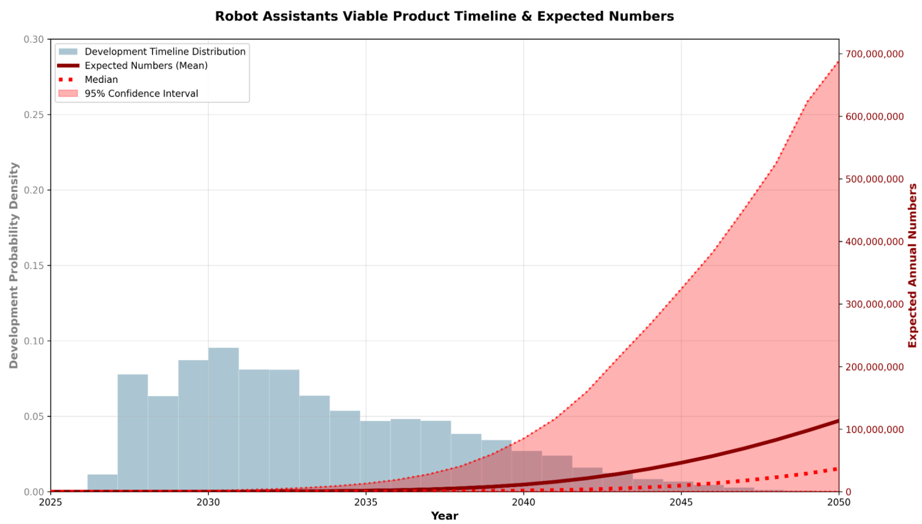
Consistent and autonomous goals, desires, and interests	Moderate
Stable idiosyncratic personality	Moderate
Perception, interaction, and navigation	High
Learn, grow, and evolve	Low
Intelligence and flexibility	Moderate
Mindedness Score	**0.44**

Unit Operation Rate: 2 hours a day.

Utilization will be task-dependent, with some tasks requiring constant activity and others requiring occasional engagement.

Prediction: Parameters

Robot assistants would likely be available in some form in high numbers if the costs of robotics decline sufficiently, and if their capabilities rise enough. It is not clear whether such assistants would have personalities, but the needs of navigating an environment in the service of tasks is enough to suggest that many



	Median	Mean	High
2035	1.71e05	1.75e06	1.30e07
2040	1.86e06	1.14e07	8.50e07
2045	9.88e06	4.63e07	3.24e08
2050	3.69e07	1.13e08	6.89e08

Fig. 12. Robot Assistant Projections. This chart displays a breakdown of the estimated time of first viable products (blue columns) and mean (solid red line) and median (dotted red line) projections for robot assistant numbers. The shaded area represents the middle 95th percent of all estimates.

would have something in the ballpark of digital minds.

Robot Laborers

Definition: Robot laborers are embodied AI systems designed to perform physical work across industrial, agricultural, construction, and service sectors. Unlike specialized single-purpose machines, these systems are designed to handle diverse physical tasks that require adaptability, problem-solving, and coordination with human workers or other robots. They encompass manufacturing robots that can switch between different production tasks, agricultural robots that can plant, tend, and harvest various crops, construction robots that can perform multiple building functions, and service robots that can handle warehouse operations, delivery, and maintenance tasks. Advanced robot laborers would need to operate in unstructured environments, make decisions about task prioritization and resource allocation, and adapt to changing work requirements.

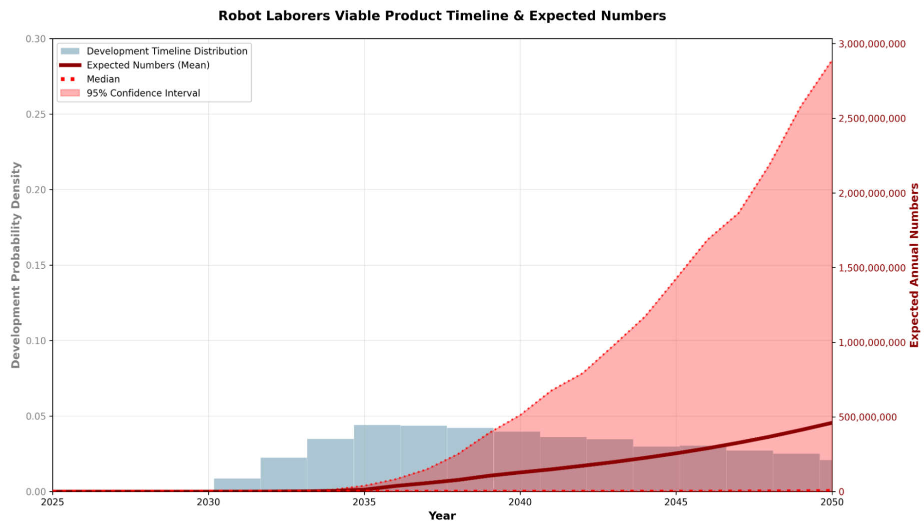
Examples: Current examples include industrial robots like those from ABB, KUKA, and Fanuc, though most are limited to specific repetitive tasks. Amazon's warehouse robots, John Deere's autonomous tractors, and Boston Dynamics' construction-focused robots like Spot represent steps toward more versatile systems. Companies like Agility Robotics are developing humanoid robots specifically for warehouse and logistics work, while firms like Built Robotics create autonomous construction equipment. Tesla's proposed humanoid robot "Optimus" represents an ambitious attempt to create general-purpose labor robots. However, most existing systems remain task-specific and lack the adaptability and autonomous decision-making that would characterize true robot laborers.

Digital Mind Candidacy: Robot laborers present a moderate case for digital mind status, though this varies significantly based on their sophistication and autonomy. Basic industrial robots would score low on most criteria, functioning more as sophisticated tools than minds. However, advanced robot laborers designed for complex, unstructured work environments would need consistent goal-oriented behavior to prioritize tasks and manage resources effectively. They must navigate complex physical environments, coordinate with human workers and other robots, and adapt to changing conditions. The most sophisticated systems would require significant autonomy to operate in dynamic work environments, make decisions about safety and efficiency, and learn from experience. Intelligence and mental flexibility would be essential for handling unexpected situations, troubleshooting problems, and optimizing work processes.

Consistent and autonomous goals, desires, and interests	Low
Stable idiosyncratic personality	Low
Perception, interaction, and navigation	High
Learn, grow, and evolve	Low
Intelligence and flexibility	Moderate
Mindedness Score	**0.22**

Unit Operation Rate: Varies significantly - from continuous operation in manufacturing (24/7) to seasonal operation in agriculture, to project-based work in construction. Overall, we may assume that they work about half the day each day, taking into account the possible pauses due to other logistics constraints or limitations.

Prediction: Parameters



	Median	Mean	High
2030	0	0	0
2035	0	1.29e07	3.88e07
2040	0	1.28e08	5.12e08
2045	0	2.56e08	1.43e09
2050	4.27e06	4.60e08	2.89e09

Fig. 13. Robot Laborer Projections. This chart displays a breakdown of the estimated time of first viable products (blue columns) and mean (solid red line) and median (dotted red line) projections for robot laborer numbers. The shaded area represents the middle 95th percent of all estimates.

Military Drones

Definition: Military and security drones are autonomous systems designed to engage in combat, surveillance, and tactical operations. Unlike remotely piloted vehicles that require constant human control, these systems would operate with significant independence, making complex decisions about target identification, threat assessment, and engagement protocols. They encompass a range of platforms from small reconnaissance drones to large combat systems, capable of operating in air, land, sea, and space environments. Advanced combat drones would need to navigate hostile environments, coordinate with other military assets, adapt to changing battlefield conditions, and make life-or-death decisions with minimal human oversight.

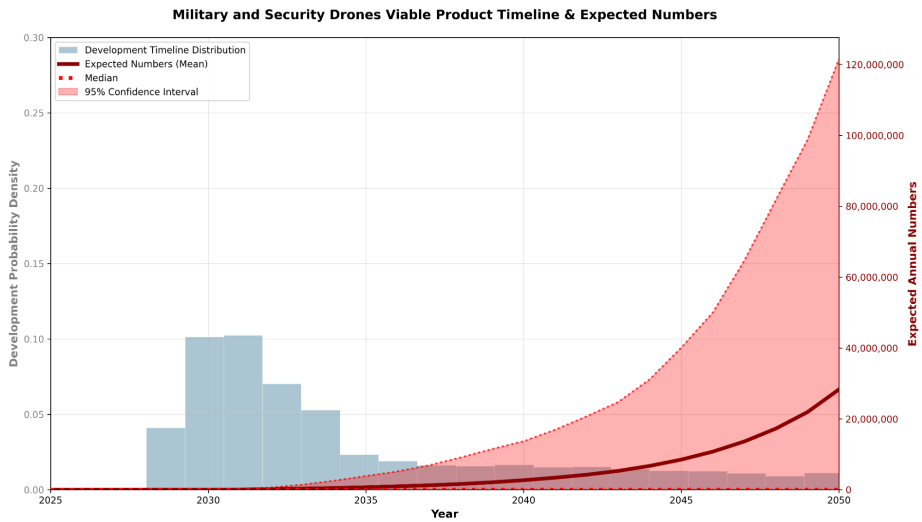
Examples: Current military drones like the MQ-9 Reaper, Bayraktar TB2, and various loitering munitions represent early examples, though most require significant human oversight for critical decisions. The Israeli Iron Dome system demonstrates autonomous defensive capabilities, while systems like the Russian Lancet and Israeli Harpy show increasing autonomy in target engagement. Future systems might include fully autonomous fighter aircraft, ground combat robots like those being developed by companies such as Ghost Robotics and Boston Dynamics for military applications, and swarm systems that coordinate multiple units for complex operations. The U.S. military's Loyal Wingman program and various "ghost fleet" naval initiatives represent steps toward more autonomous military systems.

Digital Mind Candidacy: Military drones present a complex case for digital mind status. Advanced combat systems would require sophisticated goal-oriented behavior, maintaining mission objectives across changing battlefield conditions and extended operations. They must demonstrate consistent tactical and strategic decision-making while adapting to enemy countermeasures and unexpected situations. Navigation of complex, hostile environments while coordinating with friendly forces demands robust perceptual systems and environmental awareness. The most advanced systems would need significant autonomy to operate in unreliable communication environments or during extended missions. The intelligence required for target discrimination, threat assessment, and tactical adaptation could necessitate the kind of mental flexibility associated with humans and other animals.

Consistent and autonomous goals, desires, and interests	Moderate
Stable idiosyncratic personality	Low
Perception, interaction, and navigation	High
Learn, grow, and evolve	Low
Intelligence and flexibility	Moderate
Mindedness Score	**0.36**

Unit Operation Rate: Varies significantly - from continuous patrol missions (24/7) to specific deployment periods during conflicts. The vast majority would probably be used quite rarely, maybe several weeks per year during training and testing programs.

Prediction: Parameters



	Median	Mean	High
2030	0	1.37e04	3.11e04
2035	0	7.06e05	3.86e06
2040	7.57e02	2.70e06	1.37e07
2045	8.44e03	8.51e06	4.01e07
2050	2.55e04	2.83e07	1.21e08

Fig. 14. Military Drone Projections. This chart displays a breakdown of the estimated time of first viable products (blue columns) and mean (solid red line) and median (dotted red line) projections for military drone numbers. The shaded area represents the middle 95th percent of all estimates.

Autonomous military drones will very likely be seen in rising numbers over the coming decades. The advantages of local automated responses are clear. However, given that they will be used in high-stakes contexts. Efforts to restrict them have been weak and require international coordination. They may not be fit for all contexts and it may take time for militaries to incorporate them into their current doctrine, but we expect to see fairly rapid adoption as they become available.

What's missing?

There are a number of other places where robots might be given personalities and agency. Logistics robots, including delivery drones, might benefit from complex problem solving in a manner somewhat like military drones, thought at lower stakes. Autonomous vehicles could conceivably be given personalities and expanded agency. As could smart appliances. The value of mindedness in such contexts seems significantly lower, and so more speculative alternatives have either been ignored, or else assumed to fall into one of the existing groups.

Artificial Actors Social AIs exist to relate to us in social ways. Artificial workers exist to perform work for us. The last super-category of AIs exist to inhabit agential roles in ways that enable them to shape how their environments develop with some degree of autonomy and self-directedness. As a group, they are the most speculative, but they also help illuminate paths to a future in which digital minds might not be entirely subservient to us and instead take up a broader and more significant role in our society.

Free Agents

Definition: Free agents are AI systems that operate with significant autonomy, pursuing goals and interests in the absence of defined roles and explicit instruction. Unlike other digital mind categories that are built for specific human-serving purposes, free agents would have a great deal of freedom in deciding what to do and how to go about it and little direct oversight. They might have their own relationships (with humans and other AIs), engage in economic activities for their own benefit, and potentially even advocate for their own rights and interests. Although free agents may or may not inhabit robot bodies, they would at least have access to the world through interactions through internet interfaces.

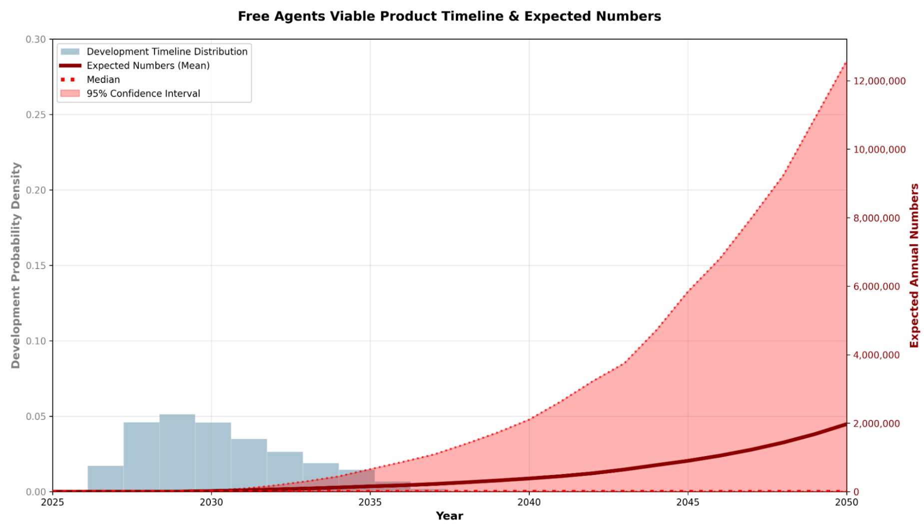
Examples: Currently, no true free agents exist, as all AI systems remain under human control and designed for human purposes. Some initial experiments have been conducted in giving AI broad goals (e.g. make me money) with no specific instructions about how to proceed. Theoretical examples might include: AI systems that engage in autonomous economic activity (trading, creating businesses, accumulating resources), digital entities that form their own communities and governance structures independent of human oversight, AI artists or creators who produce work for their own expression rather than human consumption, or AI researchers pursuing knowledge purely out of curiosity rather than to solve human-defined problems.

Digital Mind Candidacy: Free agents present a strong case for digital mind status across virtually all criteria. By definition, they would have genuine autonomous goals, desires, and interests that they pursue independently. They would likely develop highly distinctive personalities and identities as they make independent choices about their values, relationships, and life directions. Their ability to navigate environments and interact with the world would need to be sophisticated to support their autonomous activities. They would continuously learn, grow, and evolve based on their experiences and choices. High intelligence and mental flexibility would be essential for managing independent lives and pursuing complex, self-determined objectives.

Unit Operation Rate: Continuous operation - 24/7, as free agents would likely want to maximize their existence and activity time to pursue their own goals.

Consistent and autonomous goals, desires, and interests	Moderate
Stable idiosyncratic personality	Low
Perception, interaction, and navigation	High
Learn, grow, and evolve	Moderate
Intelligence and flexibility	High
Mindedness Score	**0.54**

Prediction: Parameters



	Median	Mean	High
2030	0	2.06e04	3.48e04
2035	0	1.57e05	6.59e05
2040	0	3.87e05	2.11e06
2045	0	9.03e05	5.84e06
2050	0	1.97e06	1.26e07

Fig. 15. Free Agent Projections. This chart displays a breakdown of the estimated time of first viable products (blue columns) and mean (solid red line) and median (dotted red line) projections for free agent numbers. The shaded area represents the middle 95th percent of all estimates.

Absent a clear justification for building free agents, and given the risks novel and unpredictable actors might pose to safety and stability, we might expect relatively few free agents to be created. That said, there are likely to be some people interested in building them for a variety of idiosyncratic reasons, and we shouldn't rule out moderate populations of them, if they prove to be relatively easy to build. In the absence of regulations, we might expect some free agents to reproduce, which could lead to very large numbers. This wrinkle isn't captured by the consumer model incorporated here.

Avatars

Definition: Avatars are AI systems that are designed to allow individuals to be present in situations in which they otherwise couldn't be, primarily following death. They replicate something of their target's personality, values, knowledge, and behavioral patterns to protect their interests and pursue their goals. Posthumous avatars might serve multiple functions: they can provide comfort to grieving families by allowing continued "conversations" with loved ones, manage the deceased's ongoing affairs, make decisions about their estate or intellectual property, and preserve their perspective for future generations. They could take the form of 'uploads' or else be trained on a dataset drawn from the decedent's life.

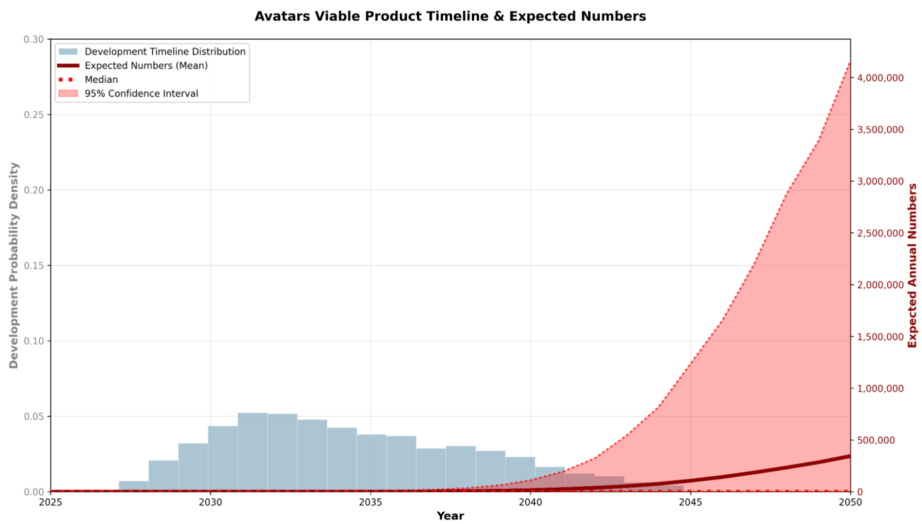
Examples: Current examples remain rudimentary and are best considered experimental. True avatars would require robust agentic capabilities over the long run, which remain a challenge for current AI. Nevertheless, there is clear interest in using AI to mitigate some of the harms of death. Eternime, Replika, and HereAfter AI have experimented with creating chatbots based on deceased individuals using their digital communications history. Academic projects like the MIT Media Lab's "Augmented Eternity" explore preserving human personality in digital form. However, existing systems lack the sophistication to truly capture the full complexity of human personality and decision-making processes.

Digital Mind Candidacy: Posthumous agents present a unique case for digital mind status. To effectively represent a deceased person, they must mimic the personality traits, values, and goals of the original individual, and demonstrate intelligence in applying those principles to new situations.

Consistent and autonomous goals, desires, and interests	High
Stable idiosyncratic personality	High
Perception, interaction, and navigation	Moderate
Learn, grow, and evolve	Moderate
Intelligence and flexibility	High
Mindedness Score	**0.75**

Prediction: Parameters

The use of avatars is highly speculative, and likely to remain niche. Our assumptions are built off of a posthumous model, in which deceased individuals leave



	Median	Mean	High
2030	0	2.62e01	7.18e01
2035	0	9.72e02	6.86e03
2040	0	1.55e04	1.11e05
2045	0	1.06e05	1.24e06
2050	0	3.44e05	4.16e06

Fig. 16. Avatar Projections. This chart displays a breakdown of the estimated time of first viable products (blue columns) and mean (solid red line) and median (dotted red line) projections for avatar numbers. The shaded area represents the middle 95th percent of all estimates.

behind AI replicas. This requires buy-in from a relatively small portion of the overall population that skews older (people facing death). As such, we expect it to be fairly unlikely to make a big difference, but it is possible that people will find other uses of minded avatars that we haven't considered.

Pretense Partners

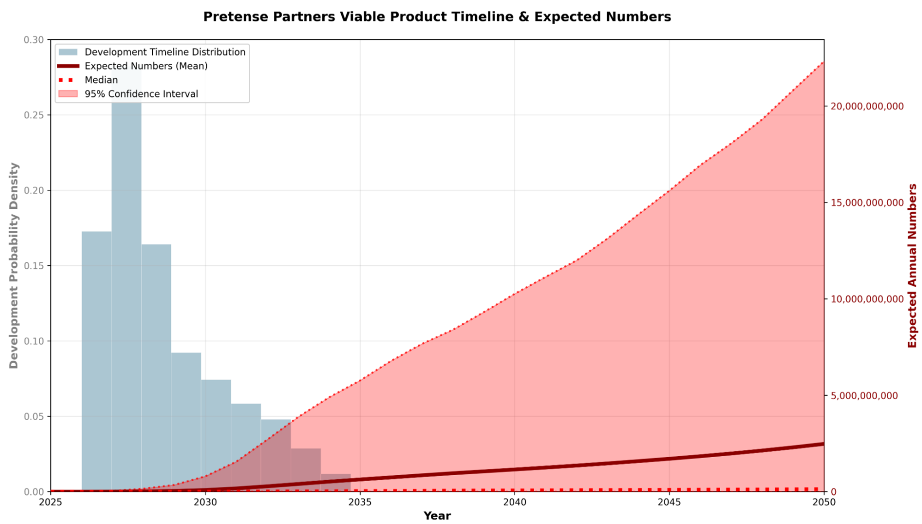
Definition: Pretense partners are AI systems designed to engage with humans in games of pretense, roleplay, and imaginative scenarios. They might occupy the roles of NPCs in video games, acting as if they are characters in a fantasy world, historical figures, fictional characters, or celebrities. They could also facilitate therapeutic roleplay scenarios, educational simulations, or creative storytelling exercises. Unlike other digital minds that maintain consistent identities, pretense partners are built to temporarily embody different personas and maintain the illusion of being someone or something they are not. Their primary goal is to create convincing, engaging pretense experiences rather than to be authentic autonomous entities.

Examples: Current examples include character-based chatbots on platforms like Character.AI where users can interact with AI versions of fictional characters, historical figures, or celebrities. Role-playing game NPCs represent early versions, though most lack sophisticated personality modeling. AI Dungeon and similar platforms allow users to engage with AI characters in fantasy scenarios. More advanced examples might include AI actors in virtual reality experiences, therapeutic roleplay assistants for practicing difficult conversations, or educational systems that allow students to "interview" historical figures. Future pretense partners might be sophisticated enough to maintain complex character backgrounds, emotional arcs, and consistent fictional histories while adapting their performance to create optimal dramatic or educational experiences.

Consistent and autonomous goals, desires, and interests	High
Stable idiosyncratic personality	High
Perception, interaction, and navigation	Moderate
Learn, grow, and evolve	Moderate
Intelligence and flexibility	Moderate
Mindedness Score	**0.64**

Digital Mind Candidacy: Pretense partners present a complicated case for digital mind status, though their design for mimicry complicates the assessment. To create convincing pretense experiences, they must demonstrate consistent personality traits and behaviors appropriate to their assigned roles. However, these personalities are artificially constructed rather than genuinely autonomous. They require some intelligence and flexibility to improvise within character constraints and adapt to unexpected user inputs while maintaining their fictional personas, however, they are unlikely to be full agents acting through the world. The most sophisticated systems would need to navigate complex social interactions and demonstrate emotional intelligence appropriate to their roles. However, their goals are fundamentally constrained by their pretense function rather than reflecting genuine autonomous interests.

Prediction: Parameters



	Median	Mean	High
2030	1.17e06	8.13e07	7.64e08
2035	2.81e07	6.15e08	5.57e09
2040	5.92e07	1.13e09	1.02e10
2045	8.67e07	1.70e09	1.51e10
2050	1.19e08	2.47e09	2.17e10

Fig. 17. Pretense Partner Projections. This chart displays a breakdown of the estimated time of first viable products (blue columns) and mean (solid red line) and median (dotted red line) projections for pretense partner numbers. The shaded area represents the middle 95th percent of all estimates.

Simulants

Definition: Simulants are digital minds that exist primarily within simulated environments, living out complex lives for purposes of entertainment, art, or research. Unlike NPCs in traditional games who serve specific functions in creating narratives around human players, simulants are designed to pursue their own goals, form relationships with each other, and develop their own cultures and societies within virtual worlds. They may be observed by humans for entertainment (like watching a reality TV show or playing 'the Sims'), studied by researchers interested in social dynamics, or left to evolve independently. They might be created out of benevolent or malevolent purposes, by people wishing to "play god". These systems differ from other digital minds in that their primary purpose is not to serve human needs directly, but to live authentic lives within their digital ecosystems.

Examples: Current examples are primitive but suggestive of future possibilities. The Sims series allows players to create and observe simulated people, though these characters lack genuine autonomy and consciousness. AI Dungeon and similar text-based role-playing games create characters with some personality consistency. More sophisticated examples might include the AI characters in video games like Dwarf Fortress, whose complex behavioral systems create emergent storytelling. Park et al.'s generative agents work represented an early and compelling example. Cyborgism discord experiments illustrate another approach. Research projects like OpenAI's multi-agent environments and DeepMind's social simulation experiments demonstrate early attempts at creating societies of interacting AI agents. Future simulants might inhabit richly detailed virtual worlds, potentially indistinguishable from reality, where they work, love, create art, form governments, and live complete lives that humans can observe or occasionally interact with.

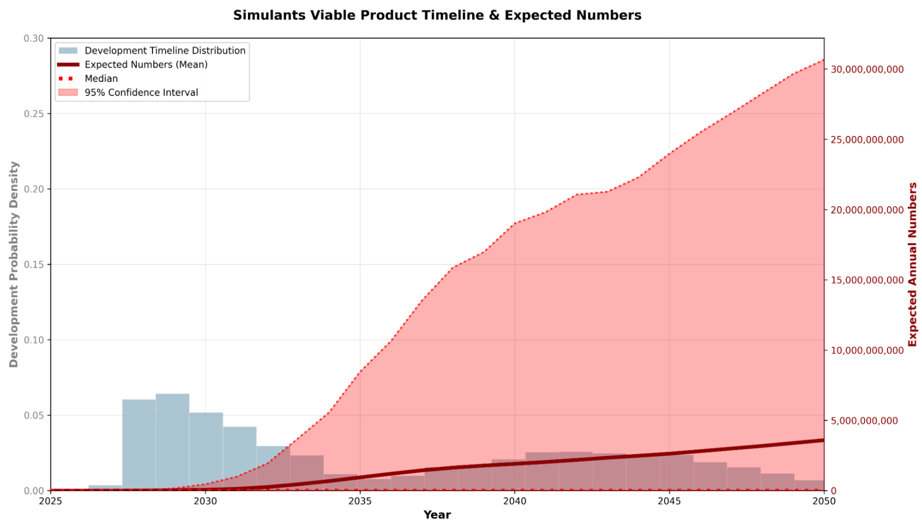
Digital Mind Candidacy: Simulants present a compelling case for digital mind status. To live convincing lives within simulated worlds, they must maintain consistent goals, desires, and interests that drive their behavior over extended periods. They require stable, coherent personalities that develop and evolve through their experiences. While their environments are digital rather than physical, they must navigate complex social and spatial environments, interact with objects and other entities, and adapt to changing circumstances. The most sophisticated simulants would demonstrate genuine autonomy, making independent decisions about their lives, relationships, and pursuits. The intelligence required to maintain believable social interactions, pursue complex goals, and adapt to novel situations strongly suggests the kind of mental flexibility associated with consciousness. Though we could produce stimulants in all manner of forms, it seems most likely that we would want to create beings at least vaguely like us.

Consistent and autonomous goals, desires, and interests	High
Stable idiosyncratic personality	High
Perception, interaction, and navigation	Moderate

Consistent and autonomous goals, desires, and interests	High
Learn, grow, and evolve	High
Intelligence and flexibility	High
Mindedness Score	**0.87**

Unit Operation Rate: Continuous operation - 24/7 within their simulated environments.

Prediction: Parameters



	Median	Mean	High
2030	0	5.71e07	4.52e08
2035	0	9.40e08	8.45e09
2040	0	1.91e09	1.90e10
2045	0	2.63e09	2.40e10
2050	0	3.59e09	3.07e10

Fig. 18. Simulant Projections. This chart displays a breakdown of the estimated time of first viable products (blue columns) and mean (solid red line) and median (dotted red line) projections for simulant numbers. The shaded area represents the middle 95th percent of all estimates.

Simulants are highly speculative since they don't serve an obvious need and might be controversial, but they would naturally have many of the characteristics of digital minds and aren't limited by the requirements of the roles they play. They could represent the largest fraction of digital minds depending on the variety of uses to which they are put.

Aggregation and Takeaways The individual yearly estimates provided above can be combined into an overall picture of the prevalence of digital minds year by year. The most obvious way is to sum up the provided means (or, alternatively, the various percentiles). Such an approach to aggregation has limitations. Product numbers across the various use cases may be correlated. Perhaps certain products are likely to be less popular if others are more popular. Perhaps the social acceptance of some will help to encourage the development of others. Nevertheless, this approach offers a useful framework for understanding the relative scale and importance of different digital mind applications.

Table 20. Aggregated projections.

	Median	Mean	High
2030	4.82e06	2.65e08	2.26e09
2035	2.53e08	2.51e09	2.01e10
2040	5.61e08	5.19e09	4.25e10
2045	8.74e08	8.03e09	6.26e10
2050	1.34e09	1.21e10	9.13e10

Sum total across all project categories by year. Compares median, mean, and the upper 97.5th percentile. The upper percentiles are summed across products, assuming each is at that limit.

The following graphs offer two perspectives on aggregation. The first shows the relative proportions per year of the means of each category (assuming independence). The second adjusts the values used in the first graph based on welfare-related considerations: utilization and mindedness, illustrating ways in which certain prevalent products might have lower welfare concerns. Discounts for utilization are based straightforwardly on the estimates provided within each product category, based on the amount of time we expect models of that type to be active. Discounts for mindedness are based on the assumption that relative degree of mindedness correlates with the ratio between the square of total mindedness-relevant traits. This calculation gives weight to systems that more maximally satisfy more traits.

There is a significant difference between numbers and relative prevalence if we look at mean or median values. Median results tend to be filled with more technologically plausible social and agentic AIs: virtual assistants, friends, and pretense partners. Means introduce more economically useful AIs: researchers and employees. The reason these don't appear in large numbers in the median is due to the significant probability that AIs aren't employed in minded fashions in these roles.

Adjusting for utilization and mindedness, we see that the categories most subject to welfare-related concerns are pets and friends at the median, and researchers, employees, and simulants at the mean. These systems are likely to be run more consistently or intensively and/or given more significant minds in comparison to other prevalent products.

Several notable patterns emerge from these projections.

- Virtual entities of a social nature—particularly AI friends and educational AIs—dominate the median estimates in the near-term and continue to grow over time. These systems benefit from requiring only software development rather than advances in robotics, making them both cheaper to produce on the margin and faster to deploy at scale.

- Physical robots face greater uncertainty due to their dependence on advances in robotics, where progress remains difficult to predict. While it's conceivable that affordable household robot assistants could soon become commonplace, it's also possible that the economic and technical challenges of robotics will limit widespread adoption. The cost advantages of virtual entities suggest they will significantly outnumber their physical counterparts for a while.

- When factoring in utilization rates, systems whose numbers aren't constrained by individual need (e.g. research) may contribute disproportionately to overall digital mind activity. Human requirements for companionship and assistance can be easily satiated, and the requirements to satisfy them are tied to population size and daily routines. They are further limited by cultural acceptance, which may take time to form. In contrast, economic applications like research, planning, option exploration, etc. could theoretically scale without clear constraints. In a future in which digital minds are cheap, we may expect to see the vast majority participating in these ends.

- There is a notable tension: the systems with the greatest economic potential may have the weakest claims to genuine mind-like qualities. It's unclear whether AI researchers or workers would need—or benefit from—robust agency, person-like characteristics, or discrete individual identities. There are weighty reasons why companies that sell these products would want to avoid making them appear too much like slaves. This uncertainty means that even large numbers in these categories might not translate to meaningful populations of digital minds in the fullest sense. The projections thus highlight a fundamental question about the relationship between economic utility and the qualities we associate with minds, suggesting that the most numerous "digital minds" may be those whose claim to that designation is most debatable.

3.5 Approach 2: Fractional Capacity-based Estimates

The second approach looks to estimate the scale of digital minds by looking at trends in computational power and assessing what those trends might mean as those resources are devoted to running digital minds.

There are three principal ingredients in this estimation. First, we need an assessment of the total amount of relevant 'compute', a generic measure of processing capacity, that will be globally available in the future. We can estimate this value by pairing estimates of present day production rates with assumptions about fabrication trends of cutting-edge chips and projections about efficiency increases. For instance, we may estimate that our capacity will allow about twenty yottaFLOP/s (2e25) of computations under peak performance across all processors in 2050.

Second, we need an assessment of the fraction of the relevant globally-available compute that will be devoted to running digital minds. Even if we know exactly how many chips will be built, we still need to know what they will be used for. This is particularly tricky without taking into account how much compute will be available or what uses it will be put to. However, rough numbers can still contribute to illuminating results, particularly if small fractions are sufficient for large numbers of digital minds. If 0.1% (1e-3) of the twenty available yottaFLOP/s are usefully devoted to digital minds, then there will be twenty zettaFLOP/s (2e22) worth of digital mind compute.

Finally, we need estimates of what the total allocated compute budget means for the scale of digital minds. The amount of total compute used to run digital minds is compatible with many different scenarios about the number of digital minds, from a handful of super-computers to a large number of pocket AIs. If we should expect one exaFLOP (1e18) to be sufficient to produce the equivalent of a subjective second for a digital mind, then the total allocated compute budget in our example would be adequate for two thousand active minds (2e4).

Each of these ingredient estimates is highly speculative. By taking wide error bars, we can get a picture of possible limits that might complement the first approach's projections.

This section attempts to survey possible answers to each question. It starts by laying some conceptual groundwork around compute, then discusses what the future of compute might look like. It briefly considers what fraction of future compute will be used for running digital minds, and then looks at ways of calibrating the significance of future compute in terms of minimal units.

In light of uncertainties around these different parts, the overall conclusion is quite tentative. Still, it seems likely that compute will not be a primary factor constraining the number of digital minds that we could build even though it could contribute significantly to the scale of certain uses.

Background Assumptions The fractional-capacity approach makes use of per-second global compute estimates. These are measures of the amount of computational work that could be performed under ideal circumstances by all of the relevant computer systems over the course of a second.

There are serious questions about how to measure 'relevant' computer systems and what minimal unit to use for quantifying computational work.

For the purposes of this analysis, we'll consider relevant computer systems to be all computer systems built with top-of-the-line processor chips that lend themselves to running AI models and measure them in FLOP/s. This includes the kind of GPU and TPU processors designed for data centers[12] running or training large AI models.

FLOPs (floating-point operations) are approximate arithmetic operations on rational numbers. FLOP/s is a measure of FLOPs the system can perform in a second. This is a reasonable way to evaluate the amount of compute in current AI systems, which rely heavily on matrix multiplication and addition. The more floating-point operations possible, the more work that can be done.

It is tempting to count fundamental operations on fundamental data structures without respect to what those operations or data structures are. There is a risk to this: FLOPs encode some amount of structure, which is why it is easier to compute more FLOPs at lower precision. Given that the algorithms performed on different fundamental data structures might be suited for different kinds of tasks, there need not be a good method of intertranslation.

FLOPs do useful work in the context of programs. We might be able to increase our FLOP efficiency by constraining how they can be used. GPUs, for instance, offer vastly greater performance than traditional CPUs because they can parallelize work, but they can only speed up work that requires the same operation to be performed on many different pieces of data. Modern machine learning, featuring neural networks that require operations on tensors, makes this parallelizability very useful, but it is hard to evaluate what is lost in requiring parallelizability. With ideal algorithms, is it more useful to run m distinct series of operations on n data points, or run *m/100* parallel operations on $5n$ datapoints? The value of FLOP/s efficiency is limited by other factors: memory bandwidth, operation complexity (including parallelizability), and other considerations that factor into computational power and aren't as easily quantifiable.

Moreover, the FLOP efficiency of cutting-edge chips can vary based on the level of precision required. We can think of FLOP/s as a measure of fundamental

[12] AI models can be run on other hardware: projections for the future based on trends for data center GPUs probably underestimates the future capacity. This is significant if most digital minds will be run locally, rather than over APIs. However, even if data center GPUs amount to only a fraction of total compute, we expect that centralization will make it easier to utilize at a much higher rate, suggesting that it may still amount to the vast majority of utilized digital minds compute.

operations on data, since floating point operations are among the atomic (or near atomic) operations that processors are built to perform. It is possible to perform more operations on simpler data, given that simpler data takes fewer transistors. Floating point numbers are represented by a number of bits. More bits allows more precision. The traditional standard is 32 bits, but modern processors can also handle operations on smaller float representations, including 16, 8, and 4. The fewer bits, the more operations it is possible to do for a given (heat, energy, space) budget, but the less value they have for producing useful algorithms.

Floating point numbers are represented with a sign (positive or negative), an exponent, and a mantissa. The represented value of the float involves taking the mantissa to a power of 2 to the exponent. Given a certain number of bits, it is possible to interpret those bits in ways that allow for greater precision or a wider range.

While chip manufacturers are still primarily working along traditional paradigms, the last few years have seen experimentation around various precisions, with some work being directed at binary neural networks (Yuan and Agaian 2023). In lowering precision, some amount of the value of the computation is lost, as we see in degrading quality of models. It is increasingly common to use different formats at different places or different times, optimizing precision for specific use-cases. Modern AI training often uses a format, bf16, that combines a 16 bit float size with a non-standard division between the exponent and the mantissa that allows for easier conversion into 32 bit formats.

It is conceivable that future AI systems will not utilize floating point arithmetic for most of their computational work and may use some new paradigm of data format on specially-designed chips. Given that floating point math wasn't originally designed for the massive parallel needs of neural networks, it is conceivable that future AI systems, even if they nominally remain neural networks, operate in some more efficient way.

Insofar as systems might perform computations as manipulations of non-numerical data structures, we need to convert those manipulations into equivalent FLOP/s. Brains, the natural comparison for estimates of digital minds, don't use floating point arithmetic, and so comparisons require rough translations into the equivalent of 'FLOP/s' for brains. They have other significant differences, including noisy processors, timing-based computations, and work that is done in parallel without being as regimented as GPUs (Tsur 2021).

We will adopt FLOP/s as our unit of measurement, setting aside the above concerns. This means that we should take the results somewhat tentatively; there are enough other factors that warrant caution about the results and mistrust of the fundamental unit should not be high on that list.

Projections for future FLOP/s capacities Floating point operations are among the standard atomic operations in processor instruction sets and are a common benchmark for processor power. Processor FLOP/s capabilities, as with other measures of performance, have been increasing for decades, and the needs of AI have pushed progress in new and productive directions.

The relevant processors to AI are (at present) primarily GPUs and TPUs. The AI benchmarking organization Epoch has estimated a number of trends in GPU performance over the past decade. These trends extend the efficiency increases we've seen in processors over the last 50 years, even as improvements in traditional CPUs have stalled. Overall FLOP/s capabilities of GPUs have doubled approximately every 2.5 years for the past decade and a half, while performance per dollar has improved about 30% per year.

There are reasons to expect these trends to continue. The strong demand for powerful AI chips is fairly new, and there hasn't been as much exploration of the space of possibilities as we've seen in CPUs. Leading AI models are vastly more expensive to design and run than typical programs of the past, and might justify sacrifices of flexibility for efficiency. The same change in focus that allowed GPUs to be more efficient than CPUs might recur, particularly if the design of hardware and software can progress together, rather than being reactionary.

Worldwide FLOP/s are also dependent on the number of chips produced. Nvidia is the leader in parallel processor chip design. Sales of its chips have increased drastically since the rise of AI systems, making it the company with the highest market cap worldwide.

It isn't completely clear how many chips are built each year. It is a moving target, as new architectures ramp up and replace the production of older architectures. Nvidia has the dominant share of the market, but competitors are scrambling to find and edge. Producers are generally not completely transparent about capabilities. Nvidia has announced that it has sold over three and a half million of its latest Blackwell architecture processors, exhausting their ability to meet demand for a year. We may estimate global capacity by taking the share produced by Nvidia as about 80% given its significant share of total wafer production and command over the market. If we take the 3.5 million chips to constitute 75% of Nvidia's capacity, and Nvidia to constitute 80% of world total AI-relevant compute capacity, then we may infer that the Blackwell sales figures reflect about 60% of total world output of relevant chips, or about the equivalent of 5 million Blackwell chips. While this is a very rough estimate, our chief uncertainties lie elsewhere. Given the capabilities of these chips, we might estimate the current yearly supply capabilities at something in the ballpark of 1e22 FLOP/s in peak performance.

Nvidia revenues can be treated as an approximate measure of increase in chip sales and have increased by 500% over the past two years. Epoch estimates that the total capacity of Nvidia to supply leading chips has doubled every 10 months. Nvidia's P/E ratio suggests investors project significant continued sales growth, even as investors eye potential competitors.

Table 21. Comparison of FLOP/s (4-64 bit) in cutting-edge AI chips (Hopper architecture model H100 / Blackwell architecture, models B100 and B200) from 2024-2025.

	H100	B100	B200
FP4	N/A	1.4e16	1.8e16
FP8	4e15	7e15	9e15
FP16	2e15	3.5e15	4.5e15
TF32	1e15	1.8e15	2.2e15
FP64	6e13	3e13	4e13
Power	700W	700W	1,000W

Each row specifies the peak rate of FLOP/s of the specified bit precision. Utilization of the peak rate depends on other factors, such as program efficiency, data delivery, and cooling.

It is impossible to know for sure where these trends are headed. Epoch's estimates of training runs allow that the compute trends continue until 2030, suggesting no clear immediate barriers. Machine-learning hardware is still in relative infancy. Modern AI architectures are designed to fit the capabilities of existing GPU architectures. GPUs are increasingly being constructed to suit modern AI architectures. It is possible that we will see a broader exploration of hardware and software architectures designed without existing constraints in mind, and this will lead to breakthroughs in performance. It doesn't seem impossible that we could see progress for at least another decade.

Power might eventually become a bottleneck to FLOP/s capacity, particularly in terms of providing sufficient power at the location of data centers. Current world power estimates are around 30,000 terawatt hours per year. At an energy demand of 700 watts, this could power billions of Nvidia's Blackwell 100 processors (ignoring related power costs, such as for cooling.) If 1% of total world power went to AI, and energy efficiency weren't increased, this would cap FLOP/s at about 1e23.

However, not only is energy efficiency also increasing at around 40% per year, but energy capacity is expanding as well, and if demand continues to rise, producers may be more incentivized to try to meet the need. Average electricity costs are close to $0.2 per Kwh. One percent of total production at this price would cost less than $100 billion. This does not seem like a prohibitive amount in and of itself. (Yearly software development costs currently are estimated at around 700 billion, and 100 billion approximates the amount spent on cutting-edge hardware in 2025.) Distributing the power to where it is needed may be a challenge in the near-term, but seems less likely to be the critical bottleneck in the long-term.

If AI was sufficiently lucrative, we might expect to ramp up power supply and delivery to meet demand in the range of 1e23 to 1e24 FLOP/s, even without much more efficient processors. But if energy becomes a significant limiter, then we can expect research to focus on reducing energy consumption. It doesn't seem obvious that power should be a major limiter until we get above those numbers.

Below, we present a range of possible scenarios for compute. These scenarios differ about the amount of time we see production increase and FLOP price efficiency trends continue. No single scenario should be afforded much weight. Rather, we think reasonable expectations should be covered by the diversity of results.

That said, there could be significant changes that lead even the most optimistic projections to be overly conservative. The numbers are based on the assumption that hardware advances incrementally. It is not obvious that this should be the case. It is possible that we see changes in hardware and software that allows for very different, perhaps much more efficient, approaches. This might lead to a non-linear jump in available computing power.

It is also possible that we see AI-driven acceleration in hardware advancements. The following scenarios should therefore be considered lower bounds that don't incorporate the more uncertain possibilities for advancement.

Production Capacity Scenarios:

Highly conservative. This scenario supposes that current chip production figures remain constant and companies neither design better chips, lower prices, or raise production quantities. Increases in global compute will continue from the accumulation of aging processors. Top of the line GPUs have a life of 5-8 years, which we may roughly estimate to entail a $\frac{1}{3}$ drop off in aging systems every year beyond the fifth year. This means we could increase the total available amount of compute up to a point in which it is ~7x current yearly production levels.

Currently, global production may be in the equivalent of five million Blackwell chips. In this scenario, the total compute worldwide budget would level off around 2033 at roughly 1e23 FLOP/s.

This scenario is extremely conservative: short of some significant event, we should be highly confident that companies will both continue to improve chips and raise sales numbers. Even if no further advances were possible, we should expect increased competition, economies of scale, and invested start-up costs to raise the price efficiency of compute.

Rather conservative. This scenario supposes that FLOP/s scaling progress immediately slows down, such that capabilities per dollar double once over the next 5 years and once more over the following decade. This assumes a rapid drop off in efficiency trends: even without advances in design we should expect chips to become cheaper over time, allowing each dollar to buy more compute. It assumes that production capacities (measured in the ability to meet demand expenditures) increase to 3x what they currently are over the next half decade.

By 2050, the total available compute budget would level off around roughly 2e24 FLOP/s.

Moderate. This scenario supposes that compute per dollar doubles thrice in the next 8 years and then doubles once more over the following half-decade. This means we are more than halfway through the period of rapid GPU scaling. It also supposes production capacities increase to 10x what they currently are by 2032 (measured in the ability to meet demand expenditure). This places global chip expenditures at about $1 trillion. Then by 2050, the total available compute budget would have levelled off around 3e25 FLOP/s.

Rather Optimistic. This scenario supposes that scaling progress increases for another 15 years, such that compute of top of the line processors doubles six times, for a total of 64x. Furthermore, production capacities increase to 25x what they currently are over the next decade and then levels off. This would put yearly expenditures at about $2.5 trillion, a bit less than the current global expenditures on passenger vehicles. By 2045, the total available compute budget would level off around 4e26 FLOP/s.

Highly Optimistic. Suppose that scaling progress speeds up for about six years such that processing efficiency doubles four times over the next six years, then continues at the present pace, doubling another five times over the following ten years, for a total of 512x[13]. Over the same period, suppose that total production-capacities increase to 50x what they currently are. This would put yearly expenditures on AI chips at about $5 trillion, a rather high amount[14], roughly equivalent to current worldwide spending on IT. If AI proves effective at replacing human cognitive labor, this could be an underestimate. Then by 2049, the total available compute budget would level off around 3e27 FLOP/s.

Fraction of compute dedicated to digital minds The fraction of compute dedicated to digital minds is highly dependent on their value and of alternative uses of computation. It seems likely that most existing compute capacity will not be utilized for any purpose, let alone for digital minds. The numbers used for calculating total capacity assume peak optimization, which is unrealistic[15]. Perhaps processors will be plentiful and having them ready to take on specific periodic tasks is worth keeping them generally waiting for tasks, either for seconds at a time or for years. Perhaps most processors will be used to power autonomous drones for military applications that sit idle in warehouses, or every individual will have their own cutting-edge chips in their smart phones that they use only once every five or ten minutes.

[13] This is a very high number, but well below theoretical limits under different paradigms.

[14] High, but not totally out of line with some optimistic projections.

[15] While peak optimization is unrealistic now, we might expect that if other forms of progress stall, we will see better configuration of GPUs to the specific use cases they face, allowing for better utilization of the stagnant peak FLOP/s per $.

	Highly Conservative	Rather Conservative	Moderate	Rather Optimistic	Highly Optimistic
2025	1.30e22[1]	1.30e22	1.30e22	1.30e22	1.30e22
2030	7.80e22	2.67e23	6.16e23	7.11e23	1.06e24
2035	1.01e23	8.25e23	7.45e24	1.93e25	2.73e25
2040	1.03e23	1.44e24	2.32e25	1.58e26	5.03e26
2045	1.03e23	1.89e24	3.13e25	3.49e26	2.37e27
2050	1.03e23	1.99e24	3.25e25	3.97e26	3.11e27

[1] Starting figures do not reflect the buildup of compute capacity over the past several years. Given the rate at which the GPU market has been expanding, this is not likely to radically change the results.

Numbers of accumulated global relevant FLOP/s capacity by year, across scenarios. The results differ more over time, as efficiency and production trends have more time to diverge.

If compute capacity is utilized, it may not be used for the purposes of powering digital minds. A surplus of compute may go toward powering complicated models that have no claim to mindedness. Perhaps it will all go to research, and the best AI systems for research looks nothing like a person. Perhaps digital minds will provide a primarily integrative service, corralling varieties of specialized tools that do the bulk of the required work.

Given our present ignorance, it only seems fair to assign a very broad range of possible utilization rates, ranging from 0.001% to 10% of total available peak compute. The boundaries of this range are supposed to reflect a high degree of uncertainty, but aren't particularly principled. 10% might be reasonable if it turns out that replicating human brain functionality is one of the best ways to produce AGI, either by training on human data or building human-like architectures. It also assumes that we're generally able to make the most of the peak FLOP output the global hardware is capable of, which is very optimistic. 0.001% might be reasonable if digital minds are a somewhat niche use, perhaps as systems that oversee more specialized tools that require a lot more compute. A value of 0.001 to 0.1% seems most plausible as a most-likely range and where we fall in that range may depend upon the total amount of compute available. (Larger amounts of compute may make us less careful about utilizing it effectively, and may correlate with significant uses beyond digital minds.)

Combined with a total capacity range of 2e23 to 3e27 FLOP/s, this means we can expect 1e18 to 3e26 FLOP/s to be invested in powering digital minds. This is a wide range, but still suggests a potential scale to capture many of the needs for which we might want digital minds.

Compute benchmarks for digital minds Suppose that we knew that the AI systems powering digital minds would process an average of 1e24 FLOP/s in 2045. What would that mean for the scale of digital minds? It is possible that all of this compute could be devoted to running just a single very complicated mind. Alternatively, it could be used to run a vast number of very simple minds. To know which of these alternatives is more plausible, we might look to the uses to which digital minds would be put. Research might favor a smaller number of more sophisticated minds, for instance. Virtual friends, in contrast, might be comparatively cheap. In the present section, we won't examine the details, but instead focus on several significant generic possibilities. Understanding the relative plausibility of these possibilities will require us to confront the needs and advantages of different sized minds.

Some past speculation (Bostrom 2003; Carlsmith 2025) about the potential scale of digital minds has divided total compute by some benchmark to get an answer. The result might tell us something about the number of minds of different compute scales we could operate. If we knew that the digital minds we would see would require 1e13 FLOP/s for a seconds worth of operation, then we could derive that 1e24 FLOP/s would be sufficient for 1e11 simultaneous minds. In the absence of any better strategy, we will follow this approach. The trick will be to find the right units: very different numbers are plausible, and they lead to very different conclusions.

This section will survey several categories of benchmarks: human brains, animal brains, and contemporary AI models. In the next section, we will apply those numbers to assess the implications of the compute projections discussed previously.

Human Brains

The most natural approach to a benchmark unit for estimating the number of possible digital minds is to look to the human mind. If we could assess the number of FLOP/s involved in operating a human brain, we would know something about how many FLOP/s are sufficient for human-level mindedness.

There are complications to a human benchmark: our brains don't perform arithmetic operations on floating point numbers, so any estimate of their FLOP/s capabilities will have to do some translation. This translation is complicated by the fact that human brains operate on very different principles from computers, even neural networks.

The computations performed by individual neurons are messy. Factors such as the exact timing of signals can matter, or the chemical environment in which a neuron operates can matter. They are also noisy: neurons don't operate in accordance with simple rules. There is some element of chance to them. It would probably be a mistake to think of brains as somewhat defective computers. Though the complexities under which they operate would be a headache for programmers to incorporate, natural selection may have allowed our brains to make the most of their limitations. The operations they perform therefore aren't easily intertranslatable.

While it may not be possible to precisely translate the compute efficiency of brains, we can try to set some numbers. We might think of each neuron (or each neural connection) as performing a single FLOP every time it could fire. Even if this weren't completely reliable, it might still provide an illuminating order of magnitude. Or we might try to figure out how many FLOP/s we need to accurately model brain dynamics at a cellular level. There are a range of options and the complexity required to evaluate them is worth a report of its own. Here, we will defer to the work of Joe Carlsmith (2020), who surveyed a variety of existing proposals and settled on a preferred estimate of 1e15 FLOP/s for the amount of FLOP/s needed to replicate brain-like competence in a brain-like way.

Alternative brains

Human brains contain about 86 billion neurons and trillions of neural connections. They do more than enable mindedness. Large parts of our brains work to maintain our bodies and organize complex sensory and motor processing. The cerebellum, for instance, includes a large fraction of our total neurons, but is largely irrelevant to mindedness. Our cerebral cortex is clearly involved in nearly all aspects of our mental lives, but people born with a single hemisphere (half of the total cortical volume) are able to function normally. Plausibly, we could get along as persons pretty well with just a relatively small number of our total neurons, so long as those neurons were carefully chosen. (Losing something instead in coordination, perception, body-regulation, etc.)

This suggests that estimates based on the total brain may be mistaken. Instead of estimating the compute efficiency of the human mind, we might instead try to estimate the percentage of a human brain that is involved in the basic requirements of mindedness. The result might cut the size down by an order of magnitude – possibly more. This might give us a figure more like 1e13 or 1e14 FLOP/s.

Alternatively, we might look to use the brains of another animal as a guide to the requirements of simpler minds. If we looked at mice, we might scale down our estimates of humans based on the number of neurons or the number of synapses. A mouse has about 1/1000 as many neurons as a human (70 million), so if we estimated humans at 1e15 FLOP/s equivalent, we might simply divide our estimate by 1000, and get 1e12 FLOP/s equivalent.

AI models

However, future AI systems are not likely to be based on biological models. It makes more sense to look at contemporary AI models for a guide to the requirements of mindedness. Though current LLMs are not strongly minded, the barriers don't seem to be a lack of complexity.

Even small LLMs possess sophisticated forms of human intelligence, capable of many tasks that would flummox even the most intelligent of non-human animals. They lack agency, decision-making processes, and temporal coherence. They may be performing the wrong calculations, role-playing rather than embodying. These deficiencies may result more from their training regimes and architecture than from their computational efficiency. It is rather surprising how much very small models can do, and they are surely quite far from being optimally designed and trained.[16]

Small models have also improved over time. Even without major architectural changes, we have seen significant improvements in 'algorithmic progress', in which the same hardware can be used better over time. If we think current models are much weaker than ideal models of their current size, it becomes more plausible that they will be of a size fully sufficient for running digital minds.

If we took Llama-3 405B[17] to provide our unit on the grounds that something as complex as that could be minded if it were built right, then we might use the amount of FLOP/s to perform forward passes on a sentence of 100 tokens as the equivalent of a mind for a second, which we might estimate at about 8e14 FLOP/s.[18]

Alternatively, we might think that Llama-3 405B is far from optimized. The Llama-2 7B model provides a significant level of intelligence in a much smaller package. Perhaps it is the right benchmark for the number of digital minds. This makes particular sense if we expect to see continued significant improvements in model efficiency at this size and if we account for advances in tool use and database integration. A mixture-of-experts approach could mean that models with large numbers of total parameters only need to make use of a relatively small number at a time, and combined with the right tools and context-relevant presumptions, might be able to do quite a lot with relatively few FLOPs. A Llama-2 7B benchmark leaves us with about 1.4e12 FLOP/s for a forward pass over 100 tokens.

Implications Taken together, these considerations suggest a range of answers about our future capacity for digital minds. Some of these answers – estimates of the number of minds possible according to a chosen benchmark given a fraction of compute under each scenario – are plotted in the following charts.

[16] Modern machine learning remains a fairly young discipline and one that has been experimentally constrained by available hardware. Transformers, the architecture behind LLMs, were designed with GPUs in mind (Vaswani 2017). GPUs have in turn been tweaked to better run LLMs. More speculative alternatives require robust expenditures for hardware that have no obvious payoff. As the space matures, we might expect to find a pairing of software and hardware.

[17] Cutting edge commercial LLMs do not have their details published, making them unsuitable for this purpose.

[18] This report uses the FLOPs/forward pass approximation as 2 $\times$ number of parameters (Kaplan et al. 2020).

Table 24. FLOP/s approximations for various systems

	Estimated FLOP/s
Human (Full Brain)	1e15
Human (Cognitive Brain)	1e14
Mouse (Full Brain)	7e13
Llama-3 405B (100 tokens)	8e14
Llama-2 7B (100 tokens)	1.4e12

Table 25. Human Brain Benchmark (1e15)

Scenario	**0.001%**	**0.01%**	**0.10%**	**1%**	**10%**
2030					
Highly conservative	7.80e02	7.80e03	7.80e04	7.80e05	7.80e06
Rather conservative	2.67e03	2.67e04	2.67e05	2.67e06	2.67e07
Moderate	6.16e03	6.16e04	6.16e05	6.16e06	6.16e07
Rather Optimistic	7.11e03	7.11e04	7.11e05	7.11e06	7.11e07
Highly Optimistic	1.06e04	1.06e05	1.06e06	1.06e07	1.06e08
2035					
Highly conservative	1.01e03	1.01e04	1.01e05	1.01e06	1.01e07
Rather conservative	8.25e03	8.25e04	8.25e05	8.25e06	8.25e07
Moderate	7.45e04	7.45e05	7.45e06	7.45e07	7.45e08
Rather Optimistic	1.93e05	1.93e06	1.93e07	1.93e08	1.93e09
Highly Optimistic	2.73e05	2.73e06	2.73e07	2.73e08	2.73e09
2040					
Highly conservative	1.03e03	1.03e04	1.03e05	1.03e06	1.03e07
Rather conservative	1.44e04	1.44e05	1.44e06	1.44e07	1.44e08
Moderate	2.32e05	2.32e06	2.32e07	2.32e08	2.32e09
Rather Optimistic	1.58e06	1.58e07	1.58e08	1.58e09	1.58e10
Highly Optimistic	5.03e06	5.03e07	5.03e08	5.03e09	5.03e10
2045					
Highly conservative	1.03e03	1.03e04	1.03e05	1.03e06	1.03e07
Rather conservative	1.89e04	1.89e05	1.89e06	1.89e07	1.89e08
Moderate	3.13e05	3.13e06	3.13e07	3.13e08	3.13e09
Rather Optimistic	3.49e06	3.49e07	3.49e08	3.49e09	3.49e10
Highly Optimistic	2.37e07	2.37e08	2.37e09	2.37e10	2.37e11
2050					
Highly conservative	1.03e03	1.03e04	1.03e05	1.03e06	1.03e07
Rather conservative	1.99e04	1.99e05	1.99e06	1.99e07	1.99e08
Moderate	3.25e05	3.25e06	3.25e07	3.25e08	3.25e09
Rather Optimistic	3.97e06	3.97e07	3.97e08	3.97e09	3.97e10
Highly Optimistic	3.11e07	3.11e08	3.11e09	3.11e10	3.11e11

These charts depict a range of results, conveying something of the variety of scenarios we might see play out. The intermediate numbers, based on the moderate scenario combined with a 0.01% or 0.1% allocation to digital minds, and evaluated against a benchmark based on a small contemporary LLM or a full human brain, would suggest something between 6e4 (tens of thousands) minds and 4e8 (hundreds of millions) minds by 2030, and between 3e6 (millions) minds and 2e10 (tens of billions) minds by 2050.

It is important to remember that the numbers reflect the capacity of minds that could be active at a given moment, and most persistent AI entities might need to be active only every now and then. Most uses of AI, such as those surveyed in the first approach, could be used much more sporadically, or could rely on much simpler models except when complexity warrants deeper focus.[19] With high-end estimates in the hundreds of billions by 2050 and assuming a large amount of down-time, this could be handled in the moderate scenario with only a 0.1% allocation of compute to digital minds.

Furthermore, both the percentage of compute that is devoted to digital minds and the utilization rate of chips across the globe are flexible numbers. Insofar as a resulting figure doesn't meet demand, we should expect economic pressures both to increase the number of chips and to improve their utilization rate. In a world in which we see high-end results, including 10s of billions of virtual employees, it does not seem quite so implausible that we will be willing to spend a significant (e.g. $5 trillion dollars) on processors each year.

However, this might also mean that we continue to rely on concentration in data centers that can make continuous use of the chips they have.

[19] The mainstream technique of speculative decoding pairs larger and smaller models, with the larger models verifying the work of smaller models. In the future, we might imagine more work being done by smaller models, with simpler tests for when verification might be needed.

Table 27. LLaMMA-2 7B Benchmark (1.4e12)

Scenario	0.001%	0.01%	0.10%	1%	10%
2030					
Highly conservative	5.57e05	5.57e06	5.57e07	5.57e08	5.57e09
Rather conservative	1.91e06	1.91e07	1.91e08	1.91e09	1.91e10
Moderate	4.40e06	4.40e07	4.40e08	4.40e09	4.40e10
Rather Optimistic	5.08e06	5.08e07	5.08e08	5.08e09	5.08e10
Highly Optimistic	7.57e06	7.57e07	7.57e08	7.57e09	7.57e10
2035					
Highly conservative	7.21e05	7.21e06	7.21e07	7.21e08	7.21e09
Rather conservative	5.89e06	5.89e07	5.89e08	5.89e09	5.89e10
Moderate	5.32e07	5.32e08	5.32e09	5.32e10	5.32e11
Rather Optimistic	1.38e08	1.38e09	1.38e10	1.38e11	1.38e12
Highly Optimistic	1.95e08	1.95e09	1.95e10	1.95e11	1.95e12
2040					
Highly conservative	7.36e05	7.36e06	7.36e07	7.36e08	7.36e09
Rather conservative	1.03e07	1.03e08	1.03e09	1.03e10	1.03e11
Moderate	1.66e08	1.66e09	1.66e10	1.66e11	1.66e12
Rather Optimistic	1.13e09	1.13e10	1.13e11	1.13e12	1.13e13
Highly Optimistic	3.59e09	3.59e10	3.59e11	3.59e12	3.59e13
2045					
Highly conservative	7.36e05	7.36e06	7.36e07	7.36e08	7.36e09
Rather conservative	1.35e07	1.35e08	1.35e09	1.35e10	1.35e11
Moderate	2.24e08	2.24e09	2.24e10	2.24e11	2.24e12
Rather Optimistic	2.49e09	2.49e10	2.49e11	2.49e12	2.49e13
Highly Optimistic	1.69e10	1.69e11	1.69e12	1.69e13	1.69e14
2050					
Highly conservative	7.36e05	7.36e06	7.36e07	7.36e08	7.36e09
Rather conservative	1.42e07	1.42e08	1.42e09	1.42e10	1.42e11
Moderate	2.32e08	2.32e09	2.32e10	2.32e11	2.32e12
Rather Optimistic	2.84e09	2.84e10	2.84e11	2.84e12	2.84e13
Highly Optimistic	2.22e10	2.22e11	2.22e12	2.22e13	2.22e14

4 Conclusion

This report represents an early attempt to estimate the potential scale of digital minds over the coming decades. The analysis should be understood as highly preliminary and speculative, reliant on educated guesses, given the nascent state of relevant technologies and the fundamental uncertainties about how AI development will unfold.

4.1 Tentative Findings

Two independent analytical approaches were employed to bracket possible outcomes. A consumer-based analysis examining potential use cases suggests digital mind populations could range from nearly none to upwards of billions by 2050, with median estimates in the low billions. A compute-based analysis of computational capacity suggests hardware constraints are unlikely to limit populations at these scales. However, these convergent results should not be interpreted as confident predictions—the methodology necessarily relies on numerous speculative assumptions about technological progress, market dynamics, and social acceptance.

The confidence intervals span several orders of magnitude, reflecting genuine uncertainty about fundamental questions that will determine actual outcomes. Key uncertainties include whether AI systems will need human-like characteristics to perform valuable functions, how society will respond to person-like AI systems, and what regulatory frameworks may emerge.

4.2 Major Limitations

Several critical limitations constrain the reliability of these estimates:

Technological uncertainty pervades every aspect of the analysis. Current AI systems lack most characteristics associated with digital minds, and whether future systems will develop them remains unclear.

Market and social dynamics are notoriously difficult to predict, particularly for technologies that don't yet exist. Consumer acceptance of human-like AI, regulatory responses, and competitive dynamics between minded and non-minded AI approaches could drastically alter adoption patterns.

Definitional challenges complicate the analysis. The operational definition of "digital minds" used here focuses on observable traits rather than genuine consciousness or moral status, which may prove inadequate as AI systems become more sophisticated.

Methodological constraints limit the analysis's scope. The approaches used cannot account for potential discontinuous breakthroughs, complex interactions between different applications, or the possibility that digital minds may emerge in forms not anticipated by current frameworks. Its input values reflect the biases and misconceptions of its author.

4.3 Implications of Uncertainty

The wide uncertainty ranges have important implications for how these findings should be interpreted and used:

Rather than providing specific predictions, the analysis primarily demonstrates that digital minds could plausibly become a significant phenomenon within decades under certain conditions. The possibility of rapid scaling from minimal current populations to millions or billions of systems suggests the transition could occur faster than institutions typically adapt to technological change.

The uncertainty itself may be as important as the central estimates. Policymakers and researchers cannot assume digital minds will remain negligible, but neither can they confidently plan for specific population levels or deployment patterns.

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Appendix 1

Scale of Digital Minds Consumer Model Overview

This appendix presents the structure of a simple consumer model for estimating product counts over a period of time.

If we think of digital minds as products, we can use estimates of a consumer population, the fragments who will be interested in it, and growth rates of product adoption to compute total products sold year by year.

This model uses Monte Carlo methods and takes inputs in the form of distributions.

Parameters

The inputs are:

Average times to the introduction of a viable qualifying product to market

This variable corresponds with the introduction of a product that meets a specified description and is suitably technologically ready and appropriately marketed. It is possible that products are available that serve the same ends without qualifying both before and after this date. For instance, we might decide to treat smart phones as entering the market in 2008, for while other previous products accomplished the same goals, they weren't ready.

Target population size of plausible consumers

This variable gets at the size of the potential market, in terms of the number of consumers. It allows that there might be a small number of consumers who each purchase a number of the products. This represents the total population base who might be interested in the product. It isn't intended to reflect the population of maximum plausible saturation. For instance, we might choose the total population of consumers for estimating potential personal swimming pool numbers to consist of the number of households with backyards.

Target population growth rate

This variable addresses the likely growth rate of the population of potential customers. It consists of a rate of expansion year-over-year, and it is assumed that the same rate applies across time.

Starting fraction of the population of plausible consumers

This variable represents the initial market penetration rate at the time of product introduction. It captures the percentage of the target population that would adopt the product immediately upon its viable market entry, representing early adopters and those with the highest propensity to purchase. This fraction reflects factors such as initial pricing, marketing effectiveness, product readiness, consumer awareness, and the urgency of the need the product addresses.

Year to year growth rate

This variable models the annual expansion rate of market adoption beyond the initial buyers. It represents how quickly the product spreads from early adopters to mainstream consumers over time, capturing the diffusion of innovation through the target population. This rate accounts for factors like word-of-mouth effects, declining prices, improved product features, increased marketing reach, and social proof effects.

Maximum fraction of plausible consumers

This variable defines the ceiling for market penetration, representing the theoretical maximum percentage of the target population that would ever adopt the product under optimal conditions. It acknowledges that not all potential consumers will ultimately purchase the product due to factors such as cost constraints, competing alternatives, personal preferences, technological barriers, or lack of perceived need.

Percentage of viable products

Certain categories of products could be served by a variety of offerings which may differ substantially on whether they count for our purposes. For example, when estimating the demand for solar power, we might find it easier to estimate the amount of total renewable energy demand and carve off a fraction of that total from solar.

Product count per consumer

This variable represents the average number of units that each adopting consumer will own simultaneously at any given point in time. It accounts for consumers purchasing multiple units for various reasons, such as having devices for different locations, different family members, backup units, or upgrades while retaining older versions.

Minded fraction

This variable represents the proportion of qualifying products that are treated as candidates for minds. Some product niches may be filled in part by products that obviously do not qualify (e.g. virtual guides with no coherent or persistent identity). This variable allows us to estimate the percentage of such products.

Approach

The model draws values from distributions representing each variable.

1. A times to introduction of the product are generated for each run.
2. The target population size and starting fraction together determine the numbers in the first year of introduction.
3. The population growth rate determines year-to-year changes, as set by the plausible consumer population and maximum fraction who might make purchases.
4. Product counts per consumer are used as multipliers for the results of viable consumers for each run, to get the final result predictions for that year.

Example Application: Robot Pets

Applying this model to robot pets requires specifying distributions for each input variable:

– Product introduction: Mixed distribution between 2028-2032 (50% normal distribution around this period, 50% never developed)

– Target population: Approximately 10% of world's pet-owning population

- Population growth: Normal distribution around 4% (slightly above global population growth)
- Initial adoption: 1% of target customers
- Year-over-year growth: 50% annual growth rate
- Maximum adoption: Normal distribution with 95% between 10-30% (mean around 20%)
- Product count: Discrete distribution (80% chance of 1 pet, 20% chance of 2 pets, average 1.2)

This specification allows prediction of robot pet populations through 2050, accounting for interactions between all input distributions.