

Will AI and Technology Disrupt Our Jobs? Insights for Transformation for the Greater Good from Experiential Matrix Theory

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ABSTRACT

Transformation of worldly phenomena for the greater good requires change. Although some analytically rigorous theoretical micro-foundations explain causal mechanisms of technologically driven and other sources of growth, absent from literature at this time is a theoretical synthesis that bridges this theorising with qualitative outcomes of growth in the production of goods and services- the holistic humanist experience of the ‘matrix’ or ‘universe’ of experiences of the world around us comprised of goods and services. It is argued here that such a theoretical synthesis- that already seems to describe a ‘general theory’ of innovation- can be used to navigate different theoretical perspectives with a focus on enabling societal transformation for the greater good.

Key words: innovation; technological change; knowledge; dystopia; utopia

1. Introduction

Some suggest may be reaching the ‘point of no return’ regarding climate change (Callaghan & Mitchell, 2023b) and rising temperatures (Malakouti, 2023). Others highlight the existential risk of geopolitical conflict (Chang-Liao, 2023), dangerous and accelerating technological change (Bostrom, 2013, 2017), and other existential threats. Despite profoundly beneficial historical contributions of technological change (Hall, Rosenberg, & Mokyr, 2008; Mokyr, 1994), and its failure to date to yet (fundamentally) disrupt human employment, questions persist, and some keep asking, “Is this time different?” (Mokyr, Vickers, & Ziebarth, 2015: 31).

Innovation, often path dependent and influenced by initial states, does not necessarily unfold optimally, or in a socially beneficial way (Arthur, 2013; Kay, 2013). Accordingly, innovation cannot be assumed to always be ‘good’, or that more always ‘better’ (Coad, Nightingale, Stilgoe, & Vezzani, 2021). It is in this context that we must consider the notion of ‘transformational’ change for the greater good, in that transformation entails change, and, necessarily the creation of relative ‘winners’ and ‘loses’ due to disruption. Given this paradox- that our social scientific system seems to have failed to (yet) solve impending existential threats, how might we understand a need for transformation for societal good across personal, organisational, and societal levels of human phenomena? What would the precise nature of this transformation be? What might such a transformation entail?

Considering this lack of clarity, with a focus on one of the current debates concerning transformation for the greater good- the displacement of human labour by technology- the objective of this paper is to develop a conceptual model that relates different theoretical frameworks regarding this potential displacement, and its consequences.

Accordingly, the purpose of this paper is to provoke novel thinking and to problematise ideas regarding the capacity and consequences of artificial intelligence (AI) developing capabilities to ‘ideate’ or generate and create solutions to problems. We argue that a central theoretical idea

regarding the limits of scalability of AI has not been sufficiently considered- its ability to exponentially expand into a virtually unlimited ‘space.’ For example, whereas one unit of human labour- a human knowledge worker- needs to sleep, AI not only works 24/7, but can make unlimited copies of itself, whereby its expansion faces few constraints, due to digital economics of marginal cost. Another example from the literature is the potential for self-replication of nanotechnology, whereby the physical expansion ‘crowds out’ all other forms of life on a planet (Callaghan, 2018). Such an expansion of productive capabilities might also displace many forms of human work. Using these ideas to delimit the scope of the paper, it seeks to make the following main contributions.

First, it contributes to emerging debates concerning the ‘dark side’ of innovation (Coad et al., 2021) to highlight problematic consequences of technological advances, such as those already documented across diverse contexts such as agricultural biotechnology (Cumming, Johan, Oberst, & Uzuegbunam, 2020), social innovation (Fougère & Meriläinen, 2021), business model innovation (Sabaruddin, MacBryde, & D'Ippolito, 2023), professional occupations such as accountancy (Gardner & Bryson, 2021), open innovation (Purdy, Eslami, Eshghi, & Rod, 2023), environmental upgrading in global value chains (Hansen, Nygaard, & Dal Maso, 2021), and medical practice (McKelvey & Saemundsson, 2021), to name a few.

Second, our synthesis of theoretical ideas and development of an overarching model that relates AI to production contributes to debates highlighting the importance of responsible innovation (Owen, Pansera, Macnaghten, & Randles, 2021; Stilgoe, Owen, & Macnaghten, 2013), in a context of accelerating technological change and seemingly increasing global geopolitical uncertainties. Whereas technological change has been modelled as a residual (Abramovitz, 1993), representing productivity improvements from better combinations of human and physical capital that in turn contribute to output (Solow, 1956), others ‘endogenize’ it, explicitly incorporating it into models to explain output and growth (Romer, 1986). What seems to differentiate Romer’s work from

Solow's is the prediction of economies of scale in knowledge production. Others, such as Kurzweil seem to describe a similar pattern of economies of scale in technological change, in that it exhibits 'double exponential growth' (Kurzweil, 2001).

Third, extending ideas relating to experiential matrix theory (Callaghan, 2023a, b), we contribute to management theorizing by incorporating endogenous growth theory into a model that *links production and consumption* to highlight the potential *systemic influences* of AI. We therefore contribute to endogenous growth literature, and make explicit in our model Romer's predictions of constant or exponential returns to investments in knowledge creation and productivity growth (Romer, 1990). These ideas are associated with foundational work in endogenous growth theory (Aghion & Howitt, 1992; Grossman & Helpman, 1991).

Fourth, the paper contributes to debates regarding a paradox- that productivity growth seems to be declining, an empirical phenomenon that contests Romer's (1990) predictions of scale effects of knowledge recipes, whereby productivity growth seems to have declined since the 1970s (Cowen, 2011; Gordon, 2016), as have returns to research and research and investment (R&D) across contexts, whereby evidence suggests 'ideas' might be becoming 'harder to find' (Bloom, Jones, Van Reenen, & Webb, 2020). If so, this recalls the Solow paradox, a longstanding observation that 'you can see the computer age everywhere but in the productivity statistics' (Solow, 1987a).

Finally, we contribute to literature by developing a conceptual theoretical model that incorporates the primary theoretical mechanism, or the 'meta idea' behind Romer's (1990) prediction of increasing returns to investments in knowledge/research. By locating debates about AI within a theoretical model that synthesizes some relevant theoretical perspectives we enable a holistic understanding of the causal structure of AI's productivity contributions to growth, to derive theoretical and practical forecasts.

The paper proceeds as follows. First, the methodology of the paper is explained. Next, a model is developed and discussed. The work then concludes with a summary of its objectives.

2. Methodology

The methodology of the work here flows from its objectives. In that it seeks to provoke novel thinking about theoretical and practical aspects of technological change, a conceptual review methodology is applied, to identify theoretical conversations and debates regarding technological change and its consequences. The theoretical ideas of Romer (1990) shape the argumentation of the work. It relates these ideas to theory regarding artificial intelligence (AI) to contribute to debates about responsible innovation, or collective stewardship of innovation to ensure science and innovation have beneficial outcomes for human societies (Owen et al., 2021; Stilgoe et al., 2013), and the dark side of innovation- its potential negative societal consequences (Biggi & Giuliani, 2021; Coad et al., 2021) by identifying some concerning predictions of innovation theory, and suggesting an immediate reconceptualization of the ‘world of work’ and the role of human labour within it.

We apply analysis of frames, or the cognitive filters used to perceive and categorize phenomena, at individual, group, or organisational level (Goffman, 1974). A frame is conceptualized here as a shared understanding of a phenomenon, or similarities in theoretical understandings. These frames represent shared assumptions, and we identify clusters of papers with similar differences and commonalities in their conceptions of technological change, and implied forecasts, thereof. In doing so, we broadly extend previous recent work that takes a similar methodological approach, such as Dzhengiz and Hockerts (2022), who derived a categorization of frames from the organisational sustainability literature. The work therefore follows a broad narrative structure to integrate frames of understandings of endogenous growth theory and of its qualitative implications for human lived experience.

We suggest that Romer's (1990) endogenous growth theory offers a plausible mechanism of growth that unites micro-level cognitive, meso-level organisational and macro-level social frames in a concern for growth. An integrative review approach is therefore used to synthesize and analyze research to develop a categorization of theoretical models, following the approach of Dzhengiz and Hockerts (2022). Integrative reviews (Elsbach & van Knippenberg, 2020) provide theoretical insights appropriate for our synthesis of growth theory across its formal modelling and qualitative modelling domains.

3. Theory and transformation for societal good

Our theoretical model draws together different strands of theoretical literature to offer a conceptual ordering of theory that might act as a heuristic to 'make visible' the dynamics of Romer's productivity mechanism channels, and AI's potential role within the 'system' of human activity, that crosses individual, organisational, and societal levels of growth.

3.1. Theoretical literature

The core theoretical ideas of our model draw from Romer's endogenous growth theory. According to Romer (1990), ideas drive growth and development, and 'knowledge recipes' for how to combine human and capital resources more productively are not rivalrous- and can hence be shared and used by others, often at low or no cost.

3.1.1. Transformative change for the greater good: theory predicting explosive change

Our model captures a profound implication of Romer's theory- that growth should be 'explosive' under certain conditions. If 'transformation' for the greater good were to be defined according to an increase in per capita income- income per person, measured as the production of goods and services- then a measure of this would be gross domestic product (GDP). Although most of the theoretical frameworks we discuss here model growth in per capita GDP terms, and although we introduce these theoretical ideas with this in mind, we will shift our discussions in the coming

sections to consider shortcomings in this measure and suggest our own, based on phenomenological lived experiences, including humanist needs, of individuals. We will argue that such a measure better captures impacts of potentially transformative changes in terms of societal good. For a theoretical understanding of how changes in the world can be transformative, theory predicting explosive change in growth is therefore relevant.

Accordingly, Romer's theory suggests discoveries can therefore be shared to generate increasing scale in productivity, and should produce a "combinatorial explosion" in that there are "incomprehensively many discoveries yet to be found" (Romer, 2016: 1). This theoretical idea finds support in recombinant innovation theory (Weitzman, 1998) that predicts large numbers of permutations of combinations of already existing ideas are possible. Accordingly, whereas knowledge recipes concern improvements in combinations of resources (such as human and physical capital), meta ideas are ideas about ideas that act as recipes for social interaction that radically improve production and transmission of ideas (Romer, 2016). With its focus on information technology and more specifically developments in artificial intelligence (AI), Kurzweil's (2001) law of accelerating returns may provide useful insights regarding implications of Romer's theoretical predictions.

The theoretical framework therefore models explosive increases in the production of goods and services, taking Romer's model literally in this respect, to derive *Proposition 1- that the experiential matrix comprising produced goods and services is increasing exponentially*. We define the experiential matrix of produced goods and services as the phenomenological experiences of individuals or groups of individuals of the 'space' or 'world' of products, services, or combinations of products and services that surround them. Humans are considered to be nested, or embedded, within buildings, surrounded by a material reality of a product/service 'matrix' that has largely been produced as part of the production processes of entrepreneurial firms. By phenomenological we mean this matrix is experienced by human consciousness and direct experience. When referring to goods

production, as shorthand, this will mean the production of goods or services, or their combinations.

How realistic is this notion of exponential growth in the production of goods and services? In a later section we explore the ‘upper bound’ of Romer’s idea productivity theory by considering a minor modification to Romer’s model, while changing none of its fundamental assumptions, to derive three different possible outcomes regarding technological change. Accordingly, by relating these insights to the theoretical model we derive some novel and surprising implications for theory and policy.

3.1.2. A theoretical model to locate fragmented literature

Whereas much previous work has identified mechanisms through which innovation can affect real world phenomena, we use Romer’s theory to relate product development to real world outcomes in the form of changes to the experiential matrix, or lived experiences of products. Recent work has made novel contributions to understandings of innovation through different mechanism, such as use of social ties (Xie, Gao, Jiang, & Fey, 2015), collaborative ties (Xie, Gao, Zang, & Meng, 2020), intrafirm networks (Broekhuizen & Zhu, 2021), and digital innovation (Soluk, 2022), for example, and the work here seeks to locate causal mechanisms of innovation identified in previous research in relation to an overarching model of the innovation process premised on Romer’s logics.

By locating the causal influences of AI in relation to overarching causal effects predicted by Romer’s theoretical model, and extending his model to consider qualitative, or phenomenological, experiences of goods and services, we provide a heuristic framework that ‘makes visible’ the most important theoretical thrusts of endogenous growth theory. In turn, by making visible this experiential matrix of experienced goods and services we reconcile ideas relating to one of the most important theoretical debates in productivity literature. This ongoing debate relates to criticisms of Romer’s model premised on exponential returns from non-rivalrous idea production and dissemination, based on evidence of declining returns to investments in research across

contexts, the latest work on this being that of Bloom et al. (2020). This will be discussed in more detail in a later section, where the relevance of this debate to the model is explained.

The model considers a novel source of innovation- the potential ability of AI to ideate- thereby contributing to knowledge recipe creation in creative ways. Recent work documents increasing contributions of AI to firm innovation (Rammer, Fernández, & Czarnitzki, 2022), to how AI might ideate, or how it might be becoming an emerging general method of invention (Bianchini, Müller, & Pelletier, 2022), how a cluster of technologies associated with data science and machine learning already seem to be displaying characteristics of a general purpose technology (Goldfarb, Taska, & Teodoridis, 2023), and how the fundamental nature of the techno-economic paradigm may be changing (Lundvall, 2017). This literature places AI in relation to radical changes in productivity, a focus of the model here.

3.1.3. AI and explosive growth

As will be discussed, AI might enter Romer's production function in different ways, and it is an empirical question in which ways this happens. The model here suggests an exponentially increasing experiential matrix already exists, and as AI increases its capabilities this exponential growth may only accelerate. Viewed positively, four scenarios seem plausible, each suggesting an amplification effect of AI on productivity, and, therefore, reduction of resource scarcity.

First, AI might accelerate the production of goods, either by amplifying the effects of non-rivalry through radically enhanced communications and dissemination of productivity-enhancing knowledge recipes. Real-time dissemination of non-rival knowledge would be expected to radically enhance the key mechanism of Romer's model, and enhanced explosiveness of goods production might be sufficient to reverse the marginal effects of tangible, or capital-integrated declining returns.

Second, according to predictions of recombinant growth theory (Weitzman, 1998), as acknowledged by Romer, there are theoretically no limits to the re-combinations of ideas, and this should not be a limit to exponential growth. Instead, recombinant growth theory predicts that the actual constraint to exponential productivity growth is the capacity to identify and exploit very large numbers of potential combinations and re-combinations of resources. In other words, ideas can be recombined to overcome any fishing out of ideas, but the real constraint to growth is how we process this knowledge. AI might therefore contribute to the processing capability that is the primary constraint to growth. If so, then acceleration in the exponential expansion of the experiential product matrix would be expected.

Third, AI might simply act multiplicatively with any of the other terms in Romer's model, to amplify their effectiveness in their growth contributions. Overall, some well-known characteristics of AI and its productivity-enhancing potential suggest that it can radically extend production possibility frontiers, dramatically reducing global resource scarcity. Whereas human capabilities are bounded and unscalable (a knowledge worker cannot be cloned in an unlimited way), AI works 24/7 and is scalable.

Fourth, the incorporation of AI into Romer's modelling as a source of 'ideation' also gives rise to interesting predictions. If humans are taken to largely recombine productive ideas, and if AI essentially does the same, then human and AI contributions may act as substitutes, and may be interchangeable in the production function. If so, then ideation would primarily be subject to the constraints suggested by recombinant growth theory (Weitzman, 1998).

Viewed negatively, AI might be taken to affect the experiential matrix in certain ways. First, it might displace human labour, diminishing the size of the matrix through reducing income available for consumption. This effect may be offset by increased productivity, whereby more goods are produced at lower cost. Models might suggest different outcomes according to spectrum of outcomes- at the 'positive' extreme, goods become so plentiful the matrix expands to fulfill almost

all human needs and reduces scarcity. At the ‘negative’ extreme, human employment is eliminated and the matrix shrinks together with the satisfaction of human needs.

The consequences of an exponential increase in AI are also unclear. Employment losses as well as gains increase with the technological intensity of a sector (Dachs, Hud, Koehler, & Peters, 2017), but the shape of the expansion, or combinatory explosion of ideas or recombination of ideas driven by an underlying exponential increase in AI proliferation is uncertain, a priori. Some seminal technological change scholars predict that outcomes and consequences of technological change will be measured on exponential scales. For example, Kurzweil (2001) explains what he describes as a law of accelerating returns:

But a serious assessment of the history of technology shows that technological change is exponential. In exponential growth, we find that a key measurement such as computational power is multiplied by a constant factor for each unit of time (e.g., doubling every year) rather than just being added to incrementally. Exponential growth is a feature of any evolutionary process, of which technology is a primary example. One can examine the data in different ways, on different time scales, and for a wide variety of technologies ranging from electronic to biological, and the acceleration of progress and growth applies. *Indeed, we find not just simple exponential growth, but “double” exponential growth, meaning that the rate of exponential growth is itself growing exponentially.* These observations do not rely merely on an assumption of the continuation of Moore’s law (i.e., the exponential shrinking of transistor sizes on an integrated circuit), but is based on a rich model of diverse technological processes. What it clearly shows is that technology, particularly the pace of technological change, advances (at least) exponentially, not linearly, and has been doing so since the advent of technology, indeed since the advent of evolution on Earth.

If correct, these observations suggest an inexorable march of technology and that its ability to exceed human intelligence- attainment of the singularity- is inevitable, and what is uncertain is only when, and not if, this will happen (Kurzweil, 2000). AI now has the capacity to use deep neural networks that “mimic the way the human brain learns” and comprehensive training data to produce ‘creative’ work, evidenced in the production of movie trailers, music, and other tasks previously limited to human creativity (Kirkpatrick, 2023).

Theoretically, the potential for the full replacement of human labour by AI might represent a ‘human labour cliff’. AI can work 24/7, and whereas a highly skilled human worker cannot be

‘copied’, an AI ‘unit’ equivalent to a human worker can be ‘multiplied’ at almost zero marginal cost. If so then AI might exhibit potentially unlimited increases in its capabilities and use. A simple extension of Romer’s model might be used to argue these marginal cost dynamics may in some areas produce exponentially increasing productivity, represented by a *vertical productivity curve*.

Therefore, with few marginal cost limits to an exponential proliferation of AI capacity, *it may fill almost all ‘available space’, raising questions about this ‘space’ it will expand into, and about its ultimate limits.*

If so, it may have two important humanist implications.

On the one hand, the experiential matrix may experience a growth explosion akin to that represented by a vertical growth curve, with a radically increased satisfaction of human needs, but only if production is channeled to human needs.

How might experiential matrix theory help to envision a humanist future under conditions of explosive growth? Humanist needs include those for freedom from scarcity, safety and security, health, and egalitarian life experiences, but also for human autonomy and agency. The experiential matrix described here comprises these needs. So, an explosion of need-fulfilling productive capability might deliver on these needs, but production would need to be channeled accordingly.

On the other hand, AI might not channel productive activity into the experiential matrix at all, or may even develop goals that conflict with the matrix, and reduce it or eliminate it entirely. Such scenarios are explicated by Jones (2023), and are beyond the scope of the model here, which provides a heuristic understanding of the mechanisms of growth, and do not consider the potential development of goals on the part of AI. Certain policy implications derive from our model.

3.1.4. Technological labour obsolescence

It is unclear if AI will come to be able to do all tasks humans can, but if AI can ideate to create new productive non-rival knowledge recipes, it would still need to relate to humans to develop human need-satisfying products. It is also unclear if AI will at some point develop its own goals,

and, if so, whether these goals will conflict with human goals. If AI could direct autonomous robots, for example, it could develop agency. If AI does advance to direct robots, there may come a time when human labour becomes technically obsolete. It is unclear to what extent AI may act benevolently if its goals differ from those of humans.

These issues would need to be considered by policymakers, whose main task would be to ensure a humanist future. New institutions may need to be developed to anticipate a post-work future. A basic income grant might be needed to prepare for technological labour obsolescence, together with a re-envisioning of the role of human labour considering coming changes. A deepening is also needed, about uncomfortable issues, to provoke new thinking about how to prepare for the possibility of unimagined change to our understandings of the lived experiences of human work.

Are severances of highly skilled workers by AI firms a leading indicator of an improving capacity to replace skilled labour? If so, recent layoffs of about 12 000 by Google and 11 000 by Meta may be a harbinger of improving AI capabilities; similarly, layoffs of 55 000 technology professionals in January 2023, and 150 000 in 2022 (Kelly, 2023b) raise questions about the impact of explosive advances in technology on jobs. By February 2023, other firms including Amazon, Salesforce, and Microsoft were already announcing further layoffs, suggesting AI and robotics may now threaten job security of even the most highly skilled technology workers (Kelly, 2023a).

Debates about threats of the ‘end of work’, or full substitution of human labour by technology, are not new (Brynjolfsson & McAfee, 2014; Callaghan, 2018; Rifkin, 1996), but recent high technology job losses coinciding with the emergence of popular AI applications is concerning. Whereas second machine age literature predicts a rising ‘water line’ of technological capabilities that displace low-skilled workers first, initially leaving creative and highly skilled workers unscathed, recent job cuts of highly skilled technology workers suggest jobs at different skills levels may now technically be at risk.

Comments such as those by Microsoft's Chief Economist, Michael Schwarz that AI might be used by 'bad actors to cause damage' (Baschuk, 2023) also raise questions about human malevolence, and the destructive capability of AI, particularly in a context of geopolitical conflict.

3.2. The experiential matrix model

The experiential matrix model is premised on the concept of exponentially increasing growth that arises from non-rivalrous productivity knowledge recipes, that increase productivity as they diffuse across contexts, as per Romer's (1990) model. If this is taken to represent a topographical map in three dimensions, the 'surface' of the mapped 'space' would rise as more productively produced need-satisfying goods emerge. This mapping corresponds with a real-world context of the experiential matrix comprising the material world surrounding us, which is primarily comprised of products. This idea is based on Nordhaus's (1997) work on the productivity of generating light, which has increased exponentially. He highlights the limitations of measures of growth based on GDP that do not capture many of these productivity gains.

Bresnahan and Gordon (2008) also question the usefulness of per capita GDP as an index of the welfare value of new goods to consumers. They suggest a 'true' cost of living index exists, related to the costs of achieving a given level of well-being, but that it is difficult to quantify precisely. Often, the diffusion of goods can be affected by complementarities, whereby combinations of goods can increase welfare, and these complementarities can increase over time, and complementarities can set off a series of complementary innovations (Bresnahan & Gordon, 2008). They point to the time savings involved in new product innovations, and to Becker's (1965) modelling of the value of time. Bresnahan and Gordon (2008) use an example of comparisons of an 1893 shopping catalogue with one from 1993 from the same retailer. This example illustrates the richness of welfare-increasing innovations in products over time, with the new catalogue offering "a vast array of useful and attractive items not available or even imagined in 1893...The value of these changes is central to an understanding of how much richer society has become over

time, in dimensions that are neglected by official measures of inflation” (Bresnahan & Gordon, 2008: 3). We suggest that over time products have become more plentiful, as has their variety and quality, and that the ‘depth’ and ‘breadth’ of the experiences offered by these products have increased. Each generation has, therefore, experienced- or is nested or embedded within, a much richer experiential matrix. We suggest that this matrix is essentially qualitative, and phenomenological in nature, despite having some measurable characteristics. This model therefore links Romer’s (1990) productivity function with output, but what is novel here is that this output represents the experiential matrix. The output variable in his model is therefore a latent construct when used to describe the experiential matrix, and in empirical tests would only represent the portion of the experiential matrix that corresponds with what can be measured as inputs.

It is also difficult to measure the totality of time-saving and quality improvements in products, and there is a gap between the measurable and the qualitative nature of the system of human needs, itself drawing from biological, social, and neurological/psychological needs and values, as described by Schwartz’s (2012) theory, amongst others. Consumers can also benefit from novelty, but novelty itself can depreciate, with diminishing returns to quality and variety amidst the opening up of new categories of goods that increase consumer welfare, or consumer surplus (Bresnahan & Gordon, 2008), although some outputs of the production process, however, add little or even negative value to the matrix, such as pollution. The experiential matrix is therefore dynamic, but it has a structure in the observed reality surrounding us.

Becker acknowledges the complexities inherent in separating consumption and production activities and literature describing households as small ‘factories’ combining capital, labour, and other resources to produce useful commodities (Becker, 1965). He also models time investments between consumption and production, suggesting that time-intensive consumption activity is more likely to be characterized as luxury consumption. The experiential matrix model bridges the production and consumption function by framing the former according to Romer’s (1990) logics,

and the latter according to qualitative and phenomenological descriptions. This entails an epistemological shift in thinking about how the production function affects the real world, in that a rigorous theoretical framework, replete with voluminous mathematical proofs, is linked to the qualitative, and essentially (currently) unmeasurable experiential matrix of human experiences of products. We argue this synthesis is necessary, to embrace the reality of human lived experiences, and their essentially phenomenological nature, which differs fundamentally from the mathematical paradigm of modelling production functions. This synthesis is in line with epistemological panarchy (Callaghan & Mitchell, 2023a), and the need to ensure lived experiences of humanist reality are related to theoretical ideas that emerge (and which might only be able to emerge in the abstraction of modelling, including mathematical) in other paradigms.

Becker's (1965) household production function of consumer welfare, for example, is based on combinations of household time and market commodities. It reveals mechanisms through which new goods represent a series of technological advances that lower household costs. When related to qualitative understandings of humanist experiences of such goods, we have a model that more accurately captures the reality of human lived experiences. As such, the experiential matrix model may be useful as a heuristic to understand the full 'chain' of causal mechanisms, through which human ideas 'manifest' in the material world.

The experiential matrix is therefore taken to represent the lived experiences of human beings of the products that surround them. For a product to be taken up by the matrix it would need to correspond with a human need. According to Romer's (1990) logics, the source of growth is primarily the product development process of entrepreneurial firms. As such, the system of production in these firms is aligned with satisfying human needs. The experiential matrix, as a phenomenological phenomenon, is difficult to quantify, and modelling it is a qualitative process. What is novel about the model is how it links Romer's (1990) production function logics with humanist needs, in that the experiential matrix includes needs for peace, health, equity, and other

needs, some of which are described in psychological models, including Maslow’s (1970), that offers some kind of an ordering of these needs. Discussions of relative needs is beyond scope here but asymmetry in the structure and importance of human needs, and variance of attributes across and within them, needs to be acknowledged. The experiential matrix model provides a heuristic understanding of how to link endogenous growth theory and the qualitative matrix of human needs, and further research might consider these asymmetries. Missing from literature generally has been a heuristic framework that links these seemingly incommensurate ‘paradigmatic’ schools in the spirit of epistemological panarchy. Given that Romer’s (1990) theory, and the development of endogenous growth theory that models technology within the model (as endogenous) seems represent a watershed in growth theorizing, this body of work that came to prominence in the 1990s may be at odds with pre-existing path dependencies in the creation of knowledge. As such, we suggest that Romer’s non-rivalry may be the core causal ‘ground zero’ mechanism that drives growth across contexts. An important implication of this is that product development of entrepreneurial firms is also in this ‘ground zero space’, and this is illustrated in Figure 1, which summarises the experiential matrix model in terms of its key constituent literatures.

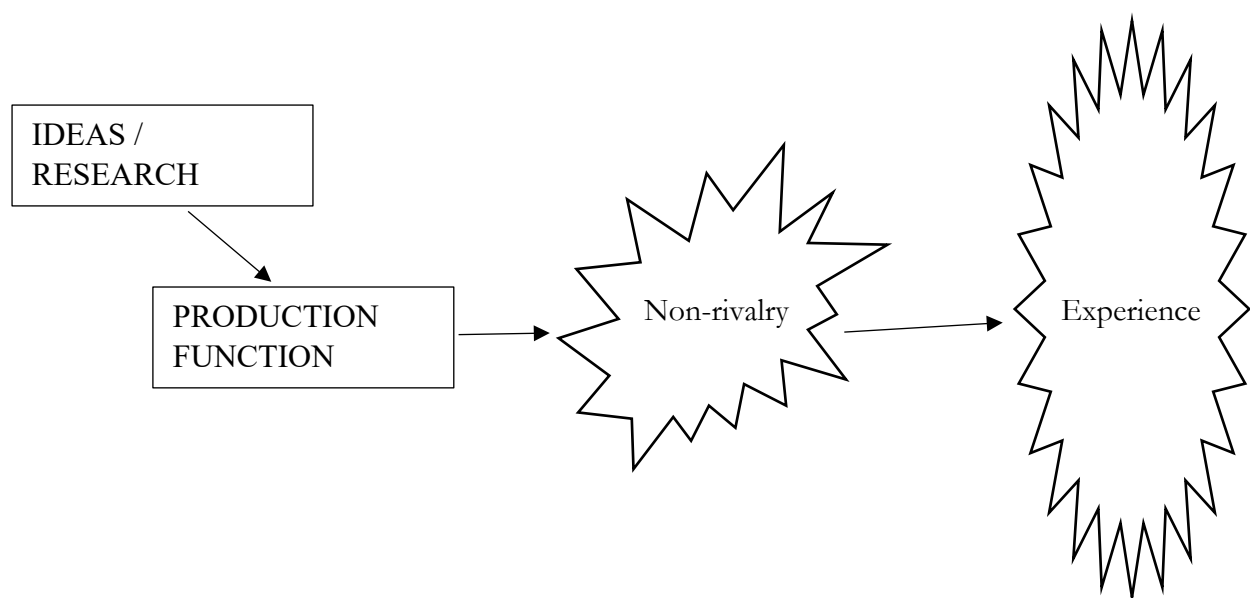


Figure 1. Core Experiential Matrix Model (Callaghan, 2023a; 2023b)

Following Romer (1990) Figure 1 shows ideas and research as inputs into the production function, representing the production of continually improving non-rivalrous knowledge recipes of combinations of resources to produce products. Romer's mechanism of non-rivalry is then the source of growth, as more productive recipes are shared by others, to create explosive growth. The rectangular blocks represent aspects of theoretical models that are rigorously developed, and represented in quantitative terms. The 'explosive' growth caused by non-rivalry is theoretically exponential, but essentially a qualitative phenomenon because it is difficult to measure and at this time it is better described qualitatively. Similarly, we suggest the experiences of exponential growth in product development is resulting in exponential growth in the experiential richness of the experiential matrix. The jagged edges of the non-rivalry and experience constructs signify their exponential, or explosive systemic growth, as well as the systemic and qualitative nature of this growth, which to date defies precise quantification.

The novelty of this model is that it synthesizes a body of work based on mathematical formal models (that suggest certain regularities in the way knowledge is transmitted through a production function to create exponential growth due to the non-rivalry mechanism) with theory relating to the 'fully dimensional' phenomenological human experiences of a material world comprised of products.

Although Romer's (1990) theory suggests that growth primarily derives from the product development process of entrepreneurial firms, which is captured in this model, what is not captured is the possibility of a wedge between human-oriented production, termed humanist production because it incorporates all human needs, and non-human-oriented production. The key issue facing humans then might be how to ensure production remains human, or humanist-oriented. If AI were to develop its own goals, then there is no guarantee that AI-governed productivity would be humanist-oriented. This issue might become increasingly important if the invention process were to itself become automated.

3.3. Automating the invention process itself

At the extreme, the most consequential advance in AI for human societies might be its ability to ideate, or to itself create knowledge recipes. Recent work on AI as an emerging general method of invention (Bianchini et al., 2022) suggests we are ‘already there’. Similarly, recent work has modelled automation of the process of invention itself. For example, Clancy (2022) demonstrates how automating invention can overcome the forces making innovation harder, as well as declining human population growth. His model suggests we will ultimately achieve almost vertical productivity measured on the Kardashev scale (that measures the technological level of a civilization based on its ability to harness energy).

However, the innovation ‘chain’ may only be as strong as its weakest link. According to Clancy (p. 1):

An artificial intelligence or some kind of digital brain scan and emulation technology would, in a stroke, automate many remaining cognitive tasks. But even there, the automation of the innovation pipeline would only be partial, so long as we continued to rely on humans to do work in the physical world and do the entrepreneurial work that translates discoveries into social value...As discussed earlier, we have seen a continuous succession of new technologies that allowed us to hand off previously human tasks to machines. And yet, through it all, overall growth has been steady or slowing...if we can automate the entire innovation pipeline, then growth accelerates and things get crazy at some point. But if we cannot automate everything, then the results are quite different. We don’t get acceleration merely at a slower rate- we get no acceleration at all. This is because when economic tasks are essential, then we are constrained not by what we are best at, but what we are worst at.

However, it is difficult to imagine that some innovation tasks could become bottlenecks to invention and innovation because they remain the exclusive domain of humans if we consider the potential development of AI-enabled robotics. Would creativity be the last exclusive work domain of humans, or could AI replace human creativity, and effectively automate the discovery process of new product development research?

Creative work now also seems to be vulnerable to AI, as shown by recent advances such as Chat Generative Pre-Trained Transformer (ChatGPT) (OpenAI, 2022) with some suggesting it will have an uncertain impact on academia itself (Lund & Wang, 2023). Although it is unclear yet if

generative AI represents a General Purpose Technology (GPT), a drastic productivity-enhancing innovation with pervasive use and application across most sectors of the economy (Bresnahan & Trajtenberg, 1995), the broader set of technologies associated with AI, data science, and machine learning already displays characteristics of a GPT (Goldfarb et al., 2023).

GPTs can disrupt human labour markets. Accelerating speed of capital-embodied technological change can also worsen wage inequality (Aghion, Howitt, & Violante, 2002). Although technological changes have usually generated enough new types of jobs to offset job losses, this time the impact of AI on jobs may be different. We may need to reconceptualize the structural conditions of ‘work’ itself, and its societal role, to anticipate, and moderate, these coming changes.

OpenAI, the company that released ChatGPT, estimates about 80% of the U.S. workforce could have at least 10% of their work tasks disrupted (Hurst, 2023a). These events coincide with reports of the likes of Elon Musk and Steve Wozniak signing an open letter to call for an immediate halt to AI development research, in light of its potential threat to humanity, and potential to replace ‘all jobs’ (Hurst, 2023b). A recent report by Goldman Sachs using data from the US and Europe finds about “two-thirds of current jobs are exposed to some degree of AI automation, and that generative AI could substitute up to one-fourth of current work”, exposing about 300 million full time jobs to automation, although this might nevertheless increase labour productivity growth and could ultimately increase annual gross domestic product (GDP) by 7% (Hatzius, Briggs, Dodnani, & Pierdomenico, 2023).

Investment in development of AI is unlikely to slow, particularly for industry leaders. Of the big five technology firms, patent keyword searches mentioning AI are highest for Alphabet, followed in order by Amazon, Microsoft, Meta, and then Apple; in 2022 these firms accounted for \$223 billion in research and development (R&D), equivalent to 26% of their combined yearly revenues, compared to 16% in 2015 (Economist, 2023). These indicators suggest investments in

technological change are increasing and there is therefore little reason to expect a slowdown in AI research and exploration, notwithstanding calls for a slowdown.

4. Modelling theoretical micro foundations

The intuition of the ideas and the model suggested in the previous sections might best be expressed in terms of the notion that all growth emerges from ideas, and the process whereby ideas are ‘transmitted’ to generate the fabric of the material world around us, structured by the products that have ‘manifested’ from these ideas. Our epistemologies can therefore, through this channel, causally influence our real world. Growth is therefore considered to primarily be driven by ideas, and ideation. In Romer’s own words (Romer, 2008: np):

Perhaps the most important of ideas of all are meta-ideas. These are ideas about how to support the production and transmission of other ideas. The British invented patents and copyrights in the seventeenth century. North Americans invented the modern research university and the agricultural extension service in the nineteenth century, and peer-reviewed competitive grants for basic research in the 20th century. The challenge now facing all of the industrialised countries is to invent new institutions that encourage a higher level of applied, commercially relevant research and development in the private sector...*We do not know what the next major idea about how to support ideas will be.* [Our italics.] Nor do we know where it will emerge. There are, however, two safe predictions. First, the country that takes the lead in the 21st century will be the one that implements an innovation that more effectively supports the production of new ideas in the private sector. Second, new meta ideas of this kind will be found.

At this point, we have discussed ideas and have formulated a model that relates a body of theory about the production function with a body of largely qualitative theory that describes the lived experience of the experiential matrix. It might be useful to now consider the micro-foundations of the theory underlying the prediction that ideas are the source of almost all growth. This is a very strong assumption and our model, and its derived implications, derive from it.

The formulations discussed from this point- from equations (1) to (12) follow C. I. Jones’s (1998) logics based on Romer’s (1990) model of endogenous growth. This modelling is used because it predicts scale effects in knowledge creation- that returns to investments in knowledge are expected to increase over time. As discussed, we believe this model to be the most relevant in light of the

Solow paradox (Solow, 1987b) and evidence suggesting fishing out and duplication effects (Jones, 1995a, b) better explain the declining returns to investments in research evidenced to date over the past decades.

In this model, combinations of the capital stock, K , and labour, L_Y , produce output, Y , with the incorporation of the stock of ideas, A . As discussed models (1) to (12) and their rationales are drawn from C. I. Jones (1998), who provides a more detailed discussion of these relationships that are summarised here.

$$Y = K^\alpha (AL_Y)^{1-\alpha} \quad (1)$$

In this model, the parameter α has a value of between 0 and 1. We assume that for A , a given level of technology, (1) exhibits constant returns to scale in K and L_Y , but increasing returns are associated with the role of A in production, generated due to the non-rivalrous characteristics of ideas.

Accordingly, as per Solow's capital accumulation function, capital will increase as consumption is forgone at a certain rate, s_K , and depreciates exogenously, at rate d .

$$\dot{K} = s_K Y - dK \quad (2)$$

Labour, which represents the population, grows exponentially at the constant rate n , which is exogenous.

$$\dot{L}/L = n \quad (3)$$

Whereas in Solow's model A is exogeneous, growing constantly, here it is endogenous, representing $A(t)$, the stock of ideas invented to date, up to time t . The growth rate of A , $\dot{A}$ equals the number of people seeking to develop new ideas, L_A , at the rate of idea discovery.

$$\dot{A} = \bar{\delta} L_A \quad (4)$$

Accordingly, labour is used to produce output or to produce new ideas, and there is a resource constraint.

$$L_A + L_Y = L \quad (5)$$

However, the rate of new idea creation may depend on the stock of previous ideas, or may even be a constant. If past inventions increase the productivity of present researchers, then $\bar{\delta}$ is an increasing function of A . It would be a decreasing function if ideas are easier to find initially but get harder to find over time. This suggests the rate of production of new ideas $\bar{\delta}$ can be represented as follows:

$$\bar{\delta} = \delta A^\varphi \quad (6)$$

Here, δ and φ are constants, and $\varphi > 0$ implies that research productivity increases with the stock of previous ideas, and $\varphi < 0$ that a fishing out effect is present, where the discoveries become harder to find over time. $\varphi = 0$ represents the case where the fishing out effect is exactly offset and productivity is independent of the knowledge stock. Average research productivity may however be affected by duplication of research effort.

$$\dot{A} = \bar{\delta} L_A^\lambda A^\varphi \quad (7)$$

L_A^λ here represents the potential for duplication of research effort, where λ as a parameter between 0 and 1 captures this potential. According to Romer's model an individual relative to the economy takes $\bar{\delta}$ as given, experiencing constant returns to research effort, but across the entire economy constant returns to scale may no longer reflect the production function for ideas, as $\bar{\delta}$ then reflects aggregate research effort. The rate of production with duplication and knowledge spillover effects included is:

$$\bar{\delta} = \delta L_A^{\lambda-1} A^\varphi \quad (8)$$

At the aggregate level there will be some duplication of research effort, representing an externality when $\lambda < 1$, a congestion, or standing on toes effect; similarly, if $\varphi > 0$, a positive externality, a knowledge spillover exists, a standing on toes effect (Jones, 1998: 93).

What of rapid advances in technology that are radically increasing the data and information analysis capabilities- what do these advances imply for λ , φ , and $\bar{\delta}$? Some suggest we have started to experience an “acceleration of acceleration”, caused by exponential growth in computing power, in that:

...accelerating individual technologies are converging with other accelerating technologies, producing overlapping waves of change that threaten to wash away almost everything in their path- or what happens when AI and robots converge and hundreds of millions of jobs disappear (Diamandis & Kotler, 2020: 69).

Regarding information processing capability as a key constraint to the acceleration of the impacts of technology, Diamandis and Kotler observe that exponential growth predicted by Moore’s Law based on binary bits could accelerate further, for example, due to a switch to quantum computing’s quantum bits. They suggest this acceleration will co-occur with advances in different kinds of networks, fifth generation (5G) and subsequent generations of telecommunications enabled by full satellite coverage, proliferation of sensors and the Internet of Things, robotics, 3-D printing, blockchain, material sciences and nanotechnology, and biotechnology, amongst others.

We suggest the possibility of the duplication effect being driven down as AI picks up duplication of research effort in real time. This might better locate and clarify the knowledge frontier and reduce wasted time. If so, λ could ultimately be minimized. As discussed previously, it might be the ability of AI to assist with the interpretation and synthesis of information that solves the bottleneck constraint to growth identified in recombinant growth theory by Weitzman (1998).

It therefore also needs to be asked- under what conditions could duplication be increased rather than decreased in an AI-enabled world? Exponentially increasing volumes of data and information

pose problems for their conversion to knowledge, if this increase is not matched by synthesis and processing capabilities. This has perhaps until now created ‘noise’, contributing to the burden of knowledge effect (Jones, 2009) where an individual struggles to keep up with a rapidly expanding frontier of knowledge. This effect would act to maximize the fishing out effect, as fish become harder to catch, requiring teaming up with others to counteract it. As Jones observes, research teams are getting bigger, and ages are increasing at which Nobel Prizes and other research prizes are awarded.

This fishing out effect, with $\varphi < 1$ until now, seems predicted in a host of different theoretical models (Jones, 2009; Kortum, 1997; Segerstrom, 1998) that explain a paradox whereby despite increasing numbers of researchers employed in research and increasing research activity across the board returns to these investments seem to have been declining over the past decades.

This burden might disappear as AI itself intelligently converts the noise of exponentially increasing data and information into useful and synthesized knowledge. We might then expect to see a declining size of the duplication of research effort coefficient λ together with increasing size of the positive standing on shoulders effect φ in regressions over time, as the noise-reducing and knowledge-increasing potential of AI becomes stronger.

This corresponds with debates questioning the predictions of the Romer model of its prediction of increasing returns to scale in the production function due to endogenous technological change, and the emergence of alternative models that exclude this prediction (Jones, 1999). The rapid economic growth of many Asian ‘economic miracles’ such as South Korea, Hong Kong, Singapore, and Taiwan was also largely due to factor accumulation and structural change associated with labour shifts out of agriculture into manufacturing rather than rapid increases in total factor productivity associated with technological change (Young, 1995). By reducing the burden of knowledge effect, AI might address criticism that evidence has yet to support the Romer model and recombinant growth theory which predicts that idea creation is essentially not limited by

numbers of existing ideas because of the infinite potential to combine and recombine ideas (Weitzman, 1998). It is a contribution of this work to relate these theoretical ideas to the qualitative experience of the experiential produce matrix, which, we argue, is akin to an exponentially growing frontier of human experience of products reflected in the material universe that surrounds us.

This paradoxical failure of Romer's prediction of increasing returns to scale in the production function (when GDP is used as a measure) is also reflected in a large body of work suggesting that an era of technological progress and large-scale innovations evidenced across the century 1870-1970 has been followed by one of declining productivity growth (Cowen, 2011; Gordon, 2012, 2016) with the exception of internet and communication technologies and entertainment that stands out from other real sectors of the economy (Brynjolfsson & McAfee, 2014).

This is also evidenced in decreasing returns to investments in pharmaceutical innovation (Munos, 2009; Munos & Chin, 2011; Scannell, Blanckley, Boldon, & Warrington, 2012), with pernicious consequences for the poor and most vulnerable in societies (Callaghan, 2019; Nathan, 2007). According to (Scannell et al., 2012: 191):

The past 60 years have seen huge advances in many of the scientific, technological and managerial factors that should tend to raise the efficiency of commercial drug research and development (R&D). Yet the number of new drugs approved per billion US dollars spent on R&D has halved roughly every 9 years since 1950, falling 80-fold in inflation-adjusted terms.

We acknowledge this literature, and recent evidence that shows returns to investments in R&D are declining across contexts (Bloom et al., 2020), but we differentiate between what seems to be evidence of diminishing returns to research effort, and an off-setting exponential increase, akin to an explosion, in need satisfying product development. We suggest that this radical increase is difficult to quantify at present, and that it might best be described in qualitative terms, as we do in the form of our experiential matrix model.

Regarding measures like per capita GDP, will we reach a turning/inflection point- a switch from an era of decreasing returns to investments in research ($\varphi < 1$)- as seems to be evidenced in this literature- to a Romerian era of increasing returns ($\varphi > 1$)? If AI helps to remove the primary constraint suggested by recombinant growth theory (Weitzman, 1998), this may be enough to reduce these diminish returns to research effort, which, we suggest, seem to arise from the inseparability of human resources and physical resources in the production of knowledge. Our qualitative experiential matrix model suggests that exponential growth is nevertheless occurring in the ‘humanist experience’ of goods production. We also suggest that the strength of Romer’s theoretical ideas will ultimately be matched in tests of conventional measures of growth such as per capita GDP, as long as the fishing out and duplication effects are off-set by research into these effects themselves, accompanied by sufficient investments of resources to prioritize these efforts.

In that we suggest that it is the inseparability of capital from the human-dependent ideation process that accounts for diminishing returns to investments in research, it might be useful to differentiate Solow’s capital-oriented model from Romer’s, and to consider in more detail the fishing out and duplication effects. Whereas in Solow’s model A is exogenous, growing constantly, here in Romer’s model it is endogenous, representing $A(t)$, the stock of ideas invented to date, up to time t . The growth rate of A , $\dot{A}$ equals the number of people seeking to develop new ideas, L_A , at the rate of idea discovery,

$$\dot{A} = \bar{\delta} L_A \quad (4)$$

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L_A^λ here represents the potential for duplication of research effort, where λ as a parameter between 0 and 1 captures this potential. According to Romer's model an individual relative to the economy takes $\bar{\delta}$ as given, experiencing constant returns to research effort, but across the entire economy constant returns to scale may no longer reflect the production function for ideas, as $\bar{\delta}$ then reflects aggregate research effort. The rate of production with duplication and knowledge spillover effects included is:

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At the aggregate level there will be some duplication of research effort, representing an externality when $\lambda < 1$, a congestion, or standing on toes effect; similarly, if $\varphi > 0$, a positive externality, a knowledge spillover exists, a standing on toes effect (Jones, 1998: 93). What of rapid advances in

technology that are radically increasing the data and information analysis capabilities- what do these advances imply for λ , φ , and $\bar{\delta}$?

Some suggest we have started to experience an “acceleration of acceleration”, caused by exponential growth in computing power, in that the rapid transformation of knowledge creation, whereby the research process itself has been radically innovated by novel technologies (Callaghan, 2016). How, then, could the rate of production of new ideas be increased in response to a need to solve an existential problem? For example, in the face of a global pandemic there would be a need for ideas in real time on how to solve it and manage it. If the problem cannot be solved in real time by the current scientific system, the value of φ would need to be increased such that $A^\varphi > L_A^{\lambda-1}$. There have been instances where problems have been solved by open calls- by exposing the problem to very large numbers of potential solvers. Some have suggested radical solutions to obtain real-time research responses to disasters (Callaghan, 2015, 2016), suggesting some future avenues for extending these models

However, how does this relate to growth? With the standard Solow-type assumptions of a balanced growth path, with a constant proportion of population employed to produce ideas, all growth is due to technological progress. This implies that (Jones, 2002):

$$g_y = g_k = g_A. \quad (9)$$

Here these are per capita growth rates of output y , capital-labour ratio k , and stock of new ideas A . Dividing by A gives us:

$$\frac{\dot{A}}{A} = \frac{L_A^\lambda}{A^{1-\Phi}}. \quad (10)$$

$\frac{\dot{A}}{A} \equiv g_A$ is constant along a balanced growth path, but the numerator and denominator need to demonstrate proportional growth. Taking logs and derivatives:

$$0 = \lambda \frac{\dot{L}_A}{L_A} - (1 - \varphi) \frac{\dot{A}}{A} \quad (11)$$

The growth rate of researchers must equal that of the population along a balanced growth path, so $\frac{\dot{L}_A}{L_A}$ must equal n , thus, incorporating this logic into (11):

$$g_A = \frac{\lambda n}{1 - \phi} \quad (12)$$

Accordingly, the growth of the economy long term is determined by the production function for ideas together with the growth rate of researchers, which here is the population growth rate. By implication, if $\lambda = 1$ and $\varphi = 0$ then researcher productivity is the constant δ and no duplication would occur and production of researchers would be independent of the historical stock of ideas. Ultimately, according to Jones (1998: 95/96), this extending this logic suggests that:

...if research effort in the world were constant over time, would economic growth eventually grind to a halt? This model suggests it would. A constant research effort cannot continue the proportional increases in the stock of ideas needed to generate long-term growth.

If technology now substitutes for labour, then how would this technology differ fundamentally from human capabilities? What does it mean to come up with a new idea? As discussed, according to Weitzman (1998), ideas represent permutations of possibilities, and if human creativity in goods production is primarily about combining pre-existing ideas, then AI might act as a substitute for human ideators. If so, the production of output could conceivably occur without humans. How then might we model the difference between complement versus substitute contributions of AI regarding human intellect, or idea creation? If AI has a substitution effect and is itself scalable (the limits to its scalability still need to be modelled), it can expand output with almost no limit, with no duplication effect, and even growth measures such as per capita GDP might exhibit vertical growth curves.

How then might we incorporate the second machine age into Romer's model- the notion that technology can substitute for human work (Brynjolfsson & McAfee, 2014)? If (7) were modified to include this technological effect m , we would have:

$$\dot{A} = \bar{\delta} L_A^\lambda L_A^m A^\varphi \quad (13)$$

Here, we suggest m can take the form of either complementing human labour, in which case its value would be smaller than if it fully substituted human labour. Technically, in a Cobb-Douglas-type production function, all input terms are complements rather than substitutes (Griliches, 1979), and we focus here on the contribution of the labour function in production whereby full substitution simply reflects a higher complementary effect. L here continues to represent labour, but either technologically augmented labour or technological labour that has replaced human labour.

We suggest that although the functional form, and all the logics of Romer's model remain relevant, the value of $m > 1$, but could be much higher. As such, we expect it to dominate productivity relationships and increase $\dot{A}$ accordingly, affecting the chain of effects to increase growth as per (8) to (12).

Hence, the larger the substitution effect, the larger its expected value would be. For example, a technological equivalent of a human worker could work 24 hours a day 7 days a week and could be scalable- its productive working capacity could be replicated across contexts. A fully automated factory of AI-enabled robots that replaces its parts using 3D technology could also work 24/7. This might entail an inversion of the real-world economics of productivity- according to which marginal costs of labour are a major component of a firm's costs and a firm operates to match large marginal costs with marginal benefits. In this case, most of the costs of developing technologically substituted labour would be high in fixed costs but with much lower marginal costs. Thus, technology might produce the low marginal costs associated with what has been popularized

as the zero marginal cost revolution (Rifkin, 2014) arising from technological changes associated with a ‘third industrial revolution’ (Rifkin, 2011).

Keeping with Rifkin’s popular use of the term ‘end of work’ (Rifkin, 1996), we use this term to represent the potential extreme case of high complementation of human labour by technology, equivalent to the potential for full substitution in labour markets. An end of work scenario as described above might be expected to radically increase growth and returns to investments in knowledge creation, but at the expense of human labour. How socio-institutional forces react- both proactively and reactively- to these potential changes will dictate the extent to which the world of work is inclusive to human labour needs. Human labour needs include intrinsic needs of work (Callaghan, 2018), however, and this is might be considered a qualitative effect better modelled within our qualitative experiential matrix framework.

5. Social returns to innovation

A criticism might be leveled at the specification (13), in that it fails to consider the consequences to social returns to innovation of the effects of Schumpeter’s predicted effects of creative destruction (Schumpeter, 1942). These effects have been modelled to show the potential of new innovations to make older technologies obsolescent, or speed up the obsolescence of currently valuable knowledge- whereby “technological progress creates losses as well as gains, by rendering obsolete old skills, goods, markets, and manufacturing processes...obsolescence creates a negative externality from innovations” (Aghion & Howitt, 1990: 1). Of course, disruption of human labour by technology will be highly disruptive, and it is necessary to also therefore ask- *to what extent would radically increased productivity have social returns that can match its disruptive consequences?*

Innovation can have different spillover effects caused by imitation, business stealing, and intertemporal spillovers that complicate efforts to measure its social returns (Jones & Summers, 2020). In estimating social returns to innovation, Jones and Summers model effects of capital embodiment, diffusion delays, productivity mismeasurement, learning-by-doing, international

spillovers, and health outcomes. They find social returns to investments in innovation to be substantial. Given this unambiguous theoretical and empirical evidence of social returns to innovation, and of contributions of innovation in turn to growth, the productivity gains due to technological contributions to labour may have substantial societal benefits.

Benefits to society also, however, depend on how we prepare for ‘end of work’ scenario. Of course, extreme outcomes may be less likely, but by considering them we can prepare for coming changes, whether incremental or radical.

6. Conclusion

The objective of this paper was to suggest a holistic model to link literature on production functions with that on the phenomenological experience of products and growth in production as it ‘manifests’ in the real world around us. The model contributes to understandings of the implications of Romer’s (1990) Nobel-recognised work, drawing out implications of its core theoretical ‘meta’ idea- that nonrivalry of productive ideas is the theoretical ‘ground zero’ of exponential growth. It was argued that Romer’s predictions of exponential growth are borne out in qualitative terms, reflected in the ‘experiential matrix’ of human experience, or a radically increasing richness of subjective experience created by products that include social media and virtual experiences that defy attempts at quantification, but nevertheless increase the depth of the experience of being human. We hope that future research also seeks to develop theory to draw out experiential implications of seminal work, making it ever more relatable to the lived experiences of humans, and the goal of preserving a human-centric future.

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