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The Impact of Artificial Intelligence on Personal Identity

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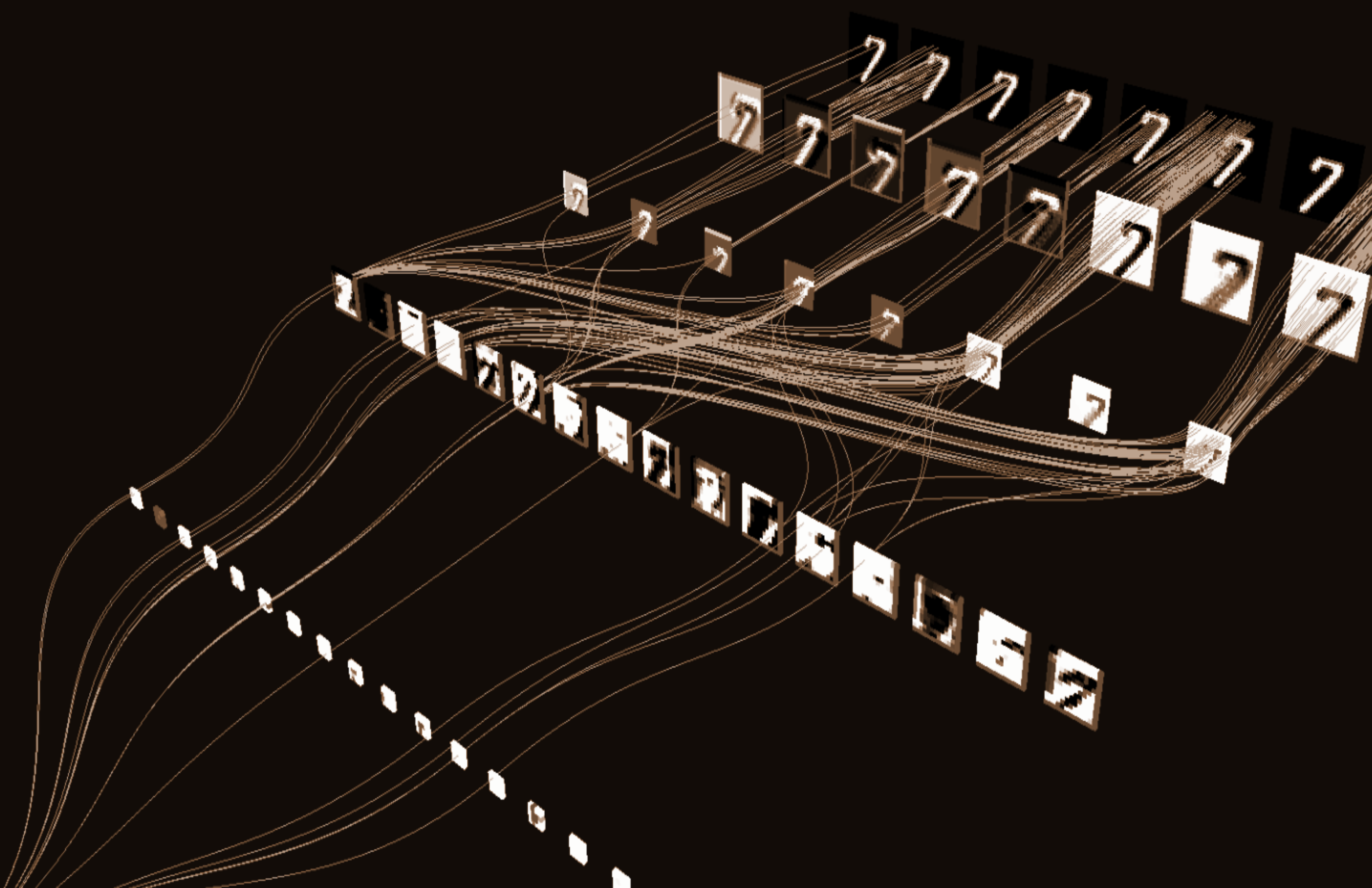

Contents

1 Introduction

The invention of the clock was not merely a tool for measuring hours but a radical development that revolutionized human society. This shift from natural, cyclical time to a more rigid, linear conception of time enabled the regulation of daily routines, the organization of labor, and the rise of industrial society. The clock's impact was so profound that it altered the rhythm of human life, making punctuality and time management central aspects of social and economic life. Over the Millenia, there have been many waves of dramatic innovation: fire, wheels, the printing press, electricity. Notably, each of these developments are *general purpose* in their nature; they serve to enable other technologies. Whilst there exists a clear tradition in understanding how each of these innovations impacted the established economic, moral and political presuppositions of the status-quo, what is less monitored in our anthology is the way in which these technologies subverted the sense of personal identity for individuals. Just as the clock and calendar provided a framework to narrativize our lives, allowing individuals to structure their personal histories along a linear timeline, our identities seem to develop in tangent to our material world. Indeed, a sense of self without clocks, calendars, and linear temporality is not one in which we can associate nor comprehend, as this technology has mediated our self-understanding at each moment. We now face a new turning point in innovation; Artificial Intelligence (AI). AI can be considered the closest approximation to the cartesian "thinking thing" that we humans have ever endeavored to create. Just as the agricultural or industrial revolution required a new ethos, the age of AI will bolster its own.

This paper examines the intersection of artificial intelligence (AI) and personal identity, exploring how AI technologies reshape our self-conception within the context of surveillance capitalism. By applying McAdam's narrative identity framework, the paper investigates how AI's influence alters the categories that constitute individual identity. The paper situates these developments within broader socio-economic structures to reveal the extent to which AI undermines or merely complicates our understanding of self-determination. It argues that AI's new role in curating and mediating personal narratives is so pervasive that we can no longer operate under the illusion of having autonomy (with regards to our identity). Through this analysis, the paper seeks to provide a nuanced perspective on the ethical and existential implications of AI's integration into the fabric of human identity.

2 Artificial Intelligence

2.1 Definitions and Characterization of the Field

The question "What is AI?" has been foundational to the discipline since its inception in the 1950s. At the behest of John McCarthy, one of AI's pioneers, it was initially defined it as "the science and engineering of making intelligent machines," with intelligence having the circular definition of 'human-like behaviors'. However, as AI has evolved, so too has our understanding of what constitutes the term 'artificial intelligence'. In this essay, I propose a working definition of AI as: a non-human system capable of simulating cognitive functions traditionally associated with human intelligence, whether embodied in physical form or existing as disembodied software. These systems operate autonomously, often driven by motives and purposes that may be opaque or even incomprehensible to us[1]. From spell-check to self-driving cars, AI encompasses a wide range of technologies and approaches. Consequently, outcomes classified under "Artificial Intelligence" can be so diverse that they resist easy generalization. A clear distinction can be made between Symbolic AI and Connectionist AI. Where Symbolic AI focuses on manipulating explicit symbols and rules to represent knowledge and reasoning (e.g., using logic-based systems like expert systems to solve problems), Connectionist AI, such as neural networks, models intelligence through distributed, interconnected units that learn patterns from data (e.g., a neural network recognizing images by adjusting weights between neurons)[2]. Machine learning, deep learning, and neural networks are interconnected sub-fields of artificial intelligence.[3] Machine learning involves using algorithms that often require human intervention to identify features in data, to allow AI to imitate the mechanisms of humans learning, gradually improving it's accuracy over time. Deep learning, a subset of machine learning, leverages neural networks with multiple layers to automatically process large, unstructured datasets with minimal human input, making it highly scalable. Neural networks, the foundation of deep learning, consist of interconnected nodes that simulate human brain functions, with deep learning referring specifically to networks with more than three layers[4]. What unites all of these varied technologies is their capacity to mimic human-like cognitive processes, such as learning, reasoning, problem-solving, and decision-making.

I will take intelligence to indicate the computational part of the ability to achieve goals in the world. Whilst this definition may appear incomplete, we should note that it is not yet possible to characterise, in general, what kind of computational processes we want to call intelligence without relating it to human intelligence. The cognitive sciences have not yet fully determined [5] the exact nature of human cognitive abilities, leaving ambiguity in our understanding of intelligence, both artificial and biological.

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[1]Wischmeyer, Thomas. 'Artificial Intelligence and Transparency: Opening the Black Box'. Regulating Artificial Intelligence, edited by Thomas Wischmeyer and Timo Rademacher, Springer International Publishing, 2020, pp. 75–101. DOI.org (Crossref), https://doi.org/10.1007/978-3-030-32361-5_4.

[2]Ai for beginners—The difference between symbolic & connectionist ai. (2020, September 24). RE•WORK Blog - AI & Deep Learning News. https://blog.re-work.co/the-difference-between-symbolic-ai-and-connectionist-ai/

[3]What Is Machine Learning (ML)? — IBM. 22 Sept. 2021, https://www.ibm.com/topics/machine-learning.

[4]What are Neural Networks? — Updated 2024. (n.d.). The Interaction Design Foundation. Retrieved 26 August 2024, from https://www.interaction-design.org/literature/topics/neural-networks

[5]Sabharwal, A., & Selman, B. (2011). Book review. Artificial Intelligence, 175(5–6), 935–937. https://doi.org/10.1016/j.artint.2011.01.005

2.2 Data and Algorithms

Additionally, it is worthwhile to consider that if it was possible to have a corpus of data large enough to map every possible input to a specific output (consider the "rulebook" in Searle's Chinese Room Argument) then, of course, there is no purpose for Artificial intelligence; no purpose for learning of any kind. Therefore, *learning* in AI can be defined as the ability to improve performance on a task through experience, without being explicitly programmed for every possible scenario. This foregrounds a necessary junction in engineering Artificially Intelligent systems; the relationship between the Dataset and the Algorithm. As Pedro Domingos, a prominent AI researcher, puts it, "as a rule of thumb, a dumb algorithm with lots and lots of data beats a clever one with modest amounts of it"[6]. In essence, an algorithm is a process for accomplishing a task. An instruction manual for an Ikea closet is a simple type of algorithm. Artificial Intelligence represents the most complex kinds of algorithms. Back in 2007, University of Alberta created an algorithm that could process over 500 quintillion (500 billion billion) games of checkers to have a completely deterministic model that would never lose a game (["computer program can't lose," 2007]. There are also unsupervised learning algorithms which researchers can shove in unstructured data and rely on machine learning methods to allow AI to find, otherwise undetectable, patterns. Many of these algorithms are imperfect and leading researchers, like those at OpenAI, use a variety of training methods (supervised pre-training, reinforcement learning, fine-tuning) to improve the performance of these algorithms. The primary distinction in cases like chatGPT and the game of checkers is that, many of our general purpose technologies that we desire (chatbots, image generators or even chess algorithms) are dealing with exponentially larger possible input sets. Although hard to conceptualise, the difference between checkers and chess, in terms of data points necessary for a deterministic algorithm, is incalculably large and quickly exceeds our processing capabilities as humans; we will not have a deterministic chess playing algorithm any time soon. This exponential increase in complexity is often associated with what is known as the "long tail" problem (Bengio et al., 2013)[7] .

Primarily, the data used in AI applications is observational—data collected without directly manipulating the variables being studied. Unlike experimental data where researchers would intentionally change the variables to observe the effects, some machine learning algorithms can attempt to uncover causal relationships from observational data, but their effectiveness is limited. This is because, without controlled experiments, it is challenging to distinguish between mere correlation and true causality. However, even though observational data cannot definitively prove causality, correlations found within it can be useful. A strong correlation between two variables might suggest a potential causal link, which can guide further research to explore the underlying cause-and-effect relationship. It should be noted that many researchers consider causality to be a convenient fiction[8]; for instance, physical laws do not inherently include the concept of causality. Whether causality truly exists is a profound philosophical question without a known definitive answer. However, for machine learning practitioners, the practical consideration is that,

[6]Domingos, P. (2012). A few useful things to know about machine learning. Communications of the ACM, 55(10), 78–87. https://doi.org/10.1145/2347736.2347755

[7]Bengio, Y., Courville, A., & Vincent, P. (2013). Representation learning: A review and new perspectives. IEEE Transactions on Pattern Analysis and Machine Intelligence, 35(8), 1798–1828. https://doi.org/10.1109/TPAMI.2013.50

[8]Neuberg, L. G. (2003). Causality: Models, reasoning, and inference, by Judea Pearl, Cambridge University Press, 2000. Econometric Theory, 19(04). https://doi.org/10.1017/S0266466603004109

regardless of how we label these relationships—causal or not—the objective of predictive models is to guide decision-making and action.[9] For countless companies and contemporary AI applications, this form of induction has proven to be highly effective, driving critical business decisions and operational strategies. For instance, in the manufacturing sector, companies like Siemens and General Electric use AI-driven predictive maintenance systems to anticipate machinery failures based on sensor data. Although these systems may not establish direct causal links between specific readings and failures, the correlations they identify are sufficient to guide timely maintenance actions[10], reducing costs and minimizing downtime. Ultimately, one key resource is needed to establish any correlation: data. This presents a clear dual incentive; firstly, for AI engineers, the drive is to collect more data, and secondly, for individuals or organizations with an excess of data, AI becomes the most effective tool to utilize that data.

3 Personal Identity

3.1 Key Concepts

What makes a specific individual that very individual? Many different answers to this question have been aired in the western philosophical canon. I will provide a very brief overview and then focus on two important features. The purpose of this section is not to argue for a particular account of personal identity being more complete (or metaphysically grounded), but to provide a framework of relevant features of the individual's personal identity to facilitate productive analysis of how our Artificial Intelligence will go on to impact it.

Outside of the philosophical canon, the term 'personal identity' references the features of ourselves to which we have a sense of attachment or ownership. The identity is made up of those properties which one uses to "make the person who they are" or to define their unique person-hood. Whilst the precise meaning of these phrases are hard to provide a-priori definitions of, this kind of personal identity is clearly ephemeral and contingent. In the way that it can vary across time and be built up on self-selected categories. I may identify as a student and comedian but not a man or weightlifter. Whereas an equivalent individual with the same properties may feel differently towards them; there is some self-selection at play here. The features which determine personal identity is known as the "characterisation question" [11]. Adjacent to this is the question of persistence; what does it take for a person to persist from on time to another. This second line of questioning wants to know what is necessary and sufficient for a past or future being to be someone existing now. The persistence of personal identity over time has previously been argued to be constituted by an individual's biological and/or psychological continuity, including memories, beliefs, desires, and crucially, their physical body. The emphasis on psychological continuity, perhaps most famously exemplified by John Locke's memory theory, posits that personal

[9] Kohavi, R., Longbotham, R., Sommerfield, D., & Henne, R. M. (2009). Controlled experiments on the web: Survey and practical guide. Data Mining and Knowledge Discovery, 18(1), 140–181. https://doi.org/10.1007/s10618-008-0114-1

[10] Predictive maintenance. (n.d.). [fw_Inspiring]. Siemens.Com Global Website. Retrieved 26 August 2024, from https://www.siemens.com/global/en/products/services/digital-enterprise-services/analytics-artificial-intelligence-services/predictive-services.htm

[11] Helm, P. (1979). Locke's theory of personal identity. Philosophy, 54(208), 173–185. https://www.jstor.org/stable/3750072

identity persists over time through the continuity of consciousness and autobiographical memory. Indeed, if a person woke up one morning with no memories of their past life, they would essentially be a different person, despite inhabiting the same body. In recent decades, philosophers have continued to expand this concept, recognising that identity is also shaped by our life stories and biological factors. For example, Marya Schechtam (1996) and other Neo-Lockean thinkers argue that we summarise and condense our past experiences into a cohesive autobiographical narrative, often referred to as the diachronic self[12], emphasising our ability to remember and connect past experiences as fundamental to our sense of self. Significant portions of the anglophone literature has also focused on enquiries about what makes a person as opposed to a non-person, what constitutes our personal ontology and what evidence can we use to qualify identity. These questions, albeit significant, will not be the focus of this paper. Instead, I will offer specific analysis on the impact of AI on the questions of characterisation and persistence.

3.2 A Framework for Personal Identity

In this vein, Dan P. McAdams' narrative identity theory offers a compelling framework for understanding personal identity through the lens of storytelling. McAdams suggests that our identities are shaped by the internalized and evolving narratives we create about our lives—stories that integrate our past experiences, present actions, and future aspirations into a cohesive whole. This narrative approach aligns closely with the Neo-Lockean emphasis on the diachronic (across-time) self but extends it by focusing on the ways in which we actively construct meaning and coherence in our lives. McAdams' model offers a framework that emphasizes the narrative construction of the self, which encompasses both the characterisation aspect (how we define ourselves at a moment) and the persistence aspect (how we see ourselves as the same person over time). This narrative identity model can be loseley divided into four different components[13]. Firstly, the individual's life-story is situated within an 'Ideological Setting' which can represent the backdrop of fundamental beliefs/values/principles that frame one's life story. For many parts of the Western world, ideological structures, such as a foundation of Judeo-Christian ethics and liberal democracy[14], frame the axioms from which other beliefs and decisions are built. Secondly, Personal Imagoes, where the Latin word "imago" for 'image' or 'representation' refers to the idealized and personified versions of 'the self' that we place upon other people in our lives. These characters are incorporated by an individual into their narrative as archetypes, personas, or antagonists, and thereby shape how the individual sees themselves in relation to others. The "caregiver" Imago might symbolize a nurturing and compassionate presence, perhaps in the form of a grandmother. It resonates with the common phrase "you are the average of the five people you spend the most time with", or at least, the labels you associate with seems to correlate with the 'imagoes' you choose to spend time with. Thirdly, referencing the role of key events in the past, McAdams calls 'nuclear episodes' to indicate particular turning points (moments of great success, joy, trauma, shock, or fear) in life where the experience of such events might serve to either reaffirm the person's continuity over time or indicate key moments of change. When we look back on our life

[12] Schechtman, M. (1996). The constitution of selves. Cornell University Press. https://www.jstor.org/stable/10.7591/j.ctv75d3xw

[13] McAdams, D. P. (2017). Life-story approach to identity. In V. Zeigler-Hill & T. K. Shackelford (Eds.), Encyclopedia of Personality and Individual Differences (pp. 1–4). Springer International Publishing. https://doi.org/10.1007/978-3-319-28099-8$_5$30 − 1

[14] Foucault, M. (1977). Discipline and punish: The birth of the prison (1st American ed). Pantheon Books.

narrative, it seems we often gravitate towards these climatic moments as reference points for our identity across time. Finally, the fourth category that the life story may contain is a 'Generality Script', which is a plan within the life story that outlines how the person intends to leave a positive legacy for future generations or represents the desire to extend their influence beyond their own life.

Across all four of these categories, McAdam argues that the there are "thematic lines" which represent the reoccuring themes or patterns in a person's narrative that reflect their core motivations. These themes often revolve around "agency and communion" (McAdams 1985, 1990). Agency in this case relates to the individuals pursuit of power, achievement and control over their life story; their desire to accomplish goals. Communion is the pursuit for intimacy and connection, which often manifests in a sense of belonging. The last variable, as resembled in figure 1, is identified as 'narrative complexity' to refer to the level of detail, nuance and interconnectedness of the plot of a person's life story. Some individuals have more straightforward and simpler connections between events nuclear episodes or imagoes.

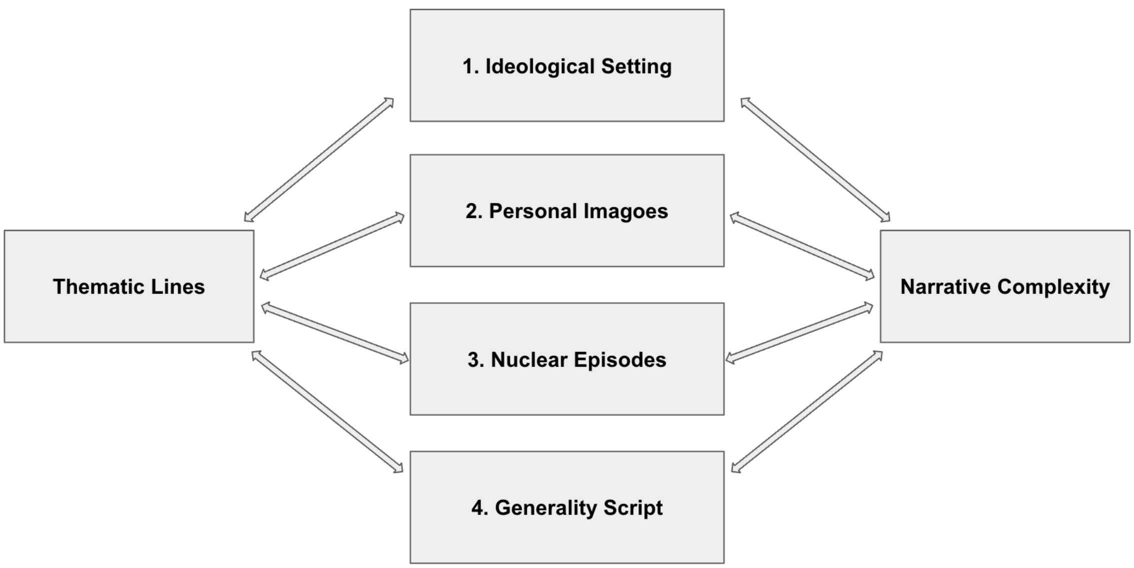


Figure 1: Identity as life story and its components – The model of Dan P. McAdams (McAdams, 1988, p. 61)

Contemporary researchers have examined how narrative identity develops (Fivush 2011) and conclude that variations in the depth and comprehensiveness of these self-stories are influenced by factors like gender and socioeconomic status[15]. Girls and children from higher socioeconomic backgrounds tend to create more elaborate narratives. These differences may also stem from the distinct ways parents engage in conversation with their children. As children grow, they begin to understand the typical life milestones expected within their culture—such as attending school, moving out, getting married, securing employment, and starting a family. It should be also noted that personal identity in this individualist

[15] Fivush, R. (2011). The development of autobiographical memory. Annual Review of Psychology, 62(1), 559–582. https://doi.org/10.1146/annurev.psych.121208.131702

and narrative form is a symptom of contemporary social structures. For a large portion of individuals who have been raised in isolation from traditional norms and rules thanks to increasing opportunities available to the average civilian, the rise in globalisation, digital connectivity and cultural pluralism.

> *"The patient of today suffers most under the problem of what he should believe and who he should—or... might—be or become; while the patient of early psychoanalysis suffered most under inhibitions which prevented him from being what and who he thought he knew he was"*
>
> –Erik Erikson, Childhood and Society (1993)[16]

In parrallel, it is simply the case that improved health and the widespread increasing in life spans has provided more opportunities for the internal life of the self to mature. As such, adolescents of today accept that life has become an "open-ended reality to be discovered rather than a certainty to be enacted." (Shoshana Zuboff, 2019) which is a certainty that would have otherwise been imposed by your blood, sex, kin, rank, religion and geography. Whilst this modern identity has risen prominently in wealthier countries, particularly those apart of the western imperial core, significant research reveals[17] pluralities of hyper-individualised constructions of the self in nearly every region of the world[18]. One reference point to illustrate this trend could be the self-improvement market which was valued at $38.69 billion in 2019 and is projected to reach $56.5 billion by 2024[19].

[16] Erikson, E. H. (1993). Childhood and society. Norton.

[17] Inglehart, R., & Baker, W. E. (2000). Modernization, cultural change, and the persistence of traditional values. American Sociological Review, 65(1), 19.https://doi.org/10.2307/2657288

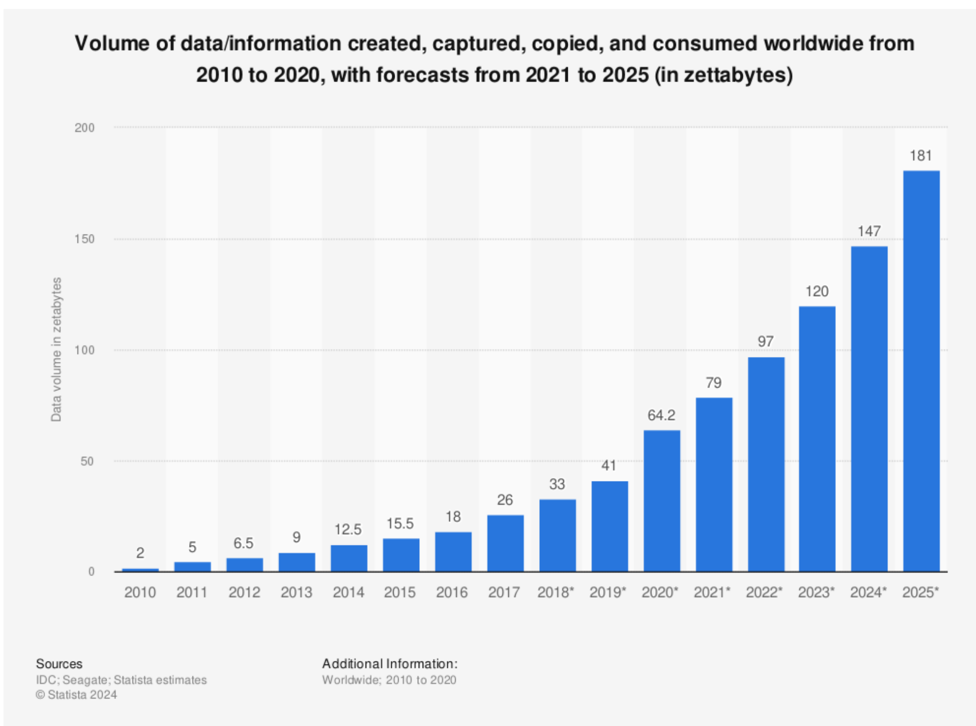
[18] Inglehart, R. F. (2008). Changing Values among Western Publics from 1970 to 2006. West European Politics, 31(1–2), 130–146. https://doi.org/10.1080/01402380701834747

[19] Us self improvement market size likely to grow at a cagr of 6. 2% by 2033. (n.d.). Custom Market Insights. Retrieved 30 August 2024, from https://www.custommarketinsights.com/press-releases/us-self-improvement-market-size/

4 Data and Digital Economies: The Socio-Economic Context of AI Implementation

4.1 The Rise of Data

In the late 1980s, less than 1% of the world's technologically stored information was in digital format, while it was 94% in 2007, with more than 99% by 2014[20]. Similarly, as an example of the increasing scale of data becoming available, it's estimated that Google processes over 8.5 billion searches per day, while facebook contributes 150 billion content interactions (including likes, comments, and shares) daily, all of which are stored and analyzed by various companies. Estimates suggest the global datasphere, encompassing all created, captured, and replicated data, reached a staggering 2.7 Zettabytes (1-Billion Terabytes) in 2017[21]. It is important to note that it is also increasingly difficult to escape the tracking of personal data due to the proliferation of digital devices and sensors embedded into our environments. Aside from our online activity, it is also the case that our phones, cars, home assistants, smartwatches, and other connected devices constantly collect data about our offline behaviors. This data is being used in a new economic system where human experiences and behaviours are commodified and exploited for profit through the extraction, analysis and sale of personal data. This fundamental transformation of the economic relationship between technology and power was proliferated by Shoshana Zuboff in her seminal work 'The Age of Surveillance Capitalism'.



[20]Hilbert, M., López, P. (2011). The world's technological capacity to store, communicate, and compute information. Science, 332(6025), 60–65. https://doi.org/10.1126/science.1200970

[21]Services. (n.d.). Health IT. Retrieved 30 August 2024, from https://healthit.com.au/

4.2 Surveillance Capitalism: A New Paradigm

As a socio-economic system, capitalism has historically been defined by private ownership of the means of production, reliance on wage labor, and the relentless pursuit of profit through commodity production and exchange. Central to capitalism is the continuous accumulation of capital, where wealth is reinvested to generate more wealth, driving economic growth (Harvey, 2010)[22]. However, as traditional avenues for capital accumulation have become saturated or less profitable, capitalism has adapted by finding new resources and methods to sustain growth. To illustrate how 5.45 billion users of technology are commodified, consider the development of the news in the US as one of the earliest iterations of the attention economy[23]. Whereas the initial newspapers were predominantly political instruments designed to mobilize and inform citizens, the advent of commercial newspapers marked a shift toward content that catered to entertainment and lifestyle interests, thereby addressing readers more as consumers than as engaged citizens. By the turn of the 20th century, the economic model of newspapers had transformed: advertising, rather than subscriptions, became the primary revenue source (Jones J)[24]. Advertisers, in their quest to maintain and grow their market, encouraged the press to focus on the "bright side of life" (Baldasty, 1992, p. 78), reasoning that content which fostered a sense of happiness and satisfaction would produce more receptive consumers. In this way, unlike commercial or industrial capitalism, the commodity for Surveillance capitalism is—as Zuboff identified—the users of technology. The data around our routines, feelings, activity, desires are for sale in a capitalist system where power is centralised around the digital sector. There seems to be a reluctance to confront the fact that some of biggest companies in the world (Goggle, Meta, Wechat, Youtube, Tiktok) have products that are entirely free and what is for sale is merely your attention. Notably, this data is heavily centralised, with 72% of global advertising spending is controlled by just two companies; Google and Facebook (Couldry & Mejias, 2019)[25]. Similarly, in 2014, Acxiom, a leading data broker, claimed to have 700 million customers worldwide and held over 3,000 pieces of information on every U.S. citizen.[26]

> *"We've seen the attention merchant's basic modus operandi: draw attention with apparently free stuff and then resell it ... This means that under competition, the race will naturally run to the bottom; attention will almost invariably gravitate to the more garish, lurid, outrageous alternative, whatever stimulus may more likely engage what cognitive scientists call our "automatic" attention as opposed to our "controlled" attention, the kind we direct with intent"*
> — Tim Wu, The Attention Merchants: The Epic Scramble to Get Inside Our Heads[27]

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[22]Harvey, D. (2011). The enigma of capital: And the crises of capitalism (Pbk. ed). Oxford University Press.

[23]White, P. B. (1994). The Commercialization of News in the Nineteenth Century by Gerald J. Baldasty (University of wisconsin press, usa, 1992), pp. Xii + 227, US$19.95, ISBN 0-299-13404-0 (Pbk). Prometheus, 12(2). https://doi.org/10.1080/08109029408629182

[24]Jones, J. (2024). Don't fear artificial intelligence, question the business model: How surveillance capitalists use media to invade privacy, disrupt moral autonomy, and harm democracy. Journal of Communication Inquiry, 01968599241235209. https://doi.org/10.1177/01968599241235209

[25]Couldry, N., Mejias, U. A. (2019). The costs of connection: How data is colonizing human life and appropriating it for capitalism. Stanford University Press.

[26]Reynolds, A. (2018). Web of deceit: Misinformation and manipulation in the age of social media. NATO Strategic Communications Centre of Excellence.

[27]Wu, T. (2017). The attention merchants: The epic scramble to get inside our heads. Knopf Doubleday Publishing Group.

4.3 AI's Role in Surveillance Capitalism

Zuboff continues to argue that "behavioral surplus" is harvested by companies to create detailed profiles and predictive models of individual behavior. These models are not only used to enhance the services provided but, more critically, they are sold to third parties, such as advertisers, who seek to influence consumer behavior. The crux of Zuboff's argument is that this process of data extraction and commodification occurs largely without the knowledge or consent of the individuals from whom the data is taken. This asymmetry of power[28] is a hallmark of Surveillance Capitalism, where the data collectors (often large tech companies) wield significant control over the data producers (the users). Moreover, Zuboff introduces the idea of "instrumentarian power"[29] a new form of power that Surveillance Capitalism exerts over society. Unlike totalitarianism, which seeks to impose control through overt coercion, instrumentarian power works by shaping and modifying behaviour subtly and continuously. Through the use of algorithms and data analytics companies can nudge users toward certain actions or decisions, often without the users being aware of this manipulation. This power operates through the constant monitoring and analysis of behaviour, effectively turning every aspect of life into a source of data that can be translated into profit.

Ultimately, the crucial mechanism to make sense of this data is Artificial Intelligence. As outlined in the first section, Machine Learning is able to work with observational data on huge scales to make connections that would otherwise be impossible with traditional statistic techniques. AlphaGo, Google's AI powered Go playing engine, was able to utilise the enormous corpus of data from previous games of Go to innovate patterns and strategies until it surpassed the expert players.

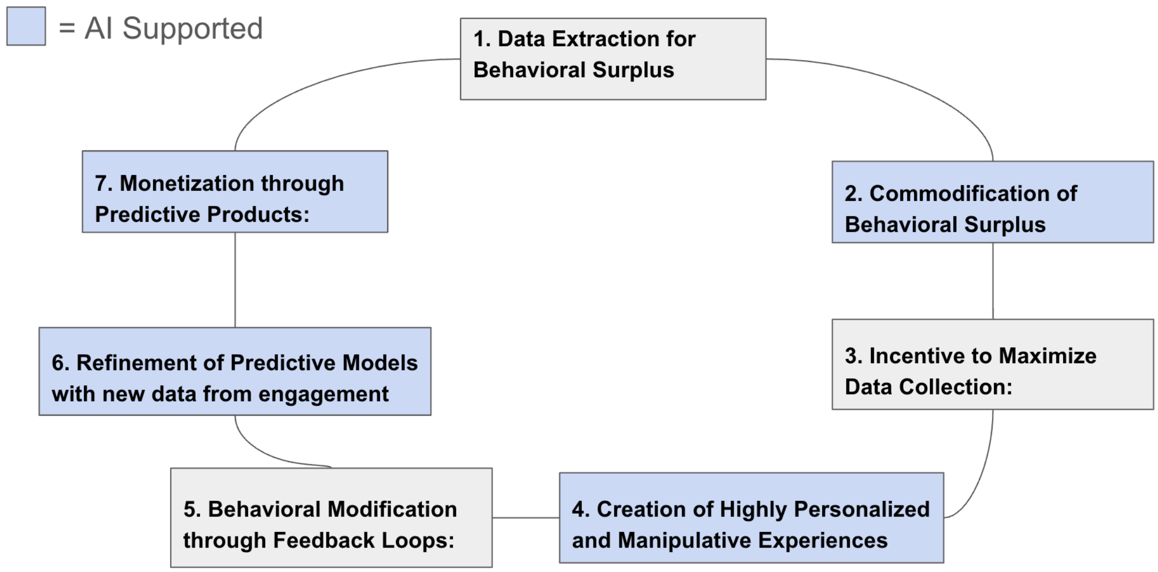
> *"big data's central power and peril is the ability to network and re-analyse datasets from highly disparate contexts—often in concert—to generate unanticipated insights. Datasets can no longer be considered static archives because they are now capable of generating new insights for researchers, and consequences for human subjects, indefinitely"* — Metcalf et al. Perspectives on Big Data, Ethics, and Society, 2016[30]

AI enhances the extraction of behavioural surplus by analysing vast datasets with unprecedented precision, enabling more refined and pervasive predictive models. This not only increases the efficiency of Surveillance Capitalism but also intensifies its expansionary logic. As AI-driven insights yield higher profits, they create powerful incentives for companies to deepen surveillance practices, further commodifying human experience.

[28] Ai and identity. (n.d.). Retrieved 29 August 2024, from Ai and identity. (n.d.). Retrieved 29 August 2024, from https://arxiv.org/html/2403.07924v2bib.bib20

[29] Risse, M. (2023). Political theory of the digital age: Where artificial intelligence might take us (1st ed.). Cambridge University Press. https://doi.org/10.1017/9781009255189

[30] Metcalf, J., Keller, E. F., & boyd, danah. (2024). Perspectives on big data, ethics, and society. Council for Big Data, Ethics, and Society. https://bdes.datasociety.net/council-output/perspectives-on-big-data-ethics-and-society/



Overview of the incentive landscape under Surveillance Capitalism; facilitated by Artificial Intelligence

Crucially, what needs to be understood is that Artificial Intelligence is not being implemented in a vacuum; it is deeply embedded within the existing socio-economic structures of Surveillance Capitalism. As AI becomes more sophisticated, it enables more granular and invasive forms of data collection. Is not a neutral tool, but has been developed and deployed within a specific incentive landscape; they are embedded with the biases, priorities, and objectives of the entities that create them. (For more on these Biases, see "Weapons of Math Destruction: How Big Data Increases Inequality and Threatens Democracy" by Cathy O'Neil[31]. Published in 2016). Whilst there are numerous ethical concerns with the possession and manipulation of this data that has been made possible by Artificial Intelligence, it is not the purpose of this essay to comment on the moral implications of these practices, but rather to set up the context within which personal identity is being impacted, focusing on an amoral analysis of the mechanisms that are shaping identity.

[31] O'Neil, C. (2016). Weapons of math destruction: How big data increases inequality and threatens democracy (First edition). Crown.

5 The Impact of AI on Personal Identity

This section seeks elucidate the extent to which an individual's personal identity is curated by the external AI systems imposed on them. In the age, where self-representation is cultivated and carried out online, the digital world has become the stage for individuals to platform their identity; "These platforms, equipped with AI algorithms, hold a dual role. They are both facilitators of self-expression and, simultaneously, influencers of how this self is portrayed" (Borivoje. (2023)[32]. Decoding identity and representation in the age of AI). For the purposes of compartmental convenience, I will go through the model of McAdam's Narrative Identity and provide analysis on the primary ways in which AI is redefining each category; crucial mechanisms that in shaping our identities. Recall that traditionally, identity representation was understood as a direct depiction of one's self-perception and how they choose to communicate this perception to the world. Indeed, this Foucauldian[33] intuition that the self was a construct of social norms and introspective reflection, may have to extend to include the digital footprint, AI metanarratives and algorithmic interpretations.

5.1 Ideological Setting

As described, an individual's 'ideological setting' is the broader set of beliefs, values and cultural norms that allow people to interpret experiences and form their life-story. Whilst autonomy over the ideological setting in which we found ourselves was never self-selected (we were simply born into a particular ideological setting), it is clear that AI and the digital 'ideological setting' presents a new modus operandi.

The newfound possession of personal data and the capacity to transform it through AI algorithms has developed into what we can call 'hyper-personalisation'—a concept that takes personalized user experiences to an unprecedented level (See Delliot's 2020 Report on Hyper-Personalisation Markets[34]). By tailoring content and recommendations to align with users' existing preferences AI facilitates an ideological setting that is no longer contingent on uniquely situated human (physicla) experiences—transcending the once-inescapable imprint of time, place, and inherited social worlds. In short, the claim here is that AI is shaping our ideological setting. A historical example is Google's search engine algorithm, which personalizes search results based on users' past behavior and data[35]. This personalization can lead to the "filter bubble" effect, where users are increasingly exposed to information that reinforces their existing viewpoints, thereby influencing their opinions, decisions. In this context, technologies like data collection, surveillance, and algorithms are seen as beneficial because they help individuals by giving them more of what they supposedly want. Whilst this level of personalisation can cause a heightened sense of belonging, they can also pigeonhole individuals into categorise predefined by the algorithm; diminishing the supposed plurality of human identity. It is important to note that data-driven behavioural predictions predates the

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[34] https://www2.deloitte.com/content/dam/Deloitte/ca/Documents/deloitte-analytics/ca-en-omnia-ai-marketing-pov-fin-jun24-aoda.pdf

[35] New Epsilon research indicates 80% of consumers are more likely to make a purchase when brands offer personalized experiences. (n.d.). Retrieved 31 August 2024, from https://www.epsilon.com/us/about-us/pressroom/new-epsilon-research-indicates-80-of-consumers-are-more-likely-to-make-a-purchase-when-bran

insurgence of AI. Indeed, throughout history, various institutions and power structures have attempted to gather information about individuals and populations to anticipate and guide their actions. From ancient census-taking and tax collection to the development of statistics and demographic studies in the 18th and 19th centuries, societies have long sought to quantify and predict human behavior. Indeed, the simple intention to systematically predict what human behaviour will be in the future is an extension of a fundamental mechanism of economics; demand. The need to understand consumers' desires and needs and predicting how these will change under various conditions helps maximise economic efficiency and profitability. Consider Target's pregnancy prediction model, first reported by Charles Duhigg in The New York Times[36] in 2012; by assigning unique Guest ID numbers to shoppers and analyzing purchase patterns across 25 product categories, Target's statisticians, using data analytics could predict pregnancies and due dates with remarkable accuracy. The results were used to send cupons for baby clothes and cribs. To avoid appearing intrusive, Target mixed pregnancy-related offers with unrelated products in their marketing materials. This has developed today as companies offer "prescriptive analytics" that have proven successful influencing behaviour. The potential for understanding human behaviour is so eminent that governments have exploited their capability, evidenced by the Cambridge Analytic scandal (Gross, 2019)[37] where data was harvested from millions of Facebook users and, with the help of machine learning, used to create highly personalized political ads. Supercomputers running machine learning models can continuously process data to refine their predictions and recommendations, learning iteratively to improve over time. Drawing on Section I and III, this ability to "search for emergent relationships among attributes in data" means that algorithms can uncover insights that users themselves may not be aware of, potentially allowing companies to "know us better than we know ourselves" (Nissenbaum, 2010, p. 44)[38].

Additionally, the application of AI for the seemingly honest end of 'personalisation' quickly shifts the ideological landscape available to individuals in the form of reinforcing specific beliefs or values while marginalising others. This curated experience reshapes the ideological setting by filtering the diversity of perspectives to which individuals are exposed, thereby moulding their values and beliefs in ways that align that which is advantageous to the AI systems. The simple asymmetry between the developers of these systems and the users (an international, intergenerational and intercultural audience) that consumes it, presents a key schism in distribution of AI algorithms. It is empirically clear that AI is inherently shaped by those that develop it and their particular 'ideological settings' play a crucial role in determining the direction and values embedded in the technology (Schiff et.al, 2020[39]). This small group of AI developers and researchers, primarily from Western, educated, industrialized, rich, and democratic (WEIRD) societies, holds significant power in shaping the values embedded in AI systems. The training data captures the obersvaetional data which is encoded with prejudice and then perpetuates it through

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[36] Duhigg, C. (2012, February 16). How companies learn your secrets. The New York Times. https://www.nytimes.com/2012/02/19/magazine/shopping-habits.html

[37] Gross, T. (2019, October 8). Whistleblower explains how cambridge analytica helped fuel u. S. 'Insurgency'. NPR. https://www.npr.org/2019/10/08/768216311/whistleblower-explains-how-cambridge-analytica-helped-fuel-u-s-insurgency

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the outcomes of the algorithms. As argued by Safiya Noble (2018) in 'Algorithms of Oppression'[40] that "algorithmic oppression is not just a glitch in the system but, rather, is fundamental to the operating system of the web". As AI becomes increasingly central to decision-making in various sectors—from healthcare to security—the values and assumptions of this minority group are being homogenized across global applications (Stathoulopoulos and Mateos-Garcia 2019[41]). Indeed, we can see that AI perpetuates a limited ideological foundation due to the concentration of its development in the hands of a small, relatively homogeneous group of individuals, particularly within the tech industry. Google Translate has been criticized for reinforcing gender stereotypes. For example, when translating gender-neutral sentences from languages like Turkish or Hungarian into English, the system often defaults to gender stereotypes (e.g., translating "o bir doktor" as "he is a doctor" and "o bir hemşire" as "she is a nurse"[42]). This bias arises from the training data, which reflects existing gender stereotypes in the languages and texts used to develop the model. More pervasive examples of this include studies, such as those by Joy Buolamwini and Timnit Gebru (2018), demonstrating that facial recognition systems from major tech companies, including IBM, Microsoft, and Amazon, had significantly higher error rates when identifying women and people of color compared to white men. This bias is attributed to the lack of diversity in the training datasets used to develop these systems, which were predominantly composed of images of white males. In this way, it is clear that the rituals, cultural events or intersectional experiences that don't conform the algorithms criteria or training data are quickly undermined (Hall, 1980)[43]. Ultimately we can observe a homogenising or narrowing of the 'Ideological setting' for casualties of these endemic AI structures.

5.2 Personal Imagoes

'Personal Imagoes' are also subverted under the paradigm of Artificial Intelligence as our our 'life stories' are detached from any semblance of the philosophical understanding established in section 2 and replaced by a set of statistical datapoints. These AI structures attempt to represent each user's unique identity through a collection of quantifiable attributes, essentially creating a digital approximation of the individual. This representation often exists in the form of high-dimensional vector fields[44] to statistically capture a specific individual. At its core, we know that machine learning operates on the principle of identifying patterns and correlations within data. When applied to human-generated data, these algorithms operate over *statistical representations* of individuals and groups. These representations are not simply mirrors of reality, but rather probabilistic models that capture tendencies, preferences, and behaviors across large populations. Allow us to consider the specific example of an algorithm

[40] Noble, S. U. (2018). Algorithms of oppression: How search engines reinforce racism. New York University Press.

[41] Stathoulopoulos, K., & Mateos-Garcia, J. C. (2019). Gender diversity in ai research (SSRN Scholarly Paper 3428240). https://doi.org/10.2139/ssrn.3428240

[42] Schulz, L. (n.d.). Beware of stereotypes in machine learning. – Lothar schulz. Retrieved 31 August 2024, from https://www.lotharschulz.info/2023/03/03/beware-of-stereotypes-in-machine-learning/

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[44] Introduction to vector databases(Ai). (n.d.). Retrieved 31 August 2024, from https://www.devlane.com/blog/introduction-to-vector-databases-ai

called ASTA[45] who is trained on approximately 50 input parameters to make a decision (high likelihood prediction) to determine the risk of long-term unemployment for Danish citizens. This model takes this set of parameters and creates a profile for each user with their respective set of 50 data points. Most of these data points are expected – age, income, gender, previous employment status – but some are not; "the longitude of the citizen's residence", "the number of different social workers involved with the citizen's case at the job placement center", "whether the citizen allows the job placement center to send him or her text messages". Intuitively, these ASTA parameters seem completely unrelated to our ordinary understanding of which factors contribute to the risk of enduring long-term unemployment. That is, the ASTA parameters do not reflect properties that we would ordinarily accept as being relevant to the questions about our occupational or professional identity.

Similar models[46] are being developed to address criminal justice requirements, including the identification of individuals and their actions in video footage related to criminal activities or public safety, DNA analysis, gunshot detection, and crime prediction. In criminal justice predictive policing algorithms use data points such as neighborhood demographics, past crime statistics, and even social media activity to forecast potential crime hotspots or identify individuals at risk of committing crimes. These models often incorporate seemingly unrelated factors like weather patterns or local events, which may not intuitively correlate with criminal behavior. All in all, being statistically related to an individual is not the same as being, narratively, psychologically or biologically related to that individual; the once philosophical category of Personal Identity is appropriated by these systems in whatever way optimises their outcomes. In this way, the concept of the "statistical individual," as defined by algorithmic predictions, undermines McAdams' idea of "personal imagoes"—the central characters in our life story that embody our aspirations, fears, and ideals—by fracturing the continuity and unity of our personal narrative identity. McAdams posits that these imagoes are integral to the coherent narrative we construct about our lives, drawing from our psychological and social experiences. However, when algorithms use non-self-relatable data points (like phone charging habits) to make decisions about us, they represent us as fragmented collections of unrelated attributes rather than as coherent, unified individuals. This statistical reduction can alienate individuals from their own life story, as the algorithmic representation fails to capture the deeper, narrative-driven aspects of their identity, thus challenging their sense of self and responsibility. Furthermore, the human tendency to anthropomorphize AI systems complicates this dynamic. As people increasingly interact with AI in education and work environments, they project human-like qualities onto these systems, which could deepen the psychological and sociological dissonance between the AI's statistical representation and the individual's narrative identity (Maher, Tadimalla, and Dhaman, 2023[47]). The human tendency to anthropomorphize AI systems can intensify the dissonance between the algorithm's statistical representation and our personal imagoes.

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[45] Denmark. (n.d.). Automating Society Report 2020. Retrieved 31 August 2024, from https://automatingsociety.algorithmwatch.org/report2020/denmark

[46] Ugwudike, P. (2022). Predictive algorithms in justice systems and the limits of tech-reformism. International Journal for Crime, Justice and Social Democracy, 11(1), 85–99. https://doi.org/10.5204/ijcjsd.2189

[47] Maher, M. L., Tadimalla, S. Y., & Dhamani, D. (2023). An exploratory study on the impact of ai tools on the student experience in programming courses: An intersectional analysis approach. 2023 IEEE Frontiers in Education Conference (FIE), 1–5. https://doi.org/10.1109/FIE58773.2023.10343037

5.3 Nuclear Episodes

In McAdams' framework, nuclear episodes represent key scenes or events from an individual's past that play a crucial role in shaping their identity narrative. These episodes, such as high points, low points, and turning points in life, serve as anchors for the life story, providing continuity and meaning As of 2024, there are 5.45 billion[48] people use the internet everyday, of which, the average global user spends approximately 6 hours and 31 minutes online. Accounting for approximately 40% of waking hours, it is unsurprising that the our interactions and experiences with these algorithms are increasingly shaping our life-narratives through altering the way in which episodes in our lives are experienced and remembered. As we know, the sophistication of AI offers the potential to capture, store, and retrieve vast amounts of personal data, including audio-visual recordings, biometric information, and contextual details of daily experiences. On one hand, this hyper-documentation might enhance the accuracy and richness of our memories, allowing for a more detailed and faithful reconstruction of pivotal moments. This could lead to what might be termed 'high-fidelity nuclear episodes,' where the subjective haziness of human memory is replaced by crystal-clear, AI-curated recollections. However, this very precision poses a philosophical conundrum: does the elimination of memory's natural malleability—its tendency to evolve and be reinterpreted over time—potentially rob nuclear episodes of their dynamic, meaning-making function in identity formation? The flexibility of human memory, often seen as a flaw, might in fact be a feature crucial to adaptive identity construction.

A counterargument to these scenarios is the idea that the essence of nuclear episodes lies not in their factual accuracy or experiential intensity, but in their subjective significance and the meaning ascribed to them by the individual. From this perspective, AI's influence on the formation and recall of nuclear episodes might seem superficial—enhancing the 'how' of remembering without fundamentally altering the 'why.' Proponents of this view might argue that the human capacity for meaning-making will always transcend the capabilities of AI, ensuring that nuclear episodes remain a deeply personal and uniquely human aspect of identity. However, this position may underestimate the profound ways in which AI could shape the context and criteria by which we assign significance to life events. As AI systems become more integrated into our decision-making processes and social interactions, they may subtly influence which experiences we perceive as pivotal. For instance, an AI assistant that continuously analyzes our emotional states and life satisfaction might highlight moments of significant change that we would otherwise overlook, effectively 'nominating' new nuclear episodes for our life story. This AI-mediated self-reflection could lead to a more analytically rigorous, but potentially less intuitively resonant, selection of nuclear episodes. Furthermore, as our experiences become more AI-mediated, the spontaneity and unpredictability that often characterize life's most memorable moments—qualities that may not align with the interests of surveillance capitalism—might be diminished, leaving us with a more uniform and externally influenced set of life-defining episodes.

[48] Digital around the world. (n.d.). DataReportal – Global Digital Insights. Retrieved 31 August 2024, from https://datareportal.com/global-digital-overview

5.4 Generality Script

When it comes to the concept of a 'Generativity Script' — the intuition to extend the self's influence beyond the temporal boundaries of one's own life — It should be noted that the categories established by McAdams are not mutually exclusive, and the shift in ones 'Ideological Setting' will undoubtably have implications on the 3 other categories. Whilst it is not the purpose of this essay to provide an analytically complete account of the impact of AI on our identity by examining this co-dependance, it is clear that, for many online agents, their Generality Script - their legacy plans - are algorithmically influenced and guided by AI-driven nudges. Just as Baudrillard claims "We live in a world where there is more and more information, and less and less meaning."[49] we could expect him to similarly argue that AI's impact on the generativity script exacerbates the detachment from reality, as the focus shifts from creating a lasting, meaningful legacy to constructing a legacy that fits the algorithmically determined norms of visibility and influence. In this sense, AI transforms the generativity script into yet another simulation or false representation of reality—a carefully curated narrative that may have more to do with how future generations perceive one's contributions than with the actual substance of those contributions.

A counterargument to the previously critical scenarios may argue that the notion of true generativity is fundamentally rooted in human values, emotions, and lived experiences - elements that AI, no matter how advanced, cannot fully replicate or understand. Proponents of this view might argue that while AI can enhance the execution of generativity scripts, it cannot supplant the deeply human motivation behind the desire to leave a lasting, positive impact. The essence of generativity, they might contend, lies not in the quantifiable outcomes but in the intentionality and emotional investment of the individual. Moreover, the global reach and interconnectedness enabled by AI technologies introduce new dimensions to how generativity scripts might be formulated. The ability to have real-time, AI-mediated impact on a global scale could lead to 'distributed generativity scripts'—legacy plans designed for a worldwide impact, transcending geographical and cultural limitations. This global perspective could foster a more cosmopolitan approach to legacy-building, aligning individual efforts with broader concerns like climate change or global inequality. Additionally, AI's potential to extend human cognitive capabilities and lifespan adds complexity to generativity scripts. The possibility of radical life extension through AI-driven medical advances could fundamentally alter the temporal scope of these scripts, leading to 'multi-generational generativity scripts,' where individuals plan their influence across several generations. Conversely, extended lifespans might paradoxically diminish the urgency of generativity, as the finitude that motivates such concerns becomes less imminent.

However, this position may underestimate the potential for AI to engage with and influence human values and motivations. As AI systems become more sophisticated in understanding and predicting human behavior, they may develop the capability to subtly shape our values and aspirations, including our generative impulses. This raises the unsettling possibility of 'algorithmically influenced generativity,' where our legacy plans are unconsciously coopted by the imperatives of AI. Such a scenario would require us to critically examine the authenticity and autonomy of our generative efforts in an AI-saturated world.

[49] Baudrillard, J. (n.d.). Simulacra and simulation. Translated by Sheila Faria Glaser. Ann Arbor: University of Michigan.

6 Conclusion

Modernity has promoted the idea that individuals are free agents, capable of shaping their own destinies through personal choice and self-determination. This meta-narrative perpetuates the assumption that we have the power to construct our personal narratives independently, free from external constraints. Many argue this notion of autonomy is often more aspirational than real. Similarly, we are reminded by Alasdair MacIntyre, in his work After Virtue[50], that our sense of self is not something we create in isolation. Instead, our personal narratives are embedded in and shaped by the larger narratives of the communities to which we belong. MacIntyre suggests that the idea of an individual completely self-determined identity is a myth; rather, our identities are co-constructed within the fabric of our social relationships and cultural traditions. On the one hand, AI might seem to threaten the already limited autonomy we have over our personal narratives by introducing new forms of external influence. On the other hand, if we accept that our autonomy was never fully real to begin with, AI might simply represent another layer in the complex web of factors that have always shaped our identities. However, whether or not it was true that we individuals had control over our identities at any point in history, the new role of AI-powered technologies dispels any hesitations of our status as deterministic agents. Suppose it was previously the case that there were some aspects of human identity that was not clearly deterministic- our ability to control private information or to cultivate personal desires- in an AI mediated world, these final vestiges of agency seem to have been usurped. Proponents of McAdam's view of identity - our personal narratives - must accept that these stories are not static and they evolve over time as we reinterpret our past experiences and adapt to new circumstances. Whilst up until this point, the aforementioned operations of AI signal a removal of autonomy from the individual over their personal narratives. The categories introduced by McAdam's are dramatically changing in the direction in which Artificial Intelligence encourages as an algorithmic creator, curator, and mediator. And if AI takes over this role, should we be concerned about handing over control specifically to this black box. Perhaps more specifically, while AI may indeed influence our narratives in new and profound ways, it also challenges us to rethink whether the autonomy we believe we have over our identities is real or merely another narrative we tell ourselves.

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