A Socio Algorithmic Systems Variant of The Bioecological Systems Theory of Human Development: AI, Big Data, and The New Challenges of Researching Youth

Avriel Epps

Harvard University

Author Note

Avriel Epps-Darling https://orcid.org/0000-0001-8887-9942

I have no conflicts of interest to disclose. This study was not preregistered. There are no data or study materials to be made available to the public. Thank you to Nancy E. Hill, Luke Miratrix, and Michael D. Smith for providing feedback on drafts of this manuscript. Correspondence concerning this article should be addressed to Avriel Epps-Darling, Harvard Graduate School of Arts and Sciences, 1350 Massachusetts Ave, Cambridge, MA 02138. E-mail: avrielepps@g.harvard.edu

Abstract

This article proposes a human development framework considering the socio-algorithmic ecology of today's world, based on Socio Technical Theory, Critical Race Digital Studies, and Relational Developmental Systems models. It addresses how AI and machine learning impact human development during sensitive periods in a unique socio-historical context. Existing frameworks should be extended to account for direct and indirect interactions with machine learning and AI, acknowledging deep inequities across race, gender, and ability, posing challenges for marginalized youth. The article concludes with suggestions for empirical research, relevant questions for developmental scientists, and methodological considerations.

Keywords: Machine Learning, Artificial Intelligence, Human Development, Human-Computer Interaction, Algorithmic Bias

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Introduction

Algorithms significantly influence our daily experiences and development in complex ways. Despite their impact on social, psychological, and biological processes, the developmental science literature scarcely examines predictive computation. This article seeks to establish a human development framework that addresses the socio-algorithmic nature of today's world and guides future research. It introduces predictive technologies and socio-algorithmic systems, discusses their biases, and proposes a new model, the Socio Algorithmic Systems Bio-Ecological Model (SASBEM) of Development, along with its potential contributions and future research directions.

Defining Socio Algorithmic Systems

Our world is increasingly socio-algorithmic, where experiences are shaped by algorithms that mediate or replace human interactions. These computational systems are supported by cloud computing, networked systems, machine learning techniques, and increasing compute power (Haenlein & Kaplan, 2019). Machine learning models make predictions based on vast amounts of data, but these predictions can be questionable.

Machine learning drives AI, which learns through trial and error to perform tasks (Haenlein & Kaplan, 2019). AI uses sequential decision-making to achieve goals while updating statistical models. However, technology is not neutral (Kranzberg, 1986), and algorithms reflect the culture, history, and biases of their creators (Nissenbaum, 2001). These biases have led to numerous negative outcomes.

Predictive technologies often subtly nudge users, and decision-makers such as doctors and judges use them in high-stakes situations. Autonomous machines may make AI more apparent in our lives, but machine learning is already pervasive. Our world can be seen as a socio-algorithmic dialectic where computational systems are produced by humans and shape how humans function within those systems.

Given the deeply embedded nature of predictive computation in society, we cannot see "society" as separate from machine learning or machine learning as separate from "society". Instead, one can conceptualize our world as a socio algorithmic dialectic, where computational systems are produced by humans with specific goals and needs and then shape how those humans function in those human-computer systems.

In the industrial age, organizational theorists defined socio technical systems as production systems requiring a technology and a relationship structure that related human operators both to the technology and each other. Scholars have mainly applied this theory to understanding labor and the workforce. However, one can apply foundational ideas about socio technical systems to understanding the socio technical realities of all aspects of life. Cooper and Foster (1971) wrote that "technology makes demands and places limits on the type of work structure possible, while the work structure itself has social and psychological properties that generate their own unique requirements with regard to the task to be done. (p. 1)" Similarly, modern computation makes demands and places limits on the type of social structures or developmental contexts that are possible. In contrast, developmental contexts themselves have social and psychological properties that generate their own unique requirements concerning the developmental task at hand. There are first and second-order socio technical units that define the relationship an individual has with their machinery. These "psycho-technical" and "socio technical" units are the direct relationships that individuals and social groups, respectively, have with technologies. In socio technical systems theory, these units create a socio technical system (Cooper & Foster, 1971).

Socio algorithmic systems are socio technical systems that are concerned with data-driven, computational, and predictive technologies. Socio Technical Theory is particularly well-suited to frame thinking about machine learning and AI. In comparison to the production machinery that early organizational theorists like Cooper and Foster referred to, machine learning explicitly exploits and makes use of the relationships between individuals and between individuals and the technologies they use by generating data about those interactions and then recycling those data back into a statistical model to improve its predictions.

The Socio Algorithmic Systems Bio-Ecological Model (SASBEM) of Development seeks to fill this gap by incorporating algorithmic influences into a comprehensive framework. It acknowledges the complex interplay between individuals, their environment, and the algorithmic systems that permeate daily life. By examining risk and resilience factors, adaptive coping mechanisms, and the impact of socio-algorithmic systems on development, SASBEM can help guide research and inform interventions.

Value Laden and Biased Algorithms in an Inequitable World

Computers have long shaped and been shaped by politics of power, racial law, and the history and long-standing culture of white supremacy in the US (Coleman, 2009; Dutton & Kraemer, 1980; McPherson, 2011; Nakamura, 2009). The widespread collection of biometric data at airports, borders, stores, and social media was motivated and normalized by the War on Terror and fears of radical Islam post 9/11 (Nakamura, 2009). The development of the UNIX operating systems is entangled with post-world-war II racial tensions and still shapes computing today, and, specifically, "the very structures of digital computation developed at least in part to cordon off race and to contain it (McPherson, 2011, p. 24)."

Computers have explicitly and inadvertently concretized racial and gender barriers to opportunity throughout history (Benjamin, 2019; Browne, 2015; McPherson, 2011). Developers of machine learning and AI have continued this horrific legacy by promulgating biases in their systems. Researchers have uncovered algorithmic bias – or the systematic errors in machine learning and AI that reinforce existing social inequities – in social media platforms, online games, governmental use technologies, criminal justice, law enforcement, education, healthcare, finance, and generalized technologies such as facial recognition

(Barocas & Selbst, 2014; Bozdag, 2013; Buolamwini & Gebru, 2018; Crawford, 2021; Eubanks, 2018; Hajian et al., 2016; Noble, 2018; Trammell & Cullen, 2021). Mounting evidence and emerging theories suggest that these biases are not only a result of technical issues arising from data limitations or their statistical models' properties but also from long-standing imperialist, white supremacist, and patriarchal social norms that permeate the tech industry and academia (Benjamin, 2019; Browne, 2015; Le Bui & Noble, 2020).

Problematic implementations of algorithmic decision-making can insidiously impact populations that are already marginalized. The types of biases recently found in data driven applications are simply the newest addition to a collection of technologies that have been used to reinforce the marginalization of certain groups, differentiated by race, ethnicity, religion, language, gender, or ability status among other things. This problem is not only systemic – rooted in unjust hierarchies instituted during the Western world's mass colonization project that now touch every facet of daily life – but it can also be evaluated as a more proximal, structural issue. In industry, it is common for data scientists to collect data and train models without legal or ethical scrutiny, so long as organizational performance indicators are met and overall prediction accuracy increases (Broussard, n.d.). At research institutions, legal and algorithmic frameworks for fair decision-making are sometimes developed in stovepipes, without consideration for what is just, given current social realities, rather than what is simply "fair" according to a homogeneous group of technologists (Broussard, n.d.). Many data scientists lack training or resources to engage scholars in other disciplines or real-world organizations that could put theoretical developments into practice (Broussard, n.d.).

Critical scholars who study biases in machine learning and AI have found intersectional frameworks to be appropriate for grounding their work (Broussard, n.d.; Le Bui & Noble, 2020; Tynes et al., 2015). Intersectional Theory applied to algorithmic fairness posits that algorithms work to uniquely privilege and disadvantage individuals based on the combination of their identity factors (Noble, 2018). This body of research posits that differential impacts of algorithms along the axes of multiple identity markers do not operate in a simple, additive fashion but rather marginalize and privilege individuals in wholly unique ways. As Noble (2018) illustrates, the way Google search once treated a query for "Black girls" was qualitatively different from the way it treated a query for "Black children" or a non-racialized query for "girls." Similarly, internal documents at Facebook revealed the discriminatory nature of their algorithms designed to differentiate between hate speech and political expression (Angwin & Grassegger, 2017). Posts that included the words "white men" were flagged and censored, but the algorithms did not give equal weight to posts that included the words "Black children" because, as Facebook argued, "children" do not belong to a protected identity class such as race/ethnicity or gender (Angwin & Grassegger, 2017).

This example illustrates how an essential aspect of identity has largely been missing from discourses on AI's deleterious effects on marginalized communities: age. A recent report found that tech companies strategically overlook the unique experiences of their teen users, which results in norming their products on adults (Lenhart & Owens, 2021). Youth of color, marginalized by their race/ethnicity and age (among potentially many other intersecting identities such as gender, sexual orientation, ability, class, immigration status, and native language), face higher risks of differential treatment by algorithms despite. Despite being targeted as an emerging consumer demographic, data sets tend to underrepresent youth, and Big Tech's data scientists do not optimize machine learning models for young people in most cases (Lenhart & Owens, 2021).

Research in developmental science supports the notion of the harmful and differential effects of screen time and social media use on youth of color (Tynes et al., 2015; Tynes et al., 2008; Tynes et al., 2012; Tynes et al., 2019; Weinstein et al., 2021). However, none has focused on the effects of biases in the underlying structures of digital technologies, rather than just the content shared on or social interactions facilitated by them. It is crucial to recognize that predictive computation is more than just new media and research on predictive technologies should extend beyond the bounds of inquiry on social media and screen time. Most of this existing research, if not all, has viewed daily-use technologies as a form of media. However, popular apps like YouTube, Instagram, and TikTok, are not necessarily concerned with the production of media as much as they are concerned with the production of data through constant surveillance of their users' behavior across devices and services not limited to their apps. One could view the technologies youth use during their screen time as surveillance technologies, and perhaps it would be more accurate to do so (Zuboff, 2019). The FAANG (Facebook, Apple, Amazon, Netflix, and Google) companies' primary business objectives are to uncover the truth about who their users are—their identities, beliefs, habits, and desires—so that they can exploit that data for financial and political gain (Zuboff, 2019). The surveillance baked into social media's technological structure makes it much more similar to the technological structure and business model of, say, predictive policing tools than to the technological structures and business models of PBS or Fox's production studios.

When theorizing social media as surveillance technology, one can more accurately view it as a small part of a larger ecosystem of digital technologies that surveil developing humans to various ends. Rather than thinking about social media as an extension of traditional media, let us conceptualize social media as existing within the ecosystem of other data-generating and data-driven technologies, such as facial recognition, risk assessment algorithms, information retrieval services, and even self-driving cars. This class of objects are different from those that humans have designed in the past – they are tools, yet they are designed to operate autonomously; they are machines but they are designed to mimic human neural processes; they are hyper-individualized yet hyper-connected and scalable. Their role in developmental contexts is nebulous, seemingly omnipresent, yet under-theorized.

Human Development in Socio Algorithmic Ecologies

Developmental Science must extend its models to reflect the socio algorithmic systems in which development processes now occur. Research should pay particular attention to the unique challenges that socio algorithmic ecologies pose for children from marginalized communities. Fortunately, well-supported, established developmental models can ground this work. By updating these established models to reflect the socio algorithmic nature of the modern world, I build upon the vast empirical literature that informs the field's current understanding of how the body, brain, and mind respond to developmental stressors and supports in various contexts.

This section will examine the existing developmental models that can be applied to the study of socio algorithmic ecologies of development with some updates: Bioecological Systems Theory, Developmental Contextualism, The Specificity Principle, and Phenomenological Variance Ecological Systems Theory (PVEST). I will argue that all of these theories fall short in that they do not account for the omnipresence of predictive technologies in many developmental contexts. Then, I propose a preliminary framework for research that seeks to combine the theories of Developmental Science and Critical Algorithm Studies to fill the aforementioned gaps.

Foundational Developmental Models

Relational Developmental Systems (RDS) theories emphasize the interplay between individual biological factors, interpersonal relationships, and social institutions that influence a child's development. Bronfenbrenner's Bioecological Systems Theory (1977) is a prominent example, asserting that various social and biological systems are nested within each other, like a set of Russian dolls. This theory enables researchers to examine development from the individual's immediate surroundings (e.g., family, peers, schools, neighborhood) to more complex and distal influences (e.g., public policies, economic systems, cultural norms).

The "concentric circles" model provides a balanced framework for studying development, avoiding an overemphasis on either individual processes (biological determinism) or institutional explanations (social determinism). Bioecological Systems Theory is practical because it helps researchers define the properties of development: Process, Person, Context, and Time (Bronfenbrenner Morris, 2007). This clarity allows for the development of targeted policies and programs that enhance youth and family development, taking into account the specific institutions and organizations that affect their lives.

In Bronfenbrenner's model, the term development refers to "stability and change in the biopsychological characteristics of human beings over the life course and across generations (U. Bronfenbrenner & Morris, 2007)(p. 796)." The model does not assume that these biopsychological processes will necessarily change, or stay constant within the same person over time. The dynamic nature of processes is usually the subject of inquiry. Bronfenbrenner also proposes that human development occurs through proximal processes. Proximal processes become progressively more complex and involve reciprocal interaction between an active, evolving human organism and the other people, objects, and symbols in the organism's immediate environment. These interactions must occur regularly over extended periods to be effective. Proximal processes vary as a function of: (1) the characteristics of the developing person and the environment within which those processes are taking place; (2) which developmental outcomes are of interest; and (3) the varying social structures throughout the life course in the historical period during which the person is living. In this model, the personal characteristics of the developing human are both an indirect producer and a product of development. Bronfenbrenner's concentric circles model is shown in Figure 1.

Algorithmic systems might fit into Bronfenbrenner's model in several ways. Algorithms can influence the immediate environment (microsystem) and interactions that an individual experiences, such as personalized content on social media, targeted advertising, or algorithm-driven recommendations. These personalized experiences shape an individual's behavior and attitudes. Algorithms can play a role in influencing the connections between different microsystems in the mesosystem, for example, by affecting communication between family members, friends, or teachers through social media and messaging platforms. Algorithms can impact exosystem contexts such as parental workplaces, community organizations, or governmental policies, for instance, by shaping hiring practices, surveillance systems, or automated policy decisions based on data analysis. Algorithms contribute to the dissemination of information, ideas, and biases at the societal level (macrosystem), thereby affecting cultural norms and attitudes. They can also perpetuate or challenge existing power structures and social inequalities. As algorithms evolve and become more pervasive, they will likely have an increasing impact on human development on the axis of the chronosystem. Studying these temporal changes and their implications is crucial for understanding the role of algorithms in the bioecological systems model.

Individual← →context relationships form the basis of modern developmental theory, such as Developmental Contextualism, which links human development to the contexts of individuals' lives (Lerner, 1991; Lerner et al., 1999). This paradigm considers the dynamic processes between and within individuals and their context as essential for scientific inquiry. Key contexts include family, peers, school, and community (Hill Redding, 2021). Development is bidirectional, meaning individuals shape and are shaped by their context (Markus Kitayama, 2010).

Lerner's Developmental Contextualism highlights individuals' active role in shaping their development, development's contextual dependency, and its life-span perspective (Richardson, 2011). Adaptation to context occurs at specific times and places for specific individuals or institutions (Bornstein, 2019; Lerner, 2015).

To integrate predictive technologies into Lerner's Relational Developmental Systems (RDS) model, researchers can treat them as a critical contextual component, examining their interactions with individuals, organization levels, temporality, diversity, and adaptation processes. By incorporating predictive technologies into the RDS model, researchers can explore their temporal influence on development and the potential for plasticity in response to these technologies. Predictive technologies may have differential effects on individuals, depending on factors such as age, gender, cultural background, or socioeconomic status. Understanding how these technologies influence individuals' ability to adapt and regulate their behavior can provide valuable insights into their role in human development.

Bornstein's Specificity Principle states just this: that specific outcomes happen with specific people occurring in specific places at specific times and in specific ways (Lerner & Bornstein, 2021). This principle complements and balances the field's focus on universals and researchers' desire to understand, on the whole, how development works by asking us to "disaggregate what is driving the development of what, in whom, when, and how" (Bornstein, 2019, p. 342). Instead of casting aside those who diverge from the mean as "outliers," specificity asks us to lean into those examples and ask what specific circumstances are at play in the lives of these outliers. Bernstein asserts that the Specificity Principle cuts through the overwhelming untestability of the RDS metamodel and allows us to understand the *how* of development. In doing so, communities are also able to craft developmental supports that serve all individuals given their specific needs and contexts, rather than designing cookie-cutter interventions that help some, but not all. Hill (2021) has argued that the Specificity Principle is in play when hyper-personalized machine learning interventions are used to provide the exact guidance or support needed in the exact time that it is needed. As such, the use of the Specificity Principle may be incredibly useful in studying socio algorithmic systems.

In short, specificity dictates that for optimal child development to occur, "experience and the domains of development in the individual must mutually coordinate" (Bornstein, 2019, p. 343). Importantly, Specificity Principal provides a much needed departure from developmental scientists' tendencies to take for granted the populations they study (i.e., white, North American, middle class) as the default and their findings about those populations as generalizable across diverse groups.

Though the Specificity Principle, Ecological Systems Theory, Developmental Contextualism and other perspectives in the RDS Metamodel can and should be used to promote social justice (Lerner, 2015), theories like Phenomenological Variance of Ecological Systems Theory have been developed for the explicit purpose of studying individuals who are understood as racialized, gendered, and navigating contexts marked by power imbalances and inequities (i.e., all youth in a postcolonial world). Phenomenological Variance of Ecological Systems Theory (PVEST) contends with the reality that youth are differentially vulnerable to developmental risks based upon experiences of interlocking systems of oppression (Spencer et al., 1997; Velez & Spencer, 2018). This theory centers identity in the process of human development, both because it determines much of the social realities that influence outcomes and because it is such a salient aspect of the internal psychological processes with which youth engage. Velez and Spencer (2018) assert that, "Risk and protective factors in the environment are not deterministic, but rather are experienced as supports or stressors, and the resulting balance or imbalance is conceptualized as the individuals' vulnerability" (p. 77). The phenomenological aspect of Spencer et al.'s variance of ecological systems theory implies that socialization and how the individual makes sense of that socialization matter. Velez and Spencer (2018) also argue that PVEST is inherently intersectional because it accounts for the unique forces of marginalization that youth face given their various identities, rather than conceiving multiple marginalizations as additive or multiplicative. "PVEST frames both the influence on the individual of structures and power relations from above and the perceptual processing and coping responses that shape identity formation from within" (Velez & Spencer, 2018, p. 84). PVEST's model is shown in Figure 2.

Incorporating predictive technologies into Spencer's PVEST involves examining their intersection with various model components: net vulnerability levels, net stress engagement, reactive coping methods, emergent identities, and stage-specific coping outcomes. Predictive technologies can serve as environmental factors, contributing to individuals' net vulnerability levels, introducing risks or acting as protective factors based on their design and implementation.

Predictive technologies can influence daily life stressors, such as information overload, cyberbullying, or social comparison, affecting individuals' net stress engagement, coping strategies, and developmental outcomes. The presence of predictive technologies may also shape reactive coping methods, such as relying on AI-driven tools for emotional support or disengaging from technology.

Predictive technologies can impact emergent identities by shaping self-concepts, social interactions, and access to information. Algorithmic content curation can influence beliefs, attitudes, and values, affecting emergent identities. The influence of predictive technologies on developmental outcomes may vary depending on individuals' life stages, with younger children potentially more susceptible to cognitive and emotional development effects and adolescents experiencing more significant impacts on social development and self-concept.

In review, existing human development models have provided valuable insights into various aspects of human development. However, they may not fully accommodate the socio algorithmic nature of our world as currently written, for the following reasons:

Technological context: Traditional models often focus on the social, cultural, and economic contexts that shape human development. They may not specifically account for the rapid advancements in digital technologies, such as artificial intelligence and machine learning, which have become an integral part of our lives and may influence human development in unique ways.

Complexity of interactions: The impact of predictive technologies on human development is multifaceted and occurs at multiple levels. Existing models may not adequately capture the complex interactions between individuals, algorithms, and the broader socio-technical systems in which they are embedded.

Data-driven decision-making: The increasing reliance on data-driven decision-making and algorithmic systems in various domains (e.g., education, healthcare, employment) has significant implications for human development. Traditional models may not fully consider how these systems shape individuals' access to resources, opportunities, and information, and how they might perpetuate or exacerbate existing social inequalities.

Ethical considerations: The use of predictive technologies raises numerous ethical concerns, such as privacy, consent, transparency, and fairness, which may not be explicitly addressed in existing human development models. These concerns can have a profound impact on individuals' well-being and development, particularly for marginalized and vulnerable populations.

Temporality and plasticity: The rapid pace of technological change necessitates a dynamic approach to understanding human development in the context of socio algorithmic systems. Traditional models may not be sufficiently flexible to account for the continuous evolution of technologies and their potential impact on development across the life span.

The Need For Socio Algorithmic Considerations in Human Development

Both existing "mainstream" developmental models and those that center issues of power and positionality in developmental trajectories do not explicitly consider the algorithmic systems in which all social processes take place. Technology, in these models, are simply part of the ecology either as mass media or communication tools between individuals. However, leaps in the abilities and uses of AI in the 21st century warrant a restructuring of the foundational conceptualizations of developmental contexts.

Here I propose a new model: the Socio Algorithmic Systems Bioecological Model of Development. This model aims to understand and contend with how predictive technologies influence, augment, and fundamentally change bioecological systems and developmental processes. A socio-algorithmic-aware developmental model would require us to consider the algorithmic (i.e., digitized, systematic, highly repetitive, massively scalable, and hyper-personalized) nature of many modern lived experiences. It also forces us to contend with the predictive nature of computational systems in that the range of future possibilities is increasingly set and limited by machines.

SASBEM Outlined

Creating a new model for human development that accounts for the socio algorithmic nature of the modern world involves building on existing theoretical foundations while incorporating the unique characteristics of today's technology-driven society. The Socio Algorithmic Systems Bioecological Model would integrate the following components:

1. Algorithmic context: This component encompasses the various ways in which predictive technologies (e.g., AI, machine learning) are embedded in individuals' lives, shaping their experiences, interactions, and environments. It includes aspects such as personalized content, targeted advertising, and algorithm-driven recommendations.

2. Individual factors: This component addresses the diverse characteristics of individuals, such as age, gender, cultural background, and socio-economic status, which can influence how they interact with and are affected by predictive technologies.

3. Physical and biological algorithmic interactions: The framework can incorporate neuroscience insights to study AI and machine learning systems' impact on brain development during critical periods of plasticity. Research can explore how digital experiences, like virtual or augmented reality, affect developing cognitive, emotional, and sensory processing. The framework can also investigate socio-algorithmic systems' role in physiological stress responses, resilience development, and the interaction of genetic factors with these environments to influence biological and physical development. Finally, the framework can examine how socio-algorithmic

systems impact motor skills, coordination, and physical fitness, exploring the benefits and drawbacks of technology-mediated physical activity on motor development across age groups.

4. Psychological Developmental processes: This component focuses on the cognitive, emotional, and social, processes that occur as individuals grow and develop within a socio algorithmic world. It investigates how predictive technologies can influence these processes and shape developmental trajectories.

5. Multilevel interactions: This component examines the interactions between predictive technologies and various levels of organization, from individual to family, community, and societal levels. It seeks to understand how algorithms can have cascading effects across these different levels and how they can amplify or mitigate developmental outcomes.

6. Temporality and plasticity: This component emphasizes the dynamic nature of human development and the rapid evolution of predictive technologies. It explores how the impact of algorithms on development changes over time and how individuals can adapt and respond to these changes.

7. Ethical considerations: This component addresses the ethical concerns related to predictive technologies, such as privacy, consent, and transparency. It seeks to inform guidelines and best practices for the development and deployment of these technologies, ensuring that they promote social justice and uphold ethical standards.

8. Diversity and equity: This component highlights the importance of understanding how predictive technologies can perpetuate existing inequalities or create new ones. It aims to investigate the differential effects of algorithms on marginalized populations and devise strategies to promote equity and inclusivity in a socio algorithmic world.

9. Real-world applications: This component focuses on the practical implications of the

Socio Algorithmic Developmental Systems Model for various domains, such as education, mental health, and public policy. It seeks to inform interventions, strategies, and policies that address the challenges and harness the opportunities presented by predictive technologies.

10. Interdisciplinary collaboration: This component emphasizes the importance of collaboration between experts in various fields, such as developmental psychology, computer science, sociology, and ethics, to ensure a comprehensive understanding of the role of predictive technologies in human development.

Further Justifying A New Model

Existing developmental models may account for media, computers, and the Internet, but predictive technologies present unique challenges. These technologies shape and are shaped by direct and indirect interactions with users and subjects, functioning differently than human, media, or institutional interactions. AI has its own goals, personalizes decisions, and influences other interactions within one's ecology. It often serves as a proxy for human interaction, like voice assistants and generative AI chatbots. In the future, AI could represent deceased family members or continue a person's life after their physical death, fundamentally altering the field's view of the lifespan. Thus, a new model is needed to address these distinct aspects of predictive technologies.

Traditionally, developmental models have assumed that family, peers, education, and healthcare are the most salient forces in the development of human beings. Algorithmic systems should be included in that "inner circle" of a person's development because they directly influence individuals through device interactions and influence the ways parents parent, teachers teach, health care providers provide care, peers interact, etc.. Recent research also suggests that children interact with micro-system level AI in unique ways (Danovitch, 2019; Danovitch & Alzahabi, 2013; Wang et al., 2019). Similarly, machine learning algorithms interact differently with adolescents than adults (author, Forthcoming).

For example, in a study on Spotify's recommendation of musical artists to users across age groups, researchers found that the platform was less likely to recommend non-male artists to adolescents than adults, further compounding gender disparities in streaming services (author, forthcoming). Danovitch and Alzahabi (2013)) found that preschoolers tracked a computer's prior accuracy and trusted information from a previously accurate computer more than from a previously inaccurate one. While anecdotal evidence suggests that children treat internet search engines as omniscient (Richler, 2015), recent findings suggest that 5- and 6-year-old children are skeptical of information retrieved from the Internet and that, in some cases, prefer to seek out facts from a person (Wang et al., 2019). In that study, researchers found that not until at least age eight do children start showing a preference to seek out information from the Internet, and, even then, they do not show strong trust in the results of internet searches. Another recent study asserts that children also approach novel internet-based devices with skepticism: when children were allowed to ask questions of a novel voice-controlled search device, some children chose to test the interface with questions for which they already knew the answer (Yarosh et al., 2018).

Illuminating as these early insights into how developing humans directly engage autonomous technologies may be, algorithmic systems are not confined to a person's "inner circle." Machine learning is regularly used to program mass media, augment the legal-judicial system, inform resource allocation across governmental bodies, influence financial markets, manipulate voting behavior and influence political elections, and augment a variety of other processes in the meso-, exo-, and macro- systems of an ecology. Algorithmic systems also provide an opportunity to further investigate Bronfenbrenner's chronograph (e.g., the time property of development). When interacting with predictive technologies, users' futures are decided for them, in many ways, by machine learning models that operate on pattern recognition of available past data and goals set by the organizations that develop them. When scrolling social media, for example, what a user sees next is always predetermined by the split-second calculation of the feed's algorithm with the goal to keep them engaged [1]. Previously, the chronograph has been challenging to study because, while past events are observable, it is impossible to view the future. However, machine learning allows us to glimpse into the future (or at least a limited likely set of scenarios) before it happens, simulate, and test those predictions in a fraction of a second.

Predictive technologies may also soon challenge the field's ideas about the lifespan, which is currently conceived of as the period between birth and death. Spar (2020), posits that when individuals can create an AI version of a loved one posthumously, they will. Those AI, recreated using the lifetime of data individuals will leave behind, will interact with their contexts, learn, and change over time long after a physical body has died. The field will then have to ask itself, does that developing AI "being" constitute a continuation of its original organism's life span? Does it warrant an ecological system separate from the ecology of the person it was designed to mimic?

Algorithms exist at all levels of the RDS metamodel and within each interaction between components of Bronfenbrenner's ecology. To adapt Bioecological Systems Theory would require us to conceptualize predictive algorithms as influences to each part of the system, touching each component, each component's encompassing layer, and each interaction between layers and components. In adapting Spencer et al.'s PVEST, predictive technologies not only shape one's identity and take advantage of biometric data that are indicators of identity to curate and manipulate future experiences but also influence which stressors and supports show up in a child's life through the allocation of resources across various institutions.

The phenomenological variance aspect of Spencer's model and Bornstein's

[1] This claim challenges the perception that the Internet is open, limitless, and full of infinite options. However, even a tool like Google, which many perceive as a vast library of knowledge, only provides us with subjective, metric-driven responses to users' queries (Noble, 2018). The order in which Google displays those results significantly influences the user's subsequent actions (Klöckner et al., 2004).

Specificity Principle inform my conceptualization of the unique ways that each individual interacts with and asserts agency over the algorithms in their lives. An individual's view of their specific socio algorithmic reality and their place within it determines how they navigate it. In other words, the various aspects of an individual's socio algorithmic ecology are mediated by that individual's beliefs about themselves and their environment.

Developmental models that do not conceptualize developmental contexts as algorithmically influenced at all levels of interaction undermine communities' ability to intervene efficaciously and lessen the harmful impacts of algorithmic bias. This is because algorithmic bias can exist in the technologies in use at all levels of the ecology. Sustained, frequent exposure to biases in automated technologies undoubtedly shapes how youth see themselves and understand how the world values them. Research suggests that being on the receiving end of discrimination is correlated with poor mental health outcomes across all ages (English et al., 2020; Pascoe & Smart Richman, 2009; Schmitt et al., 2014). Moreover, when youth of color experience discrimination, their sleep, academic performance, and self-esteem may suffer (Ayres & Leaper, 2013; Majeno et al., 2018). Experiencing discrimination can even alter gene expression across the life span (Aroke et al., 2019).

Algorithmic racism frequently functions as a type of technological microaggression—those thinly veiled, prejudiced behaviors that often happen without the aggressor intending to hurt anyone (Epps-Darling, 2020). But the algorithmic variety differs from human microaggressions in several ways. For one, a person's intent might be hard to pin down, but the computational models imbued with algorithmic bias can be exponentially more opaque. Several common machine-learning models, such as neural networks, are so complex that even the engineers who design them struggle to explain precisely how they work. Further, the frequency at which technological microaggressions occur is potentially much higher than in real life because of how much time individuals spend on devices, as well as the automatic, repetitive nature of programmed systems. And everyone knows that human opinions are subjective, but algorithms operate under the guise of computational objectivity, which obscures their existence and lends legitimacy to their behavior.

The utility and value of any developmental model are defined by its ability to support and optimize developmental processes (Garcia-Coll et al., 1996; Lerner, 2015; Velez & Spencer, 2018). If the goal is to better support and optimize developmental processes for all youth, then it logically follows that we must concentrate on those marginalized youth whose developmental success is threatened most. Because algorithmic systems do not work equally well for all people, especially along the lines of race/ethnicity, gender, and sexuality, a socio algorithmic ecology model of development must contend with these inequities.

Algorithmic systems may impact – supporting or stressing – all kinds of developmental processes, from informing parenting practices to providing access to healthcare to shaping interactions with law enforcement to the delivery of content on social media platforms. Importantly, however, these systems are value-laden despite humans' tendency to view computers as objective and impartial. Deep inequities are a defining feature of the socio algorithmic fabric of society. It is impossible to begin to understand these socio algorithmic influences without centering the disparate impacts they have on children of color, girls and other gender minorities, those with disabilities, and low-income youth. Given the well-documented biases inherent in algorithmic systems, one cannot reasonably expect to study the effects of these systems on developmental processes without also examining how they impact youth differently along axes of privilege and power.

Empirical Work Within SASBEM

In these early stages of this theoretical framework's development, discovery is more pertinent than verification. Nevertheless, as Bronfenbrenner states, "a good theory is one that can be translated into corresponding research designs that match the defining properties of the theory. In the absence of such research designs—or worse yet, in the application of research designs that fail to match or even violate the defining properties of the theory—science cannot move forward" (U. Bronfenbrenner & Morris, 2007, p.796). In addition to the properties defined by the RDS metamodel and Spencer et al.'s PVEST model, the proposed variant model makes three propositions, whose claims should be investigated in future research.

Proposition 1:

The ecology of the developing human is socio algorithmic. Predictive computation directly or indirectly shapes all levels of the ecology and all interactions between developing humans and their environments. Process, Person, Context, and Time all have the potential to involve data-driven technologies.

This property suggests that future research should investigate and catalog where algorithmic processes exist throughout the developing organism's environment over time. Additionally, research should aim to understand what biases or opportunities for differential impact these algorithms present.

Proposition 2:

Algorithmic processes vary across developmental stages. Algorithms shape both psychological development and biological development in stage-dependent ways.

Researchers should aim to design studies that understand the forces of algorithms on developmental processes over time. This research should span neurological, pubertal, epigenetic, cognitive, identity, academic, health, emotional, career, and relationship outcomes. Similarly, cross-sectional studies that compare outcomes across age groups should also examine the qualitative differences in the ways socio algorithmic systems influence development.

Proposition 3:

Predictive technologies can support or stress the developmental processes of individuals whose positionalities vary across identity markers and power structures. The way individuals experience and make meaning of predictive technologies is also related to their positionalities and identities.

Given this property, research should seek to uncover which characteristics of the predictive technologies support or stress developmental processes. Similarly, research should seek to illuminate how individuals make meaning of their experience in socio algorithmic contexts. This meaning-making may influence how individuals exert agency over the algorithms in their lives in specific ways and how they actively shape their development.

While the ecosystem of predictive technologies is vast, complex, and varied, the inner circle of commonly used technologies with which humans interact regularly is relatively small and consistent across groups due to the monopolistic nature of the tech industry. In many countries, for example, Facebook is the Internet (Wallace, 2020). The machine learning most regularly used powers search engines, recommendation engines, and voice assistants. Thus, search, social media, and voice assistants are fair preliminary sites for investigation. To systematically move inquiry outward to more distal contexts in the ecology, it would make sense to explore predictive technologies used in healthcare, medicine, and education after that. From there, predictive technology used in law enforcement, finance, human resources and the labor market, the legal system, politics, and environmental preservation may be fruitful sites of inquiry.

Today, we have a unique opportunity to study the differences between the first generation of youth who have grown up in socio algorithmic environments, who are currently adolescents and emerging adults, and those who have not. Inquiries into the differences between adolescents and adults would produce rich findings on how developmental processes differ across those who have always been immersed in socio algorithmic systems and those who have not. Teens are incredibly connected as well. Ninety-five percent of teens have access to a smartphone, and 45 percent describe themselves as being online "almost constantly" (Research, 2018). Given the heavy reliance on remote learning during the pandemic, adolescents are likely to spend even more time on the Internet than they did before. Unlike younger children, adolescents are more likely to possess their own devices and platform accounts. The data from adolescents is likely to be a more accurate representation of that individual's use, rather than a mixture of usage between a young child and the adult who owns the device or account that child uses. For these reasons, adolescents and emerging adults are fair preliminary groups to study.

We should also identify the developmental processes that may be the most practical starting point for exploration. Identity development is the primary developmental task during adolescence, and search and recommendation engines run on and produce identity-based data. Therefore, I propose that early empirical work grounded in this framework is well-suited to studying identity development. A focus on identity development would also allow us to understand how forces of privilege and marginalization based on social identities impact developmental outcomes within the socio algorithmic ecology. Below I expand on what it might mean to study adolescent identity development in socio algorithmic systems.

A Proposed Starting Point: Algorithms as Identity Agents in Adolescent Development

Identity development is a contextual process influenced by machine learning and AI, which are increasingly integrated into today's context (Hill Redding, 2021). Recommendation engines contribute to this process by connecting users with ideas and people, impacting identity formation (Erikson, 1968).

Erikson's (1968) classic stage model defines identity formation as the main task of adolescence, resulting in a stable sense of self that exhibits continuity over time (Koepke Denissen, 2012). Identity has three components: ego, personal, and social, all co-authored by individuals and their social world (Schachter Ventura, 2008).

Identity formation does not exist in a vacuum, rather all three components of an individual's identity are co-authored by themselves and their social world, much like the other processes in the RDS framework. There exist active and purposeful co-participants in a young person's identity formation and development, such as parents and teachers, who thoughtfully engage with and reassess their own goals and role with respect to guiding their child or student through the stages of identity development. These identity agents, as Schachter and Ventura (2008) coin them, determine the paths human development can take. Adolescents engage with identity agents in their ecosystem to not only separate, individuate, differentiate, and gain autonomy from their parents, but also integrate into adult society by connecting with and being recognized by their identity agents for the benefit of both the individual and society (Schachter & Ventura, 2008). Schachter and Ventura (2008) assert that identity agents are: (1) concerned with issues of the youth's developing social and ego identity; (2) have goals related to identity development; (3) implement a praxis to further those goals; (4) assess the context of development and the youth to improve their praxis; (5) rely on implicit psychological theories that guide their praxis; and (6) reflect on their practice to refine and improve their efforts.

Just like parents who actively interact with youth in order to participate in their identity formation, predictive technologies play an active role in partnering with youth and providing them with frameworks, templates, and identity materials from which they might construct their own. Recommendation systems, for example, are concerned with youths' developing identities so much as they are related to the systems' goals of furthering engagement or driving ad revenue. Algorithms by definition are a theory-informed practice to further the goals of the system (which may or may not be in alignment with healthy development), and are constantly engaged in an assessment of the context and individual end users to improve their praxis. Finally, these systems utilize the data generated through their use to refine and improve their efficacy. Importantly though, algorithms do not have the same kind of care and concern for wellbeing that a human agent might have (although one day some might).

The mechanisms by which digital natives partner with predictive technologies to co-construct their identities is a rich yet under examined site of inquiry. And yet, youth are relying on predictive technologies to connect them with communities of interest during their quest to individuate from their parents, provide them with information that will inform their beliefs and value systems, and construct idealized virtual versions of themselves to which they can aspire IRL. Further, predictive technologies benefit from and likely exploit the developmental need of adolescents to separate from their caretakers and self-explore. No other time in history has it been so easy to “venture off” into the world on one’s own without having to leave the physical confines of home. Adolescents today can satiate their need for independence, information and community seeking, and exploration in the wild wild west of the web from the comfort of their bedroom, without the knowledge of their parents, and potentially at their own peril. What the field needs is a dynamic, developmental perspective that explains how developmental change in identity evolves from transactions between individuals and predictive technologies.

Methodological Opportunities and Challenges

The above-proposed research would need to use methods traditionally used in developmental science as well as state-of-the-art data science methods to use the vast amounts of digitally generated data that hold insights on developmental processes. Online platforms present immense opportunities for small-scale, adaptive, and ongoing experimentation. Platforms like Facebook already run experiments on their recommendation algorithm’s effects on changes in user psychology over time (Kramer et al., 2014). Yet this form of experimentation is rife with ethical pitfalls. Of course, it is also challenging to use such data because of its sheer quantity and the limited tools available to developmental scientists to wrangle it. Yet, harnessing the power of big data would allow developmental scientists to apply the Specificity Principle to studying unique individuals without the worry of their statistical analyses being under-powered. In other words, in harnessing big data, researchers have the possibility of running longitudinal human development studies on effective positive youth development interventions for specific individuals given their specific circumstances while still using robust, statistical inference.

Data science, for these reasons, presents opportunities for the field of developmental science. Computational methods can not only be used to wrangle, clean, and organize massive troves of data, but they can also be used to find themes and patterns in unstructured data, without the need to create and validate scales for constructs that we do not yet know how to define. Computational methods, particularly natural language processing and computer vision, can prove helpful in collecting and analyzing large-scale textual and visual data, like the kind commonly found online. It would be impossible for a group of researchers to perform qualitative data analysis, for example, on a data set of one million YouTube video transcripts. However, a machine learning model may get us reasonably close to scaling the human interpretation of a smaller subset of those videos. Many data science projects already use human annotators (e.g., Amazon's Mechanical Turk) for labeling subsets of unlabeled data to train machine learning models to label remaining data. Developmentalists interested in using large datasets may benefit from utilizing these established methods and their offshoots that use expert annotators rather than crowd-sourced lay people (Frey et al., 2020; Patton et al., 2020; Topaz et al., 2020).

While developing an entire *Computational Developmental Science* methodology falls beyond the scope of this article, it is essential to highlight that developmental science that contends with the proliferation of machine learning technologies must also make use of machine learning, in addition to critical qualitative methods, for its analysis. However, an overreliance on computational methods risks reproducing the same biases and harms that plague commercial technologies. Thus, computational developmental scientists should proceed with caution, reflexivity, and a reliance on the expertise of digital natives and their communities through participatory research methods.

Conclusion

In this article I have attempted to motivate the creation of a Socio Algorithmic Systems Variant of Bioecological Model (SASBEM). I have argued that developing youth are living in a unique socio historical period in which a new class of objects – predictive technologies – are profoundly altering the fabric of developmental ecologies. As such, existing frameworks for understanding the individual $\leftarrow\rightarrow$ context relationships that shape development must be updated to contend with the socio algorithmic nature of the modern world. These socio algorithmic systems are defined by deep inequities across social identity markers such as race/ethnicity, gender, and ability. Thus, SASBEM is concerned with understanding the unique supports and stressors that marginalized individuals face in their specific developmental contexts so as to improve the outcomes of all youth, and especially the most vulnerable. SASBEM provides a research agenda through which we can (1) investigate and catalog where algorithmic processes exist throughout the developing organism's environment over time; (2) understand what biases or opportunities for differential impact predictive technologies present; (3) understand the forces of algorithms on both biological and psychological developmental processes over time; (4) uncover which characteristics of the predictive technologies support or stress developmental processes; and (5) illuminate how individuals make meaning of their experience in socio algorithmic contexts and exercise agency within these systems. I have also argued that data science methods will be increasingly useful in studying human development, but their use will need to be balanced with a cautious criticality that ensures the bias and techno chauvinism of commercial data science does not find its way into future studies. Building on the developmental science of the past six decades and the science and technology studies of the past three decades, the future of these complementary fields can begin to intertwine to produce cutting edge research that engenders a more humane and just world. A world where science, technology, and society collaborate to enable "human beings to be human" (D. U. Bronfenbrenner, 2004).

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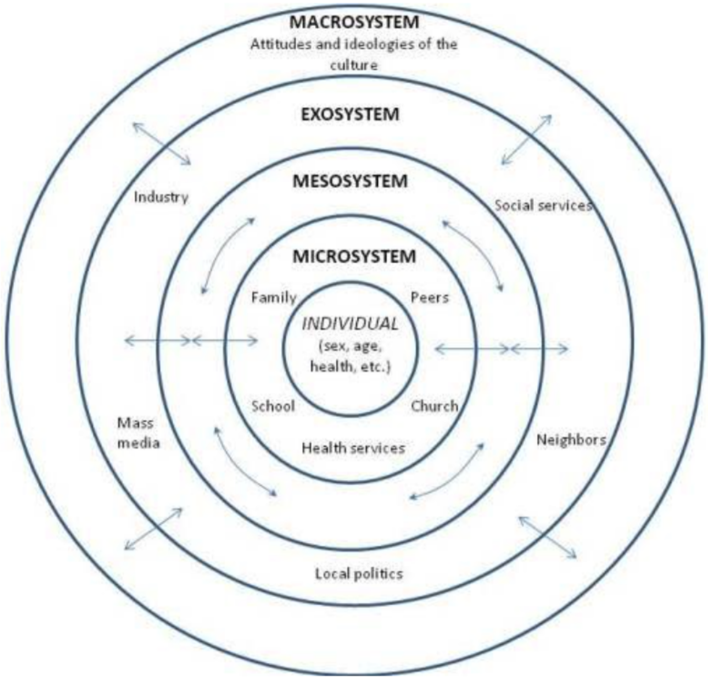

Figure 1

Bronfenbrenner's Bioecological Systems Model.

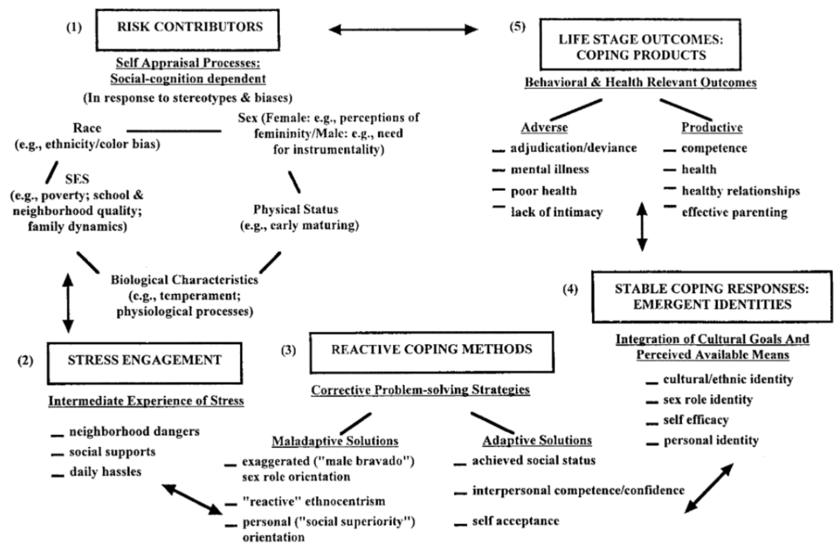

Figure 2

Phenomenological Variant of Ecological Systems Theory (Spencer, 1995)