
Human Nature Is Not a Machine: On Liberty, Attention Engineering, and Learning Analytics

SARAH HARTMAN-CAVERLY

ABSTRACT

This article undertakes a literature review to examine learning analytics through the lens of attention engineering. Informed by a critical literature synthesis from the fields of cognitive science, history, philosophy, education, technology, ethics, and library science, this analysis situates learning analytics in the context of communication and education technologies as tools in the manipulation of attention. The article begins by defining attention as both a cognitive activity and a metaphysical state intrinsic to intellectual freedom. The Progressive Era concept of attention engineering is then introduced and reinterpreted in the context of attention scarcity and academic capitalism in the Knowledge Era. The affordances of information and communications technology replicated in educational technology to facilitate data capture, analysis, and intervention in the form of “nudge” learning analytics are outlined as evidence of contemporary attention engineering in education. Attention engineering in education is critiqued as antithetical to students’ intellectual freedom and development as self-sufficient learners and independent thinkers. The academic library’s role in teaching and promoting attentional literacy and attentional autonomy is explored as a response to the intellectual freedom challenges posed by learning analytics as a form of attention engineering.

INTRODUCTION

Attention is a finite resource and valuable commodity in the Knowledge Era. Attention is also essential to the process of deep learning, and to the exercise of intellectual freedom. Student-facing learning analytics systems prompt academic behaviors by attracting and directing student attention.

Using many features similar to social media (and derived from advertising), learning analytics-enhanced educational technology provides continuous real-time status feedback to students, which prompts engagement behaviors. Like other forms of persuasive technology, nudge learning analytics intrude on students' attention and decision-making processes, disrupting learning and infringing on intellectual freedom.

This paper examines attention as a cognitive activity as well as a metaphysical state. The history of attention engineering, a Progressive Era concept, is reimagined for the attention economy of the Knowledge Era. The design of learning analytics systems to manipulate student behavior by exploiting student attention is demonstrated. Learning analytics as attention engineering is analyzed using education and social reformist critiques of the Progressive Era, in combination with contemporary critiques of academic capitalism in the Knowledge Era. The effects and consequences of learning analytics are considered. Attentional autonomy and attentional literacy are proposed as remedies for the attention engineering effects of learning analytics and other persuasive technologies, and as emerging domains in the theory and practice of intellectual freedom for librarians to explore.

ATTENTION

Attention and Cognition

Attention refers to conscious behaviors involved in processing information from intentionally selected sources. Attention is finite owing to the information-processing pathways in the brain as determined by neurobiological structures (Carrier et al. 2015; Posner and Boies 1971; J. Wu 2015). Certain executive attention traits involved in exercising control over one's attention are found to be associated with differences in genetics involved in the brain's dopamine and serotonin reward systems (Petersen and Posner 2012). Attention is often categorized as **transitory**, which is "quick, superficial, and often involuntarily provoked"; or **sustained**, which is "deep, long-lasting, and voluntary" (T. Wu 2016, 125).

Attention's Role in Learning

Attention plays an important role in learning. Information processing occurs in different regions of the brain when engaged in transitory attention compared to sustained attention, with potential implications for the depth of learning and information transfer from working memory into declarative memory (Carrier et al. 2015; J. Wu 2015). **Working memory is active in transferring new information into declarative memory in the act of deep learning.** Multitasking, more accurately described as task-switching, reduces the capacity for representational holding or working memory (Junco and Cotton 2012; Karpinski et al. 2013). Research on attention

and learning demonstrates that “meaningful learning requires sustained attention to material over time” (Junco and Cotton 2012, 507). Meta-attention, or awareness of one’s attention and ability to moderate distractions, is correlated in some studies with academic achievement (Loper and Hallahan 1982).

Inattention: Distraction and Task-Switching

Inattention negatively impacts performance on cognitive tasks. Distractions, disruptions, and task-switching compromise one’s ability to focus by engaging in conscious selective attention, leading to slowness, forgetfulness, and an increased error rate (Bowman et al. 2010; Carrier et al. 2015). While people are capable of accurately gauging their degree of distraction, they are less able to accurately assess distraction’s impact on their performance, and tend to overestimate their capacity for attention (Reisberg and McLean 1985; Simons 2010). Distractions cause elevated workload stress, frustration, time pressure, and perceived effort; people respond to interruptions by speeding up their work and reducing the quality of output (Mark, Gudith, and Klocke 2008).

Task-switching is typical of students’ academic study habits and behaviors, particularly in the presence of technology (Karpinski et al. 2013). For instance, device and account notifications trigger the brain’s orienting response to new stimulus, engaging transitory attention behaviors, incurring a cognitive switching cost, overloading working memory, interfering with the transfer of information to declarative memory, and causing an information-processing bottleneck (Bowman et al. 2010; Junco and Cotton 2012; Karpinski et al. 2013; Posner and Boies 1971; Reisberg and McLean 1985; J. Wu 2015). These impacts portend significant societal costs resulting from individuals’ collective inability to sustain deep attention (T. Wu 2016).

Attention and Intellectual Freedom

Metaphysically, attention is intrinsic to human consciousness. Attention is exercising control over one’s own consciousness and is essential for independent thought (Petersen and Posner 2012; Rheingold 2010; Tolson 2014). Executive attention, or meta-attention, is understood as “a process that provides the gate to conscious awareness” arising from self-monitoring to make intentional choices about attending to information-processing tasks (Reisberg and McLean 1985, 292). In the posthumously compiled essay “Education,” transcendentalist and American education reformer Ralph Waldo Emerson seemed to describe meta-attention when he characterized deep learning as a process by which to “enter into the quasi-omniscience of high thought” (Emerson 1946b, 249). With the rise of scientific management during the twentieth-century Progressive Era, behavioral and social sciences were applied to capture attention and influ-

ence decision-making at a subconscious level (T. Wu 2016). Because attention implicates mental privacy and the ability to freely select and process information, attention plays a key role in intellectual freedom (ALA 2008, 2014a, 2014b; Magi and Garnar 2015).

ATTENTION ENGINEERING

Progressive Era Origins of Attention Engineering

Disruptive technological advancements in mass communication during the Progressive Era gave rise to the concept of “attention engineering” (Lee 1916, 222–23, 444), a phrase coined by Gerald Stanley Lee in 1910 to refer to an “art of making things happen, the control of business and affairs . . . through the power of attracting, holding, and organizing the attention and the vision of men” (Gerald Stanley Lee in personal correspondence, quoted in Bush 1991, 113, 150). A preacher-turned-essayist and social reformer who promoted advertising and other emerging forms of mass communication as means of achieving social progress, Lee observed the attention scarcity that resulted from information overload engendered by new media and communication technologies of the time (Bush 1991, 1992; Kazi 2012). Lee’s brand of attention engineering is characterized by elitism and economic paternalism in which “certain ‘good’ people had the right to ‘interrupt’ the public” and influence mass culture through beliefs, values, and behaviors (Bush 1991, 147).

Lee was influential in developing the concepts of a mass public, crowd psychology, market society, and consumer culture (Bush 1991, 1992; Emerson 1946a). He thought that the “mystical powers of technology had revealed ‘psychic currents’” (Bush 1992, 303) and that social and moral progress could be achieved through advertising, mass persuasion, and emotional appeals (Bush 1991). His own advertising campaigns often exploited social comparison and individuals’ sensitivity to social surveillance (Bush 1991). Lee advocated “steering people’s heads inside” (Lee 1913, 147) by “employing forces that can be made extremely small, invisible, personal, penetrating, and spiritual” (224). In Lee’s worldview, influencing the public en masse was more important than understanding citizens as individuals (Bush 1991).

Attention Engineering, the Industrial Revolution, and Education Reform

Lee’s theory of attention engineering arose in the midst of the communication revolution wrought by industrialization, urbanization, commercialization, and the emergence of a mass press, concurrent with a rise in technocratic mechanization and scientific management (Bush 1991). The classical liberalism established in works by Emerson and John Stuart Mill express concern for the state of individuality in the context of emerging techniques to manipulate mass sentiment (Emerson 1946a; Mill [1859]

2004). John Dewey, another education reformer and contemporary of Lee and Emerson, characterized such attention engineering techniques as a violation of First Amendment freedoms that he viewed as essential to the health of a functional self-governing society (Dewey 2003).

The Progressive Era saw a coincident transformation of university education, including a shift in emphasis from the social reproduction of class to supporting industry-driven research and development (Slaughter and Rhoades 2004). Dewey decried the developing emphasis on producing an economically insecure and intellectually underserved class of employable “operators” through the education system, criticizing the encroachment of the market on academe as accommodating the needs of industry while abdicating the academy’s role in the production and stewardship of ethics and culture (Dewey 2003, 366). Increasing integration with the state and the economy recast the university from a site of “public discussion, debate, commentary, and critique” to one of vocational and professional preparation, later described in Slaughter and Rhoades’s theory of academic capitalism (Slaughter and Rhoades 2004, 333). In many ways, the disruptive influence of digitization on mass culture and education in the Knowledge Era parallels the influence of industrialization and mass communication in the Progressive Era. Today, the Internet plays the role of pulpit, and institutions of higher education rely on mass communication to influence student-consumers in the education marketplace (boyd 2010; Slaughter and Rhoades 2004).

ATTENTION SCARCITY AND THE ATTENTION ECONOMY

Attention Scarcity and Information Abundance

On the cusp of the information age, social scientist Herbert Simon observed the transition from information scarcity to abundance and anticipated attention scarcity as a result:

In an information-rich world, the wealth of information means a dearth of something else: a scarcity of whatever it is that information consumes. What information consumes is rather obvious: it consumes the attention of its recipients. Hence a wealth of information creates a poverty of attention and a need to allocate that attention efficiently among the overabundance of information sources that might consume it. (1971, 40–41)

As with any scarce resource, investing focal attention on a select information source poses the opportunity cost of ignoring other information inputs (Simon 1971; T. Wu 2016). Because attention is ultimately finite, increasing demands on attention resulting from disruptive technologies involved in information production, distribution, and access increases the value of attention. Likewise, the value of techniques and technologies for

exercising mass influence over individuals' attentional and information behaviors also increases (T. Wu 2016). As a result, the human environment is designed to influence, capture, and hold the public's attention (Tolson 2014; T. Wu 2016). In an information and communication technology-enriched environment, danah boyd observed that "power is now in the hands of those who control the limited resource of attention" (boyd 2010, 30).

Attention Scarcity and Technology

The concept of attention engineering has renewed relevance in the age of ubiquitous personal computing. A small group of technology-sector insiders is raising awareness about how consumer technology and social media companies are responding to the competition for scarce user attention by undermining attentional autonomy with technological affordances designed to "hook" users in a behavioral "addiction" (Andreassen 2015, 179; "Brain Hacking" 2017; T. Wu 2016, 193; see also Bosker 2016; Carr 2017; A. Cooper 2017; Harris 2016; Lewis 2017; Morgans 2017; Sullivan 2016; N. Thompson 2017). "Brain hacking" is a colloquialism referring to the manipulation of attention to form attentional habits through the application of technology design features that activate the brain's reward and fight-or-flight systems (Andreassen 2015, 178; "Brain Hacking" 2017).

Status alerts are one feature of the personal media environment that is designed to engineer users' attention. Alerting features in social media and personal technology constitute a form of operant conditioning through the behavioral reinforcements of attention, validation, boredom avoidance, and satiating a "fear of missing out" (Andreassen 2015, 179; T. Wu 2016, 186). Gabe Zichermann, an expert in gamification, asserts that "neuroscience is being used to create dependent behavior" ("Brain Hacking" 2017). Ramsay Brown, founder of the neuroscience-based technology development company Dopamine Labs, explains that engagement features are "designed to provoke a neurological response" based on an "addiction code" that stimulates the adrenal system, which creates a state of hyperawareness and anxiety ("Brain Hacking" 2017). Even the anticipation of alerts can be distracting in a way that impairs performance, as this anticipation activates the brain's hyperarousal and reward systems, motivating compulsive status-checking behaviors (Bowman et al. 2010).

Some clinical researchers seek to define a social-networking site behavioral addiction with differential diagnostic criteria, including status salience, compulsive or impulsive technology use, and interference with mood and motivation (Andreassen 2015). Communications technology saturation normalizes a "media multitasking environment" in which information and entertainment media increasingly intrude on mental privacy and consume greater shares of time and attention (Carrier et al. 2015, 65; T. Wu 2016, 125). Many innovations in communication technologies

encourage transitory rather than sustained attention—even those, like the television remote, which were designed to enable individuals to exert greater control over their own attention and information habits (T. Wu 2016).

The same pervasive communication technologies exploiting attention scarcity through attention engineering are also implicated in the normalization of surveillance, leading to the attention-conscious performance of self-tracking and impression-management behaviors (D. Cooper 2014; Macfarlane 2015). Sensitivity to social comparison and competition redirects individuals' finite attention from achieving high quality, meaningful social interactions toward achieving a high quantity of digital engagements. Attention itself is prized as a form of compensation, as in the microcelebrity of social media influencers, shifting values and beliefs toward a "quantified self" culture (D. Cooper 2014; Verbert et al. 2014, 1499; T. Wu 2016, 312). Digital communication services like e-mail and social media reinforce these compulsive status-checking behaviors in individuals, which become an "attention ritual" and emerging social norm at population scale (T. Wu 2016, 186, 213, 310; see also Tolson 2014).

EDUCATION TECHNOLOGY AND ATTENTION CAPTURE

Educational Technologies and Academic Capitalism

Like industrialization during the Progressive Era, the digital revolution that heralded the information economy and the Knowledge Era also impacted the higher education system (Shum and Ferguson 2012). Extensible educational technology is deployed at industrial scale and plays a growing role in all functions of academic institutions (Jones and Hansen 2014; Mattingly, Rice, and Berge 2012). The dollar value of the annual global educational technology sector is conservatively estimated at \$5 trillion, and institutions continue to invest heavily in analytics-enabled software (Liu et al. 2017; Perrotta and Williamson 2018; Selwyn 2014).

Performance accountability-driven governance models and consumerist, market-oriented logic dominates higher education administration (Prinsloo and Slade 2017a). Trade publications routinely emphasize a threat of competitive disadvantage predicated on an institution's failure to meet students' preference for technology-mediated learning experiences (Carmean and Mizzi 2010; Prinsloo 2017; Prinsloo and Slade 2014). This claim is particularly impactful at a time when tuition and student-financing revenue accounts for an increasing portion of institutions' operating budgets in the face of restructured public funding and tumult in the broader financial sector (Jarrett 2013; Slaughter and Rhoades 2004). The critiques of Progressive Era education reformers resonate in this environment, in which universities "have to work for large classes instead of individuals," become increasingly bureaucratized, and use quantitative

metrics to drive decision-making such that “an automaton, a machine, can be made to keep a school so” (Emerson 1946b, 265, 267).

As a form of persuasive technology, educational technology utilizes design features and real-time data capture from multiple streams as input for analysis and interventions to modify student behavior (Bodily and Verbert 2017; Kitto, Lupton, et al. 2017; Lawson et al. 2016; Leitner, Khalil, and Ebner 2017; Liu et al. 2017; Long and Siemens 2011; Mattingly, Rice, and Berge 2012; Parry 2012; Prinsloo 2017; Prinsloo and Slade 2014; Purpura et al. 2011; Roberts, Chang, and Gibson 2017; Rubel and Jones 2016; Scott and Nichols 2017; Shum and Ferguson 2012). Learning analytics is the application of statistical analysis techniques to mine these large data sets generated by and about students, using predictive modeling to yield actionable intelligence (Long and Siemens 2011). While this technique is promoted as transformative of teaching and learning, learning analytics is most frequently applied as a form of academic business intelligence to inform institutional resource allocation, and to satisfy reporting requirements for state agencies and accreditation bodies (Fritz 2011; Jarrett 2013; Jones and Hansen 2014; Kitto, Lupton, et al. 2017; Leitner, Khalil, and Ebner 2017; Mattingly, Rice, and Berge 2012; Prinsloo 2017; Scott and Nichols 2017; Shum and Ferguson 2012; Slaughter and Rhoades 2004). Consequently, learning analytics-related research focuses disproportionately on the needs and interests of administration over issues related to teaching and learning (Kruse and Pongsajapan, n.d.; Leitner, Khalil, and Ebner 2017; Prinsloo and Slade 2014; Roberts, Chang, and Gibson 2017; Shum and Ferguson 2012). Learning analytics informs institutional initiatives aimed at maintaining competitive advantage in a globalizing market for higher education (Fritz 2011; Leitner, Khalil, and Ebner 2017; Prinsloo and Slade 2014).

Technology is an active agent in Siemens’s connectivist theory of learning, which disembody learning from the learner and situates it in “nodes, relations, ties, and networks” (Haythornthwaite, de Laat, and Schreuers 2016, 252). The theory of academic capitalism highlights the role educational technology plays in processing students from consumers of higher education into products of the education system delivered to the labor market for employers (Slaughter and Rhoades 2004). Learning activities, curricula, and programs are designed to produce graduates with values, knowledge, and skills optimized for the workplace (Macfarlane 2015; Prinsloo and Slade 2014; Slaughter and Rhoades 2004). In his critique of educational technology, Neil Selwyn dubs it the “Trojan Mouse” deployed to produce the idealized worker-consumer of the knowledge economy (Selwyn 2014, 33; see also Fournier and Kop 2010; Prinsloo 2017; Tolson 2014). Investment in educational technologies positions campuses to be competitive in attracting desirable faculty and students, while also reifying an “information-based economy in which the speed of *processing* infor-

mation is prioritized over the quality and contemplation of information, knowledge, and wisdom" (Slaughter and Rhoades 2004, 302, emphasis original).

The premium placed on student presenteeism—a workplace value of willingness to work long hours and to maintain constant availability through technology-enabled real-time responsiveness—reflects a market-oriented perspective that claims “most areas of everyday life as potential sources of profit generation” (Selwyn 2014, 30, 129). In the higher education context, course participation is spatially unbound from the physical campus and expands to occupy more time outside of the traditional class period (Macfarlane 2015). Increasing expectations for student technology use contribute to a school-life imbalance; even those registered for traditional face-to-face course delivery are often compelled to adopt educational technology in some capacity (Carrier et al. 2015, 74, 76; Selwyn 2014, 133). Institutions exploit students’ “valuable mental state—open, desirous, and impressionable” (T. Wu 2016, 259), while students have “educational technology ‘done’ to them” (Selwyn 2014, 3). The features of educational technology reward continuous availability, social surveillance and comparison, a competitive orientation, and conformity to consensus authority. Students are not only expected to unquestioningly adopt educational technologies but also to avoid critical examination of the demands made on their attention, time, and privacy through these technologies.

Educational Technology Design Affordances

Educational technology acts as a disruptive technology that actively influences the directions of educational research, pedagogy, and learning (Teasley 2017; Winstrup 2017). Design choices in learning systems not only mimic the same affordances for attention engineering built into social-networking sites and other communication technologies, but also increasingly promote context collapse by co-opting social media platforms themselves as learning environments (Dabbagh and Kitsantas 2012; Fournier and Kop 2010; Gruzd et al. 2018; Kitto, Lupton, et al. 2017; Kitto, Cross, et al. 2015; Mattingly, Rice, and Berge 2012; Prinsloo and Slade 2013; Roberts, Chang, and Gibson 2017; Rubel and Jones 2016; Scott and Nichols 2017; Verbert et al. 2014; D. West, Huijser, and Heath 2016). Learning systems disproportionately emphasize superficial engagement behaviors because clickstream log data is easily accessible for collection and analysis (Kitto, Lupton, et al. 2017; Liu et al. 2017; Shum and Ferguson 2012; Verbert et al. 2014; Winstrup 2017). These analytics feed into data visualizations on student-facing dashboards to inform social surveillance, social comparison, and learner self-management (Bodily and Verbert 2017; Cai, Lewis, and Higdon 2015; Kim, Jo, and Park 2016; Kitto, Lupton, et al. 2017; Kitto, Cross, et al. 2015; de Laat and Prinsen 2014; Long and Sie-

mens 2011; Mattingly, Rice, and Berge 2012; Roberts, Howell, and Seaman 2017; Shum and Ferguson 2012; Verbert et al. 2014).

Clickstream-driven analytics reinforce student efforts to “game the system” in order to improve a grade, dashboard score, or leaderboard standing (Domínguez et al. 2013; Kitto, Lupton, et al. 2017; Macfarlane 2015; Mann 2005; Scott and Nichols 2017; Shum and Ferguson 2012; Wintrup 2017). Design features of analytics-enhanced learning systems correlate with student alienation, understood as disengagement from learning behaviors, course content, and class community. Students describe this experience of alienation as “feeling held back, blocked, inhibited, estranged, or isolated” (Mann 2005, 43; see also Godor 2017). Contrary to its purpose, such educational technology design “poses several potential threats to students’ sustained attention” and, therefore, to deep learning (J. Wu 2015, 77).

Educational Technology and Students

Attention scarcity characterizes the experience of contemporary university students (Junco and Cotton 2012). Students are in a constant state of alertness, anticipating notifications from communication technologies (including educational technology) through which they attend to a constant stream of performance-related feedback (Karpinski et al. 2013; Van der Kleij, Feskens, and Eggen 2015). This media-multitasking educational environment results in attention discontinuity, in which students self-report unconsciously engaging in off-task behaviors while ostensibly undertaking learning activities (Andreassen 2015; J. Wu 2015). Task-switching is common in online learning behaviors, and some students perceive task-switching as beneficial, but the presence of technology predicts diminished time on task while studying (Carrier et al. 2015; Wintrup 2017). The integration of technology into courses does not guarantee its adoption for learning purposes, and the assumption that educational technology is utilized to support deep learning is unsubstantiated in the literature, which reveals a reality marked by shallow student engagement with electronic course material (Bowman et al. 2010; Kruse and Pongsajapan, n.d.).

Although educational technology is prized for enhancing the student experience with anytime, anywhere connectedness and point-of-need interventions (Jarrett 2013; Prinsloo and Slade 2017b), some research findings “call into question just how educationally and developmentally beneficial connectedness [via technology] is to students” and their learning experiences (Slaughter and Rhoades 2004, 301). Counterintuitively, educational technology doesn’t necessarily counteract learner disengagement and alienation (Mann 2005). Some students perceive online learning environments as overregulated and respond by inhibiting individual thinking, conforming to the tone, knowledge content, and values of the

online class (Godor 2017). This is merely the current iteration of a long-standing model of mass-produced education that Mill might criticize as a paternalistic “education of restraint” (Mill [1859] 2004, 109). Educational technology reinforces the academy’s role in transforming students from consumers of education as a product into a product of the education system for the labor market (Slaughter and Rhoades 2004). Furthermore, students are viewed as producers of data that is valuable to the institution for its utility in allocating institutional resources and directing student behaviors (Leitner, Khalil, and Ebner 2017; Shum and Ferguson 2012; T. Wu 2016).

Student Data Capture and Learning Analytics

Learning analytics-enabled educational technology incorporates social media-like engagement affordances designed to “leverage students’ obsessive status-checking tendencies” rather than draw critical awareness to them (Fritz 2011, 95; see also Scott and Nichols 2017). While one study examining learning analytics applied to actual learning tasks found no significant effect on student achievement (Van der Kleij, Feskens, and Eggen 2015), other studies show that “real-time data are necessarily incomplete and potentially inaccurate” (Liu et al. 2017, 164) and can lead to errors in student assessment resulting in unintentional harms (Kruse and Pongsajapan, n.d.). The behavioral “learnerist” orientation of learning analytics places greater emphasis on assessment data capture than on understanding and improving the actual learning experience (Macfarlane 2015, 347). Some analytics-driven pedagogy even redirects student attention and effort to correcting algorithmic classifications of their modeled learner identities, thus exploiting student labor to train learning analytics algorithms; an approach to quality improvement confounded by the fact that students often take the assessment output of learning analytics systems uncritically and at face-value (Kitto, Lupton, et al. 2017).

Learning analytics systems ingest a constant stream of data from educational and administrative information systems which surveil a wide range of student behaviors. Because learning analytics systems are perceived as a necessary competitive advantage in institutional operations, contemporary universities compel or coax students to adopt these technologies despite impacts on their privacy (Rosen and Santesso 2018). In technology-enriched learning environments that harvest and display learner data, students experience learner performativity as a loss of privacy in the inability to control one’s classroom presence and reputation (Mann 2005). Students also encounter learning-oriented nudge analytics that seek to influence their self-perceptions, decisions, and actions on behalf of the institution (Carmean and Mizzi 2010; Rubel and Jones 2016). At the outset of scientific management in the nineteenth century, such techniques to predict and influence individual behavior based on “some small number

of patterns" (Mill [1859] 2004, 71) were decried as a dehumanizing "disgrace" (Emerson 1946a, 46).

LEARNING ANALYTICS AND ATTENTION ENGINEERING

Learning Analytics and Scientific Management

Learning analytics traces its roots back through the science of big data, business intelligence, and marketing to techniques for attention engineering and scientific management from the Progressive Era (Mattingly, Rice, and Berge 2012; Perrotta and Williamson 2018; T. Wu 2016). The segmentation of prospective students into typological groups first developed in the education sector to facilitate targeted student recruitment and financing (Slaughter and Rhoades 2004). Learning analytics instantiates algocracy in the education system—a method of governance by encoded quantitative logic (Prinsloo 2017; Prinsloo and Slade 2014). Because they are quantitatively oriented, learning analytics systems treat completion and grade achievement as target outcomes and proxies for the intellectual development of individual students (Carmean and Mizzi 2010). The continuous availability of real-time learner data contributes to an assumption that such technologically driven education delivery models are intrinsically more efficient and effective than traditional face-to-face learning (Selwyn 2014).

Learning analytics is surveillance of the learning process and the educational system. Aside from their primary use in administration, learning analytics applications seek to monitor student activity, measure student performance, identify at-risk students, optimize institutional resources, and modify student behavior (Mattingly, Rice, and Berge 2012; Shum and Ferguson 2012). Learning analytics influence the design and delivery of learning experiences by placing emphasis on quantification, standardization, factorization, massification, competition, and "nonhuman (frequently technological) control" (Purpura et al. 2011, 429), reinforced through the calculation and display of points, scores, leaderboards, and badges that facilitate progress and achievement monitoring (Hanus and Fox 2015; Liu et al. 2017; Prinsloo and Slade 2014; Selwyn 2014). Learning analytics proponents seek learning-data capture and student behavioral intervention even beyond the online classroom (Carmean and Mizzi 2010; de Laat and Prinsen 2014; Rosen and Santesso 2018).

As an agent of academic capitalism, educational technology reframes education into a product to be consumed rather than a state of being to be created (Slaughter and Rhoades 2004). Learning analytics likewise reframes learning as a process to be managed through an approach of (often public) algorithmic monitoring and parameter tuning referred to as computationalism, which exploits peer comparison and social competition and rewards "gaming the system" (Domínguez et al. 2013; Fritz

2011; Hanus and Fox 2015; Kitto, Lupton, et al. 2017; Macfarlane 2015; Scott and Nichols 2017; Selwyn 2014). Learning analytics are routinely used to flag underperforming students through comparative analysis of demographics and academic outcomes based on algorithmic risk analysis (Carmean and Mizzi 2010; Fritz 2011; Liu et al. 2017; Mattingly, Rice, and Berge 2012; Rubel and Jones 2016). Learning analytics is thus an articulation of normativity in the context of an asymmetric power relationship between institutions and students that frames the educational experience as one to be monitored and managed (Biesta 2010; Drachsler and Greller 2016; Kitto, Cross, et al. 2015; Prinsloo and Slade 2013; Scott and Nichols 2017).

Learning Analytics' Influence on Learning Behaviors

The deployment of educational technology both requires and reinforces the centralized monitoring and administration of students' learning experiences (Liu et al. 2017). Learning analytics facilitates a transfer of this "extended managerial capacity" from institutional administration to faculty and ultimately to students themselves, prompting students to monitor their learning activities in ways that do not necessarily promote metacognitive involvement in deep learning (Slaughter and Rhoades 2004, 15, 319–20; see also Kruse and Pongsajapan, n.d.; Wintrup 2017). The real-time availability of analytics-driven insights create a continuous obligation to act on intrusive advising interventions and respond to nudge analytics (Jones and Hansen 2014). Intrusive advising implicates student privacy and attention by pushing learning assessment notifications at any time and to any device (Fritz 2011; Jones and Hansen 2014; Prinsloo and Slade 2017b; Purpura et al. 2011).

Learning analytics-enhanced educational technology bears many of the same behavioral conditioning features of other persuasive technologies, which are designed to drive self-monitoring, reduce task complexity, narrow the field of choices, present performance-based and personalized interventions, and facilitate social comparison (Biesta 2010; Lawson et al. 2016; Leitner, Khalil, and Ebner 2017; Mattingly, Rice, and Berge 2012; Purpura et al. 2011; Shum and Ferguson 2012). When incorporated into institutional student success and retention initiatives, learning analytics specifically target at-risk students to modify their behavior (Mattingly, Rice, and Berge 2012). Real-time alerts directed to at-risk students place a disproportionate burden on them to respond to learning-oversight prompts by engaging in learning-management behaviors that transfer attention and effort away from substantive course engagement and learning activities (Fritz 2011; Macfarlane 2015).

Gamified educational technology incorporates analytics-driven alerts to capture student attention (Fritz 2011; Scott and Nichols 2017; Selwyn 2014). Learning-system dashboards that facilitate social comparison and

competition between students also alter their orientation to the online learning environment (Selwyn 2014). Because dashboard indicators and leaderboard rankings rely on user clicks as an indicator of student learning behavior, online learning environments are found to reinforce shallower engagement, impaired performance, less learning depth, and greater grade fixation than traditional courses (Fritz 2011; Mattingly, Rice, and Berge 2012; Strang 2016). In fact, one study found an inverse correlation between student logins and assignment engagement, suggesting that students who generated the most clickstream data also exhibited poorer self-management in completing assignments (Strang 2016). Gamification likewise correlates with lower participation in class activities and lower performance on conceptual assignments while also encouraging “gaming behaviors” (Domínguez et al. 2013; Hanus and Fox 2015; Lawson et al. 2016; Macfarlane 2015; Purpura et al. 2011; Rose 2015; Scott and Nichols 2017; Selwyn 2014; Winstrup 2017). Selwyn posits that student-players are “more accurately described as being trained rather than learning *per se*” in gamified learning environments (2014, 97, 100). Many implementations of gamification reflect a return to behaviorism that rewards superficial course engagement to the possible detriment of deep learning and information transfer into declarative memory (Lawson et al. 2016; Long and Siemens 2011; Purpura et al. 2011; Scott and Nichols 2017).

CONSEQUENCES OF LEARNING ANALYTICS

Learning analytics do not just measure but also create, reinforce, and contain teaching and learning conditions (Perrotta and Williamson 2018). As institutions welcome a significant proportion of nontraditional students with commitments and responsibilities outside of the classroom, the monastic tradition of sequestering students away from the everyday world in the service of deep learning is yielding to student expectations that educational opportunities are responsive and adaptive to the other significant priorities in their lives (Foucault 1995; Jarrett 2013; Jones and Hansen 2014). Higher education is being recast as something “to be consumed quickly, and on the run, while students are working” (Slaughter and Rhoades 2014, 298). Students triage their academic work with strategies that prioritize grade achievement but sacrifice the long-term benefits of sustained attention, substantive engagement, and intellectual challenge that lead to deep learning (Macfarlane 2015; Shum and Ferguson 2012).

Analytics and the Learning Environment

Despite the fact that reviews of learning analytics are mixed and include negative outcomes, pedagogy is nevertheless increasingly determined by what can be measured, and how (Bodily and Verbert 2017; Perrotta and Williamson 2018; Rubel and Jones 2016; Scott and Nichols 2017). Analytics-enabled educational technology is “ultimately creating education

that elicits behaviors rather than thought" (Winstrup 2017, 96). Studies find that students do not always respond to nudge analytics by improving their learning behaviors, and low rates of voluntary student adoption are prompting learning-system designers to incorporate even more intrusive tracking and persuasive technology features (Bodily and Verbert 2017; Cai, Lewis, and Higdon 2015; Kitto, Lupton, et al. 2017; de Laat and Prinsen 2014; Timmers and Veldkamp 2011). Analytics-driven nudges and alerts present an opportunity cost, as "energies focused on attending to these technologies cannot be focused on making sense of study material" (Junco and Cotton 2012, 511). As a result, students experience a state of continuous partial attention, which poses risks for a reduced state of information processing, reduced capacity for creative problem-solving, and increased anxiety (Carrier et al. 2015).

Analytics-driven interventions and learning environments often reflect a fundamental disconnect between individual students' goals and the institution's goals, bringing the two value systems into conflict (Mattingly, Rice, and Berge 2012; Prinsloo and Slade 2013; Rubel and Jones 2016; T. Wu 2016). Like social media engagement indicators, learning analytics systems employ a "shamefully visible . . . display of numbers . . . [that] are consciously designed to have an impact" (D. Cooper 2014). In some class settings, dashboard features facilitating peer comparison engender competition that is damaging to learning communities and the learning environment (Hanus and Fox 2015). Students' attention to status acquisition can interfere with learning, and instructional design that rewards superficial participation can lack support for the development of metacognition that facilitates knowledge transfer and deep learning (Purpura et al. 2011; Teasley 2017).

Analytics as Academic Surveillance

Critical studies find that learning analytics systems disproportionately rely on demographic data and on student performance indicators divorced from their original context (Prinsloo and Slade 2013; Selwyn 2014). As a result, analytics-driven nudges pose risks of data discrimination, stigma, and a self-fulfilling prophecy of constant negative academic feedback (Drachsler and Greller 2016; Liu et al. 2017; O'Neil 2017; Prinsloo and Slade 2014; Roberts, Chang, and Gibson 2017; Roberts, Howell, and Seaman 2017; Rubel and Jones 2016; Winstrup 2017). Learning metrics also increasingly influence student beliefs, attitudes, and self-efficacy through the internalization of scrutiny from their classmates and instructors (Macfarlane 2015). Within a course, students adapt to this state of academic surveillance by inhibiting certain learning behaviors, such as debating or presenting a different opinion (Godor 2017; Mann 2005). Thus, rather than increasing students' opportunities for academic success, learning

analytics–driven interventions act to narrow and foreclose on learning opportunities (Perrotta and Williamson 2018; Prinsloo and Slade 2013). In analytics-driven learning environments, students acknowledge concerns about discrimination, privacy violations, identifiability, data security, performance pressures, lack of transparency, loss of human control to artificial intelligence, and exploitation (Drachsler and Geller 2016; Roberts, Howell, and Seaman 2017). These conditions—particularly loss of anonymity and confidentiality in learning—contribute to increased stress, anxiety, and insecurity (Macfarlane 2015; Purpura et al. 2011; T. Wu 2016).

Critics observe that learning analytics' overreliance on superficial weblog data capture is simultaneously exploitative and of questionable utility (Rose 2015; Winstrup 2017). Learning analytics not only report on students' performance but also drive interventions to influence it (Kitto, Lupton, et al. 2017; Prinsloo 2017). Such "shallow metrics" have very real consequences for students, who are actively manipulated by nudge analytics to conform to an idealized "data double" (Kitto, Lupton, et al. 2017, 155; Perrotta and Williamson 2018, 7). Furthermore, learning analytics inform the transformation of the learning experience, as the ingestion of usable data relies upon the standardization, factorization, and modularization of learning (Slaughter and Rhoades 2004). These analytics-driven instructional-design approaches increase the frequency and means of assessments, contributing to student anxiety, while also coinciding with triage-based distribution of learner support resources and reduced human interaction (Liu et al. 2017; Macfarlane 2015).

Analytics, Competition, and Conformity

Gamified learning environments place undue emphasis on external rewards and extrinsic motivation, which condition students to seek external feedback rather than cultivate interest, curiosity, and innate metacognitive and self-regulatory abilities (Loper and Hallahan 1982; Shum and Ferguson 2012). Rewards provided through gamified learning environments are perceived by some students as controlling, impede knowledge transfer, and counteract and reduce students' intrinsic motivation (Domínguez et al. 2013; Hanus and Fox 2015; Kim, Jo, and Park 2016; Verbert et al. 2014). Leaderboards and other forms of social surveillance in analytics-enhanced courseware engender student performativity that exerts a chilling effect on learning behavior, resulting in self-censorship, inhibition, silencing, and conformity (Domínguez et al. 2013; Godor 2017; Kitto, Lupton, et al. 2017; Macfarlane 2015; Mann 2005; Prinsloo and Slade 2013; Rubel and Jones 2016). Students perceive that leaderboards do not necessarily identify those who learned the most in the course (Domínguez et al. 2013; Verbert et al. 2014), but rather reward the "commodified promotion of self and exchange of personal 'microdetails' in pursuit of digital advantage

and ‘one-upmanship’ (Selwyn 2014, 121–22). In a comparison study between standard and gamified versions of the same course, results indicate that “at best, [the] combination of leaderboards, badges, and competition mechanics do not improve educational outcomes and at worst can harm motivation, satisfaction, and empowerment” (Hanus and Fox 2015, 159; see also Lawson et al. 2016; Scott and Nichols 2017).

A learning space should enable “experimentation and self-discovery” (Kruse and Pongsajapan, n.d., 5), but instead, analytics-enhanced courses tend to enforce rather than enrich the learning experience (Carmean and Mizzi 2010). Critics warn that learning analytics appear to be “domesticating rather than empowering students” (Macfarlane 2015, 347), calling to mind Progressive Era social reformers who admonished that conformance to custom is not the same thing as education (Emerson 1946a; Mill [1859] 2004). Nudge analytics function more like nag analytics, deploying either shame or approval in order to elicit desirable student behaviors. Analytics-driven pedagogies reinforce the kind of passivity that Dewey warned “leads to toleration of ignorance and to willingness to be misled and to see others misled”; acting contrary to democratically aligned educational institutions, which he asserted should “awaken curiosity and inquiry” and render participants “more disposed to act in creative ways” (Dewey 2003, 359, 364). Such learning technologies leave little room for spontaneity and contribute minimally to the cultivation of individuality as a means of enriching the entire human experience (Mill [1859] 2004). Instead, students experience a form of “social tyranny . . . penetrating much more deeply into the details of life, and enslaving the soul itself” (Mill [1859] 2004, 5).

Possible Futures

Learning analytics is but one node in a broader network of surveillance capitalism, in which the power to accumulate information harvested from human behavior creates control over others’ lived realities (S. West 2019; Zuboff 2015). Analytics-enhanced educational technology is an opportunity that institutions should maximize to engage students in critical awareness of the individual and societal benefits and risks of big data. Such discussions would, of course, threaten the value of learning analytics systems as totalizing sites of learner-data extraction. Instead, studies find that gamified and analytics-enhanced educational technology contributes to student anxiety, conformity, and alienation. These are hardly ideal conditions in which to welcome new members into the scholarly community, or to prepare engaged citizens for participation in a self-governing nation-state and a globalized society (Kubitschko 2015). They portend a diminishing of the individual and a devaluing of human dignity, and provoke a cognitive flaw that leaves humans struggling to achieve empathy at

population (and network) scale (Garibaldo and Rebecchi 2018; Tsekeris, Tsekeris, and Katerelos 2018).

One way to imagine possible futures engendered by learning analytics is through dialectical reasoning. In this framework, the thesis of learning analytics is the status quo: students, along with faculty and staff, acquiesce to an administrative prerogative that sees their learning (and laboring) data aggregated and modeled for the benefit of the institution derived from achievement metrics. People in the academy, and the work they do, adapt in response to the needs and directives of an idealized institution-scale data double comprised of metrics like demographics, on-time graduation rates, graduate placement rates, program rankings, financial numbers, and productivity indicators. The context collapse between the learning environment and the world from which it seeks distance, all the better to examine it, accelerates; the seclusion and sustained attention necessary for study and creativity become scarcer; the research enterprise retreats from the exploratory and unknown; and obsolescence threatens the methods available for understanding and improving the human condition (Hartman-Caverly 2017; Kristensen and Ruckenstein 2018).

This deployment of educational technology and learning analytics follows the infusion of ubiquitous computing technology into daily life activities. The digitization of everyday life is looked to as a correlate, if not a cause, of declining trends in young adult mental health (Howell et al. 2018; Huang et al. 2018; Twenge 2017). Educational technology reduces student engagement, degrading the quality of student-student and student-faculty interactions, restricting exposure to diverse ideas, undermining independence and independent thinking, and reducing opportunities for collaborative learning (Dumford and Miller 2018; Howell et al. 2018). Each of these conditions inhibits curiosity and creativity, two innately human traits that are both essential to learning and invaluable in the Knowledge Era (Jahnke, Haertel, and Wildt 2017; Oriol et al. 2016; Price et al. 2016). Attention engineering through learning analytics poses observable adverse effects; just because human behavior is programmable does not mean human nature has the fault tolerance to withstand these kinds of bugs.

The antithesis to learning analytics will take myriad forms of resistance. One form already underway is student subversion of analytics-enhanced educational technology, including gaming behaviors that optimize engagement metrics (and grades) at the opportunity cost of deep learning behaviors. Performative subversion includes strategies like scrolling through an embedded text file to make it seem as though one has read it, or letting a streaming file play while one's attention is focused elsewhere to satisfy a course content engagement metric. Outright cheating in the online learning environment is another. These approaches mir-

ror other data-obfuscation efforts by introducing inauthentic behaviors to the learner's data model (C. Thompson 2015). Some systems permit students to opt-out of or restrict notifications; in other instances, students can block or automatically delete notifications in their email clients and on their personal devices. Where options are available, students can disable learner-data tracking, and faculty can configure learning environments that preempt or minimize learner-data collection. Hacking learning analytics or educational technology systems puts the resistance on offense, but even ethical hacking poses the risks of violating terms of use of institutional information-technology resources (Ettlinger 2018; Kubitschko 2015). In instances where student-data aggregation and sharing implicates legal rights and regulations, such as FERPA, whistleblowing and lawfare are opportunities for resistance (Lynch 2017). Some institutions might decide to decommission systems and strategically differentiate themselves as high-touch/low-tech, although the sunk-cost fallacy in decision-making makes it unlikely that institutions will walk away from analytics-enhanced educational technology wholesale. Given what we know about how learner data is currently used and what further capabilities exist, the likelihood of educational technology having its Cambridge Analytica moment seems inevitable ("Cambridge Analytica Controversy" 2018; Schildt 2017; S. West 2019).

As learning analytics and educational technology matures, the field of action will stabilize on some synthesis of these responses. Technology abstinence or abolitionism is both unrealistic and ignorant to the benefits that big data is capable of delivering to both individuals and society (Havens 2018). The academy's role in the ongoing development of big data capabilities must be complemented by its role to facilitate students' (and the public's) understanding of how big data systems work and how to engage with them in order to maximize benefits and acknowledge, avoid, and minimize risks (Kristensen and Ruckenstein 2018; Kubitschko 2015). Faculty with expertise in data science and privacy—librarians in particular—can influence institutional governance around the use of learner data and provide co-curricular and community-based learning opportunities for topics in big data (Ettlinger 2018; Hartman-Caverly 2018). These initiatives should, among other things, expand the conversation beyond privacy and extend the value system of intellectual freedom to include attentional autonomy.

ATTENTIONAL LITERACY AND INTELLECTUAL FREEDOM

Attentional Autonomy

The cognitive processes of attention involve one's conscious control over the selection, analysis, and processing of information. Attentional autonomy is central to intellectual freedom—the ability to access information of

one's choosing free from monitoring and without restriction (ALA 2008, 2014a, 2014b; Berkeley Office of Ethics 2018; Magi and Garnar 2015). The same conditions necessary for intellectual freedom, including privacy and respect for individuality, also promote attentional autonomy.

Attention engineering informs the "choice architecture" that scaffolds the underlying logic of nudge analytics (Carmean and Mizzi 2010). Attention engineering in educational technology is realized through the surveillance, social surveillance, social comparison, and competition-promoting features of learning analytics systems, and through real-time nudge interventions (Hanus and Fox 2015; Prinsloo 2017; Prinsloo and Slade 2017a; Roberts, Howell, and Seaman 2017; Tolson 2014; T. Wu 2016). The implementation of technologies to facilitate constant data capture and real-time analysis intrude increasingly on mental privacy and preempt individuals' ability to respond intentionally to their information environment (James 1948; Petersen and Posner 2012; Rosen and Santesso 2018; T. Wu 2016). While deep learning is traditionally thought to require "periods of solitude, inquest, and self-recovery" (Emerson 1946a, 29) and retreats into "solitude and privation" (Emerson 1946b, 259), the alerting and point-of-need intervention affordances of learning analytics-enhanced educational technology constantly disrupt study and divide students' attention. Control over one's attention is intrinsic intellectual freedom, but mental privacy and attentional autonomy are endangered by the ubiquity of digital technology (T. Wu 2016).

Lack of transparency regarding the implementation and use of learning analytics undermines students' ability to exert control over their own attention in educational spaces (Fritz 2011; Kruse and Pongsajapan, n.d.; Lawson et al. 2016). As a form of persuasive technology, learning analytics seeks to optimize student behavior by detecting patterns in large datasets, often committing "data subversion" (Prinsloo and Slade 2013, 1516) through covert mechanisms of student-data capture and analysis (Drachsler and Greller 2016; Haythornthwaite, de Laat, and Schreurs 2016; Kitto, Lupton, et al. 2017; Leitner, Khalil, and Ebner 2017; Rubel and Jones 2016; Shum and Ferguson 2012). Though nudge analytics is purported to preserve freedom of choice, this approach violates students' intellectual freedom by infringing on their privacy and manipulating their decisions and behaviors, and such claims are disingenuous unless students have the informed ability to opt-out (Carmean and Mizzi 2010; Prinsloo and Slade 2013; Rubel and Jones 2016). Nudge analytics interventions can also devolve into shame and coercion that exploits students' academic performance anxiety (Mill [1859] 2004; Purpura et al. 2011; Roberts, Howell, and Seaman 2017; Verbert et al. 2014; T. Wu 2016). Furthermore, not all nudges are created equal; at some institutions, students failing to meet data-driven achievement benchmarks are automatically advised to enroll in courses in which they have a higher predicted likelihood of success, or

are forced to change academic majors (Jarrett 2013; Parry 2012). Overreliance on data-driven advising and structured pathways in academic planning compromises the richness and serendipity of exploratory learning, decreasing learner challenge and exposure to diverse ideas (Jarrett 2013; Parry 2012; Selwyn 2014). An attempt at “total attention control,” nudge analytics restrict intellectual range of motion by defining what is possible for students in the interest of the institution (T. Wu 2016, 119).

Education and the Individual

In his “Education” address, Emerson asserted that approaches to teaching and learning should be “as broad as [hu]mankind” (Emerson 1946b, 254). As the education system integrated with the turn-of-the-century industrial economy, reformers observed a devaluing of individual cultivation by which “wit, fancy, imagination, and thought” became illicit (Emerson 1946b, 269; see also Mill [1859] 2004, 59). The contemporary role of higher education in the knowledge economy gives rise to similar developments. In repurposing features from systems designed to promote “mass socialization” and “mass participation” (Selwyn 2014, 106), educational technology is found to promote conformity and to undermine independent critical thinking, viewpoint plurality, intrinsic motivation, learning autonomy, and self-efficacy (Bodily and Verbert 2017; Hanus and Fox 2015; Lee 1903; Macfarlane 2015; Mill [1859] 2004; Purpura et al. 2011; Roberts, Chang, and Gibson 2017; Selwyn 2014; T. Wu 2016). Nudge analytics and gamified learning environments provide inadequate affordances for forethought, self-reflection, metacognition, self-regulation, and motivation in students (Dabbagh and Kitsantas 2012; Kitto, Lupton, et al. 2017). In this way, educators who incorporate educational technology into a course without intentionally integrating it into authentic teaching and learning practices risk “sacrific[ing] the genius of the pupil” in favor of “a neat and safe uniformity” (Emerson 1946b, 257).

Education and social reformers in the Progressive Era promoted deep learning as a process of individual liberation achieved through intellectual capacity-building (Emerson 1946a and 1946b; Mill [1859] 2004). At present, *attentional literacy* refers to the development of executive function and its application to problem solving, attention shifting, planning, and goal setting (Petersen and Posner 2012). Attentional literacy is cultivated through self-regulated learning, which encourages students’ intentional engagement in learning behaviors, and by cognitive presence, deep engagement with information and co-creation of meaning (Fournier and Kop 2010; Kim, Jo, and Park 2016). Learning analytics interventions should prioritize “develop[ing] students’ self-awareness as well as their ownership of and responsibility for their own learning” (Shum and Ferguson 2012, 14) by first respecting attentional autonomy (Drachsler and Greller 2016).

Attentional Literacy

The attention engineering affordances of educational technology are precipitating “attention failure” (J. Wu 2015, 77). Students exhibit a decreasing ability to sustain focal attention, experience elevated rates of task-switching and continuous partial attention, and are less able to filter out noise in the information signal (Karpinski et al. 2013; J. Wu 2015). The distraction triggered by notification alerts and nudge analytics correlates with feelings of disorientation and lower assessment scores, but cultivating attentional literacy with mental and behavioral strategies for managing attention can counteract these negative effects (J. Wu 2015). Attentional literacy is especially important as online learning environments increasingly mimic and incorporate the features and affordances of social-networking sites designed to capture and direct users’ attention (J. Wu 2015).

Writing for *EDUCAUSE Review*, technology culture critic Howard Rheingold declared attention to be an essential literacy for the Knowledge Era. Attentional literacy involves consciously engaging one’s attention, the use of task-appropriate attentional strategies, and exercising discretion in determining what to pay attention to (Rheingold 2010). Attentional autonomy as a facet of intellectual freedom is undermined by the attention engineering affordances of nudge learning analytics (Prinsloo and Slade 2013). Analytics initiatives should be partnered with attentional literacy programming to cultivate students’ consideration that “we give power to people when we give them our attention” (boyd 2010, 34) and to support students’ informed decision-making around the adoption of technologies designed to engineer attention. Instruction on digital metacognition or meta-attention can include practices like self-monitoring, sustaining focal attention, and the exercise of strategic control and conscious regulation over one’s own attention (Carrier et al. 2015; J. Wu 2015).

Attention and Ethics

Because it implicates an individual’s will, attention engineering implicates ethics; thus, questions about learning analytics features that capture student attention and nudge their decisions are inherently ethical questions (James 1948; D. West, Huijser, and Heath 2016; T. Wu 2016). Although ethics are often perceived as a barrier to wider deployment and adoption of learning analytics, ethical design features and implementation strategies should be considered on par with functional and business requirements for analytics-enhanced educational technology (Drachsler and Greller 2016; Kitto, Lupton, et al. 2017; Leitner, Khalil, and Ebner 2017). Fundamental ethical considerations for nudge analytics include autonomy; beneficence; nonmaleficence; justice through transparency in data collection, analysis, and application; adequate oversight; and a corrective appeal mechanism (Prinsloo and Slade 2014; D. West, Huijser, and Heath 2016). Attentional literacy programming that discusses autonomy

privacy and the “right of information self-determination” (A. F. Westin, as quoted in Drachsler and Greller 2016, sec. 3.2) would facilitate students’ autonomy and informed, intentional participation in learning analytics initiatives (ACRL 2016; Rosen and Santesso 2018). The ethical deployment of nudge analytics demands “algorithmic accountability” (Liu et al. 2017, 150) and the restoration of transparency and student agency (Lawson et al. 2016; Prinsloo and Slade 2017b).

As libraries assess the benefits and risks of participating in institutional learning analytics initiatives, they should critically examine the ethics of competing for students’ attention by “perforating their psychological environment” (Kazi 2012, 7). Academic libraries are shaped externally by their host institutions, broader education culture, and resource availability; but they also have intrinsic ethics, expertise, and disciplinary practices. Perhaps privacy and attention autonomy, more so than information discovery and access, will be academic libraries’ primary strategic differentiators in the attention economy (Kazi 2012).

In his later writings, Gerald Stanley Lee, inventor of the modern concept of attention engineering, composed polemics against the loss of individuality resulting from the “misuse of technology” to further “civilization by the numbers” (Bush 1991, 8). He criticized the popular press as “a huge, crunching mass-machine—a machine for arranging every man’s mind from outside” (Bush 1991, 59). Lee’s later works evoke a sense of regret for his role in the promotion of mass persuasion, confessing, “What I believe now is that most people, if they would stop trying to get other people’s attention and try to get their own, would do more good” (Lee 1920, 211).

Emerson asserted that mental privacy was essential to learning, admonishing teachers that “the secret of Education lies in respecting the pupil” (Emerson 1946b, 260). In contemporary times, even educational technology super-users acknowledge a need for solitude, metacognition, and sustained attention to achieve deep learning and knowledge transfer (Fournier and Kop 2010). Attentional autonomy and the capacity to engage in sustained focal attention are fundamental to substantive learning, intellectual freedom, and informed engagement in a democratic society. Attention engineering undermines individual autonomy, erodes deep learning, inhibits creativity, and diminishes pluralism. Academic libraries and their host institutions would be wise to heed Mill’s observations on the impact of automation and scientific management during the industrial revolution:

Human nature is not a machine to be built after a model, and set to do exactly the work prescribed for it. . . . The perfection of machinery to which [society] has sacrificed everything, will in the end avail to nothing, for want of the vital power which, in order that the machine might work more smoothly, it has preferred to banish. (Mill [1859] 2004, 62, 124)

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Sarah Hartman-Caverly is an assistant librarian at Penn State Berks, where she liaises with the Engineering, Business and Computing division. Her scholarship examines the compatibility of human and machine autonomy from the perspective of intellectual freedom. Recent contributions include "Version Control" (ACRL 2017); "Our 'Special Obligation': Library Assessment, Learning Analytics, and Intellectual Freedom" (ACRL 2018); and "TRUTH Always Wins": Dispatches from the Information War" (forthcoming ACRL 2019). Hartman-Caverly earned her MS(LIS) and MSIS from Drexel University.