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REVIEW ARTICLE

A Model of Technology Incidental Learning Effects

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Abstract
Increases in technology use, among youth and adults, are concerning given the volume of information produced and disseminated in the modern world. Conceptual models have been developed to understand how people manage the large volume of information encountered during intentional learning activities with technology. What, if anything, do people learn when they happen upon news and other information while using technology for purposes other than learning? Questions like this highlight the need to understand incidental learning, i.e., learning that occurs when people, who are pursuing a goal other than learning such as entertainment, encounter information that leads to a change in thinking or behavior. In this article, we integrate theory and research from multiple scholarly literatures into the Technology Incidental Learning Effects (TILE) model, which provides a framework for future research on how incidental learning occurs and what factors affect this process. Current research on incidental learning can be informed by educational psychology scholarship on dual-processing, motivation, interest, source evaluation, and knowledge reconstruction. The TILE model points to many promising future directions for research with direct implications for modern society, including the need to better understand how and why people move from merely noticing to engaging with incidentally exposed information as well as how to help people successfully manage the large amounts of information they encounter when using technology for purposes other than learning.

Keywords Incidental learning · Technology · Dual-processing · Knowledge

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> While waiting in line at the grocery store, you open your Twitter app and begin scrolling through your feed. The posts slide by as you glance at titles, looking for something entertaining. You notice one headline proclaiming a political figure is a member of a secret organized crime syndicate. You quickly dismiss the headline and scroll on to other posts. Why did you notice the headline, and how did you decide to dismiss it? Further, what, if anything, did you learn from that headline?

In the modern world, more and more people are getting their news and other forms of information via technology, particularly online sources (Fedeli and Matsa 2018; Pew Research Center 2017; Reuters 2016), with evidence that this trend is even more pronounced for younger people (Masip et al. 2018). Such trends in information consumption are concerning given the sheer volume of information found online as well as the recent rise in "fake news"[1] (Barzilai and Chinn 2020; Britt et al. 2019; Rapp and Salovich 2018), in particular on social media (Allcott and Gentzkow 2017; Hills 2019). In addition, there is growing concern that technology, including but not limited to social media, exposes people to a homogeneous diet of information and perspectives that, regardless of their veracity, can hinder people's ability to think critically about important civic, scientific, and ethical issues (i.e., filter bubbles, echo chambers; Pariser 2011). Yet, there is some evidence that the negative effects of social media on knowledge and polarization are either overblown or are more nuanced than once believed (Allcott et al. 2019; Bakshy et al. 2015; Guess et al. 2020; Scharkow et al. in press). Similarly, initial concerns about the negative effects of excessive technology use on academic performance (Karpinski 2009) and general well-being have given way to empirical evidence showing more complex relations involving mediators of those effects (e.g., academic distraction; Feng et al. 2019) and moderators of these effects (e.g., academic learning skills; Loh and Kanai 2016), as well as unclear evidence regarding whether or not those effects are practically significant or causal (Coyne et al. 2020; Michikyan et al. 2015; Orben 2020; Orben et al. 2019). The growing use of twenty-first-century technology and the mixed findings regarding its effects necessitate more research regarding how and why technology influences people's well-being (Orben et al. 2019), learning (Greenhow et al. 2019; Lee and Xenos 2019), and behavior (e.g., political participation; Gil de Zúñiga et al. 2012).

Often people use twenty-first-century technology for goals other than learning (e.g., entertainment, interpersonal connections; Lee and Ma 2012; Vraga et al. 2016), and in so doing, they are frequently exposed to large amounts of various kinds of information they were not seeking out (e.g., news headlines, knowledge claims; Tewksbury et al. 2001). What factors guide their interaction with this information? What do they merely notice versus contemplate deeply? How do they decide what information to attend to and what information to dismiss? Do they remember this information? Does it influence their perceptions or beliefs? Given concerns regarding how people do and do not successfully manage the large amount of information afforded by technological environments, and its effects upon how people think and engage as informed citizens (Flaxman et al. 2016), incidental exposure and learning effects have become an increasingly prominent area of focus for researchers in political science, journalism, communications, and health sciences among other scholarly disciplines

[1] Wardle (2019) argued the term "fake news" is vague and that there are, in fact, three relevant types of problematic information: misinformation, which is false (e.g., unintentionally incorrect headlines); malinformation, which is intended to harm (e.g., revenge porn); and disinformation, which is both false and intended to harm (e.g., fabricating information to manipulate public opinion). Acknowledging these differences, in this article, we will use the term "misinformation" to include all of these types.

(Bergström and Belfrage 2018; Bode 2016a; Feezell 2018; Hermida et al. 2012; Kelly et al. 2009; Lee and Kim 2017; Thorson and Wells 2016).

Educational psychologists have conducted relatively little research regarding incidental learning with modern technology. This is particularly surprising given Alexander et al. (2009) reviewed numerous perspectives on learning and identified nine shared principles, including that "much of learning is tacit and incidental" (p. 179), citing Bargh and Chartrand's (1999) work on the importance of automaticity in everyday functioning. In a subsequent article, Reynolds et al. (2009) elaborated on their findings regarding a lack of scholarship on incidental learning, arguing that, instead, "researchers have focused much of their work on… learning that is active, potentially strategic in nature, and conscious" (p. 211). Indeed, educational psychology researchers and theories have contributed greatly to the scholarship on how people actively and intentionally engage in learning with technology (e.g., Mayer 2019; Winne and Hadwin 2008; Winters et al. 2008), but less so to the scholarship on incidental learning. Such scholarship would benefit from greater integration of educational psychology theory and empirical research.

In this article, we present the Technology Incidental Learning Effects (TILE) model, which elaborates upon existing incidental exposure and learning research from a variety of scholarly disciplines (e.g., political science, journalism, communications) by integrating scholarship from educational psychology, including work on dual-processing (Stanovich and Toplak 2012), interest (Harackiewicz and Knogler 2017), academic goals (Wormington and Linnenbrink-Garcia 2017), source evaluation (Braasch et al. 2018), and knowledge reconstruction (Kendeou and O'Brien 2014). This model broadens existing conceptual work on incidental learning while also identifying promising directions for much-needed future empirical research. The TILE model directly addresses Reynolds et al.'s (2009) call for more scholarship on incidental learning and the model has particular relevance to research on how people experience twenty-first-century technology (e.g., Internet, mobile technology, social media), including how their prior decisions and actions affect what they encounter, what they choose to deliberatively engage with versus move past, and how they make decisions regarding the kinds of engagement the information warrants.

Educational psychologists, particularly those familiar with theories of self-regulated learning (SRL; Winne and Hadwin 2008), multimedia learning (Mayer 2019), or mobile learning (Bernacki et al. 2020) may wonder why yet another model of learning is needed. Indeed, we adhere to the idea that science is best when it is parsimonious. Nonetheless, we argue that incidental learning with technology differs substantively from more intentional learning in several ways, including differences due to the lack of intentionality (i.e., incidental learning is not driven by a learning goal) as well as differences in the kinds of learning effects expected from incidental exposure (Kahneman 2011; Stanovich 2016; Stanovich and Toplak 2012). Finally, as we will show, much of the modern research on incidental learning has involved a particular type of twenty-first-century technology: social media platforms (cf. Jiang et al. 2015). Therefore, we honor this focus in our discussion of the research supporting our model but acknowledge that incidental learning research must be expanded to other types of twenty-first-century technologies including online videos (e.g., YouTube) and streaming services (e.g., Netflix) available in both traditional and mobile environments. Before presenting how educational psychology research can elaborate current conceptual and empirical literature on incidental exposure and learning, we provide an overview of how we chose to define incidental learning.

Defining Incidental Learning

Downs (1957) defined incidental learning as instances when individuals (1) are exposed to information and (2) acquire a lasting trace of it, both without the intention of doing so. The first studies of incidental learning involved people who chose to watch television for entertainment reasons but while doing so were exposed to news content, such as when they turned on the television a few minutes before their favorite entertainment show and thus watched the end of a news program (Neuman et al. 1992). This research revealed people did retain some trace of the incidentally exposed information, informing public service broadcasters' decisions to schedule news programs during or just before prime viewing hours. Incidental learning scholarship has evolved over time to include other forms of media and has gone by numerous terms such as serendipitous exposure, accidental exposure, information encountering, and scanning behaviors (Jiang et al. 2015; Makri and Blandford 2012; Yadamsuren and Erdelez 2017). Mirroring Downs (1957), researchers in fields such as information and library sciences have stressed that a defining aspect of incidental exposure and learning is that the user was not looking for or intending to find the content (Jiang et al. 2015; Yadamsuren and Erdelez 2017).

In our definition of incidental learning, similar to Downs and other modern researchers, we exclude instances when people actively and intentionally use technology for learning (e.g., Greenhow et al. 2019; Kimmerle et al. 2015). Such intentional learning activities have been well-articulated in models of multimedia learning (Mayer 2019), self-regulated learning (SRL; Greene 2018), mobile learning (Bernacki et al. 2020), and source evaluation (Braasch et al. 2018), among others. On the other hand, we have a broader definition of incidental learning than some researchers who limit the term to only those instances when the content is discrepant with the user's own knowledge or views (e.g., Weeks et al. 2017). We are interested in the incidental learning effects of all content, including concordant and discrepant information. Likewise, some researchers in information and library sciences have included in their definition of incidental learning the criterion that the outcome of the learning be beneficial to the user (Jiang et al. 2015; Makri and Blandford 2012). We have not adopted that criterion given work by Alexander et al. (2009), among others, who have stressed that learning can sometimes be maladaptive. Understanding the negative effects of incidental learning with modern technology is as important as understanding its positive effects (cf. Hills 2019). Finally, incidental learning of misinformation is certainly a timely and important topic (Rapp and Salovich 2018) but our focus includes incidental learning of all information, including misinformation but also accurate information.

Some areas of educational psychology research involve incidental acquisition of information but differ from the focus of our model in important ways. For example, there is ample research on incidental vocabulary acquisition during general reading (e.g., Swanborn and De Glopper 1999), particularly in the context of secondary language acquisition (SLA; Hulstijn 2013). In this literature, the "incidental" aspect of learning is not that the learner had a goal other than to learn, as in our definition, but rather that the vocabulary and grammar were learned while engaging in a related learning activity, i.e., reading. Researchers have shown the more elaborative the processing during reading, the greater the likelihood of committing the incidentally exposed vocabulary or grammar to long-term memory. This focus on the role of elaborative processing has informed our TILE model, but the scope of the activities and goals covered in incidental learning with modern technology is broader than the goals addressed in the vocabulary and SLA literature (cf. Hulstijn 2013). However, we have benefitted from SLA research showing that both declarative (e.g., vocabulary) and more conceptual or abstract knowledge (e.g., grammatical phenomena) can be acquired incidentally (e.g., Chan and Leung 2018; Rogers et al. 2016).

Our work is related to, and draws from, research on implicit learning, typically defined as learning that occurs without conscious awareness or intention (e.g., statistical learning, grammatical or language learning; Reber et al. 2019). Such research has largely focused on how repeated exposure to stimuli can lead to non-conscious learning of patterns or rules that affect subsequent performance, in terms of knowledge, biases, and skills. Kahneman's (2011) work with Tversky in behavioral economics can be considered an applied version of implicit learning. Our work is similar; in fact, we argue incidental exposure and learning research would be productively informed by such work, as described below. Nonetheless, implicit learning research has tended to be more basic in nature and focused on the effects of repeated exposure to stimuli; our work is more applied and focused on solitary or infrequent exposure to content.

Finally, research on the positive relationship between general text or media exposure and reading comprehension performance (e.g., Mol and Bus 2011; West and Stanovich 1991) is certainly informative in terms of how prior exposure activity can predict the volume and types of knowledge acquired. However, we are interested in how exposure to particular information and claims (e.g., the false claim that vaccines are dangerous) can affect people's related knowledge, beliefs, attitudes, and values (e.g., decisions to vaccinate, views of science), rather than volume or type effects. Therefore, our work on incidental learning is broader than, and different from, research on general text exposure.

In sum, we have adopted and adapted Downs' (1957) definition of incidental learning for the modern world, taking into account research across educational psychology and other fields such as media studies. Incidental learning with modern technology occurs when (1) the exposure occurs in a technology context, (2) the person was using technology for a goal other than learning, and (3) exposure to the content led to a change in thinking, behavior, beliefs, attitudes, or values. Importantly, we do not restrict incidental learning to only those instances when the content does not align with the user's knowledge or views (Weeks et al. 2017), is inaccurate (Rapp and Salovich 2018), or has benevolent effects (Makri and Blandford 2012). Having defined incidental learning with modern technology, next we present a brief review of extant models of incidental exposure and learning developed outside of educational psychology.

Extant Incidental Exposure and Learning Models

Models of how incidental exposure happens, and what is learned from it, exist in the academic literatures on political science, library sciences, information literacy, and media and communications (Cappella et al. 2015; Gil de Zúñiga et al. 2017; Jiang et al. 2015; Lee and Ma 2012; McCay-Peet and Toms 2015; Thorson and Wells 2016; Yadamsuren and Erdelez 2017). Researchers in political science have tended to study the effects of incidental learning on news and political knowledge, whereas researchers in other fields have examined a broader array of outcomes including scientific knowledge acquisition. One influential model of how incidental exposure and learning occur in modern technology is the Information Encountering in Online News (IEON) model (see Fig. 1; Yadamsuren and Erdelez 2017).

The IEON model applies to situations where people are not actively pursuing particular information. The first step in the IEON model is noticing the content, which occurs when a

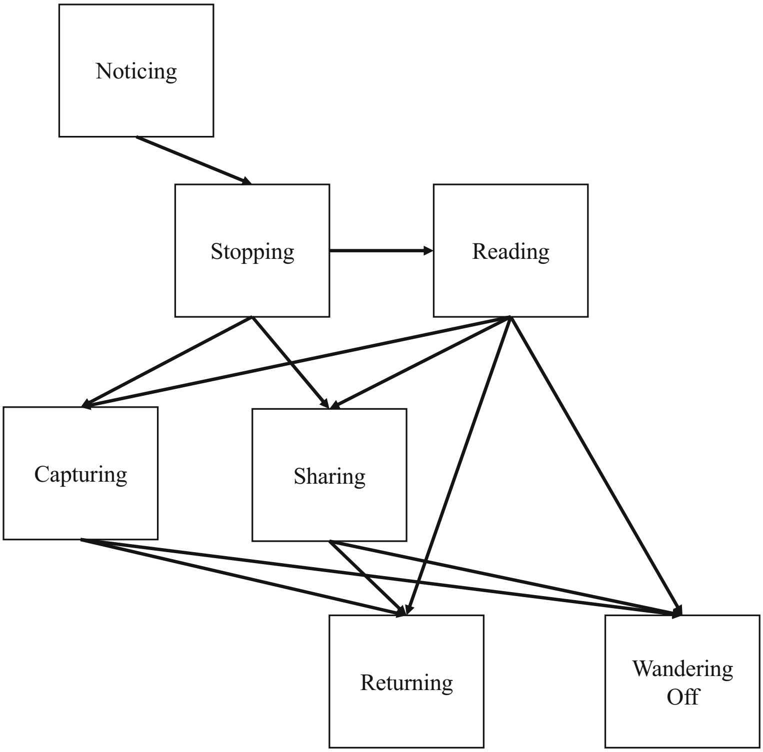

Fig. 1 Information Encountering in Online News model

person's attention is drawn to the information via particular cues (Yadamsuren and Erdelez 2017). Yadamsuren and Erdelez (2017) claimed noticing was more likely to occur when the unanticipated information is salient, personally relevant, linked to a professional need, consistent with the person's values or beliefs, or considered bizarre. They argued noticing alone is usually not enough to produce long-lasting effects; individuals must engage in what they called "stopping," which involves a conscious interruption of their initial activity to direct their full attention to the information. In Yadamsuren and Erdelez's interview research, they found that participants reported stopping to read a noticed headline when it was perceived to be important, relevant, or surprising, as well as when it elicited a strong positive or negative emotion. The context in which the information was encountered also mattered: participants made stopping decisions based upon whether there was time to stop, and whether stopping would be appropriate in the context (e.g., stopping to read an entertainment article in the workplace v. home).

After stopping, users can engage in a number of processes for internalizing or using the information, including reading, capturing (e.g., not reading or viewing the information immediately but saving it for future review), and sharing. Yadamsuren and Erdelez identified three potential outcomes of incidental exposure, including changes in knowledge or perception, emotional responses, and a feeling of personal connection with people or ideas in the incidentally exposed content (Yadamsuren and Heinström 2011). Jiang et al. (2015) contributed a useful elaboration of the IEON model by highlighting how differences in users, the information encountered, and the environment can affect noticing and engagement with incidentally exposed content. Together, these models provide a framework of behaviors, individual difference factors, and outcomes regarding incidental exposure and learning, but these models can and should be supplemented with additional components relevant to the incidental learning process, including educational psychology theory and research on user, information, and environment factors that can affect how incidental learning occurs, or not. Such work can result in a more generative model of how people encounter, process, and respond to incidental exposure and learning with technology.

Technology Incidental Learning Effects Model

In Fig. 2, we present the TILE model, which is an evolution of the work on incidental learning in information and library sciences, and political science, among other disciplines (e.g., Jiang et al. 2015; McCay-Peet and Toms 2017; Yadamsuren and Erdelez 2017) by integrating relevant theory and findings from educational psychology, including work on motivation, emotions, and individual differences. The TILE model is different from other models in educational psychology (e.g., SRL), because it describes responses to incidental exposure, which means it is not relevant in instances where users are intentionally using technology to achieve a learning goal. Incidental exposure in a technology environment occurs when the user had a non-learning goal (e.g., entertainment) while using the technology and then is incidentally exposed to either verbal or visual information different from what was sought. A review of our TILE model must begin with the acknowledgment that it contains some of the same aspects as IEON and other models of incidental learning (e.g., Jiang et al. 2015; Yadamsuren and Erdelez 2017). However, it begins from a novel contribution: user interests and motivations, which drive what appears in technology content and media feeds. Noticing (i.e., incidental exposure) plays a central role in the TILE model, as it does in other models of incidental learning, because unnoticed content cannot affect learning outcomes. User, information, and environment factors can influence whether people notice content. Once content is noticed, people can engage in either automatic or deliberative processing. As we describe in more detail below, we define automatic processing as akin to Type 1 processing per dual-processing models of cognition, whereas we define deliberative processing as akin to Type 2 processing (Evans et al. 2013; Kahneman 2011). Automatic processing is rapid, intuitive, and non-conscious, thus not requiring working memory or controlled attention, whereas deliberative processing is slow, reflective, and engages working memory (Evans 2019). Automatic processing leads to particular incidental learning effects, which we synthesize from empirical research, below. These effects can, in turn, drive user interests and motivations. On the other hand, deliberative processing involves elaboration and meaning-making of the noticed content via connections with prior knowledge. Once completed, deliberative processing of noticed content can lead to one of three types of behaviors, returning to the previous activity (e.g., going back to a Facebook feed), responding relatively briefly (i.e., capturing, sharing, reacting), or actually selecting and reading or engaging with the content (e.g., clicking on a link in an Instagram post). Again, similar to Jiang et al.'s (2015) work, in the TILE model, user, information, and environment-based processing factors affect people's choice of behavior after deliberative processing. Deliberative processing incidental learning effects occur when users choose to either respond to the content or return to what they were previously doing (i.e., continuing scrolling through their social media feed). We have differentiated deliberative processing incidental learning effects from automatic processing incidental learning effects because empirical research has suggested that the former can affect a wide variety of knowledge, attitudes, and future behaviors, compared with the latter, which tends to have a narrower effect on knowledge, as we review below. Deliberative processing incidental learning effects, in turn, can affect user, content, and environment factors (e.g., changes to beliefs, selection of different environments) as well as users' interests and motivation, which would begin a new cycle of incidental exposure and learning. We characterize any effects due to selecting and reading as intentional learning effects, because these behaviors, in essence, transform incidental exposure into intentional learning (i.e., the user adopts a learning goal to read the material). Such behaviors connect clearly to existing models of intentional learning in educational psychology (e.g., self-regulated learning, multimedia learning).

We believe the TILE model makes numerous unique contributions to the field of incidental learning by combining aspects of incidental exposure and educational psychology research. We describe these contributions, which in turn point to a number of promising directions for future research, by positing the following six claims:

1 Users' interests and motivations shape the content available for incidental exposure.
2 User, content, and environmental factors affect whether noticing happens.
3 Noticing results in either automatic or deliberative processing.
4 Behavior resulting from deliberative processing is predicted by user, content, and environmental factors.
5 Deliberative processing incidental learning effects vary across behaviors and user, content, and environmental factors.
6 Incidental learning is cyclical and recursive.

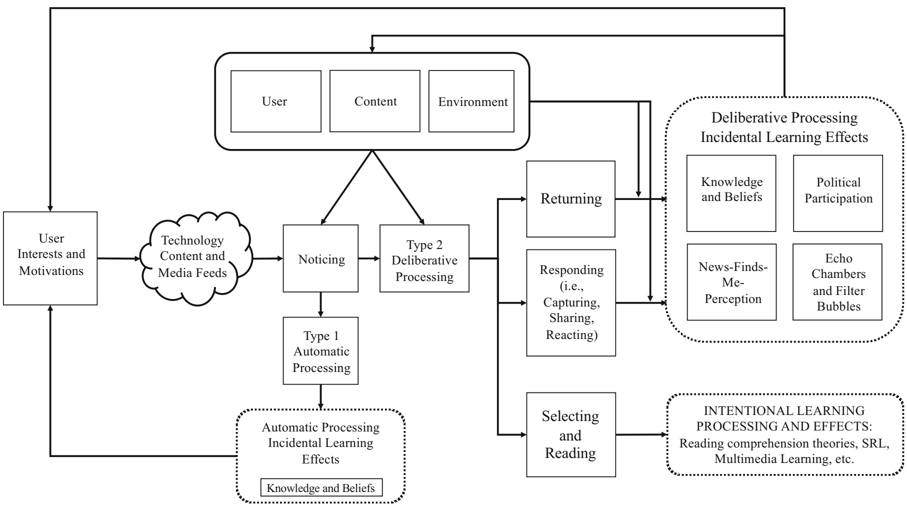

Fig. 2 The Technology Incidental Learning Effects model

Users' Interests and Motivations Shape the Content Available for Incidental Exposure

As shown in Fig. 2, users' interests and motivations directly affect what they seek via technology, and they also influence the kinds of information modern media "pushes" to them. Thorson and Wells (2016) created the Curated Flows Framework to categorize the five "actors" (p. 310) who select, organize, and refine (i.e., curate) what information appears in the user's media. These actors include the user, their social contacts, journalists, strategic communicators, and algorithmic filters of the technology platforms themselves. Users' decisions about whom to connect with affects what information they see in their feed (e.g., when social media apps "push" information from contacts into the user's feed). Likewise, their contacts' decisions about whom to connect with also affect what the user sees, as many technology platforms propagate material from contacts' feeds into the user's feed. Many users follow traditional news organizations' online presence; thus, journalists and media companies continue to serve a gatekeeping role in terms of the information users encounter (e.g., making editorial decisions about what to publish). However, traditional media companies' influence has been diminished with the rise of strategic communicators, including individuals and organizations (e.g., celebrities, politicians, commercial companies) who wish to directly reach users without a media company acting as a mediator. Technology platforms themselves are actors in the Curated Flows Framework, because they use algorithms to determine users' interests, and then push related information into the user's feed (Baumgartner and Morris 2010). In sum, any consideration of the content appearing in a user's feed must include the user's motivations and interests, the user's curation decisions, as well as curation decisions made by other actors in the Curated Flows Framework.

Focusing on users' own interests and motivations, Ruggiero (2000) proposed a Uses and Gratification Theory, arguing that users curate their media based upon their desired uses for it, as well as what aspects of media they find most rewarding. Typical media uses and gratifications include information-seeking, socializing, status-seeking, and entertainment. Users may have fairly stable preferred uses and desired gratifications for particular media platforms, such as when someone uses a news website for information but Instagram for social connection. On the other hand, at any particular moment, a user may have specific uses or desired gratifications that can differ from their more stable preferences, such as when a person who typically uses Twitter for entertainment instead accesses their feed to find information on a recent event. Such distinctions have been discussed but not thoroughly researched within the literature (e.g., Lee and Ma 2012; Ruggiero 2000). Thus, educational psychologists can contribute to the research on incidental learning with modern technology by distinguishing relatively stable preferences from state-like uses and gratifications. This dual-level of analysis is common in research on interest (Harackiewicz and Knogler 2017). Interest has been modeled as having both dispositional qualities, called individual interest, as well as state-like aspects, called situational interest. Uses and Gratification Theory seems to capture the dispositional aspects of interest theory, whereas aspects of content that elicit noticing (e.g., surprising, novel) seem well-aligned to situational interest factors. A comprehensive model of incidental learning with modern technology should account for both stable preferences for using technology as well as situational factors.

In addition, findings from educational psychology studies of multiple goal pursuits are informative for studies of technology uses and gratifications. There is growing evidence that people simultaneously hold multiple academic goals, such as endorsing both mastery and performance approach goals (Barron and Harackiewicz 2001). As such, it seems reasonable to examine whether people have multiple technology uses and gratifications, which may affect what content appears in their feed as well as subsequent aspects of the TILE model, described later. As but one example, people might intend to use social media for information-seeking but be most gratified by its entertainment value. Each combination of achievement goals can have a unique relationship with outcomes, including well-being, engagement, and achievement (Wormington and Linnenbrink-Garcia 2017); therefore, different combinations of interests and motivations for using technology should be explored for differential effects on (1) what content appears in a user's feed as well as (2) other aspects of the TILE model, such as noticing.

User, Content, and Environmental Factors Affect whether Noticing Happens

As shown in Fig. 2, content must be present to be noticed, but other factors can determine what is noticed or not among the high-volume of information in technological environments. Much of the existing literature on factors affecting whether users notice incidentally exposed content has been derived from qualitative interviews with participants either while they use media or via interviews about those experiences after they occurred. The factors affecting the likelihood of noticing fall into three main groups: user factors, information factors, and contextual factors (Jiang et al. 2015).

User Factors Traditional cognitive factors such as prior knowledge (Karnowski et al. 2017; McCay-Peet and Toms 2017) and cognitive capacity (McCay-Peet and Toms 2017) have been implicated as positive predictors of noticing. Some participants have reported a sensitivity or predisposition to notice relevant information even when using technology for other purposes, such as making connections with others. More general dispositions regarding approaches to learning, such as deep versus surface strategy use, have also been associated with increased noticing (Heinström 2006). In contradiction to current prevailing narratives about echo chambers and filter bubbles (Hills 2019; Pariser 2011), Garnett et al. (2013) found partisanship did not relate to the likelihood of noticing, rather overall frequency of news site usage, regardless of whether the content aligned with the user's own political beliefs, was associated with greater incidental exposure and learning when using social media. Beyond cognitive factors, there have been numerous motivational and affective factors identified as predictors of noticing information, including intrinsic motivation, personal interest, and curiosity (Jiang et al. 2015; Karnowski et al. 2017; Masip et al. 2018). Qualitative interviews have revealed that user perceptions of salience, including novelty and bizarreness, often increase the likelihood of information being noticed. People who use social media primarily for socializing tend to have closer ties with their contacts and friends, making it more likely they are familiar with the information in their feed, thus decreasing the likelihood that they will find the information in their feed surprising or novel (Ahmadi and Wohn 2018), which are two qualities that can increase the likelihood of noticing (Yadamsuren and Erdelez 2017). Likewise, confidence and positive emotionality, both in state and trait forms, were predictive of noticing whereas insecurity, stress, and negative emotions were negatively related (Heinström 2006; Jiang et al. 2015; Karnowski et al. 2017).

Content and Environmental Factors Regarding content factors, several researchers have found that information is more likely to be noticed when it is perceived to be personally relevant, linked to a professional need, or consistent with the user's values (Jiang et al. 2015; Yadamsuren and Erdelez 2017). Information quality has also been implicated as a factor in noticing, but only in a single study (Jiang et al. 2015). Finally, environmental or contextual factors are also relevant, with users remarking that time pressures and poor online interface usability negatively related to noticing. Usability issues are likely moderated by users' familiarity with the technology being used, which also has been identified as a predictor of noticing (Jiang et al. 2015).

Noticing Results in either Automatic or Deliberative Processing

Our opening scenario depicts an instance of noticing: while accessing social media for a non-learning goal, a user comes across a headline or other short post and this information enters their consciousness. A review of the incidental exposure literature revealed a lack of clarity regarding whether noticing involved attention, and if it does, how noticing is different than stopping, the next step in the IEON model (Yadamsuren and Erdelez 2017). Yadamsuren and Erdelez characterized noticing both in terms of an automatic, non-conscious response to visual triggers (e.g., a photo, font color, presence of a label or link) and also as a thoughtful consideration of characteristics of the content, such as its urgency, relevance, or novelty, implying attention and some level of processing or evaluation. Their description of stopping included more definitive language regarding attention: "it is a point when a person interrupts the activity that was under way to devote attention to the information that was encountered" (Yadamsuren and Erdelez 2017, p. 35) and leads to a "decision about how to pursue further" (p. 47), either to capture, share, or read the content. Other models of incidental exposure had a similar lack of clarity regarding what, if anything, differentiates noticing and stopping and what predicts people's decision to stop and think about content versus simply moving on to other content, as in our initial example (e.g., Jiang et al. 2015). Therefore, we hypothesize it is important to differentiate how people process noticed content, as well as any subsequent effects of that processing, as shown in Fig. 2. We argue noticing incidentally encountered content without some kind of engagement with it is akin to Type 1 automatic processing as outlined in dual-process[2] models of cognition (Evans et al. 2013; Kahneman 2011), whereas choosing to deliberatively think about content is akin to Type 2 processing.

Dual-process models remain prominent in cognitive psychology research on implicit learning and decision-making, despite considerable drift in the literature regarding what does and does not comprise Type 1 and Type 2 processing (Evans 2019). Type 1 processing has been described as fast and intuitive whereas type 2 is slow and reflective. Evans, Stanovich, and colleagues have argued that the key discriminator between the intuitive response generated by Type 1 processing, including "processes of implicit learning" (Stanovich 2016, p. 5), and the more effortful or deliberative reflection that typifies Type 2 processing is that the latter involves the use of working memory (Evans 2019; Evans et al. 2013). Evans (2019) argued that Type 1 processing does not use working memory resources but the results of such processing (e.g., judgment of the validity of content and a sense of confidence in that judgment) do move into working memory and thus can affect future thinking and responses.

[2] The authors thank one of the anonymous reviews of this article for their suggestion to include this connection.

Critically, such Type 1 processing can lead to automatic processing incidental learning effects, as shown in Fig. 2, including increased retention and recall of declarative knowledge, but elaboration and manipulation in working memory (i.e., Type 2 processing) are required to commit complex conceptual knowledge and meaning to long-term memory for later retrieval (Baddeley 2012).

Evidence indicates that content that aligns with prior knowledge, or for which there is no relevant prior knowledge that could be used to evaluate it, will most likely be comprehended and accepted via Type 1 processing (Evans 2019). On the other hand, there are cases when users enact more effortful Type 2 deliberative processing of incidentally exposed content, most notably when the content is salient and clearly contradicts well-organized and accessible prior knowledge (Richter et al. 2009). Yet, such Type 2 processing can still appear to be so quick as to be automatic: information clearly discrepant with prior knowledge (e.g., "The sky is green") can be relatively quickly rejected (Rapp 2016; Richter et al. 2009). Another predictor of rejection of a knowledge claim is the person's mindset. There is evidence of a distrust mindset, cued by deliberative evaluation of content, which then affects subsequent non-conscious evaluations of other content (Mayo 2019). For example, after deciding the social media discourse on a particular topic comes from unreliable sources, subsequent automatic evaluations of other content can trend negative; in essence, users can be provoked into adopting a distrusting mindset even for content and sources that are totally different from what they deliberatively evaluated as unreliable.

However, as Evans (2019) has argued recently via a default-interventionist model, on the whole, Type 2 processes are biased to justify and support the intuitions that drive Type 1 processes; therefore, even when content triggers some degree of deliberative processing, often that processing leads toward acceptance of claims that align with prior knowledge and beliefs. Effortful processing that leads to a response different from the Type 1 response is likely only under certain conditions. People enact Type 2 processing to scrutinize Type 1 responses for accuracy or appropriateness only when motivated, the situation affords it, and cognitive resources are available. However, popular assumptions that motivated reasoning drives the acceptance of misinformation have not been supported by empirical research, with a possible exception for users who are particularly partisan (e.g., Bago et al. 2020; Pennycook and Rand 2019). Such findings suggest more research is needed regarding how the conditions affording Type 2 processing, including user, content, and environment factors, interact to affect the results of that processing. Likewise, more research is needed regarding the characteristics of content that might trigger more effortful processing. What behaviors a person enacts as a result of this Type 2 processing (i.e., returning, responding, or selecting) likely depends upon a person's prior knowledge, attitudes, and beliefs, as well as the context in which the information is encountered.

Behavior Resulting from Deliberative Processing Is Predicted by User, Content, and Environmental Factors

In the TILE model, deliberative processing leads to one of three decisions: returning, responding, or selecting and reading (see Fig. 2). Returning is a conscious choice made after engaging in deliberative processing, for example when a user encounters a website claiming the earth is flat, decides it is not worth further attention because it so dramatically differs from their prior knowledge or beliefs (i.e., plausibility judgment, Sinatra and Lombardi 2020), and returns to their previous activities (e.g., scrolling through a Google search). Reacting includes the many ways technology allows users to publicly register a response to content, such as by "liking" a post or sharing it with others. Finally, in some cases, users decide to move beyond merely noticing content to reading it or engaging with it closely. Many researchers have focused upon factors affecting whether users choose to return to previous activities or read noticed content. Research studies on how or why users decide to react are less common, a point we elaborate upon below. Incidental exposure and learning research results have supported the same broad categories of user, content, and environmental factors as predictors of behaviors after deliberative processing as those that predicted noticing (Jiang et al. 2015; Kümpel 2019; Yadamsuren and Erdelez 2017). These processing factors mirror the conditions Evans (2019) and others have identified as determining whether Type 2 processing supports or interrogates Type 1 processing. This alignment between our TILE model and dual-process models substantiates our decision to highlight processing factors in incidental learning.

User Factors

Motivation and Interest Interest and relevance are particularly strong predictors of the decision to read incidentally exposed content, as opposed to returning (Masip et al. 2018). There has been initial evidence of a trait-like motivation factor, with some participants reporting decisions to select and read incidentally exposed online news content for fear of missing out on important information or due to feeling a duty to stay informed (Kümpel 2019). Such motivation may be akin to a mastery avoidance academic goal orientation (Elliot and McGregor 2001). In addition, in recent years, researchers have begun exploring how social media behaviors can vary according to a person's desired use or gratification, finding, for example, that sharing behaviors are less likely when social media is used for entertainment compared to other purposes (Lee and Ma 2012). Likewise, entertainment goals tend to positively predict reacting behaviors, social interaction goals predict commenting, and information-seeking predicts sharing and comment reading behaviors (Khan 2017). None of these studies, however, involved an examination of how these uses and gratifications relate to intentional learning decisions such as selecting and reading content (Khan 2017). Clearly, more research is needed regarding how motivation and interest drive decisions to return versus other more elaborative behaviors.

Knowledge, cognitive dissonance, and identity management Decisions to select and read content, or not, often rely on its degree of coherence with prior knowledge, as well as the desire to protect existing beliefs from discrepant information (Cappella et al. 2015). Much of the argument for these findings has been grounded in cognitive dissonance theory (i.e., people actively seek to eliminate psychological discomfort created by holding contradictory attitudes, beliefs, or thoughts; Harmon-Jones and Mills 2019; Hills 2019). The decision to share information with others seems to depend upon its coherence with prior knowledge but can also be affected by a desire for self-promotion or identity management (Cappella et al. 2015). Finally, users reported being more likely to read incidentally exposed content that they perceived was directly targeted or personalized to them (Kümpel 2019), such as when contacts share posts directly with users by mentioning them.

Emotions Yadamsuren and Erdelez (2017) argued the decision to turn attention away from incidentally exposed content (i.e., returning) could be driven by negative feelings derived from the content. Research in educational psychology has shown that a simple positive versus negative conceptualization of emotions, and their effects, is underspecified. As Pekrun (2006) has shown, activity emotions such as enjoyment, anger, or frustration are driven by appraisals of both the value of the activity as well as one's control over it. Furthermore, emotions can be activating or deactivating, whether they are positive or negative. Therefore, technology incidental learning researchers should take into account this more nuanced perspective on how emotions vary and how they can affect decision-making and learning.

Recently, Muis et al. (2018) have described how epistemic emotions affect intentional learning processes including SRL and epistemic cognition (Chinn et al. 2011). Epistemic emotions, in comparison with other academic emotions, occur as users evaluate the alignment, or lack thereof, of their prior knowledge and beliefs with encountered information. Muis and colleagues argued that epistemic emotions are precipitated by control, value, novelty of information, complexity of information, and pursuit of epistemic aims (Chinn et al. 2011). Each of these phenomena, except for the last that is explicitly intentional, has either been explicitly or implicitly identified in the incidental learning literature as predictors of engagement with content (e.g., Jiang et al. 2015; Yadamsuren and Erdelez 2017). Muis and colleagues argued information with high novelty, in relation to prior knowledge and beliefs, will lead to surprise followed by an appraisal of information complexity, the user's evaluation of their ability to understand the content, and a judgment of its value. The confusion or curiosity emotions that result subsequently drive decision-making and strategies enacted. Such findings in intentional learning contexts align with the limited research conducted in incidental learning contexts, particularly those regarding factors predicting noticing such as motivation and positive emotionality (Heinström 2006), interest and prior knowledge (Karnowski et al., 2007), and values (McCay-Peet and Toms 2015, 2017).

Information and Environment Factors

Content Qualitative interviews have revealed much about how people experience incidental exposure but have not led to clear distinctions between the information factors affecting noticing versus those that influence deliberative processing decisions (Jiang et al. 2015; Kümpel 2019; Yadamsuren and Erdelez 2017). Decisions to read incidentally exposed content seem to be driven by perceptions of utility or relevance as well as novelty. Users' geographical proximity to the content also predicted reading (i.e., people were more likely to read content that referenced events or locations close to them; Kümpel 2019).

Source evaluation The source of the incidentally exposed information (e.g., Anspach 2017) and perceptions of its reliability (Karnowski et al. 2017) also predict behaviors that result from deliberative processing. In many technology contexts, such as social media, there can be multiple sources for content, including who originally wrote the content as well as who pushed the content into a user's feed (e.g., a friend who shared the content, a social media algorithm). This suggests the need for the integration of multiple source use literature (Braasch et al. 2018) into incidental learning effect research, particularly research on how source evaluations can influence metacognitive judgment processes that likely influence deliberative decisions (Braasch et al. 2018). Often, when incidentally exposed to content, users reported focusing upon their relationship with the other user who shared the content (Anspach 2017; Masip et al. 2018; Kümpel 2019). Positive relations with that other user predicted reading, but in some cases, participants said they read content from negatively viewed users to get a sense of their perspective. In particular, participants were more likely to engage with content shared by negatively viewed family members, even when those family members were perceived to be unreliable sources of quality information. Furthermore, participants reported that friends who were perceived as opinion leaders could lend credibility to the media outlets whose content they shared (Turcotte et al. 2015). In general, social media users rely on their contacts to act as filters, expecting that they will share with them relevant or useful content (Boczkowski et al. 2018). These findings align with the literature on source evaluation in that source features drive people's decisions regarding whether and how to engage with content (Braasch 2020). These features can include the content's origin, context, and purpose, as well as the competence and benevolence of the author.

Environment Factors Finally, there has been some interview research suggesting that contextual factors play an even larger role in the decision to deliberate upon as opposed to simply notice incidentally exposed information. Such contextual factors included whether there was time to stop, and whether stopping would be appropriate in that context (e.g., stopping to read an entertainment article in the workplace v. home; Yadamsuren and Erdelez 2017). Environmental factors affecting technology incidental learning require much more research (e.g., mobile learning scholarship; Bernacki et al. 2020).

Deliberative Processing Incidental Learning Effects Vary across Behaviors and User, Content, and Environmental Factors

In the TILE model, deliberative processing leads to one of three options: returning (i.e., ending engagement with the content), responding (i.e., capturing, sharing, or reacting), or selecting and reading (see Fig. 2). Learning effects seem to differ across each of these three response options. Given we have argued that selecting and reading transforms incidental exposure into intentional learning, with the latter well-described by models currently studied in educational psychology (e.g., multimedia learning, SRL), here we define deliberative processing technology incidental learning effects as those that occur after the decision to either return or capture, share, or react. Yadamsuren and Erdelez (2017) posited a number of incidental learning effects, including changes to knowledge, motivation, and emotion. However, the majority of the empirical findings have involved changes to knowledge, participation, and information-seeking. Furthermore, incidental learning researchers have argued user, content, and environment processing factors moderate the learning effects of returning, responding, or reacting, but to date, only user factor research has been conducted. Therefore, we synthesize the incidental learning effects literature on how various user factors can moderate those effects and identify aligned literature from educational psychology regarding content and environment factors.

User Factors

Knowledge and Beliefs In some studies, incidental exposure to content has been positively related to knowledge gain (Tewksbury et al. 2001), whereas, in other research, there has been a negative (Lee and Xenos 2019) or even no (Cacciatore et al. 2018; Edgerly et al. 2018) relationship established. Failure to account for the type of behaviors that occur after incidental exposure may explain these seemingly contradictory findings. In one of the few studies to capture participants' engagement decisions after incidental exposure, and one of a small set of experimental studies on incidental learning, Lee and Kim (2017) found that mere exposure followed by low engagement (e.g., returning) led to increased recognition of content but only higher levels of behavioral engagement (e.g., clicking on and reading content) were positively associated with actual recall. Furthermore, clarity regarding the effects of incidental exposure upon knowledge gain likely requires more careful accounting for user factors that might moderate these effects. For example, Morris and Morris (2017) found that low, middle, and high socioeconomic status (SES) samples all reported increased incidental exposure between 1998 and 2012, with parallel increases in political knowledge, but there were stronger effects for low SES groups. The degree of trust in the incidentally exposed content has been associated with stronger incidental learning effects (Bode 2016a). Users with lower levels of education have displayed stronger incidental learning effects than users with higher levels (Baum 2003). Finally, there is some evidence that the experience of flow (Csikszentmihalyi 2014) can increase users' incidental knowledge gain (Barker et al. 2015).

Noticeably absent from the literature on technology incidental learning are investigations of motivated reasoning (Sinatra et al. 2014) and how it might drive deliberative processing decisions (e.g., users may be more inclined to return from discrepant information). Several researchers have posited that active information-seeking and intentional learning in online environments are influenced by users' desire to identify and disseminate information that aligns with their prior beliefs, often driven by a need to resolve cognitive dissonance (Cappella et al. 2015; Hills 2019; Zimmer et al. 2019). However, recent experimental research has shown that during intentional engagement with online news headlines and stories (e.g., being asked to review information as opposed to being incidentally exposed to it), subsequent belief in misinformation is driven by automatic thinking rather than deliberative thinking such as motivated reasoning (Pennycook and Rand 2019). In essence, it is a failure to think critically about content that leads to acceptance of misinformation, rather than a motivation to reconcile new information with prior beliefs or avoid cognitive dissonance. In addition, there is evidence that partisanship can strengthen belief in misinformation only when people enact automatic thinking, and not during deliberative or intentional thinking (Bago et al. 2020). Similar research on the effects of motivated reasoning are needed for incidentally exposed content.

Political Participation Researchers have also explored how technology incidental exposure relates to political participation, both offline (e.g., attending town meetings, calling elected officials, voting) and online (e.g., using the Internet to contact a politician, send a political message, make a campaign contribution). In general, incidental exposure seems to be positively related to both online and offline forms of political participation (Kim et al. 2013; Weeks et al. 2017), similar to the relationship between general social media use and political participation (Boulianne 2015). There is some evidence that the effects of incidental exposure on political participation are stronger for highly partisan people, because it may drive them to seek out and share views aligned with their own (Edgerly et al. 2018; Weeks et al. 2017). Likewise, researchers have provided evidence of the potential insulating effects of political knowledge and interest on subsequent political participation, with stronger incidental exposure effects for those participants who had lower levels of these individual characteristics (Bode 2017; Feezell 2018; Valeriana and Vaccari 2016). However, Kim et al. (2013) found those participants who used social media more for political as opposed to entertainment information-seeking reported higher levels of online political participation. It may be that these researchers captured similar but sufficiently different moderators, as political interest may vary depending upon one's goals (e.g., to learn about the world versus to follow the salacious aspects of political celebrities). Finally, in one of the only longitudinal studies of incidental exposure effects, Theocharis and Quintelier (2016) found no evidence that Facebook use was related to political participation. Instead, these authors found support for the opposite relationship: greater political participation over time led to greater use of Facebook. This finding suggests researchers should be cautious when positing relations from cross-sectional or panel data, as temporal ordering may not be obvious.

News-Finds-Me Perception In recent years, social media users, particularly those who are younger, have reported increased frequency of incidental exposure (Hermida et al. 2012). Such frequent incidental exposure to a variety of news content may explain why a majority of participants said they believe social media provides them with more news and a broader variety of news and information than solely relying on traditional news sources, and therefore, they have stopped actively seeking out news. These users now expect news to be pushed to them by the platform (Bergström and Belfrage 2018). This passive dependence upon social media to provide information has been called the "news-finds-me perception" which is defined as "the extent to which individuals believe they can indirectly stay informed about public affairs – despite not actively following the news – through general Internet use, information received from peers, and connections with online social networks" (Gil de Zúñiga et al. 2017, p. 107). Individuals who held a news-finds-me perception were less knowledgeable about politics and less likely to use traditional media (e.g., journalistic websites) to acquire news information than those who did not hold this perception, but nonetheless, they reported greater feelings of knowing about politics (Gil de Zúñiga et al. 2017). Research has shown incidental exposure is positively related to adopting a news-finds-me perception, with subsequent decreases in information or news-seeking as a social media use or gratification (Müller et al. 2016). However, this effect is stronger for users with low need for cognition (Cacioppo and Petty 1982), suggesting again that incidental learning can be moderated by individual factors.

Echo Chambers and Filter Bubbles Users who rely upon incidental exposure to get their information (e.g., news-finds-me perception) may be particularly susceptible to technology curation effects, and in particular echo chamber or filter bubble effects (Flaxman et al. 2016; Hills 2019; Nikolov et al. 2015; Pariser 2011), typified by increased confidence in one's views due to the prominence of social media feed information that is congruent with one's beliefs. However, research suggests echo chamber effects are mixed and modest. Bakshy et al. (2015) analyzed Facebook data and found that both self-identified liberals and conservatives maintained approximately 20% of friends from the other group. These friends did share attitudinally discrepant content, leading to incidental exposure (e.g., a self-identified liberal Facebook user sees conservative-leaning news shared from a conservative friend) and users did engage with this cross-cutting, incidentally exposed content: approximately 24% of the news links selected and read by liberals were cross-cutting content typically shared by their conservative friends, with the conservatives viewing cross-cutting content 35% of the time. Likewise, evidence suggests that the use of social networking sites actually increases the amount and diversity of users' news access, although this evidence also indicates that these effects are stronger for those who actively seek out news online, as opposed to encountering it incidentally (Scharkow et al. 2020).

Moral panic about echo chambers and filter bubbles should be further moderated by findings that many people use technology to actively seek out alternative opinions and content in an attempt to gain a pluralistic view (Masip et al. 2018). These participants also reported that their distrust of news sources could be moderated by their friends; in essence, people imbued greater trust in news sources that were endorsed or shared by their trusted friends. On the other hand, highly partisan social media users are more likely to disconnect from friends and sources who hold disparate views (Bode 2016b), which in turn could create a more homogeneous and partisan social media feed (Hills 2019). In sum, the evidence suggests researchers concerned about echo chambers should be focused upon users' curation decisions (e.g., unfriending due to partisanship) at least as much as they are focused upon how users respond to the content they notice and deliberatively process.

Content and Environment Factors In the TILE model, we posited that the nature of the content and the environment moderate the relationship between deliberative processing decisions and technology incidental learning effects. Support for such relations can be found in studies of repeated exposure to information and the effect of retractions (Ecker et al. 2015). Some researchers have found repeated exposure to misinformation, even if that exposure includes a retraction, merely reinforces memory and use of the false information (i.e., continued influence effect; Lewandowsky et al. 2012). Yet, concerns that social media's rapid dissemination capability can exacerbate the continued influence effect (Hills 2019) must be nuanced based upon findings that the effect can be moderated by user factors such as working memory capacity (i.e., the effect is stronger for those with lower working memory capacity; Brydges et al. 2018). Moderating information factors include whether the repeated information is plausible or not, with the latter judgment decreasing the likelihood of continued influence (Pennycook et al. 2018).

Likewise, the construction of retractions plays a critical role in whether the continued influence effect occurs, per findings encompassed in Kendeou and O'Brien's (2014) Knowledge Revision Components (KReC) framework. According to these researchers, encoded misinformation cannot be erased; instead, users must co-activate the misinformation and the correct information, with repeated exposure to the latter eventually overriding the effect of the former (Kendeou et al. 2019). In line with the KReC, evidence shows that retractions that explicitly highlight the misinformation and present an alternative, correct set of information are most likely to overcome the continued influence effect (Ecker et al. 2017). However, the volume of retractions presented does not seem to affect people's views regarding politicians' overall veracity (Swire-Thompson et al. 2020), suggesting that people's beliefs about misinformation are more malleable than their beliefs about the people providing that misinformation. What is less clear is the degree to which the necessary integration of the misinformation and the correct information occurs in incidental learning, particularly if the decision is made to return or simply respond to the co-activated information (e.g., a retraction is read, liked, and then the user wanders off).

Finally, as technology platforms rise, morph, and fade, researchers will need to attend to how differences among them might moderate incidental learning effects. For example, some social media networks have begun identifying posts with misinformation and providing additional information alongside them, such as links to reliable information and sources. These links have led to reductions in the recall of misinformation (Bode and Vraga 2015). The technology platforms themselves may moderate incidental learning effects as well, given that users report using certain platforms more often for information (i.e., Twitter, YouTube) and others more for social connection (i.e., Instagram; Kim and Lee 2016). Fletcher and Nielsen (2018) found self-reported incidental exposure effects on the number of online news sources used were stronger for users of Twitter and YouTube, compared with Facebook. It may be the case that long-term retention of information is more likely when users typically use the platform for information-seeking, as opposed to entertainment, even if their momentary goal is the latter.

Incidental Learning Is Cyclical and Recursive

Many modern models of intentional learning are cyclical and recursive, where the products of learning and people's reflections upon those products can lead to changes in how they approach future learning tasks (e.g., Cleary et al. 2012; Winne and Hadwin 2008). Indeed, there is ample evidence indicating that people adjust their knowledge, beliefs, attitudes, and dispositions based upon what they intentionally learn and how they interpret it (e.g., Pekrun et al. 2017; Weiner 2018). On the other hand, there is a lack of research on whether and how technology incidental exposure and learning can affect subsequent exposure and learning, as well as how people process such exposures (e.g., Jiang et al. 2015; Yadamsuren and Erdelez 2017). Recursive effects are plausible, given the Curated Flows Framework suggests that users' curation decisions can affect the content of their feed, and incidental learning effects are likely to drive such curation decisions. Likewise, the continued influence effect suggests that changes in mental representations can be stubbornly persistent (Lewandowsky et al. 2012). Clearly, there is a need for longitudinal research to determine how incidental learning effects, derived from both automatic and deliberative processing, influence subsequent technology use and responses to what appears in technology content and media feeds, as shown in Fig. 2.

Future Directions for Research

The growing prominence of technology as a context for learning, both incidental and intentional, makes it an exciting venue for future research. In particular, the high-volume of information presented in this context poses challenges for learners, particularly when those challenges are incidental to their goal. The TILE model synthesizes current theoretical and empirical literature regarding incidental learning with modern technology and integrates it with contemporary research and thinking in educational psychology. In so doing, the model expands upon previous research by identifying new processes and decision points within incidental learning (e.g., user curation decisions affecting what they encounter in technology) while also elaborating upon the types of processing that can result (i.e., automatic v. deliberative) as well as the factors affecting incidental learning processing (e.g., emotions, distrust mindsets). The established corpus of findings regarding incidental learning in modern technology (e.g., Jiang et al. 2015; Kümpel 2019; Pennycook and Rand 2019) substantiate the main aspects of the TILE model while also identifying gaps in the scholarly literature. One general but nonetheless accurate summary of that literature is this: more empirical work is needed regarding each aspect of the TILE model. In many cases, there is a relatively small but promising set of findings regarding relations among the model's many aspects (e.g., Ahmadi and Wohn 2018). We believe the TILE model is a productive synthesis of incidental learning and educational psychology conceptual and empirical research that can galvanize and direct numerous directions for future research. Here, we review these directions, including a promising first research question for each area.

Differentiating and Measuring Effects of Incidental Exposure

After noticing content, users can respond in three ways: they can enact Type 1 automatic processing, resulting in particular incidental learning effects; they can enact Type 2 deliberative processing and then decide to either return to what they were doing or merely respond to content, leading to different incidental learning effects; or they can deliberatively decide to select and read more about the content, which results in intentional learning processing and effects well-captured by other models of learning (e.g., SRL; Greene 2018). We acknowledge it will be challenging for researchers to differentiate automatic processing and deliberative processing incidental learning effects, particularly if users' observable behaviors are similar (i.e., noticing content and then returning to seek out other content). Nonetheless, given the findings that the kinds of knowledge people retain can differ between automatic and deliberative thinking (Baddeley 2012), we feel it is worthwhile to investigate how to differentiate and subsequently measure automatic and deliberative processing, so that researchers can determine whether they have different effects on knowledge, beliefs, and attitudes. In more controlled studies, researchers could measure users' knowledge prior to them being incidentally to content. Once users' prior knowledge is determined, only responses to content that is discrepant to their prior knowledge could be treated as the result of deliberative processing, given that such content would be unlikely to prompt Type 1 processing (Evans et al. 2013).

Another option would be to ask users to engage in think-aloud protocols as they use technology and incidentally encounter content (Greene et al. 2018; Ericsson and Simon 1993). Participants' deliberative processing would result in different verbalizations than would automatic processing; indeed, the latter might not result in verbalizations at all. Retrospective interviewing could be used to ask participants to recall their responses to incidentally exposed content. Finally, the research design could allow for differentiation as well. By asking participants to use technology without giving them a specific learning goal, researchers could invoke the circumstances of incidental exposure (i.e., no learning goal) and then measure its effects on knowledge, values, and attitudes (i.e., incidental learning; cf. Richter et al. 2009). Such a design ensures effects are not due to intentional learning, assuming participants do not select and read incidentally exposed content. Given more research is needed on these issues, a relevant question for the field would be: *How can behavioral or verbalization methods inform the differentiation and measurement of automatic and deliberative processing?*

Motivation and Interest

Within the incidental exposure and learning literature, uses and gratifications have been treated as somewhat static or even dispositional factors affecting how people curate their social media feeds (Ruggiero 2000). Such static or dispositional factors may exist but taking a more nuanced view of uses and gratifications, as has been done in the motivation and interest literature (Harackiewicz and Knogler 2017; Wormington and Linnenbrink-Garcia 2017), may reveal additional insights into the moment-to-moment decisions people make regarding whether or not to engage with social media content. Motivations and interest have both trait-like and state-like instantiations. For example, users who primarily log onto Facebook for social connection uses (i.e., trait-like motivation for using social media) may delve deeply into informational content in their feed when a highly influential event occurs near them (i.e., state-like motivation). As another example, repeated exposure to content intended to invoke situational interest (i.e., state-like interest) can accelerate the development of individual interest (i.e., trait-like interest; Rotgans and Schmidt 2017). Within a social media context, repeated exposure to situationally interesting content (e.g., salacious or compelling political content) may lead to the development of new uses and gratifications for social media sites (e.g., motivation to use Twitter for political information-seeking). Combinations of relatively static trait-like and dynamic state-like views of motivation and interest may elucidate the sometimes-confusing variance found in people's decisions regarding whether or not to engage in deliberative processing. In addition, studies could be conducted regarding whether and how people maintain multiple uses and gratifications for technology and how they affect the kinds of curation behaviors people enact, the subsequent content they encounter online, and how they affect noticing. Naturalistic studies of trace data regarding technology use trends could be paralleled with laboratory think-aloud protocol studies (Ericsson and Simon 1993) to understand the thinking that leads to changes in motivations and interest, and how they affect curation, noticing, and deliberative processing. Given this, a reasonable first research question would be: *How do uses and gratifications act as trait- or state-like manifestations of motivation and interest, and how do they change over the course of incidental learning?*

Integrating and Expanding Research on Dual-Processing

As stated previously, much more research is needed regarding when, why, and how people respond to noticing with either Type 1 automatic or Type 2 deliberative processing. Much of the popular press and layperson interest in incidental learning from modern technology arises from concerns that the increased amount of misinformation, along with a general lack of thoughtfulness among users, is resulting in an ill-informed citizenry (Rapp and Salovich 2018). Thus, there is a clear need for more research on what triggers Type 1 versus Type 2 processing when using modern technology, and how deliberative processing can lead to internalized knowledge and beliefs that can affect automatic processing (Stanovich and Toplak 2012). For example, longitudinal intervention research focused on helping people make plausibility judgments (e.g., Sinatra and Lombardi 2020) could reveal how changes to prior knowledge and skill affect future automatic processing, such as what occurs when noticing implausible headlines online.

In addition, we see a need for research on reactions to inaccurate information in high-volume environments, such as social media and Google searches. It may be the case that people's reactions to inaccurate information, including any subsequent internalizations (e.g., Rapp 2016), are the same in high- and low-volume (e.g., reading a single text) contexts, but that is an empirical question worth exploring. In addition, research is needed regarding how people react to accurate information in high-volume contexts versus low-volume contexts. Thus, a research question that could address the interaction of these factors would be: *What are the effects of accurate versus inaccurate information on people's recall and comprehension, compared across high- and low-volume information environments?*

Likewise, more research is needed regarding many of the user factors posited to affect decisions to move from noticing to deliberative processing. Systematic research has pointed toward users' prior knowledge, partisanship, or need for cognition (Cacioppo and Petty 1982) as predictors of Type 2 processing (Evans 2019). More research is needed to understand how these user factors affect deliberative processing: in what ways and degrees. More dispositional factors (e.g., partisanship and need for cognition) may play a larger role in the non-conscious aspects of TILE processing (e.g., Type I processing), whereas more context- or discipline-specific aspects (e.g., prior knowledge and interest) may play a larger role in the conscious decision to deliberatively engage with noticed content. Researchers could begin to explore this area by investigating: *How do individual difference factors predict the decision to deliberatively process incidentally exposed information?*

Overall, researchers have identified numerous biases and heuristics that can affect automatic processing in both beneficial and detrimental ways (Stanovich 2016). It will be critical to transfer such findings to the technology context to determine how those factors affect TILE processing in high-volume technology environments. For example, studies of framing effects (Stanovich and West 2012) could elucidate why people tend to notice and retain headlines about the negative effects of screen time on development, rather than those suggesting more equivocal effects (Orben 2020). Experimental studies involving manipulations of social media posts to include either positive or negative information could reveal such effects. A promising first research question in this area would be: *How do Type 1 processing biases predict what information is noticed?*

Behaviors Subsequent to Deliberative Processing

It is yet unclear how and why people decide to ignore, react, or engage with technology content. Interestingly, there has been little research into whether and why users stop pursuing their previous goal (e.g., entertainment, maintaining social connections) and instead choose to actively consider and act upon noticed content. In educational psychology, there is a vast literature on active decision-making and task switching during learning (e.g., SRL; Greene 2018). Similar work should be conducted during incidental learning. Decision-making involves cognitive, motivational, and affective factors (Immordino-Yang 2016); therefore, such factors should be explored for their role in the deliberative processing that occurs in the TILE model. It will be important to examine such factors in a nuanced way. For example, research has shown emotions are complex and situational, with multiple distinguishing qualities (Pekrun 2006); therefore, their role in deliberative processing must take into account those qualities. Pekrun's work would suggest that experiencing positive activating emotions in response to incidentally exposed content may lead to more engaged behavior decisions such as selecting and reading, whereas negative activating emotions may lead to returning in search of attitudinally aligned content. Deactivating emotions, on the other hand, may be more likely to lead to returning back to activities that were interrupted by initial noticing. Similarly, epistemic emotions (Muis et al. 2018) likely affect whether and how people engage with technology content. It is possible that such emotions drive additional kinds of engagement after deliberative processing, beyond those currently listed in the TILE model. For example, what may look like returning in response to confusion may actually be the pursuit of alternative views. Microanalytic research could reveal cognitive differences in behaviorally similar actions (Cleary et al. 2012). A promising research question for this area would be: *How do epistemic emotions predict the likelihood of deliberatively processing incidentally exposed information?*

Social media is a particularly intriguing context in which to investigate another aspect of deliberative processing: users' source evaluations (Braasch et al. 2018). Identified predictors of the likelihood of engaging in successful source evaluation, such as information uses and gratifications, age, prior beliefs, and vocabulary knowledge (Braasch 2020), should be investigated in incidental exposure contexts. Furthermore, on social media, the source of a post can be the person or organization who shared the information, as well as the source of the actual information. A trusted friend can share information from a source the user believes is unreliable and vice versa. Researchers could investigate how these discrepancies in different sources affect incidental learning by asking the following question: *How do discrepancies between the source reliability of the content's author and the person who pushed the content to the user affect the likelihood of deliberatively engaging with the content?*

Expanding Incidental Learning Effects Literature

Incidental learning researchers have not systematically tested the effects of automatic versus deliberative processing on declarative versus conceptual knowledge acquisition and recall in high-volume information environments (e.g., Cacciatore et al. 2018). Research on the continued influence effect (Ecker et al. 2015), as well as work in intentional learning (e.g., SRL), would suggest there are likely important differences in incidental learning when the exposed content varies in complexity and depth. Straightforward randomized control trial studies could be conducted where incidental exposure is invoked, with the difference across conditions being whether the content is declarative versus conceptual knowledge. Memory research suggests the effects of different types of processing likely vary across types of knowledge (Baddeley 2012) but more research is needed to understand any processing effects, such as the likelihood of deliberative processing or the decisions made regarding how to respond to incidental exposure. Relevant research questions would be: *How do incidental learning effects upon recall vary across declarative versus conceptual knowledge?* and *Are there interactions between deliberative processing decisions (*e.g.*, returning versus responding) and depth of knowledge that affect recall?*

Likewise, there are a number of important factors that could and should be studied with randomized control trials. For example, does the modality of the incidentally exposed material matter (i.e., text versus graphics; Mayer 2019)? Furthermore, more research is needed regarding how incidental learning processing and effects differ, or not, across accurate and inaccurate information. Creating valid, parallel forms of misinformation and accurate information can be difficult (cf. Rapp and Salovich 2018), but researchers could systematically test relatively minor to more major deviances from accurate information (e.g., vaccines are safe, vaccines have few permanent side effects, vaccines are dangerous) to determine how they affect long-term retention and attitudes. Finally, researchers could create experimental conditions where some participants were incidentally exposed to information whereas other participants were asked to intentionally learn it, and then determine effects on recall and attitudes. Such research would illuminate the differential effects of returning versus selecting and reading. A preliminary research question would be: *How does recall of declarative information differ between incidental exposure and intentional learning conditions?*

Content Areas beyond Politics

Outside of educational psychology, incidental learning researchers' focus on political knowledge and outcomes is understandable (e.g., Ecker et al. 2017), given scholarly and layperson concerns about the effects of misinformation on civic engagement (Hills 2019). Nonetheless, technology incidental learning effects almost certainly occur for a wide variety of topics ranging from those with strong political aspects (e.g., socio-scientific issues) to scientific (e.g., vaccines, genetically modified organisms) and historical (e.g., discussions of past events' role in the modern world) topics, among other kinds of content. More empirical research utilizing such topics is needed. Particularly given increased focus on how educators should use technology to promote learning (e.g., Greenhow et al. 2019; Kimmerle et al. 2015), it will be important to understand what happens when learners only incidentally engage with topics typically studied in educational psychology intentional learning research, such as climate change (e.g., Lombardi et al. 2018), science (Kendeou et al. 2019), or history (Greene et al. 2010).

Measurement of Technology Use

Much of the literature on modern technology use has relied upon participant self-report measures (Costera Meijer and Groot Kormelink 2015). Some researchers have asked participants to self-report both general social media use and intentional social media use and then partialled the latter from the former to create a measure of incidental exposure (e.g., Cacciatore et al. 2018; Lee and Xenos 2019). Such statistical controls allow researchers to avoid directly asking participants about incidental exposure. However, Vraga et al. (2016) used eye tracking to show people were not adept at self-reporting the topic and style (i.e., multimedia, plain text) of posts they saw on Facebook, overreporting news and political posts and underreporting personal posts. These findings call into question the utility of self-report measures of technology incidental exposure, suggesting the need for the use of eye tracking and verbal reports as ways of measuring noticing and attention (e.g., Kim et al. 2020), as well as the need for more experimental research to establish causal links between incidental exposure and learning (e.g., Anspach 2017). Finally, when reviewing the literature on effects of technology on knowledge outcomes, it is important to differentiate between findings involving incidental learning (i.e., when people are not intentionally seeking out information) and more intentional learning. A number of researchers have measured technology use via self-report items such as “Please select how often you might or might not use the different sources listed below to get news information” (Beam et al. 2016, p. 217). Such items do not clearly target incidental learning, particularly when contrasted with items such as “When you go on-line, are you ever exposed to news and information on current events, public issues, or politics when you may have been going online for a purpose other than to get the news?” (Tewksbury et al. 2001, p. 548).

Conclusion

Rapid growth in technology use, the high volume of produced information in the modern world, and people’s expectation that sources will “push” news to them necessitate a better understanding of what is learned when people happen across information incidentally. This concern brings new light to an old concern: much of learning is implicit, but educational psychology researchers have not deeply engaged in understanding how that learning occurs or what actually is learned (Alexander et al. 2009). Researchers in other fields have studied incidental exposure and learning (Yadamsuren and Erdelez 2017), but that work would benefit from the integration of educational psychology theory and research. The TILE model provides a framework for synthesizing incidental exposure research with scholarship on interests and motivations, a more elaborated process for noticing and subsequent automatic or deliberative processing via dual-process models, a larger number of moderators of incidental learning processing, and a variety of automatic and deliberative processing learning effects that previously have not been coalesced in a single model. These contributions lead to generative research questions about how incidental learning occurs and what effects it has on a variety of outcomes. A better understanding of how users respond to incidental exposure would provide a foundation for interventions to help people be more informed, critical, and reflective users of modern technologies. Effective interventions for intentionally learning from such technologies (e.g., Wineburg and McGrew 2017) could be even more powerful when incorporating direct instruction on how to manage incidentally exposed content, as well.

Compliance with Ethical Standards

Conflict of Interest The authors declare that they have no conflict of interest.

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