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REVIEW ARTICLE

The Cognitive Architecture of Digital Externalization

Alexander Skulmowski[1]

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Abstract

This review is aimed at synthesizing current findings concerning technology-based cognitive offloading and the associated effects on learning and memory. While cognitive externalization (i.e., using the environment to outsource mental computation) is a highly useful technique in various problem-solving tasks, a growing body of research suggests that the offloading of information into the environment (and digital storage in particular) can have negative effects on learning. Based on this review, a model of offloading with cognitive load at its core is developed to summarize when learners offload information. A high intrinsic cognitive load (i.e., a high difficulty), a high extraneous load (i.e., unnecessary design elements), and a low perceived or actual working memory capacity trigger offloading. Crucially, the value attributed to information also affects whether information is externalized. In this model, extraneous cognitive load in the design of technology-enhanced learning acts as a triple barrier: (1) It prevents information from entering working memory, (2) it inhibits information being stored in long-term memory, and (3) it can prevent learners from externalizing information using technology. As a result, in many instances, only the gist of information (or its location) is retained, while learners often gain the illusion of having memorized that information. Furthermore, offloading substantially increases the risk of memory manipulation, potentially posing a societal problem. Consequently, educational approaches should maximize the meaningfulness of the residual information that is often retained in the form of "biological pointers." In addition, current issues surrounding the use of generative artificial intelligence pertaining to externalization are discussed.

Keywords Offloading · Extended cognition · Cognitive load · Technology · Generative AI

✉ Alexander Skulmowski
alexander.skulmowski@ph-karlsruhe.de

[1] Digital Education, Institute for Informatics and Digital Education, Karlsruhe University of Education, Bismarckstr. 10, 76133 Karlsruhe, Germany

Introduction

The ubiquitous use of digital technology in education has fundamentally changed how learners acquire knowledge and continues to reshape many processes involved in learning. Traditionally, learning has been conceptualized as the memorization of facts, the mastery of procedures, and acquiring the competency to apply this knowledge to new problems or tasks. The widespread adoption of the Internet has altered the common view of knowledge—people increasingly tend to regard the memorization of large amounts of specialized knowledge as less desirable, since they perceive it as readily available from external sources. Technologies such as smartphones that further propagate the reliance on external sources of knowledge reinforce this common impression. This trend complements the exponential growth of knowledge (Zhang et al., 2015) which challenges traditional norms concerning what constitutes general knowledge and casts doubt on whether humans will ever be able to store all "relevant" knowledge. At the same time, the habitual reliance on external (digital) memory stores is considered to be a potential problem for the development and health of the human brain (Fasoli, 2021; Firth et al., 2019). Considerable research has been conducted on when and why people rely on external memory stores (for an overview, see Risko & Gilbert, 2016). According to Risko and Gilbert's (2016) definition, cognitive offloading occurs when people reduce their mental load by deploying actions that change the demands of a task. This definition already includes a decrease in cognitive load as the aim of externalization. In their review, they describe different facets of offloading: (1) external normalization (i.e., altering the environment to accommodate cognitive processes), (2) intention offloading (i.e., creating external reminders for delayed actions), and (3) transactive memory systems (i.e., the distribution of information between different people, technology, or both). They arrive at a metacognitive model in which humans perform a metacognitive evaluation on whether to use internal or external resources for a task, select a strategy, and subsequently apply it. In their model, the utilization of internal and external resources is monitored and evaluated, resulting in future tendencies toward either of these strategies for particular tasks. Furthermore, they also mention that the deployment of external means can affect cognition, for instance, by the resulting reductions in training for specific mental faculties. While Risko and Gilbert (2016) present several instances in which offloading is a crucial aspect that enhances cognition, their review already brings up the negative aspects that cognitive externalization may have, particularly on memory. The focus of the current review lies on the effects of an ever-growing tendency to use technologies such as smartphones and artificial intelligence (AI) on memory and learning.

The present review summarizes current research on cognitive externalization in the context of digital learning. Furthermore, this paper offers a cognitive model of digital externalization in which cognitive load plays a major role. This model is then discussed as it relates to current developments in the field of generative AI and its impact on learning. Based on this overview and model, hypotheses for the field of technology-based cognitive externalization in the context of learning are developed. While this paper is focused on the effects of technology-enhanced forms of offloading, foundational research is discussed at relevant points. In particular, research on non-digital forms of externalization is used to demonstrate how deeply embedded the tendency of offloading is in humans, with several studies on issues besides learning and memory often showing considerable advantages accrued using this strategy (e.g., Armitage et al., 2020; Dunn & Risko, 2016). This contrast already highlights the dilemma faced regarding externalization: Should we use (external) digital tools to boost performance despite the potentially negative effects this strategy may have on (internal) cognitive faculties? Before delving into research results on cognitive offloading with a relevance for this question, the following section offers an overview of the theoretical framework guiding the discussion on the cognitive aspects of learning.

Cognitive Load as the Basis for Optimizing Instruction

In order to analyze the factors that can impact cognitive offloading, it is necessary to consider the cognitive architecture of learning. As learning can be studied on several levels, including the neural and behavioral levels, a suitable level of description for offloading during learning is the instructional level. One of the most influential theories of instruction is cognitive load theory (CLT; Sweller et al., 1998, 2019). CLT is rooted in the assumption that humans' limited working memory capacity needs to be considered in the design of learning (Sweller et al., 1998). While the theory makes us aware that we usually cannot reduce the amount of information that learners need to acquire in a learning task (constituting the *intrinsic cognitive load*), the theory outlines that obstacles to learning can be removed by improving the design of a learning task (thereby reducing the unnecessary, *extraneous cognitive load*, Sweller et al., 1998, 2019). It should be noted that in earlier iterations of CLT, it was assumed that the cognitive load related to memorization processes constitutes a third type of cognitive load, *germane cognitive load*, that can increase the total cognitive load stored in working memory (Sweller et al., 1998). After a controversial debate (e.g., Kalyuga, 2011), the current iteration of CLT no longer considers germane cognitive load as a component that can obstruct working memory capacity (Sweller et al., 2019). Instead, the current version highlights that there are *germane processes* that stimulate learning which can, for example, be triggered by presenting tasks in a variable manner that leads learners to compare the differences between the problems, resulting in deeper learning. Other interpretations present germane processes as the motivational tendency of learners to invest their cognitive resources (Skulmowski & Xu, 2022, based on Whelan, 2007).

It is remarkable that CLT has incorporated a number of theoretical and empirical advances from numerous disciplines (including philosophy and neuroscience) that allow researchers to use CLT as their basis without (explicitly) buying into the computationalist paradigm that was cutting-edge at the time of its conception. For instance, there has been a considerable amount of research on how to apply CLT to settings in which collaboration (Janssen & Kirschner, 2020; Kirschner et al., 2018; Paas & Sweller, 2012), bodily perception and action (Lindgren & Johnson-Glenberg, 2013; Sepp et al., 2019), and other methods play a major role. These approaches are far removed from reductionist notions of cognition as computation. Although some of these theoretical perspectives even go so far as to reject theoretical entities such as mental representations altogether (for overviews, see Chemero, 2013; Duijzer et al., 2019) that are central to computationalist views on cognition, CLT interestingly has managed to mostly avoid being entangled in such controversial debates. Some authors even utilize CLT alongside approaches such as phenomenological analyses (Aldridge & McQuagge, 2021). Thus, the basic ideas of CLT appear to be palatable even for noncognitivists, thereby providing a unifying perspective (or at least a set of shared guidelines) for the educational sciences. Depending on the level of description necessary for a given task, it is possible to use CLT without relying on computationalist metaphors, or even to delve further into a more precise definition at the neural level (e.g., Whelan, 2007). The following sections equally can be read with such an "agnostic" outlook, as they are focused on higher-level aspects of CLT. Therefore, various theoretical foundations found in the offloading literature should be compatible with CLT.

Biologically Primary and Secondary Knowledge

In order to understand why some types of knowledge are more effortful to learn (and therefore are often targets for offloading behavior), relevant distinctions between innate and acquired knowledge are discussed. Geary's (2002, 2008) evolutionary approach of distinguishing between *biologically primary* and *biologically secondary knowledge* has been a major influence on cognitive load theory in recent years (Paas & Sweller, 2012; Sweller, 2008). This distinction is based on the idea that humans have a set of certain innate capabilities, such as being able to speak or to recognize faces, that do not require explicit instruction (Paas & Sweller, 2012). These faculties are thought to be modular (Paas & Sweller, 2012), with support from the field of developmental cognitive science (Carey, 2009). In addition to biologically primary knowledge, humans can acquire biologically secondary knowledge, which encompasses all knowledge that must be explicitly learned, such as different languages, school subjects, and other knowledge that is neither innate nor acquired in an evolutionary automated fashion (Geary, 2008).

The distinction between biologically primary and secondary knowledge has been used to explain why some forms of learning are more effective and less demanding than others. Importantly, the use of biologically primary knowledge is considered to spare learners from investing cognitive load (e.g., Agostinho et al., 2015), while acquiring biologically secondary knowledge is thought to require conscious mental effort (Geary, 2008). Thus, one strategy that has been developed based on this distinction is that biologically primary knowledge should be relied on for learning biologically secondary knowledge (Paas & Sweller, 2012; Sweller et al., 2019). Several studies have utilized biologically primary knowledge in the form of intuitive actions, such as pointing gestures on tablets, with positive effects on learning (e.g., Agostinho et al., 2015; Ginns & King, 2021), confirming that the use of primary biological knowledge may indeed keep cognitive load at a minimum.

In contrast, several studies in which additional biologically secondary knowledge involving technology-based factors was necessary to complete a learning task have often failed to show an advantage of digital forms of learning. For example, educational computer games ("serious games") often require learners to internalize the rules of such a game, thereby causing extraneous cognitive load (Skulmowski & Xu, 2022). These elements of digital learning may be thought of as their own forms of biologically secondary knowledge that need to be mastered before starting to learn the intrinsically relevant content. Following this analysis, (certain forms of) digital learning can be said to encumber learning if learners are required to learn or engage with a substantial amount of technology-related biologically secondary knowledge before being able to learn the content they originally set out to learn.

In sum, the design of digital learning should involve an analysis of whether a task could be optimized by replacing elements relying on biologically secondary knowledge with counterparts involving biologically primary knowledge. After having discussed how information can "enter" the cognitive system more easily, the following section describes when and why learners choose to "remove" information from their memory by externalizing it.

Cognitive Externalization

The extended mind hypothesis developed by Clark and Chalmers (1998) posits that the human cognitive system cannot be adequately described solely as the brain and nervous system. Instead, the cognitive system is thought to include bodily resources as well as environmental artifacts (Clark & Chalmers, 1998; Hollnagel, 2001). In this perspective, a notebook can be regarded as a part of the cognitive system that extends the biological memory of the brain (Clark & Chalmers, 1998). While the debate whether external objects can indeed be regarded as equally important constituents of the human cognitive system as the brain has been controversial (e.g., Adams & Aizawa, 2001; Ludwig, 2015), the notion that the cognitive system can extend over entities outside the cranium has found considerable appreciation in many fields of the cognitive sciences and psychology. The strategy of *cognitive offloading* is a prime example of the complex interactions between learners and artifacts. The following sections provide an overview of the developmental aspects, potentially negative effects, and everyday examples of offloading.

The Developmental Roots of Offloading

Humans alter their environment to save on internal computation from an early age. In a study investigating the development of offloading behavior in the non-digital space, even 4-year-old children physically rotated objects in order to avoid mental rotation (Armitage et al., 2020). A follow-up study demonstrated that children are able to distinguish between situations in which the manipulation of the environment saves them mental computation and those in which it does not, with their age determining whether they avoid superfluous physical actions (Armitage et al., 2020).

While these studies do not pertain to learning, they highlight that young children already develop offloading strategies.

In another series of studies, the determining factors of offloading behavior in 11-year-old children using laptops were investigated (Dong et al., 2022). In the first study, the participating children were asked to memorize 24 word pairs and could choose to offload certain items (by "saving" them, i.e., marking these words to receive hints for them in a later test). More difficult (i.e., unrelated) word pairs were offloaded more than easier pairs, but an assigned value (one or five stars) did not affect offloading behavior. Recall performance was significantly enhanced by offloading. In a second study in which item difficulty was kept constant, a higher value of word pairs increased the tendency to offload these items, leading to higher recall scores for items of a higher value. A third study revealed that if value is emphasized (through the promise of rewards for reaching a certain score), both value and difficulty determine which items are offloaded. Thus, these three studies further suggest that difficulty and value can affect the strategic choice of offloading behavior (Dong et al., 2022).

Two related studies showed that children aged 4 to 11 years used offloading in a non-digital memory task, but only older children were able to arrive at their own offloading strategy without being prompted to do so (Bulley et al., 2020). Again, difficulty increased the tendency to offload. In addition to performing one's own offloading behavior, being presented with a more structured physical environment that removes the need for internal rearrangement can be useful for children, in particular, for those with lower working memory capacities (Berry et al., 2019).

The Detrimental Effects of Offloading on Learning

Although the studies just summarized contain several examples of how the limited working memory capacity of children can be supported in various tasks, the literature on adult learning often emphasizes the risks of cognitive externalization. In a series of studies, Grinschgl, Papenmeier, and Meyerhoff (2021a) varied the costs of offloading and their participants' awareness of their goal (i.e., a later test). In their first study, participants were given a computer-based visual pattern copying task without knowledge of being tested later. Using the original layout of visual items for the copying task was possible but incurred a temporal cost for half of the participants. Those participants who did not experience a temporal cost of offloading used this strategy more often but were less successful in a memory test. Based on these results, Grinschgl, Papenmeier, and Meyerhoff (2021a) assumed that this result may be an artifact of not having informed their participants concerning the later test, thus withholding crucial information for the cost-benefit assessment of offloading. In a second experiment, they investigated whether being informed of a later test affects offloading and memory performance. Not being informed regarding a subsequent test increased offloading behavior and decreased memory performance. Crucially, not receiving temporal costs for offloading also reduced memory performance. In addition, they found that being aware of a later test reduced offloading behavior. Consequently, they conclude that offloading behavior generally is associated with lower memory performance. Importantly, their third experiment confirmed that not being aware of a later test combined with offloading results in a negative effect on memorization. However, Grinschgl, Papenmeier, and Meyerhoff (2021a) found in that study that participants' awareness of a later test was able to reduce the negative impact of offloading.

Adding to the complexity of the summarized results, other studies have shown that individual differences in memory can also affect offloading behavior. It was demonstrated that people with a lower working memory capacity choose to offload more information (Ball et al., 2022; Gilbert, 2015; Meyerhoff et al., 2021; Risko & Dunn, 2015; but see also Morrison & Richmond, 2020).

It is important to note that different types of information are distinctly affected by externalization. Lu et al. (2020) investigated cognitive externalization using written lists in a word memorization task. Being told that they could use their list during a later test increased their participants' false recall. However, in another experiment, Lu et al. (2022) found that strong semantic relationships between items established through categorized rather than randomly shuffled lists can minimize the harmful effect of offloading. They conclude that externalization does not have a negative effect on *gist memory*. Similarly, Kelly and Risko (2019b) found that more distinct items are less strongly negatively impacted by offloading than less distinct items. A recent paper links offloading to *intentional forgetting* (Kelly & Risko, 2019a; for an overview of intentional forgetting, see Anderson & Hulbert, 2021). In another study, the effect of note-taking was compared to intentionally forgetting certain types of information (Eskritt & Ma, 2014). The authors of that study found that people tend to forget location-related information in a card game when using notes, while the memory for other types of information remained unaffected by externalization. In sum, the type of information to be learned appears to affect the strength of the negative effect that offloading can have, potentially with a smaller effect on essential information.

Offloading can result in a number of problematic consequences, including being prone to manipulation of one's memory. Risko et al. (2019) conducted a study in which they let participants offload information to a digital external store. In certain trials of the study, the offloaded information was manipulated by the experimenters. Participants rarely took note of this change and even replaced their internal memory with this altered information, which Risko et al. (2019) compared to the formation of false memories. However, findings by Pereira et al. (2022) suggest that people become less easily manipulable by the falsification of their (digitally) externalized memories if they are made aware of previous manipulations and the low reliability of the external storage. Nevertheless, people's susceptibility to manipulation using externalized information demonstrates the grave consequences that increased offloading behavior can have beyond immediate negative consequences for memory performance.

This form of "memory corruption" could be seen as the biological simulacrum of an issue often encountered in computer programming. Programming languages such as C enable the storage of data in variables but also provide the functionality to use so-called *pointers* that do not actually contain data themselves. Instead, pointers only consist of addresses in memory that "point" toward the location of data stored in variables. This is done to save computer memory, as it is often computationally more economical to utilize pointers instead of copying the—often quite large—data stored in variables during operations. Interestingly, the use of pointers in programming is considered a major source of errors and code vulnerabilities resulting from pointers being easily manipulated, potentially pointing toward data they were not intended to point toward (Patil & Fischer, 1997; Simpson & Barua, 2013). Therefore, the manipulation of biological memory can be compared to the memory corruption that can occur in computers. This comparison raises the question of what exactly the "pointers" in our biological memory could be comprised of, an issue that will be discussed in a later section.

Value and Metacognition as Driving Factors of Offloading Behavior

The value assigned to information plays an essential part in decisions regarding whether that information will be stored internally. Knowlton and Castel (2022) proposed a dual-process model in which deliberate and automatic pathways can be utilized for memorization. While information that is explicitly recognized as being important is often intentionally practiced using various techniques, automatic processes can trigger memorization based on value. For the latter, Knowlton and Castel use the example of a restaurant that surpasses expectations and is therefore automatically remembered without deliberate memorization. Furthermore, they cite neuroimaging studies investigating value-based learning in which the learning of high-value words led to stronger activation in certain areas of the brain associated with semantic processing (Cohen et al., 2014). In addition, that study revealed that the value assigned to learning targets affects activation in the brain reward system (Cohen et al., 2014). Importantly, Knowlton and Castel (2022) stress that the awareness of one's memory capacity limitations plays a crucial part in strategy selection. They describe that learners being (or becoming) aware of this bottleneck make better decisions that in turn optimize the number of high-value items they are able to store by being more selective. Related selective strategies in which people prioritize the memorization of important information to avoid negative consequences have been called "responsible remembering" (Murphy & Castel, 2021b) and "responsible forgetting" (Murphy & Castel, 2021a, 2021b). It needs to be noted that the effect of value has been shown to degrade when people are told that they can externalize information (Park et al., 2022). The research presented in this section highlights that the value assigned to information represents a crucial variable in the decision of whether information is offloaded or not (see also Gilbert, 2023), and that people prioritize remembering information deemed important (at times driven by automatic, reward-related processes).

Dunn and Risko (2016) found that externalization behavior does not necessarily align with actual benefits or costs, but rather people's *perceived* benefits and costs of that behavior, therefore linking their choices to metacognition (though their studies did not investigate learning, but physical action). Grinschgl, Meyerhoff, et al. (2021b) sought to influence the metacognitive basis for offloading behavior by manipulating the performance feedback their participants received. They found that they could not induce offloading using specific performance feedback, but participants who were told that their performance was below average rather than above average believed that they had used more offloading behavior. Another study found that people tend to use offloading if they are less confident in their memory (Boldt & Gilbert, 2019). The results reviewed in this section demonstrate that people's perception of a task and their confidence are factors driving offloading behavior.

Offloading in Everyday Life

As discussed in the preceding sections, offloading can improve performance in some tasks but can harm memory performance. Some of the negative effects of offloading become particularly obvious in real-world settings. Turning to everyday examples of cognitive externalization, Finley and Naaz (2023) analyzed for which purposes people prefer to use offloading techniques. They found that people prefer to use their biological memory for episodic and common procedural knowledge and tend to externalize less commonly required semantic and procedural knowledge.

One of the most important offloading interfaces in everyday life consists of web search engines that are often accessed via smartphones. The mobile access to all the information that can be publicly found on the Internet has been found to affect cognition and learning in several substantial ways. A recent study revealed that people tend to keep less information memorized after having been able to retrieve this information from a smartphone (Siler et al., 2022). The authors of that study concluded that keeping oneself aware of whether information is stored in the brain or externally is not a trivial task. Furthermore, they take their results as evidence for the claim that there is a tendency toward passing off externalized information as being stored in one's memory.

A crucial problem consists of illusions of learning and performance if people have access to web-based information. Searching the Internet leads to less memorization and gives learners the impression of having learned that information (Fisher et al., 2022). A related study demonstrated that *search fluency* (i.e., how long it takes to find information online) is wrongfully taken as a cue of how well one will be able to remember information (Stone & Storm, 2021). The authors consider this result as evidence for metacognition extending beyond the brain and into external memory stores (Stone & Storm, 2021). Similarly, Flanagin and Lew (2023) found that people overestimate their task performance if web-based information is available (see also Fisher & Oppenheimer, 2021). Another series of studies suggests that thinking about trivia questions before searching for the answers online improves later recall than immediately searching the Internet (Giebl et al., 2022). Importantly, reliance on Internet sources further increases the probability that one will rely on the Internet (Storm et al., 2017).

But which factors determine whether and which information is offloaded *digitally*? Digital offloading appears to be limited by the design of digital artifacts, their usability in particular. In a recent study, it was found that older participants offloaded more information (and thus had a lower cognitive load) if the input device mimicked a pen rather than using touch or mouse input (Jin et al., 2022). Furthermore, a combination of visual and auditory feedback fostered offloading compared to versions relying on a single modality for feedback (Jin et al., 2022). A related study revealed that people offload more when using a touch interface rather than mouse controls (Grinschgl et al., 2020). Beyond these results concerning controls of devices, Schooler and Storm (2021) found that the reliability of the external store affects whether people offload (and consequently forget) information.

It is important to note that the mostly negative effects of cognitive externalization discussed above mainly result from studies on learning and memory. Despite these findings, cognitive offloading is a highly important and beneficial strategy to externalize mental computation. In a seminal study on cognitive offloading, Kirsh and Maglio (1994) analyze the cognitive processes involved in a popular video game in which a specific spatial placement of block figures achieved by their rotation and placement under time pressure is the objective. In contrast to an intuitive assumption that expert players of that game would not need to rely on rotating the blocks through button presses, Kirsh and Maglio (1994) argue that it is cognitively more economical to rotate the figure on screen by pushing a controller button than to mentally simulate the correct rotation. In their analysis, it is cognitively less demanding to push a button repeatedly while immediately being presented with the results of these actions on screen than to imagine how the block figures will rotate and fit in the overall spatial arrangement. Thus, this seemingly "brute force" method in which computation is offloaded to a device is an example of simple actions saving substantial mental computation. However, in educational contexts, we usually want learners to go down the more effortful path of deeply engaging with learning content, as long-term memorization can rarely be achieved via shortcuts. As a result, we need to distinguish between the many instances in which offloading can help to minimize unnecessary routine computation and the offloading possibilities that too easily enable learners to avoid the mental effort needed for memorization. Thus, offloading may be useful to consider in situations in which high expertise has been achieved or in which additional mental resources are required to complete new tasks (for the latter aspect, see Runge et al., 2019). Runge et al. (2019) conducted a study in which the effects of offloading items from a to-be-learned word list on solving arithmetic problems were investigated. In that study, problem-solving performance was higher if the offloading of list items was possible.

Beyond the benefits of externalization just discussed, cognitive offloading could also be regarded as a promising supportive strategy for learners with disabilities. Turner (2022) reviews the potentials of brain-computer interfaces to remedy motoric and linguistic deficits. In sum, the effects of externalization in everyday life are highly varied.

The Cognitive Architecture of Digital Externalization

Based on the summarized literature, a model of digital externalization with cognitive load at its core is presented. In their review on cognitive offloading, Risko and Gilbert (2016) already considered cognitive load (and CLT) in cognitive offloading. However, their main point concerning this aspect is that offloading should target extraneous cognitive load while sparing intrinsic cognitive load. This conceptualization slightly differs from the conventional understanding of CLT in which the relevant, intrinsic cognitive load often is entangled in extraneous cognitive load or activities stemming from the design of the task. Thus, extraneous cognitive load is usually not considered as a cognitive component that is actively externalized by learners but rather as an additional challenge that needs to be overcome during learning. The model presented in this section is grounded in the conventional reading of CLT. However, the model by Risko and Gilbert (2016) provides a valuable starting point for a model of digital externalization focused on cognitive load. Importantly, they emphasize the role of metacognition and strategy selection in the decision process regarding whether or not to offload. Their model includes a strategy selection phase in which humans take their metacognitive beliefs concerning their capabilities and the task as well as past experiences of offloading into account. These metacognitive beliefs can be reframed using CLT.

The results reviewed in the present paper allow the construction of a cognitive architecture of digital externalization. At the core of this model lie the two cognitive load types as defined in the current iteration of CLT (Sweller et al., 2019), namely, intrinsic cognitive load and extraneous cognitive load. Information entering the cognitive system needs to be picked up by learners' working memory (Sweller et al., 1998), and extraneous cognitive load can pose an obstacle in this process as evidenced by CLT-based research (e.g., Sweller et al., 2019). When considering cognitive load, the probability of offloading taking place is mainly determined by five factors as summarized in previous sections:

(1) Learners with a lower working memory capacity tend to offload more information (Ball et al., 2022).
(2) Learners with a lower perceived working memory capacity also offload more information (Risko & Dunn, 2015).
(3) A higher extraneous cognitive load triggers offloading (see, e.g., Armitage et al., 2020).
(4) A higher intrinsic cognitive load leads to more offloading (see, e.g., Dong et al., 2022; Risko & Dunn, 2015).
(5) A higher (perceived) value of information prompts learners to invest more effort in their memorization, thus triggering germane processes (not to be confused with the germane cognitive load from earlier CLT iterations; see, e.g., Dong et al., 2022; for a metacognitive model, see Gilbert, 2023).

Just as extraneous cognitive load stemming from the design of digital instruction can prevent information from entering working memory (see, e.g., Harp & Mayer, 1998), extraneous cognitive load caused by the controls of digital artifacts can be an obstacle for offloading (see, e.g., Grinschgl et al., 2020; Jin et al., 2022). The relevant learning contents (i.e., intrinsic cognitive load) need to be stored in long-term memory, which can also be negatively affected by extraneous cognitive load (Sweller et al., 1998). However, as summarized above, the value that learners assign to information plays an important role in deciding whether that information is actually stored in long-term memory or whether it is externalized (e.g., Dong et al., 2022; but see also Park et al., 2022). As a result, the model presented in Fig. 1 presents extraneous cognitive load as a triple barrier for information in the selection, offloading, and long-term memorization stages.

In addition, metacognition affects whether information is offloaded (Hu et al., 2019). Rather than storing information, knowledge about where information can be found may be stored as a "pointer." It should be noted that gist memory may be less affected by offloading (Lu et al., 2022). The full model can be seen visualized in Fig. 1.

It is important to note that the offloading processes of different types of information may not be based on identical mechanisms. For instance, Meyerhoff et al. (2021) describe that memory and intention offloading differ and thus might need to be considered as distinct phenomena following their own sets of rules. The following sections outline how this cognitive architecture of digital externalization reacts with different technologies and how negative effects may be avoided.

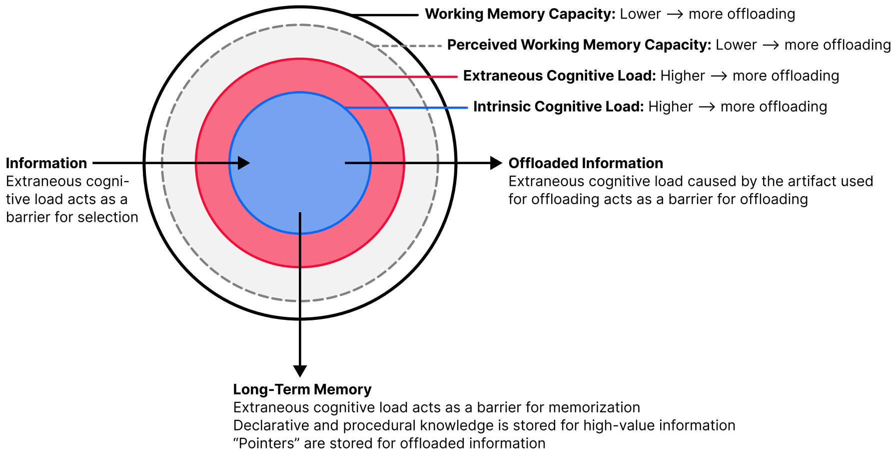

Fig. 1 The cognitive model of digital externalization. The figure depicts how external information enters the cognitive system and subsequently gets stored in long-term memory or is externalized using artifacts. Extraneous cognitive load can act as a barrier in the acquisition, memorization, and offloading of information. Information needs to be perceived and selected by learners, which is made more difficult by extraneous cognitive load. Information that enters learners' working memory may be stored in their biological long-term memory or in an external (digital) memory store. Strategy selection depends on several factors, including different forms of cognitive load. A higher intrinsic and extraneous cognitive load triggers learners to externalize rather than internalize information. A lower perceived or actual working memory capacity likewise tends to let learners choose the offloading route. In addition, the value assigned to information influences the decision to externalize it, linking the value of information to the probability of germane processes being triggered. Lastly, extraneous cognitive load may affect knowledge acquisition in a third way, namely, by making it more difficult to externalize information (for instance through complex controls of digital artifacts). It should be noted that the figure is not intended to imply that intrinsic cognitive load is "contained" within extraneous cognitive load but rather that extraneous cognitive load can act as a barrier. However, intrinsic and extraneous cognitive load are stored in learners' working memory, as illustrated in the figure

The Internet and AI as Forms of Cognitive Extension

The offloading model presented in the preceding section has various implications regarding (the analysis of) the use of digital technologies in learning. Several technologies are candidates for cognitive externalization, including the Internet and artificial intelligence (AI). The Internet is considered to be a digital cognitive offloading tool of particular importance. Firth et al. (2019) describe the Internet as a "superstimulus." On the one hand, they summarize how the Internet is a major drain on attention in everyday life. On the other hand, they highlight that the Internet is an unprecedented form of extended memory. In contrast to conventional forms of transactive memory, such as books or other humans, the Internet does not require users to store information themselves through offloading behavior. In addition, the Internet does not expect users themselves to keep track of the information stored (Firth et al., 2019). Furthermore, Firth et al. (2019) caution that more research is necessary to ascertain the positive and negative effects that the Internet can have on the brain and human capabilities. They cite research by Sparrow et al. (2011) indicates that Internet use can lead to an increased recall performance regarding the location of information but lower recall performance of actual information. Thus, knowing the "what" is replaced with knowing the "where." Smart (2017) coined the term "Internet-extended cognition" to capture this novel relationship between the biological cognitive system and technological augmentation. However, conceptualizations describing the Internet or technology in general mainly as a passive storage system that merely supports human performance and memory may already be outdated due to the rise of generative AI.

Currently, generative AI tools are mainstreaming the process of letting the computer create texts, images, and other content using short text–based instructions (Cooper, 2023; Hsu & Ching, 2023; Vartiainen & Tedre, 2023). Generative AI tools have been trained on enormous datasets and are capable of producing scientific texts, poems, and other content based on simple text commands that do not require any specialized technical knowledge. While there are many potentials for this technology in learning and instruction (for an overview, see Kasneci et al., 2023) and productivity in general (Noy & Zhang, 2023), the drastic change in everyday life these tools are likely to introduce can hardly be underestimated. Since these AI tools let users generate concise summaries, detailed paintings, and other forms of content just by typing in short commands, the present overview on externalization suggests that there is a danger of these technologies letting users overestimate their skills and abilities. Just as having access to a wealth of information using one's smartphone can induce the illusion of being knowledgeable, a tool that can easily generate texts could result in convincing users of being good writers. A recent study provides evidence for a "placebo" effect of technology-based augmentation (Villa et al., 2023). In the study, the participants wore a brain-computer interface, with the placebo group being told that the system would play inaudible sounds to enhance their cognitive ability during a task, based on their brain activity (Villa et al., 2023). The study revealed that the technological placebo increased participants' belief in an enhanced ability as well as promoting their tendency for taking risks. Future research will need to assess whether this finding will generalize to other tasks and abilities.

The current developments in the field of AI suggest that we are approaching a state that Smart (2017) called "human-extended machine cognition." From an evolutionary perspective, we may be leaving the point at which we optimize learning by removing cognitively costly calls to biologically secondary knowledge. However, an AI-driven reduction of the training of biologically primary knowledge, such as problem-solving and structuring information, could also have negative consequences, at least for young learners. While there may be a shift toward training more complex skills and abilities that are currently not adequately implemented in many AI applications, such as checking content for plausibility or content curation, the impact of these technologies could fundamentally alter how we learn and teach. This change should not come at the cost of deficits in the training of biologically primary knowledge, as this could have a negative impact on a variety of human faculties. Yet it should also be considered that research conducted in the field of robotics has shown that there may be a symbiotic relationship between offloading and development (Carvalho & Nolfi, 2016), underlining the need for more research on the long-term effects of human offloading on development. Current research demonstrates people's willingness to offload (parts of) a task to an algorithm-based partner in case a high level of cognitive load is involved in a task (Wahn et al., 2023). Results such as this one suggest that the dynamics of offloading enabled by generative AI may be complex, and some studies already revealed that the use of generative AI in educational contexts confers some tasks to the AI and others to human teachers (Jeon & Lee, 2023).

Interesting parallels between the functioning and usage of generative AI and two principles embedded into CLT, the *randomness as genesis* principle and the *borrowing and reorganizing* principle (Sweller, 2022), can be drawn. For instance, AI image generators that create images from text prompts can start off with random noise distributions which then get refined using training data (Frolov et al., 2021; Ho et al., 2020). This process is similar to human problem-solving, often involving the generation of random attempts at solving a task that is evaluated and refined (randomness as genesis, Sweller, 2022). Another important CLT principle states that people obtain most of the information they store in their minds from other people and rearrange this content according to a given task (borrowing and reorganizing, Sweller, 2022). These two principles share striking similarities with generative AI starting with random spots that are refined using a model derived from training with large image datasets (e.g., Saharia et al., 2022). The potentials for externalization and people's willingness to do so are currently being investigated (e.g., Vartiainen & Tedre, 2023), and it will be interesting to see how the relationship between humans and AI will develop in the future and whether it will be normalized to offload certain tasks to AI systems.

Pointers and the Corruptibility of Memories as a Societal Issue

As discussed in a previous section, there are parallels between the human memory system and certain programming languages that use pointers. Similar to pointers that do not contain data themselves, but rather the memory addresses of data in programming, human memory can store the "where" instead of the "what." However, the exact contents of “biological pointers” in human memory that refer to externalized information are yet unknown. In particular, in situations in which perceptually rich information is perceived but then externalized, people likely still retain some of that information. For example, this could manifest in having a vague memory of how a website looked on which certain information were found. These pointers may actually exist on a spectrum ranging from a rather amodal memory trace of the location of an information (e.g., a URL or a book title), to more elaborate, possibly multimodal (i.e., incorporating different sensory modalities) memories of where that information can be found. Thus, the boundaries between pointers and gist memory might be hard to draw.

As shown by Risko et al. (2019), people tend not to detect if externalized information is manipulated. In a society in which most people externalize substantial amounts of information they may or may not have learned previously, this can have grave consequences. For instance, if the population at large externalizes their knowledge concerning how a complex phenomenon such as monetary inflation comes about, they may not be in a position to solve this problem (or have an informed public debate) in case it occurs. Given that the spectrum of pointers may include fuzzy memories of externalized information, one way to counter this problem through instructional design could be to present information that is likely to be externalized in a manner that contains certain details that become integrated into that pointer. In the example of monetary inflation, this could mean presenting this topic in a way that inseparably links this term to an increased money supply. It could be visualized in a multimodal way, for example, by presenting inflation as a growing stack of money. Given that current theories of mental representation emphasize the multimodal nature of human information processing (e.g., Barsalou, 1999), this strategy of integrating the most important information into pointers may inoculate people against false information and manipulation. Indeed, the use of *embodied metaphors* (i.e., applying perceptually rich knowledge to process abstract knowledge) has been shown to be an effective instructional method (e.g., Bakker et al., 2012; for an overview, see Gallagher & Lindgren, 2015).

Implications

The model developed in this review can serve as the starting point for combining offloading research with predictions derived from CLT. The triple barrier of extraneous cognitive load presented in the model could have a number of uses in educational practice that should be investigated in future research. As extraneous cognitive load can prevent information from entering the cognitive system, from being stored in long-term memory, and from being externalized, these three points of the model could be systematically targeted to achieve specific outcomes. For example, learning environments could be designed in a manner that facilitates offloading less relevant information while making it difficult to externalize important information by design. Digital learning environments can be used to diagnose differences in working memory capacity in order to present information in a way that does not overwhelm them (e.g., Khenissi et al., 2017) and thus may reduce the tendency to offload information.

The growing normalization of generative AI tools in education will also be a challenge in need of systematic investigation. The potentials and problems summarized in this review could guide this research. Empirical studies could be conducted to assess whether cognitive offloading results in unfounded overconfidence in learners' abilities to generate different content types. In particular, it will be necessary to detect whether the habitual use of generative AI diminishes learners' competency in the (often quite foundational) skills and abilities that AI systems can support or even completely take over.

Additionally, the concept of biological pointers introduced in this review should be further investigated concerning how to trigger learners to arrive at pointers that are detailed enough to contain the most relevant information. If these essential contents of concepts are kept in biological memory, it may be less problematic to offload less important components. Empirical studies should be conducted to find strategies to optimize this trade-off in learning and instruction.

Conclusion

Learners have digital tools at their disposal that allow the externalization of memory and, increasingly, entire tasks. While offloading is an important tool that can facilitate everyday life by structuring the environment in ways that save cognitive computation, cognitive externalization can have various negative effects on learning. Offloading can generate the illusion of having learned information, may diminish the memorization of knowledge and instead lead learners to merely memorize where they can find information (i.e. "biological pointers"), and can lead to "memory corruption" (i.e., learners not being aware of being manipulated). Thus, strategies should be developed on how to maximize the memorization of relevant information even in situations in which learners tend to offload information. Both intrinsic and extraneous cognitive load can trigger externalization processes. As learners with an actual or perceived lower working memory capacity generally offload more information, there is a danger of reinforcing their lack of knowledge. Learners who already suffer from difficulties when attending to content may perceive it to be more effective to offload information, potentially leading to a progressively worse learning performance. Furthermore, the current rise of generative AI could, if carelessly implemented, pose a risk to the acquisition of biologically secondary knowledge and may even keep learners from developing and training essential skills and abilities, such as problem-solving. Researchers and practitioners should develop and test curricula that let students harvest the benefits of these technologies while minimizing the risk of negative outcomes.

However, the current technological developments could be seen as a necessary balance that helps humans to navigate an ever more complex world and offers tremendous opportunity. The field of educational psychology is now asked to devise solutions on how to prepare learners for their interactions with these new digital tools while avoiding potential negative consequences.

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Declarations

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