The Limited Role of Attention in the Production Effect: Converging Evidence from Behavioural and Computational Methods

by

Patrick Phillip Tsapoitis

A thesis

presented to the University of Waterloo

in fulfillment of the

thesis requirement for the degree of

Master of Arts

in

Psychology

Waterloo, Ontario, Canada, 2026

© Patrick Phillip Tsapoitis 2026

Author's Declaration

This thesis consists of material all of which I authored or co-authored: see Statement of Contributions included in the thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

Statement of Contribution

This research was conducted at the University of Waterloo by Patrick Tsapoitis under the supervision of Dr. Myra A. Fernandes. Experiments 1 and 2 form an article that is under review for publication in the journal Psychonomic Bulletin & Review (Tsapoitis & Fernandes under review, see references). This article is co-authored by myself and Myra A. Fernandes. The model discussed in Chapter 3 was built in collaboration with Jakeb Chouinard and Dr. Chris Eliasmith.

Abstract

Encoding techniques can enhance memory and may serve as a means of protection from the negative effects of multitasking on memory. The production effect refers to the reliable memory advantage observed when words are spoken aloud rather than silently during the encoding phase for a list of words. This thesis examined the effectiveness of production in boosting memory, even when encoding is performed under divided attention (DA) conditions. In so doing, I expand its potential benefit into a different context, while also specifying whether the availability of attention influences the magnitude of the effect. In Experiment 1, conducted online using the recruitment platform Prolific, participants were visually presented, in counterbalanced order, with two 20-item lists of words: one under full attention (FA) and another under DA with a concurrently performed auditory digit-monitoring task. Within lists, half of the words were prompted to be read aloud, and half were read silently. Memory was subsequently assessed based on the number of correctly recalled words, retrieved via free recall. As expected, memory was lower overall following DA than FA, but importantly, the relative benefit to memory for words read aloud at encoding was maintained. Experiment 2 replicated this pattern using an in-person sample. These results suggest a limited role of attention on the production effect. In Chapter 3, I aimed to develop a computational model that could mimic existing human data of the production effect and findings from Experiment 1. I employed Nengo, a Python package for building, testing, and deploying spiking neural networks. I used this computational tool to simulate human performance. Two sets of words were presented to the model, one under FA and the other under DA: "read aloud" words (half within each list) were reinforced during initial encoding via increasing item strength by 90%, while words "read silently" were not reinforced. We simulated DA during the encoding phase by destabilizing the model's memory representation of each word through a reduction in the signal-to-noise ratio. Subsequently, recall was simulated using a competitive accumulation process, and output was measured separately by

condition. Recall output from 50 unique simulations was compared to that of 50 human participants randomly selected from Experiment 1. In both human and model data, recall was higher for words read aloud than silently, with the general pattern preserved even under DA conditions; however, the magnitude of the production effect in the modelled data was reduced, likely due to floor effects as overall output was quite low following DA. The results of my thesis suggest that attention plays a limited role in accounting for production's benefit to memory, with converging evidence provided from two methodologies.

Acknowledgements

First and foremost, I want to express my deepest gratitude to my supervisor, Dr. Myra Fernandes. Her invaluable support and confidence laid the pivotal foundation that I am certain will continue to help me grow in my career as a researcher. The encouragement she provided in the face of both professional and personal challenges drove me to push myself beyond what I thought I was capable of. Truly, I could not be more thankful for the opportunities she provided me, and I have thoroughly enjoyed my time working with her. Even though I am leaving, I believe this will not be the last time we will get to work together.

I give my sincerest thanks to my entire family, especially my parents. Although you never fully understood academia, you provided endless support (and leftovers) as I pursued my seemingly endless schooling. Thank you to my siblings and nephews; the steady stream of adorable baby photos always managed to lift my spirits when I was stressed. I also owe a massive thank you to my friends: Shelby, Sam, Allison, Evelyn, Sabrina, and Peter. You were always there to let me talk about my work, vent about my stress, and share in my excitement about research and conferences; you guys were my rock. I want to pay homage to my grandmother, Filomena, who sadly passed shortly before I started my graduate career. She will never get to see me accomplish my goals, but I will continue her dream of building a better life than the one afforded to her.

I have not forgotten my amazing lab mates: Khalil, Brian, Tala, Pelin, Sophia, and Yadu. Thank you for your wonderful research insight and our endless conversations. You made my time both academically exciting and fun. Alongside the friends I made in the program: Jisoo, Justine, Julianna, and Miranda, you all collectively made my time here not one that I had to endure, but one I genuinely loved to be a part of. The memories we created together made my experience all the better. To Moe, Phoebe, Squirtle, and Noodle, thank you for the love only a pet could provide.

Table of Contents

Author's Declaration ii

Statement of Contribution iii

Abstract iv

Acknowledgements vi

List of Figures x

List of Tables xi

Chapter 1 General Introduction 1

1.1 Factors affecting learning and memory 1

1.2 The negative effects of divided attention on memory 3

1.3 The beneficial effect of encoding techniques 7

1.3.1 Other accounts of the Production effect 9

1.4 Why production may benefit memory under divided attention 9

1.5 Computational Modelling 11

1.6 The current thesis 15

Chapter 2 17

2.1 Experiment 1 17

2.1.1 Methods 17

2.1.2 Materials 18

2.1.3 Procedure 19
2.1.4 Results 20
2.1.5 Discussion 23
2.2 Experiment 2 25
2.2.1 Methods 25
2.2.2 Materials 26
2.2.3 Procedure 26
2.2.4 Results 26
2.2.5 Discussion 28
2.3 General Discussion of Chapter 2 29
Chapter 3 34
3.1 Spiking Neural Networks and Nengo 34
3.1.1 Encoding-based Strength Representation in Memory 35
3.2 Methods 36
3.2.1 Participants 36
3.3 Materials 36
3.4 Procedure 36
3.4.1 Human experiment 36
3.4.2 Computational model simulation 37

3.5 Results 40

3.5.1 Human memory performance 40

3.5.2 Evaluating model performance 41

3.6 Discussion 42

Chapter 4 45

4.1 Attention's role in the production effect 46

4.2 The importance of multi-modal representations 51

4.3 Encoding-based strength representation in memory 52

4.4 Conclusion 54

References 56

Appendix A 69

Appendix B: Supplementary Material 72

List of Figures

Figure 1. *Conceptualization of attention as a limited resource*.....6

Figure 2. *Memory for words read silently and aloud, under full or divided attention conditions during encoding in Experiments 1 and 2* 31

Figure 3. *Flowchart depicting the encoding process for targets with "ALOUD" or "SILENT" prompts within Encoding-based Strength Representation in Memory*.....38

Figure 4. *Retrieval instances of words from memory over sixty seconds*.....40

Figure 5. *Recall performance in humans and model by encoding type under full and divided attention* 43

Figure 6. *Experiment 1b: Memory performance under full and divided attention by encoding type*...75

List of Tables

Table 1. *Mean Recall of Words in each Attention Condition by Encoding Type in Experiment 1* 21

Table 2. *Mean proportion of recall outputs, across participants, that contained words produced at encoding* 23

Table 3. *Mean Recall of Words in each Condition following each Encoding Type in Experiment 2* .. 28

Table 4. *Recall performance following Full and Divided attention conditions at encoding, by Source* 41

Table 5. *Characteristics of Word Stimuli Used in Experiments 1 and 2, from the English Lexicon Project (Balota et al., 2007)* 69

Table 6. *Mean Number (and standard deviation in parentheses) of Words Recalled in each Condition following each Encoding Type in Experiment 1b* 74

Chapter 1

General Introduction

1.1 Factors affecting learning and memory

The ability to remember has long served as the foundation of the human experience. It allows us to remember some of the most beautiful and harrowing days in our lives, from the birth of a child to the devastation when a loved one passes. It helps shape us, based on experiences throughout our lifetime. These are examples of episodic memory: stored events associated with a specific time and place. They are distinct from other forms of long-term memory, such as semantic memory, which consists of acquired knowledge about the world (Tulving, 1972), and implicit forms of memory in which it is indexed by an increased fluency with previously experienced information (e.g. classical conditioning or priming; Brooks & Baddeley, 1976; Weiskrantz & Warrington, 1979). The formal study of episodic memory, and how it works, started in 1885 when Ebbinghaus first demonstrated how time spent learning a set of nonsense syllables (pronounceable but meaningless three-letter items) influenced later memory for these items. Today, we understand memory as consisting of three main stages: encoding, maintenance, and retrieval. The focus of this thesis is on the influence of various conditions experienced during the encoding stage.

Encoding is the initial experience of perceiving information from our environment, and several factors are known to influence the process. Ebbinghaus (1885) demonstrated that time spent 'on task', rehearsing the to-be-remembered (target) information enhances retention, with more time leading to enhanced memory. By distributing the encoding/learning of target items, rather than massed learning (i.e. "cramming"), memory will be improved (Melton, 1970). The emotional valence of stimuli also affects retention; memory is better for negative and positive information compared to neutral information, though this effect is more pronounced for negative stimuli (Finkenauer et al.,

1998; Hamann, 2001). Recent work also shows that the more motivated one is to learn, the better their memory is as well (Knowlton & Castel, 2022). Notably, available attention during encoding has repeatedly been shown to affect memory, such that splitting attention during encoding with another concurrently performed task typically hurts performance (Baddeley et al., 1984; Craik et al., 1996).

To gain a deeper understanding of how these factors influence episodic memory, researchers have employed various techniques over the years. Most commonly, psychologists use cognitive behavioural experiments in which participants are presented with a list of words, and at a later time, memory is assessed using a free recall or a recognition test (Richardson-Klavehn & Bjork, 1988). Using word lists provides greater experimental control as researchers can strictly manipulate the information presented at encoding, and the conditions in which the words occur. Such experiments are the basis of Chapter 2 of this thesis.

More recently, with the development of technology and greater access to participant pools, a wider variety of methodologies are now available to study memory and the mechanisms underlying it. These include computational modelling (Hintzman, 1984; Jamieson et al., 2016; Penzkofer et al., 2025), neuroimaging (Bailey et al., 2021; Cabeza & Moscovitch, 2013), and case studies of clinical populations (Rosenbaum et al., 2014). Chapter 3 of this thesis adapts an existing computational modelling framework to simulate human memory performance. Some existing models use purely mathematical principles and operations to represent memory, while others attempt to incorporate principles from neuroscience (Hintzman, 1984; Kahana, 2020). By branching into neuroscience, these models aim for greater biological plausibility and attempt to represent memory through computations that simulate how neurons fire and transmit information (Bekolay et al., 2014; Marrero et al., 2024). Computational modelling allows us to break down the process of encoding into quantifiable components and then test proposed mechanisms underlying human memory. Developing such a model provides an opportunity to assess the mechanism of action that underlies the encoding process,

without the presence of additional noise that can occur from factors not of interest, such as the subject's internal state during the study. Computational modelling offers an opportunity to bridge the gap between cognitive-behavioural studies traditionally employed in psychological research and the advancement of computer capabilities, thereby enriching our understanding of the mechanisms underlying human memory.

1.2 The negative effects of divided attention on memory

With the rise of technology and its ever-growing presence in our daily lives, engaging in multiple tasks simultaneously, such as watching T.V. while studying, has become increasingly widespread. This type of multitasking is prevalent among students (Joshi et al., 2023), where distractions arising from their devices, whether said distractions are intentional or not, can have serious implications for their memory performance. Extensive empirical evidence indicates that divided attention (DA) during the encoding of new information significantly reduces subsequent memory performance compared to when encoding occurs under full attention (FA) conditions (Anderson et al., 1998, 2000; Baddeley et al., 1984; Buchsbaum et al., 2024; Castel & Craik, 2003; Craik et al., 1996, 2000, 2010, 2018; Fernandes & Moscovitch, 2000; Greene et al., 2021; Greene & Naveh-Benjamin, 2022b, 2022a; Guez & Naveh-Benjamin, 2006, 2013; Iidaka et al., 2000; Lozito & Mulligan, 2006; Naveh-Benjamin et al., 1998, 2000, 2005, 2006, 2007, 2014; Naveh-Benjamin & Brubaker, 2019; Sahakyan & Malmberg, 2018). Put another way, past studies have shown that attempting to commit information to memory while simultaneously completing a task that also demands attention will reliably result in poor memory. That is, DA, while studying new information, hinders subsequent memory for that information.

The effect of completing a concurrent task on memory performance has been well documented. The impairment of memory performance resulting from dual-tasking was initially

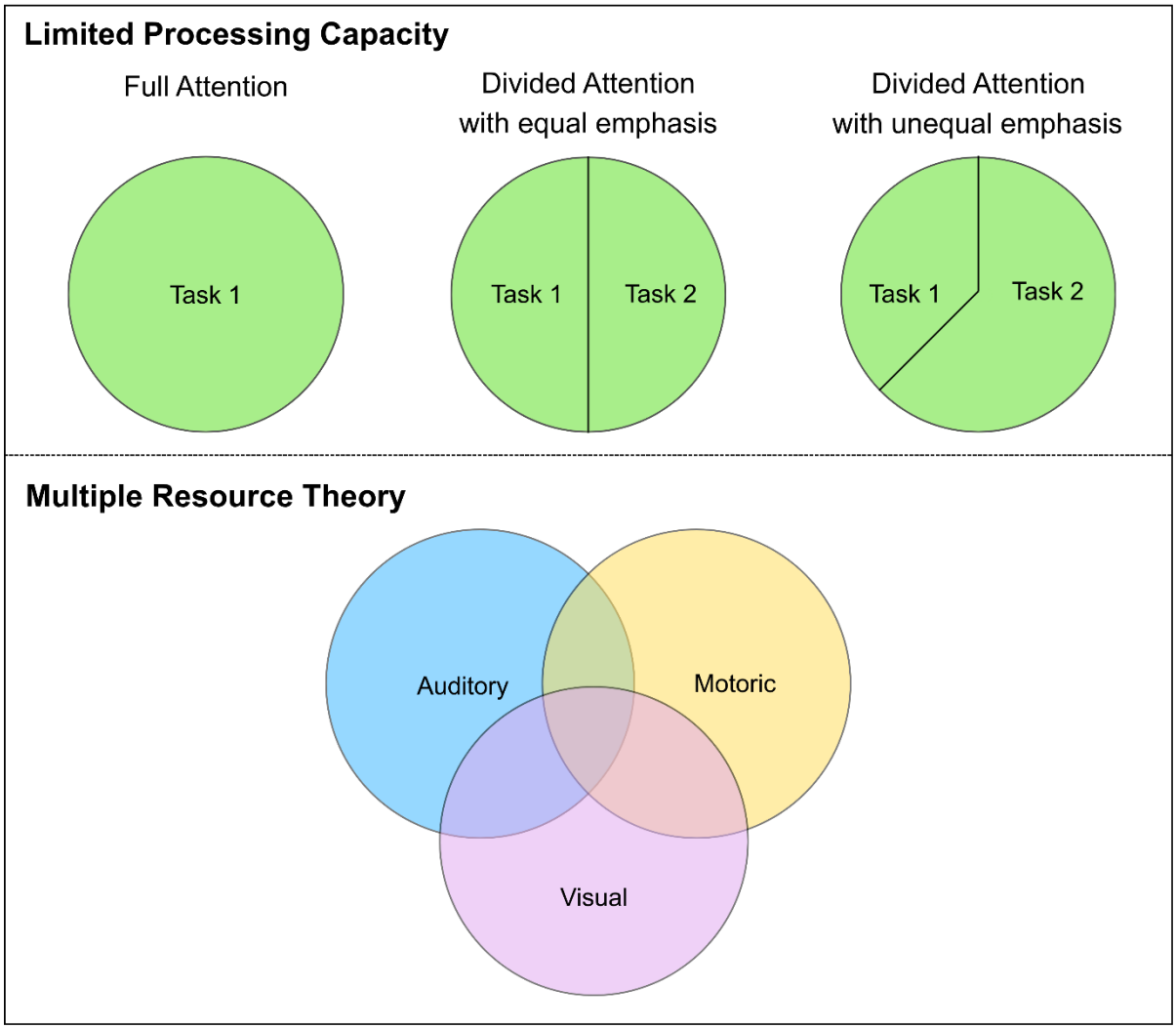
demonstrated by Murdock (1965). He found that greater demands imposed by a concurrent card-sorting task during encoding were associated with worse subsequent memory for the simultaneously encoded words. This demonstrated the importance of attention during encoding to maximize subsequent memory for targets. Baddeley et al. (1984) extended this line of work by comparing different concurrent task loads during both encoding and retrieval. They found that the cost from a concurrent task, performed simultaneously during the encoding or retrieval phase of memory, was asymmetric. DA at encoding incurred significant costs to memory (about 50% drop from FA), while DA at retrieval left memory largely unaffected (5% to 15% drop from FA conditions). This led the authors to conclude that encoding, relative to retrieval, demanded significant attention or recruitment of attentional resources. Critically, Craik et al. (1996) demonstrated that relative to FA, DA at encoding significantly impaired subsequent memory performance, with the magnitude of deficit being dependent on which of the concurrent tasks the participant was instructed to emphasize. In this way, Craik and colleagues (1996) showed how the amount of available attention determined memory performance. These seminal findings demonstrated the fragility of the encoding process and the importance of devoting attentional resources to maximize memory performance. More recently, Naveh-Benjamin and Brubaker (2019) demonstrated that DA at encoding impairs both intentional and incidental learning, suggesting DA does not just disrupt strategic elaborative processes such as rehearsal and organization of information, but also non-strategic ones such as the initial perceptual registration of information or its consolidation (Naveh-Benjamin et al., 2007, 2014; Naveh-Benjamin & Brubaker, 2019)

The interpretation of how DA at encoding affects memory depends on the way one conceptualizes the construct of attention. Limited Processing Capacity Theory (Kahneman, 1973) proposes that attention comes from a single, limited pool of resources that must be shared across

tasks. In contrast, Multiple Resource Theory (Wickens, 1980, 1984, 2021) suggests that attention is divided into several specialized resource pools, allowing tasks that use different types of resources to be performed simultaneously with less interference. Both theories recognize that attention is limited, but they differ in whether the limitation results from one general resource or multiple distinct ones. Applied to memory under DA conditions, the Limited Processing Capacity theory (Craik & Byrd, 1982) suggests that humans can devote fewer resources to completing each of the concurrent tasks; therefore, performance on both suffers relative to FA conditions. If we were to imagine attentional resources as a circle, then when engaging in encoding under FA conditions, most, if not all, available attention can be allocated to the encoding process. However, under DA conditions, one must split the metaphorical circle in a manner that allows one to complete both tasks. Under these conditions, the available attentional resources, or the capacity to recruit attention, are divided, hindering performance in both tasks (see Figure 1).

Figure 1.

Conceptualization of attention as a limited resource



Note. The diagram does not convey the dynamic nature of attention during encoding. It exemplifies specific instances of emphasis when completing two tasks simultaneously.

In contrast, the Multiple Resource theory (Wickens, 1980, 1984, 2021) suggests that we do not have a single pool of undifferentiated attentional resources; we possess specialized pools defined by processing code (verbal versus spatial) and perceptual modality (visual versus auditory).

Experiencing information in different perceptual modalities or relying on different processing systems to code information could allow one to combine concurrent tasks while minimizing performance cost. Based on the Multiple Resource theory, encoding that engages multiple types of processing, or different perceptual modalities, could alleviate impairments to memory from DA conditions. Given this, it is possible that the known memory impairments resulting from DA at encoding could be offset by representing information using multiple codes. That is, the typical impairment from DA conditions at encoding may be mitigated by using an encoding technique that forces processing of target information across multiple modalities and uses multiple distinct pools of attention resources; the resulting impairment from DA conditions at encoding could be circumvented. While the current thesis is not intended to compare these two theories of attention directly, they provide a framework for understanding how DA conditions during encoding of to-be-remembered information may impact memory performance.

1.3 The beneficial effect of encoding techniques

There are multiple techniques known to enhance the encoding process, ultimately improving memory performance. These techniques include elaborative rehearsal (Craik & Lockhart, 1972), self-generation (Slamecka & Graf, 1978), motoric enactment (Engelkamp & Zimmer, 1989), and the hand-drawing (Wammes et al., 2016) of to-be-remembered information. Vocalizing to-be-remembered words during encoding is also known to improve memory, relative to silently reading them (MacLeod et al., 2010), a phenomenon known as the production effect (Bailey et al., 2021; Forrin et al., 2012; Forrin & MacLeod, 2018; Jones & Pyc, 2014; MacLeod, 2011; MacLeod et al., 2010; MacLeod & Bodner, 2017; Ozubko, Gopie, et al., 2012).

The production effect was described by MacLeod et al. (2010) after a series of experiments demonstrated that speaking words aloud, relative to silently reading, improved performance on a

recognition test of memory. The production effect has been shown to occur primarily in mixed-list designs where words are either read aloud or silently, intermixed within the list. There is very little benefit, if any, in pure list designs, when read-aloud and read-silently are blocked (Jones & Pyc, 2014; Lin & MacLeod, 2012; MacLeod, 2011; MacLeod et al., 2010; but see Fawcett, 2013). This differential effect, based on the experimental design, suggests that the mechanism underlying the production effect depends on the contrast between encoding types. Specifically, the prevailing mechanism purported for the production benefit is a distinctiveness-based account (MacLeod et al., 2010). This account proposes that the benefit to produced by items results from the additional motor and auditory processing that occurs when one talks aloud, in addition to the visual and semantic processing of the word. This additional cognitive processing creates a more varied representation of the target, making it more retrievable (MacLeod et al., 2010; MacLeod & Bodner, 2017). Support for the idea that speaking aloud provides additional processing through both a motor action and self-referential auditory input comes from Forrin and MacLeod (2018). They showed that listening to a recording of one's own voice produced a greater memory benefit than listening to someone else's voice; however, the benefit was lesser relative to self-producing the word aloud during encoding. These findings suggest that the production effect is driven not only by the motor act of speaking but also by self-referential auditory processing, supporting the view that multiple encoding mechanisms contribute to enhanced memory performance.

Neurological evidence further supports this account. An fMRI study conducted by Bailey et al. (2021) found greater activation of the primary sensorimotor cortex associated with articulation, and the auditory cortex associated with auditory processing, when items were read aloud, relative to being silently read. Furthermore, the activation of these regions was associated with the subsequent recognition of produced items on a later memory test. Nakamura et al. (2023) largely replicated these findings but also found increased activation of the right lingual gyrus associated with visual

processing, and the lateral precentral gyri implicated in articulation. These findings provide neurological evidence that at least part of the production effect is attributable to the recruitment of multiple additional brain regions. When using free recall, this additional processing is thought to disrupt item order information, resulting in a cost to silent items (Forrin & MacLeod, 2016; Jonker et al., 2014; MacLeod & Bodner, 2017)

1.3.1 Other accounts of the Production effect

Another account for the production benefit, which has been relatively overlooked, is an attentional one. Ozubko et al. (2012) first suggested that vocal production may boost memory because it selectively focuses attention more so during the encoding of words read aloud than silently. Similarly, Mama and colleagues (2018) suggested that attention is an important factor. They found that hearing task-unrelated, distracting audio information during encoding (e,g, fluctuating noise patterns) eliminated the production benefit. They proposed that when the distracting noise had an inconsistent pattern, it disproportionately diverted attention away from the target words that were read aloud versus silently, accounting for the reduction (elimination) of the production effect. However, no systematic assessment of the role of attention during encoding on the production benefit has been done.

1.4 Why production may benefit memory under divided attention

At present, there is a consensus that DA at encoding impairs subsequent memory performance (Baddeley et al., 1984; Craik et al., 1996, 2000, 2018; Fernandes & Moscovitch, 2000; Naveh-Benjamin et al., 2005; Naveh-Benjamin & Brubaker, 2019). This impairment can be thought of as a result of concurrently performed tasks both vying for finite resources (Baddeley et al., 1984; Craik & Byrd, 1982). However, multiple resource theory suggests we do not possess a singular pool

of attentional resources, but multiple pools that are differentially allocated for modality-specific processing (Wickens, 1980, 1984, 2021). This could enable certain concurrent tasks to be combined, given they involve different modalities or engage different representations, recruiting multiple distinct pools of attention. Relying on these differentiated pools of attention resources may be key to protecting encoding when it needs to be performed under DA conditions. That is, engaging multiple representations of target information during encoding may protect memory from the known negative effects. Production as an encoding technique has been shown to enhance memory and lead to recruitment of multiple distinct cortical areas relative to silent reading of target words (Bailey et al., 2021; Forrin et al., 2012; Forrin & MacLeod, 2018; MacLeod et al., 2010; MacLeod & Bodner, 2017; Nakamura et al., 2023). An encoding technique like production could, therefore, recruit specialized pools of resources and different cortical areas, facilitating encoding under DA conditions. As such, the production (saying aloud) of target words during encoding could enhance memory, even when encoded under DA conditions, because it creates more than one type of representation of the target, which could subserve memory.

In a conceptually similar study to the ones reported here, but looking at the effect of DA at retrieval rather than DA at encoding, Wammes and Fernandes (2017) demonstrated that the use of an encoding technique can protect memory performance. They showed that words that were enacted (an encoding technique using arm and hand movements to depict target words), relative to simply reading during encoding, were better remembered, even when attention was divided during the retrieval stage. Their findings suggest that encoding techniques can be used to protect subsequent memory performance.

1.5 Computational Modelling

Computational modelling offers a unique opportunity to help understand the mechanisms by which production enhances memory. To model any known cognitive effect, one should identify relevant components and contributing factors that could account for observed patterns in humans. These can then be used to create and implement a model whose accuracy in mimicking human data can be assessed. Since the leading mechanism underlying the production effect is the additional processing of motoric and auditory information for produced words, some computational models have represented memory as a collection of "features" and then assessed whether their presence improves memory. (Caplan & Guitard, 2024; Cyr et al., 2022; Jamieson et al., 2016; Kelly et al., 2022, 2024).

Cognitive models of the production effect have been created for recognition (Jamieson et al., 2016; Kelly et al., 2022) and recall (Saint-Aubin et al., 2021). Past work has conceptualized production through feature-space representation, where the representation of a stimulus is a vector of *n* features. Words read aloud versus silently are given more sensory-specific features in an attempt to capture the additional motoric and auditory processing that makes items more unique, as suggested by a distinctiveness account (Jamieson et al., 2016). Through this conceptualization, contrasting differing accounts of production using mixed list and pure list designs becomes simple, as the comparison in retrieval between produced and non-produced words is based on the number of features present in the memory representation. Their work showed that a greater number of features present in the representation ultimately enhances the probability of an item being successfully retrieved. This work primarily focuses on contrasting differing accounts of the production effect using list types, and so I will not delve into the details of these arguments, as it is not the focus of this thesis.

This first computational model of the production effect (Jamieson et al., 2016) used MINERVA 2 (Hintzman, 1984), which is a multi-trace model of memory; each presentation of a

stimulus during ‘encoding’ creates a new memory trace, and retrieval is based on the aggregate of similar memories stored, rather than a single representation. Retrieval involves using parallel similarity comparisons between the output and the aggregate of stored inputs of a given target. Since a leading explanation for the production effect is a “distinctiveness account”, Jamieson and colleagues (2016) modified MINERVA2 to assume that production trials generated additional sensory-based features associated with motoric and auditory processing for targets that were read aloud, compared with targets that were read silently. Thus, on ‘production’ trials, target words had additional unique sensory information added to them. More specifically, memory for each word was represented by an *m* x *n* matrix, where *m* represents the number of traces, and *n* represents the number of features per trace. The authors demonstrated that additional sensory feedback features associated with motoric and auditory processing replicated the numerous findings of the production effect.

Later work employed similar conceptualizations, relying on feature representation to quantify the additional sensory components associated with articulation for production, relative to trials for silent reading. Caplan and Guitard (2024) extended the conceptualization to include an attention component. Building upon ‘attentional subsetting theory’ (Caplan 2023; Caplan et al., 2022), they propose that a fraction of the features of a stimulus will be encoded. Furthermore, the quantity of attributes extracted during recognition may differ, but this meta-knowledge could be used to calculate likelihood ratios when making recognition judgements. The authors argue that, beyond partial encoding of features, shallow features require less effort to encode and map onto a smaller feature space, resulting in shallow feature spaces being more densely subsetted. Conversely, deeper features require more processing, meaning they would be more sparsely subsetted. The sparse nature of production-specific features is believed to mitigate potential interference from competing list items, which enhances memory for produced stimuli during recognition. Their extension successfully

reproduced the production effect, as well as results from manipulations of list type and encoding duration. They ultimately concluded that the production effect arises from a form of enhanced memory strength; such an account encapsulates elements of distinctiveness and traditional memory strengthening (Caplan & Guitard, 2024). Other research has sought to model the production effect by examining serial position curves of output (Jonker et al., 2014; Saint-Aubin et al., 2021) and has considered the influence of partial feature manipulations during encoding (Kelly et al., 2024). While a detailed discussion of this work falls beyond the scope of the present thesis, any computational model of this effect should be able to account for such behavioural findings.

While past work on modelling the production effect has focused on purely cognitive implementations relying on MINERVA 2 (Jamieson et al., 2016; Kelly et al., 2024) or Feature Models (Saint-Aubin et al., 2021), Spiking Neural Networks (SNN) offer an alternative option to computational modelling that is more biologically plausible. These models simulate how neurons communicate with one another by emulating neuron firing through event-driven spikes based on the threshold of activation, at which point a signal will be sent to the next neuron (Maass, 1997). An individual neuron can receive multiple inputs to determine whether it spikes, and by employing many spiking neurons, SNNs can represent spatial-temporal information, which more accurately captures time and can allow models to simulate learning and other human behaviour (Yamazaki et al., 2022).

Nengo (Eliasmith, 2015), a Python package created for making biologically plausible models, implements SNN on a grander scale and can simulate higher cognitive functions such as working memory (Penzkofer et al., 2025), list memory (Choo & Eliasmith, 2010), and inductive reasoning (Rasmussen & Eliasmith, 2014). This is a result of the Neurological Engineering Framework created by Eliasmith & Anderson (2003), which outlines three principles for implementing simulations of neural systems. These principles include representation, transformation, and dynamics.

Representation delineates how information can be captured in compositional high-dimensional vector spaces through patterns of neuron spiking. The second principle describes how representations can be manipulated through linear and nonlinear transformations between neural ensembles (i.e. large collections of populations of neurons). Finally, the principle of dynamics outlines how any neural state can function as a variable in a linear or nonlinear dynamic system (Eliasmith & Anderson, 2003). The Semantic Pointer Architecture (SPA; Eliasmith, 2015) in NengoSPA exploits these principles to create cognitive models that can simulate higher-level functions, such as learning and memory. The semantic pointers are high-dimensional vectors that instantiate representations of target information, via neural states containing compressed semantic information. Through *superposition* (i.e. vector addition), *binding* (via circular convolution), and *unbinding* (circular convolution using an approximate inverse of an original vector representation), individual pointers can be manipulated to create or break down structured representations (Eliasmith, 2015). The details of the exact engineering mathematics used to create Nengo are beyond the scope of this thesis, but these principles allow for Nengo to be used to create the world's largest functioning brain at present (Eliasmith et al., 2012).

Since Nengo can be used to create biologically plausible models of memory, I sought to create a model of the production effect based on the distributed activation found during encoding (Bailey et al., 2021). Nengo allowed me to model how populations of neurons represent information and perform computations in a way that is biologically grounded. I attempted to demonstrate how a strength-based implementation from distributed representations created during encoding (for read-aloud versus read-silently encoding trials) could simulate the production effect found in humans.

1.6 The current thesis

The overarching objective of this Master's thesis was to assess the effectiveness of production as an encoding technique under DA encoding conditions. In doing so, I sought to determine whether production could be used to enhance memory even in non-optional, attentionally compromised, encoding conditions. In Experiments 1 and 2, I assessed the effectiveness of production under FA and DA conditions with a concurrently performed digit monitoring task. If attention contributes significantly to the production effect, then no production benefit should emerge when encoding under DA; conversely, if attention is not necessary to elicit a benefit to produced items, then the production effect should remain under DA conditions. Furthermore, given the well documented negative influence of DA at encoding, coupled with production's known boost to memory and recruitment of additional cortical areas, I predicted that 1) DA at encoding would lead to an overall decrement to memory performance relative to FA conditions, replicating classic work in the field, 2) memory would be better for words read aloud versus silently, replicating the well-documented production benefit to memory and 3) the production benefit would be maintained even under DA conditions, based on a distinctiveness account.

In Chapter 3, my goal was to create a proof-of-concept model of the production effect by manipulating the reinforcement of memory traces created during encoding, using a Nengo spiking neural network. I then compared the model's memory output to that of humans. To accomplish this, I developed a spiking neural network model of human memory, called Encoding-Based Strength Representations in Memory (ESRM). A list of words was presented to the model in which half were 'read silently' and half 'read aloud'. I reinforced 'read aloud' words by creating an additional distinct memory representation for these target words and adding them to the original, thereby increasing the magnitude of the vector representation and thus increasing the item's strength by 90%; words 'read

silently' were not reinforced. Successful recall was determined by neural populations competitively accumulating evidence of word representations to a threshold, using a minimum of 30% to filter irrelevant evidence (Gosmann et al., 2017). An accumulation to threshold denoted successful recall. I then compared ESRM's recall to that of a matched sample of human data. Should strengthening memory by increasing the magnitude of the vector representation work as an implementation, then a production effect should emerge; otherwise, there will be no benefit to words "read aloud" relative to words "read silently".

Chapter 2

Note. A slightly adapted version of Chapter 2 of this thesis was submitted for publication:

Tsapoitis, P., & Fernandes, M.A. (submitted May 6th, 2026). The Limited Role of Attention on the Production Effect in Memory. *Psychonomic Bulletin & Review*

2.1 Experiment 1

At present, there is a consensus that DA at encoding reliably impairs subsequent memory performance (Baddeley et al., 1984; Craik et al., 1996, 2000, 2018; Fernandes & Moscovitch, 2000; Naveh-Benjamin et al., 2005, 2005; Naveh-Benjamin & Brubaker, 2019). Production as an encoding technique is known to enhance memory, likely through recruitment of additional neural regions involved in motoric and auditory processing of information (Bailey et al., 2021). As such, additional regions engaged in encoding could serve to make the memory trace more robust, ultimately protecting it from the negative effects of DA. No such additional recruitment occurs for silently read words, making them more susceptible to reductions in attention that limit the creation of durable memory traces. In Experiment 1, I examined these hypotheses.

2.1.1 Methods

2.1.1.1 Participants

One hundred twenty-eight participants were recruited via the online recruitment platform Prolific and completed the study in return for £4.00. Those with recall outputs of zero under FA on the memory or secondary task were excluded from the analysis, resulting in the removal of 28 participants (1 with a recall score of 0 in the FA condition, and 27 with scores of 0 on the secondary task performed under FA). The remaining sample consisted of 100 participants (45% men, 50% women, 3% gender non-conforming, and 2% gave no response), with a mean age of 36.13 years (*SD*

= 11.83, range = 19-77), and a mean year of education of 15.94 (*SD* = 2.59, range = 11-25). Self-reported proficiency in reading English was high: 99% with high proficiency and 1% moderate proficiency. Similarly, 97% indicated high proficiency in speaking English, with only 3% indicating moderate proficiency. Data were collected from July to September 2025.

Using the effect size found in past work (Wammes & Fernandes, 2017), a sample size of 34 (using G*Power; Faul et al., 2007) was required to achieve a power of .80. We tripled the sample size, given that we were examining an encoding manipulation that is relatively newer and possibly less robust than enactment.

2.1.2 Materials

2.1.2.1 Word lists

Words were selected from the English Lexicon Project (ELP), where their descriptive characteristics, such as word length, number of syllables, and concreteness rating, are included (Balota et al., 2007). From the ELP, 48 unique words were selected for Experiment 1. All stimuli were concrete (*M* = 3.90), neutral words (*Mean Valence* = 5.26, *Mean Arousal* = 3.35), 4-6 characters in length, and 2 syllables long. From these 48 stimuli, 20 were randomly selected for the DA condition, 20 for the FA condition, and 4 were to be used during practice trials (see Appendix A for word list). The remaining 4 words were left unused for this experiment (included only in a pilot study, not reported in this thesis). Words and their associated cues, “READ OUT LOUD” or “READ SILENTLY,” were presented in random order in both conditions.

2.1.2.2 Secondary/Concurrent Task

Digit monitoring served as the concurrent task during encoding under DA, a working memory task that has been used in several DA studies (Castel & Craik, 2003; Craik et al., 2010;

Fernandes & Moscovitch, 2000). Participants listened to a series of pseudo-randomized two-digit numbers (10-99) for 80-seconds. They had to correctly identify when three odd digits were presented in sequential order by pressing the "M" key on a standard QWERTY keyboard; otherwise, participants pressed the "N" key. Digits were audibly presented through the computer speakers, one at a time, at a rate of 2-seconds per digit. In the DA encoding condition, two numbers were presented per target word.

Materials are available on OSF.

2.1.3 Procedure

Participants completed the 30-minute online study through the recruitment platform Prolific (https://www.prolific.com). They completed the study on their personal computer, and so the screen size and angle at which they viewed their screen cannot be reliably reported. After providing informed consent, participants began audio recording themselves using their own devices to ensure compliance with task instructions. First, participants completed a baseline digit-monitoring task for 80 seconds: participants pressed the "M" key to indicate whenever three odd digits in a row were heard through their computer speakers. Double-digit numbers were played at a rate of 1 digit every 2 seconds. Then, participants completed 4 practice encoding trials. FA and DA conditions were then completed in counterbalanced order, separated by a 3-minute silent film.

During the practice and encoding stage, 20 neutral words were presented one at a time, in random order, at a rate of one word every 3.5 seconds, followed by a 0.5-second fixation cross between each word. Words were presented in Arial font and 36pt-size font; encoding prompt cues were presented in Arial 16pt-size font. Half the words were read aloud, and half were read silently. Depending on the trial type, a cue was presented at the top of the screen asking the participants to either "READ SILENTLY" or "READ OUT LOUD" the target word presented underneath, in the

center of the screen. In the FA condition, participants completed only this task. In the DA condition, they concurrently completed the digit-monitoring task, with the onset of the digits coinciding with the onset of the target word. In total, there were six instances in which participants could have identified three odd digits in a row for the secondary task. Before recall, participants drew geometric shapes for 20-seconds as a filler task to prevent the rehearsal of target words. The retrieval stage always occurred under FA. Participants were then given 1 minute to retrieve the target words by typing into a textbox.

After completing either the FA or DA condition (counterbalanced order), participants watched a 3-minute silent film to prevent the buildup of proactive interference before completing the other condition. Once the memory portion of the study was completed, to alleviate any residual feelings of stress, a 1-minute-deep breathing exercise was done. Next, participants uploaded their recording to a secure server using our provided link. The study received ethics clearance from the University of Waterloo Office of Research Ethics (Protocol #46917).

2.1.4 Results

2.1.4.1 Memory Performance

Recall was verified for accuracy and tabulated separately for words read aloud versus silently during encoding. Data were analyzed using a 2 (Attention: FA vs. DA) x 2 (Encoding type: silent vs. aloud) repeated-measures ANOVA. As expected, there was a main effect of Attention such that recall following FA (M = 5.21) was better than following DA at encoding (M =2.35), $F(1, 99) = 95.49$, $p < .001$, $MSE = 1.31$, $\eta^2_p = .49$[1]. Replicating the production effect, there was also a main effect of Encoding type, such that words read-aloud (M = 2.40) were better remembered than words read

[1] The Shapiro-Wilk test showed a significant departure from normality across conditions ($ps < .001$).

silently (M = 1.38), $F(1,99) = 55.64$, $p < .001$, MSE = 1.31, $\eta^2_p = .36$. Importantly, there was no significant Attention x Encoding type interaction, $F(1,99) = 1.10$, $p = .298$, MSE = 1.31, $\eta^2_p = .01$. See Table 1 for means.

A Bayesian repeated measures ANOVA was conducted to evaluate evidence for the null hypothesis (H_0 = the absence of an interaction) against the alternative (P(M) = .200). Results indicated the best-fitting model only included the main effects of Attention and Encoding type, $P(M|Data) = .805$. When compared to the next best model, which includes the interaction term, there was moderate evidence in favour of the null hypothesis ($BF_{01} = 4.14$). This suggests that the data are approximately four times more likely under the hypothesis that no interaction exists than under the alternative.

Table 1.

Mean Recall of Words in each Attention Condition by Encoding Type in Experiment 1

	Attention	
	M (*SD*)	
Encoding type	Full	Divided
Aloud	3.17 (1.77)	1.62 (1.41)
Silent	2.04 (1.72)	0.73(1.77)
Total recall	5.21 (2.83)	2.35 (2.27)

2.1.4.2 Secondary task performance

Accuracy on the digit-monitoring task under FA was compared to performance under DA using a paired t-test. As expected, performance under FA (M = 58.17%; SD = 21.25%) was significantly better than under DA (M = 30.17%; SD = 23.53), $t(99) = 10.84$, $SE = 2.583$, $p < .001$, $d = 1.25$.

The above ANOVA and paired t-tests plans were preregistered on OSF.

2.1.4.3 Trade-off Analysis

To examine whether there were trade-offs in task performance, a Pearson correlation was conducted between the cost to memory and the cost to digit-monitoring performance.

Memory Cost was calculated as:

$$Cost = \frac{Number\ of\ Recalled\ Words\ Learned\ Under\ FA - Number\ of\ Recalled\ Words\ Learned\ Under\ DA}{Number\ of\ Recalled\ Words\ Learned\ Under\ FA}.$$

This was calculated separately using read-aloud and read-silently items recalled.

Digit-monitoring task cost was:

$$Cost = \frac{Number\ of\ Success\ Trials\ During\ Baseline - Number\ of\ Success\ Trials\ Under\ DA}{Number\ of\ Success\ Trials\ During\ Baseline}.$$

There was no significant correlation between the cost to digit monitoring performance (M = .42; SD = .52) and cost to memory for words read-aloud (M = .42; SD = .59), $r(94) = -.20$, $p = .053$, or cost to memory for words read silently (M = .65; SD = .60), $r(78) = -.10$, $p = .382$.

The association between digit monitoring performance cost and memory for items encoded via production or silent reading under DA was also examined. There was a small positive association between cost on digit monitoring (M = .42; SD = .52) and memory for produced items (M = 1.62; SD

= 1.41), $r(98) = .22$, $p = .027$, but no relationship with memory for silently read items ($M = 0.73$; $SD = 1.28$), $r(98) = .11$, $p = .300$.

2.1.4.4 Frequency Output Analysis

We explored how DA at encoding may affect the organization of information during encoding. To do so, we separated output recall into first and second half sections and tabulated the proportion of produced words recalled in each section under both attention conditions. We then analyzed the proportion of produced words recalled in a 2 (Attention: full vs. divided) x 2 (Order: first half vs. second half) repeated measures ANOVA. There was no effect of Attention, $F(1, 61) = 2.66$, $p = .108$, $MSE = 0.14$, $\eta^2_p = .04$, Order, $F(1, 61) = 3.44$, $p = .068$, $MSE = 0.10$, $\eta^2_p = .05$, or Attention x Order interaction $F(1, 61) = 0.71$, $p = .404$, $MSE = 0.10$, $\eta^2_p = .01$ (see Table 2).

Table 2.

Mean proportion of recall outputs, across participants, that contained words produced at encoding

	Output Section	
	M (*SD*)	
Attention	First half	Second half
Full	.66 (0.32)	.61 (0.34)
Divided	.77 (0.33)	.66 (0.45)
Mean	.71 (0.33)	.64 (.40)

2.1.5 Discussion

The production effect remained under DA conditions. Consistent with past literature, words read aloud were better remembered than words read silently (Bailey et al., 2021; Cyr et al., 2022;

Forrin et al., 2012; Jones & Pyc, 2014; MacLeod, 2011; MacLeod et al., 2010), and this occurred even under DA. We also replicated past literature showing a significant decrement in overall memory performance when encoding was completed under DA (Anderson et al., 1998; Baddeley et al., 1984; Craik et al., 1996, 2018; Fernandes & Moscovitch, 2000; Guez & Naveh-Benjamin, 2006, 2013; Naveh-Benjamin et al., 2006, 2007). The resilience of the production effect under DA conditions is a novel finding. The preservation of the benefit despite attention reductions suggests the production benefit occurs regardless of attention availability. Prior work (Mama et al., 2018; Ozubko, Hourihan, et al., 2012) has suggested production may benefit memory because it enhances attention to produced items during encoding; however, our results are inconsistent with this account.

An alternative explanation is that DA benefited produced items because greater attention is devoted to the secondary task during silently read trials, leading to poorer memory. This account predicts a trade-off with secondary task performance, but across both experiments, we found no significant correlations between memory costs for read-aloud or silent items and the cost to secondary task performance. Thus, poorer memory for silently read items cannot be explained by prioritizing the secondary task. There was a small positive correlation (r = .22) between cost on digit monitoring performance and memory for produced items, which could suggest a slight emphasis on produced words. However, this correlation is small, and the trade-off analysis overall suggests there was no prioritization of tasks. The frequency of produced words recalled in output sections revealed no differences between the first and second halves. Past work has shown that recall output order does not differ for aloud vs. silently read words (Lin & MacLeod, 2012), and consistent with this, we also found no difference in the proportion of aloud words recalled in the first and second halves of retrieval.

2.2 Experiment 2

In Experiment 2, we considered whether the pattern would replicate using an in-person sample, which allows greater experimental control compared to online data collection platforms.[2]

2.2.1 Methods

2.2.1.1.1 Participants

Sixty-two undergraduate-level participants were recruited, who completed the study in return for 1.0 credit in their psychology courses. As described in Experiment 1, a sample of only 34 participants was needed to find a cognitive effect. As in Experiment 1, the data from 1 participant were removed because their performance on the memory task was 0. The remaining sample comprised of 14.75% men, 78.69% women, and 6.56% two-spirited, with a mean age of 20.05 years (*SD* = 1.86, range = 17-28), and 14.75 (*SD* = 1.87, range = 12-19) years of education. Self-reported proficiency in reading English was high: 93.44 % with high and 6.56% as moderate proficiency. Similarly, 91.80% self-reported high proficiency in speaking English, and 8.20% moderate. Data were collected from October to November 2025.

Using the effect size of Encoding type found in Experiment 1, $\eta^2_p = .36$, a sample size of 6 (using G*Power; Faul et al., 2007) was required to achieve a power of .80. However, a larger sample of 61 was collected. This is because participants were also wearing a heart rate monitor to answer a

[2] Due to a programming error, the timing of the encoding conditions was in the DA encoding condition, slightly longer than the intended 80-second period due to a software-based lag in processing time to play the audio clip of the digits. To ensure the validity of our manipulation we collected data in a smaller sample ($N = 20$) in which the timing was corrected. Regardless, there was no change in the pattern of findings. See supplementary material for comparison of the datasets.

secondary question not discussed in this thesis, and a sample of 61 was required to detect a medium effect size when conducting heart rate variability analyses (Quintana, 2017).

2.2.2 Materials

All materials were the same as in Experiment 1.

2.2.3 Procedure

The procedure was identical to Experiment 1 except that it was conducted in a testing room at the University of Waterloo campus. Participants completed the study on a 53.30cm by 36.00cm Phillips 240B monitor screen, but the differing heights of participants meant that head angle could not be reported. All procedures were cleared by the University of Waterloo's Office of Research Ethics (Protocol #46917).

2.2.4 Results

2.2.4.1 Memory Performance

Following the same analysis in Experiment 1, data were analyzed using a 2 (Attention: FA vs. DA) x 2 (Encoding type: silent vs. aloud) repeated-measures ANOVA. Replicating Experiment 1, there was a main effect of Attention such that recall following FA (M = 5.77) was higher than following DA at encoding (M =2.13), $F(1, 60) = 108.19$, $p < .001$, $MSE = 1.77$, $\eta^2_p = .64$[3]. There was also a main effect of Encoding type, such that words read-aloud (M = 2.46) were better remembered than words read silently (M = 1.49), $F(1,60) = 26.97$, $p < .001$, $MSE = 1.77$, $\eta^2_p = .31$. Critically, there

[3] The Shapiro-Wilk test showed a significant departure from normality across conditions ($ps < .05$)

was once again no significant Attention x Encoding type interaction, $F(1,60) = 1.12$, $p = .294$, $MSE = 1.77$, $\eta^2_p = .02$. See Table 3 for means.

As in Experiment 1, a Bayesian repeated measures ANOVA was conducted to evaluate evidence for the null interaction. Results indicated the best-fitting model only included the main effects of Attention and Encoding type, $P(M|\ Data) = .733$. When compared to the next best model, which includes the interaction term, there was moderate evidence in favour of the null hypothesis ($BF_{01} = 2.75$). This suggests that the data are almost 3 times more likely under the hypothesis that no interaction exists than under the alternative.

Table 3.

Mean Recall of Words in each Condition following each Encoding Type in Experiment 2

	Condition	
	M (*SD*)	
Encoding type	Full	Divided
Aloud	3.46 (1.68)	1.46 (1.19)
Silent	2.31 (1.66)	0.67 (1.83)
Total recall	5.77 (2.33)	2.13(1.47)

2.2.4.2 Digit Monitoring

To assess whether the divided attention manipulation worked as intended, performance on the digit monitoring task under FA was compared to performance under DA using a paired t-test. As expected, and like the pattern reported in Experiment 1, performance on the digit monitoring task under FA (M = 61.75%) was significantly better than under DA (M = 24.86%), $t(60) = 12.87$, SE = 2.87, $p < .001$, $d = 1.87$.

2.2.5 Discussion

Replicating our findings from Experiment 1, the production effect remained when using production as an encoding technique under DA conditions. We demonstrated that words read aloud were better remembered than words read silently, following both FA (Bailey et al., 2021; Cyr et al., 2022; Forrin et al., 2012; Jones & Pyc, 2014; MacLeod, 2011; MacLeod et al., 2010) and DA

conditions. We again replicated past literature demonstrating DA's known impairment on memory performance when experienced at encoding (Anderson et al., 1998; Craik et al., 1996, 2000, 2018). Memory performance was significantly worse for words encoded under DA than under FA, with secondary task performance also demonstrating a significant reduction.

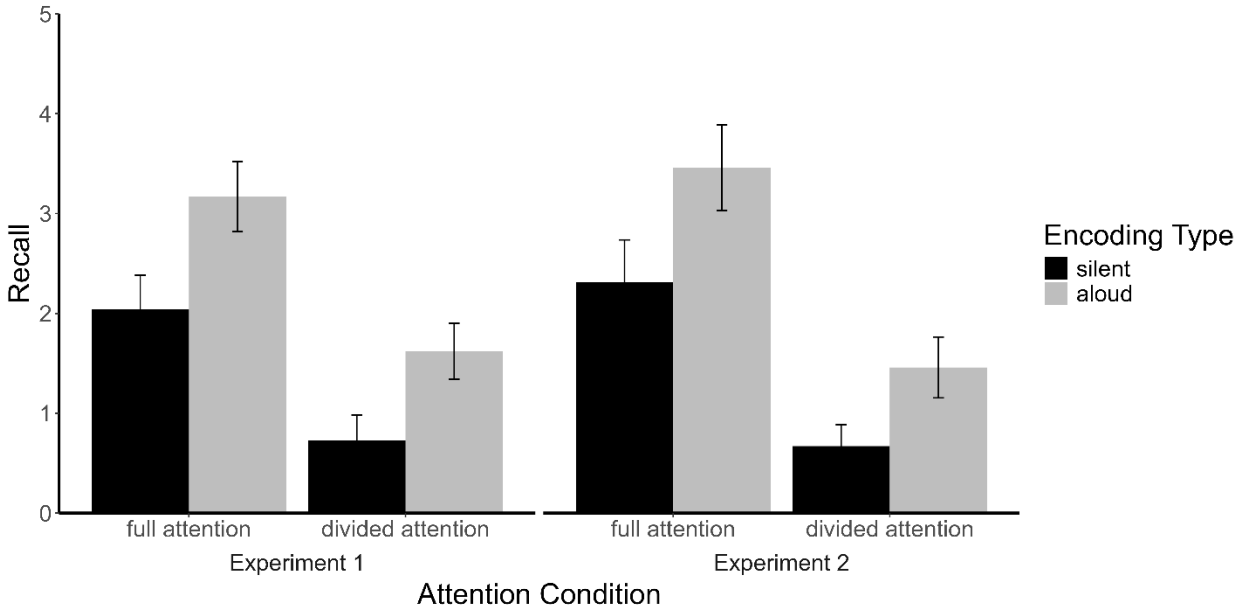
The replication of our results from Experiment 1 within the in-person sample of Experiment 2 provides additional evidence that attention plays a limited role in the production effect. This finding opposes evidence that producing draws attention towards stimuli for encoding (Mama et al., 2018; Ozubko, Hourihan, et al., 2012). The secondary task was sufficiently demanding as both memory and secondary task performance were hindered, consistent with past work (Anderson et al., 1998; Baddeley et al., 1984; Craik et al., 1996, 2018; Fernandes & Moscovitch, 2000; Guez & Naveh-Benjamin, 2006, 2013; Naveh-Benjamin et al., 2006, 2007).

2.3 General Discussion of Chapter 2

We investigated whether speaking words aloud during encoding could mitigate the well-documented memory impairments incurred when encoding under DA. As expected, memory was lower when encoding under DA relative to FA. This finding aligns with previous claims that DA conditions lead to a marked reduction in general processing resources needed for the elaboration and organization of information. Without being able to engage in processes that promote successful encoding, memory suffers (Craik et al., 1996, 2000, 2018; Fernandes & Moscovitch, 2000; Guez & Naveh-Benjamin, 2006, 2013; Iidaka et al., 2000; Lozito & Mulligan, 2006; Naveh-Benjamin et al., 1998, 2005, 2007; Naveh-Benjamin & Brubaker, 2019; Sahakyan & Malmberg, 2018). Also replicating previous work (Bailey et al., 2021; Fawcett et al., 2012; Forrin & MacLeod, 2018; Lin & MacLeod, 2012; MacLeod et al., 2010; MacLeod & Bodner, 2017), we found a benefit to memory when words were encoded by reading them aloud rather than silently. Importantly, the relative benefit

to memory from the production technique was maintained when encoding under DA (see Figure 2). These results are theoretically important as they suggest a limited role of attention in the production effect. Practically, these findings indicate that production as an encoding strategy continues to enhance memory performance even under conditions of constrained attentional resources, when attention is divided between concurrent tasks.

Figure 2. *Memory for words read silently and aloud, under full or divided attention conditions during encoding in Experiments 1 and 2*



Note. Error bars represent 95% confidence intervals.

One proposed underlying mechanism accounting for the production effect is distinctiveness; articulating information relative to silently reading is believed to engage additional cognitive processing and recruitment of motor and auditory components within the brain (Bailey et al., 2021; MacLeod et al., 2010; MacLeod & Bodner, 2017). These additional components appear to operate without the need for attentional resources, as the benefit was maintained in our study when production occurred under DA at encoding. These results are aligned with predictions from a multimodal account of encoding (Engelkamp & Zimmer, 1989; Fawcett et al., 2012; Kinjo & Snodgrass, 2000; Wammes et al., 2019; Zormpa et al., 2019), whereby engaging in multiple sensory modalities or cognitive processes creates additional representations that enhance later recollection. Production is believed to elicit greater activation of the primary sensorimotor and auditory cortex associated with articulation and auditory processing, respectively, relative to silently reading items

(Bailey et al., 2021; Nakamura et al., 2023). The additional neural processing generated by producing items could aid encoding by facilitating diverse representations, preserving retention. Our results align with this theory and with existing evidence that multi-modal encoding enhances memory (Wammes et al., 2019).

Some have suggested that attention-based resources contribute importantly to the production effect (Mama et al., 2018; Mama & Icht, 2019). Our study, however, suggests that attention plays a limited role, as the benefit was maintained when encoding under DA. This finding contradicts Mama et al.'s (2018) claim that attention is important. They found that fluctuating background noise during encoding eliminated the effect. It could be that the volume of the noise in their study was too loud, as it masked the participant's voice, overburdening their processing capacity, resulting in catastrophic interference. In our design, in contrast, participants had to process/evaluate a second information stream heard through speakers at a lower volume, lessening this concern. Further suggestions of attention's importance in the production benefit come from a study showing that those with attention deficit hyperactivity disorder (ADHD) differentially benefited from production as an encoding technique (Mama & Icht, 2019). Production's benefit was weakest for those with unmedicated ADHD, stronger for those on medication, and strongest in healthy controls. However, it is possible that the participants with ADHD approached the task differently than controls, perhaps being less motivated, as those with ADHD often struggle with tasks that are not engaging or under-stimulating (American Psychiatric Association, 2022). Here, we used a fully within-subjects design to control for such individual differences.

Given our large sample size in Experiment 1 and use of a within-subjects manipulation, we had sufficient power to detect a significant interaction. We replicated this finding in Experiment 2, and Bayesian analysis provides moderate evidence in favour of no interaction within both

experiments. The lack of such interaction suggests that attention plays a limited role in the production benefit: memory for read-aloud and read-silently items under DA would have differed if attention were driving this effect.

An alternative explanation is that DA benefits produced items because greater attention is devoted to the secondary task during silently read trials, leading to poorer memory. This account predicts a trade-off with secondary task performance, but across both experiments, we found no significant correlations between memory costs for read-aloud or silently read items and costs to secondary task performance. Thus, poorer memory for silently read items cannot be explained by prioritizing the secondary task. There was a small correlation between the cost to digit monitoring performance and memory for words read aloud, but not silently, indicating that as performance worsened on the secondary task, memory for produced words increased. This could be due to participants having to articulate read-aloud words, which provided a momentary distraction from the secondary task, when no such distraction occurred during silent trials. Despite this, the relationship size was small (r = .22), suggesting that the lower memory performance observed for silently read items is not completely explained by participants over-emphasizing the production task over the secondary digit monitoring task.

The persistence of the production benefit under DA, reported in our study, suggests that attention plays a limited role in the production effect. Practically, our work suggests that production maintains its effectiveness in divided attention situations, suggesting a means of protecting memory in multitasking conditions that are ever so prevalent in everyday life.

Chapter 3

Note. The model reported in Chapter 3 of this thesis was created in collaboration with Jakeb Chouinard and Chris Eliasmith. This work was presented at the *Cognitive Neuroscience Society* and the *Canadian Society for Brain, Behaviour and Cognitive Science*.

Tsapoitis, P., Chouinard, J., Eliasmith, C. & Fernandes, M.A. (2026). Resilience of the production effect under divided attention: Converging evidence from a spiking neural network. Talk presented at *Canadian Society for Brain, Behaviour, and Cognitive Science and Experimental Psychology Society* annual meeting, Toronto, ON, Canada.

Tsapoitis, P., Chouinard, J., Eliasmith, C. & Fernandes, M.A. (2026). Modelling Strength-Based Representations in Memory Using Spiking Neural Networks. Data Blitz and Poster presented at *Cognitive Neuroscience Society* annual meeting, Vancouver, BC, Canada

3.1 Spiking Neural Networks and Nengo

Since Nengo can be used to create biologically plausible models of memory (Eliasmith, 2015), I sought to create a model of the production effect. The fMRI study conducted by Bailey et al. (2021) found greater activation of the primary sensorimotor cortex associated with articulation, and the auditory cortex associated with auditory processing, for items read aloud, relative to read silently. Furthermore, the activation of these regions was associated with the recognition of produced items later at test, and this was largely replicated by Nakamura and colleagues (2023). Based on this, I assessed whether a strength-based implementation from distributed activation created during encoding on 'produced' trials could be simulated.

The strength-based and distinctiveness accounts are often contrasted in the production literature to determine which mechanism best explains the results observed in humans (Fawcett et al., 2012, 2023; Forrin & MacLeod, 2018; Jamieson et al., 2016; Jones & Pyc, 2014; MacLeod & Bodner, 2017). However, many existing models are purely cognitive in nature (Cyr et al., 2022; Jamieson et al., 2016; Kelly et al., 2022, 2024; Saint-Aubin et al., 2021) and neglect to consider how representations within the brain could potentially influence memory. Greater engagement across

various brain regions could help better encode produced items, relative to items silently read, thereby increasing the strength of the representation in the brain as the memory becomes more durable, and thus better remembered later.

3.1.1 Encoding-based Strength Representation in Memory

With the aforementioned information in mind, we set out to create a biologically plausible model of the production effect called "*Encoding-based Strength Representation in Memory*" (ESRM). ESRM served as a proof of concept for modelling memory effects using spiking neural networks implemented by Nengo. ESRM was created based on the assumption that articulating words during encoding recruits several brain regions (Bailey et al., 2021; Nakamura et al., 2023), which facilitates the encoding process by increasing the strength of the representation in memory, relative to words read silently. To implement this, we elected to use Nengo (Eliasmith, 2015) because it allowed us to create a biologically plausible model based on neuroanatomy. First in ESRM, the list of target words was embedded using semantic pointers. *Semantic pointers* are high-dimensional vectors that instantiate the words via neural states containing compressed semantic information (Eliasmith, 2015). The semantic pointer that defines the embedded list of target word vector representations will henceforth be referred to as "the dictionary". The dictionary can then be used to test our computational question later at retrieval. The semantic pointer that captures the memory vector representations of the items will be referred to as "memory". Both contain an instance of each target word's representation. In ESRM, when creating a memory during 'read aloud' trials, an additional memory representation is generated and added to the one formed at presentation. This increases the strength of aloud memory representations by roughly 50%, compared to 'read silently' trials. Then, by simulating the experimental procedure used in our behavioural experiments, we could assess ESRM's memory performance under full attention. The goal was to create a model of the production

effect and compare the memory data from ESRM to that of humans on these trial types. We then extended the investigation to simulate encoding under DA by reducing the signal-to-noise ratio during the encoding trials.

3.2 Methods

3.2.1 Participants

Of the one hundred participants collected and analyzed in Experiment 1, fifty randomly selected participants formed the 'Human Sample'. This served as a comparison to our computational model. This randomly selected sample (42% men, 50% women, 4% gender non-conforming, and 4% gave no response) had a mean age of 37.06 years (*SD* = 10.59, range = 20-64) and a mean year of education of 16.51 (*SD* = 2.49, range = 12-25). Self-reported proficiency in reading English was high: 98% with high proficiency and 2% moderate proficiency. Similarly, 96% indicated high proficiency in speaking English, with only 4% indicating moderate proficiency.

3.3 Materials

All materials were the same as in Experiment 1.

3.4 Procedure

3.4.1 Human experiment

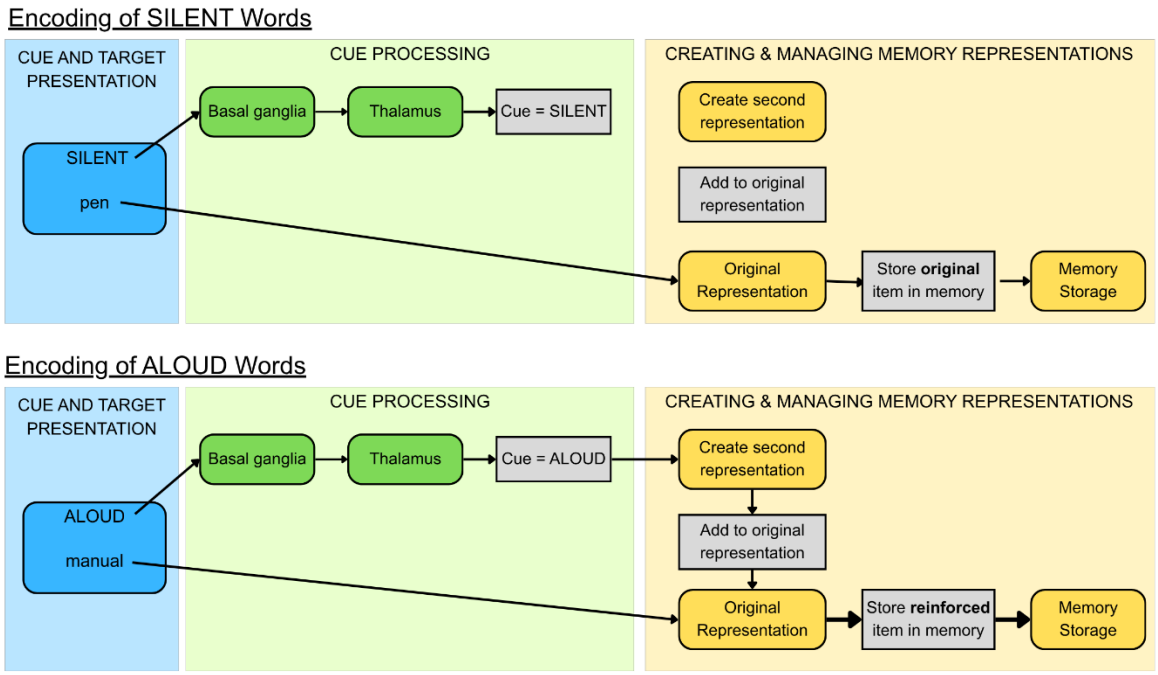
The procedure and data used were as described in Experiment 1. All procedures were cleared by the University of Waterloo's Office of Research Ethics (Protocol #46917).

3.4.2 Computational model simulation

Encoding within the ESRM model under FA was similar to the behavioural experiment. The dictionary presented contained 20 neutral words. Words were presented one at a time for 4 seconds, with an associated cue, either “ALOUD” or “SILENT”, to indicate whether a word should be reinforced or not. Target words were encoded in the model, and a basal ganglia and thalamus unit was used to determine whether a target’s memory should be strengthened or not. The basal ganglia and the thalamus were used because the current version of Nengo employs these brain regions as input controllers during cognitive tasks (Eliasmith, 2015). If the cue was “ALOUD”, ESRM created an additional memory representation and superimposed it onto the one defined at presentation, through the vector addition of the two representations. This increased the strength of that item’s representation in memory by 90%. When the cue was to read “SILENTLY”, the strength of the memory representation remained unchanged (see Figure 3). This process continued until all 20 words within the list were presented, half of which were ‘read aloud’ and half ‘read silently’. Following encoding of all the targets, there was a 30-second delay with no additional stimulation, and then the model was allotted 1 minute for free recall.

Figure 3.

Flowchart depicting the encoding process for targets cued as "ALOUD" or "SILENT" trials within Encoding-based Strength Representation in Memory



Note. This diagram depicts the encoding process under full attention.

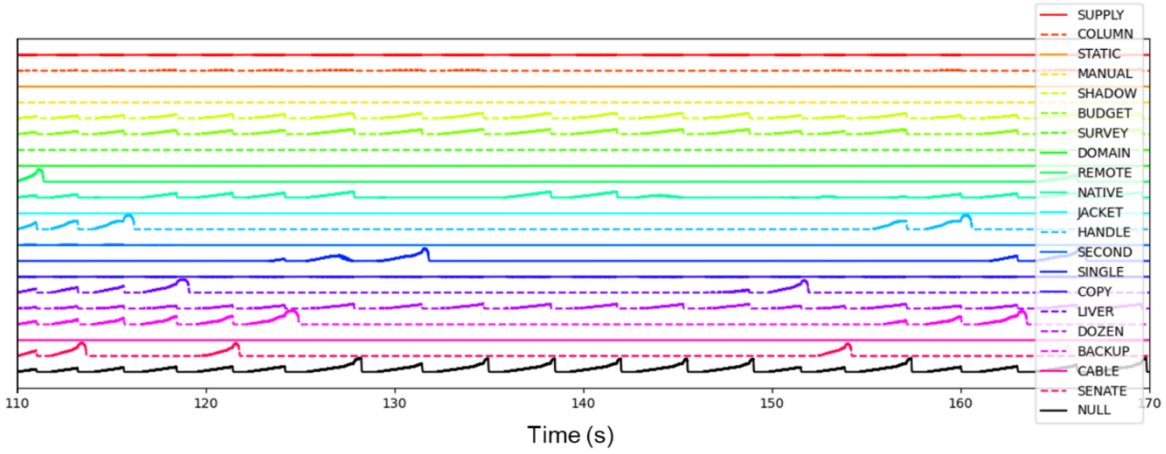
We simulated encoding under DA conditions by weakening the encoding strength of the memory representation by a magnitude of 0.4, which set our attention factor to 0.6 rather than 1.0. This parameter is a weight set when communicating the target's representation between population ensembles during the initial encoding process, before the memory is stored. Reducing it caused a loss in the strength of the representation by making the population of neurons representing that memory less stable. Effectively, the amount of noise was the same for FA and DA versions, but the signal-to-noise ratio was reduced in the DA condition within ESRM.

Retrieval in ESRM was modelled using a competitive accumulation process, where populations of neurons in long-term memory simultaneously competed to accumulate evidence for

the retrieval of all the targets. The model continuously compared the memory representation of each target word to the dictionary contained within the model. Similarity comparisons were calculated using the dot product between the memory representation and the dictionary representation of the items. If the result of the dot product between an item in the dictionary and the memory of that item was greater than 0.3, then the accumulation of evidence for that target word's retrieval was tabulated as $0.1 \times evidence$ (*evidence* = the result of the dot product). This is a cumulative process; each successful comparison generates new support for a given word target, aggregating continuously until the decision threshold of 1 was reached. At that point, the ESRM 'recalled' the word. After a word's retrieval, ESRM inhibits that target's subsequent retrieval. The recall process is doing two things simultaneously: 1) accumulating evidence for retrieval, 2) holding onto memory of retrieved targets to inhibit them from being retrieved again. That is, as retrieval occurs, the neuron firing within ensembles becomes saturated from the many inputs related to evidence accumulation and retrieval instance storage. The combination of saturation in the signal firing and the inherent limit to how much information can be stored within populations of neurons will lead to memory decay of the retrieval instance over time, and ESRM will "forget" it retrieved the item. When ESRM forgets a retrieval instance, it will begin the evidence accumulation process once again for that previously recalled word (see Figure 4).

Figure 4.

Retrieval instances of words from memory over sixty seconds



Note. Each high peak on a given line indicates a successful 'retrieval' of that word.

3.5 Results

3.5.1 Human memory performance

Before evaluating ESRM's performance against a matched sample from Experiment 1, fifty participants were randomly selected to be compared with ESRM's memory output. To ensure the subset of participants were representative of the larger Experiment 1, fifty participants were randomly sampled and evaluated using a 2 (Encoding type: aloud vs. silent) x 2 (Attention: full vs. divided) repeated measures ANOVA on the number of words successfully recalled, 5 times. All the reported results below were similar across the 5 randomly selected samples.

Replicating Experiment 1 findings, there was a significant main effect of encoding type, with higher recall for words read aloud (M = 4.62) than silently (M = 2.60), $F(1, 49) = 33.89$, $p < .001$, $MSE = 1.51$, $\eta^2_p = .41$, and a significant main effect of attention with recall higher under FA (M = 4.90), than DA (M = 2.32), $F(1, 49) = 50.62$, $p < .001$, $MSE = 1.64$, $\eta^2_p = .51$. There was no Encoding

type x Attention interaction, $F(1, 49) = 1.70$, $p = .198$, $MSE = 1.30$, $\eta^2_p = .03$. These results suggest that a randomly chosen subset of participants from Experiment 1 is representative of the larger sample of one hundred participants.

3.5.2 Evaluating model performance

Data from human and ESRM trials were analyzed using a 2 (Source: human vs. ESRM) x 2 (Encoding type: aloud vs. silent) x 2 (Attention: full vs. divided) mixed ANOVA on the number of words correctly recalled (see Table 4 for means).

Table 4.

Recall performance following Full and Divided attention conditions at encoding, by Source

Source	Attention *M* (*SD*)	
	Full	Divided
Human		
Aloud	3.06 (1.38)	1.56 (1.34)
Silent	1.84 (1.43)	0.76 (1.29)
Total recall	4.90 (2.15)	2.32 (2.14)
ESRM		
Aloud	2.98 (1.10)	1.46 (1.28)
Silent	1.62 (1.09)	0.78 (0.79)
Total recall	4.60 (1.44)	2.24 (1.62)
Combined sources		
Aloud	3.02 (1.24)	1.51 (1.31)
Silent	1.73 (1.27)	0.77 (1.06)
Total recall	4.75 (1.83)	2.28 (1.89)

As expected, there was a significant main effect of encoding type, with higher recall for words read aloud (M = 2.27) than silently (M = 1.25), $F(1, 98) = 77.53$, $p < .001$, $MSE = 1.33$, $\eta^2_p = .44$, replicating the production benefit in both human (MacLeod et al., 2010) and model data. Also replicating past work, there was a significant main effect of attention (Craik et al., 1996; Naveh-Benjamin & Brubaker, 2019), with higher recall following FA (M = 4.75) than DA (M = 2.28), $F(1, 98) = 126.22$, $p < .001$, $MSE = 1.21$, $\eta^2_p = .56$. The main effect of Source was non-significant, $F(1, 98) = 0.40$, $p = .530$, $MSE = 2.27$, $\eta^2_p = .00$. There was no Source x Attention interaction, $F(1, 98) = 0.25$, $p = .618$, $MSE = 1.21$, $\eta^2_p = .00$, and no Source x Encoding type interaction, $F(1, 98) = 0.00$, $p = .965$, $MSE = 1.33$, $\eta^2_p = .00$. Surprisingly, there was a significant Attention x Encoding type interaction, $F(1, 98) = 6.21$, $p = .014$, $MSE = 1.22$, $\eta^2_p = .01$. The Source x Encoding type x Attention interaction, $F(1, 98) = 0.35$, $p = .557$, $MSE = 1.22$, $\eta^2_p = .00$ was not significant.

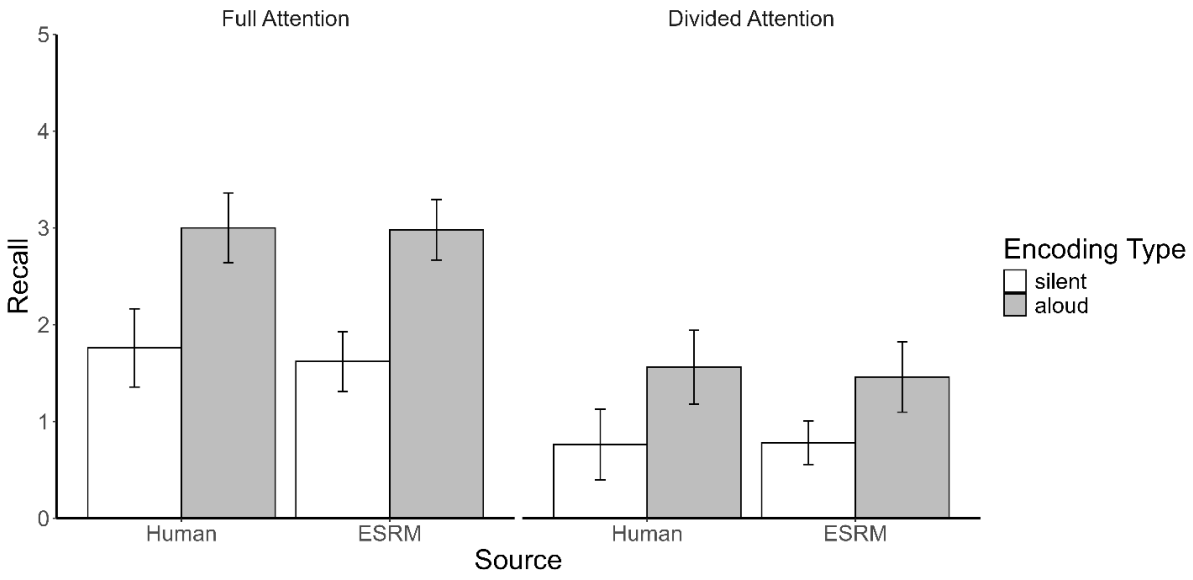
Post-hoc pair-wise analysis of the Attention x Encoding type interaction revealed that the magnitude of the production effect diminished following the DA compared to the FA condition. That is, words read aloud (M = 3.02) were better remembered than words read silently (M = 1.73) under FA, $t(98) = 7.47$, $SE = 0.173$, $p < .001$, and DA (M = 1.51; M = 0.77), $t(98) = 5.09$, $SE = 0.145$, $p < .001$, demonstrating the production effect occurred under each condition. This difference, however, was significantly smaller under DA (see Table 4).

3.6 Discussion

When comparing human and ESRM memory performance, recall was higher for words read aloud than silently, replicating the production effect (MacLeod, 2011; MacLeod et al., 2010). Critically, the production benefit was maintained even under divided attention in both sources. Both sources also replicated DA's known impairment on memory when experienced at the encoding stage (Baddeley et al., 1984; Craik et al., 1996, 2018), as shown in Figure 5.

Figure 5.

Recall performance in humans and model by encoding type under full and divided attention



Note. ESRM = Encoding-based Strength Representation in Memory. Error bars represent 95% confidence intervals.

Surprisingly, we observed an interaction between Attention and Encoding type. This is inconsistent with the results reported in Experiments 1 & 2, as well as the replications of Experiment 1 using five random samples of fifty participants. Post-hoc pairwise comparisons revealed that the production effect was larger when encoding under FA than under DA, accounting for the interaction.

The difference in the recall between produced and silently read words observed in ESRM was only slightly smaller than that observed in the human sample. One reason this might have occurred is that recall output was quite low overall following DA in the ESRM model. The smaller production effect under DA might simply be an artifact of low performance overall following the DA condition, which limited how much performance could drop in the 'Silent' compared to 'Aloud' trial types.

Chapter 4 discusses ways in which future refinements could improve the model and enhance overall output. Our findings suggest that our Nengo-based ESRM model, and spiking neural models in general, can successfully model the effectiveness of encoding techniques when implemented under FA conditions. Modifications are needed, however, before using the model to evaluate theoretical accounts of the production effect under conditions that lower overall output.

Chapter 4

General Discussion

This thesis examined the effectiveness of production as an encoding technique under divided attention conditions. By doing so, the work also examined the role of attention in the production effect. In Experiment 1, DA's known impairment on memory at encoding was replicated. Memory performance was significantly worse when encoding under DA relative to encoding under FA (Craik et al., 1996, 2000, 2018; Fernandes & Moscovitch, 2000; Guez & Naveh-Benjamin, 2006, 2013; Iidaka et al., 2000; Lozito & Mulligan, 2006; Naveh-Benjamin et al., 1998, 2005, 2007; Naveh-Benjamin & Brubaker, 2019; Sahakyan & Malmberg, 2018). The production effect was also replicated under FA; words read aloud were better remembered than words read silently (Bailey et al., 2021; Fawcett et al., 2012; Forrin & MacLeod, 2018; Lin & MacLeod, 2012; MacLeod et al., 2010; MacLeod & Bodner, 2017). Most notably, the magnitude of the production effect did not change as a function of the amount of available attention. Using a Bayesian statistical approach, we found moderate evidence in support of this null interaction. The evidence suggests that 1) production benefits memory even when encoding under divided attention, and 2) that attention plays a limited role in accounting for the production effect.

The results from Experiment 2, using an in-person sample, were consistent with those found in Experiment 1. We again replicated DA's impairment on memory (Baddeley et al., 1984; Craik et al., 2018) and found evidence for the benefit of production (Fawcett et al., 2026; MacLeod et al., 2010). Most importantly, there was no significant interaction between Encoding type and Attention once again, with converging evidence from Bayesian statistics. The results from these two experiments are theoretically important as they suggest a limited role of attention in the production

effect. Practically, these findings indicate that production as an encoding strategy continues to enhance memory performance even under conditions of constrained attentional resources.

In Chapter 3, I sought to model the production effect and the results observed in Experiment 1. I utilized Nengo to create a spiking neural network to model human performance: "read aloud" words were reinforced at encoding through representation strengthening by roughly 90%, while words "read silently" were not reinforced. To simulate DA at encoding, representations in the populations of neurons were destabilized, which reduced the signal-to-noise ratio. Recall was determined by memory neuron populations competing to gather evidence of word representations until a threshold was reached. After 50 simulations in ESRM, memory output was compared to a matched sample of human participants, who were randomly selected from Experiment 1. In both human and model data, recall was higher for words read aloud than silently, and pattern was preserved even when encoding under DA. However, in the data created using ESRM, the magnitude of the production benefit diminished. Since output was quite low overall following the DA implementation using ESRM, the smaller production effect may have arisen due to floor effects. I discuss each of these key findings in turn, below.

4.1 Attention's role in the production effect

The finding that divided attention impairs memory performance is not new; there is a plethora of evidence in support of this effect (Anderson et al., 1998; Baddeley et al., 1984; Craik et al., 1996, 2000, 2018; Fernandes & Moscovitch, 2000; Guez & Naveh-Benjamin, 2006, 2013; Iidaka et al., 2000; Lozito & Mulligan, 2006; Naveh-Benjamin et al., 1998, 2000, 2005, 2006, 2007; Sahakyan & Malmberg, 2018). What is interesting is that the impairment from divided attention cannot be circumvented using encoding techniques known to enhance memory. Within the context of Baddeley's working memory model (Baddeley, 2000), these results suggest that the 'central

executive' is overburdened by the processing demands of carrying out two concurrent tasks. It appears that any distractor task at encoding, so long as it is sufficiently demanding, will lead to an overall decrement in subsequent memory performance.

What is novel from our results is the benefit to memory observed, even under DA conditions, from reading aloud versus silently at encoding. We demonstrated that production still benefits memory relative to silently reading, in both behavioural experiments and using our computational ESRM model. Theoretically, this evidence suggests a limited role of attention in the production effect.

The leading account of the production effect is the distinctiveness-based account (MacLeod et al., 2010; MacLeod & Bodner, 2017). This suggests that the benefit of production is the result of additional processing related to motor and auditory components that occurs when one talks aloud. There is neurological evidence that further supports this account. Two fMRI studies found that words read aloud, relative to words read silently, resulted in greater activation of the primary sensorimotor cortex and the auditory cortex associated with articulation and auditory processing, respectively (Bailey et al., 2021; Nakamura et al., 2023). This evidence suggests, in part, that the production effect is also explained by greater recruitment of cortical regions during encoding. Additionally, the item-order account suggests that the cognitive processing associated with articulation and sound is thought to disrupt item order processing during encoding, leading to a cost in memory for silent items when retrieval is free recall (Forrin & MacLeod, 2016; Jonker et al., 2014). Alternatively, the strength-based account argues that the additional processing increases the overall strength of the memory representation, leading to better performance (MacLeod & Bodner, 2017). While these prior accounts are often contrasted and debated, the focus of this work was to identify the potential role of attention.

A less prominent account that some have suggested is that the amount of available attentional resources, or one's capacity to recruit attention, contributes to the production effect (Fawcett et al., 2026; Mama et al., 2018; Mama & Icht, 2019; Ozubko, Hourihan, et al., 2012). Our experiments, however, suggest that attention plays a limited role, as the benefit was maintained even when production occurred under DA. This finding contradicts the claim by Mama and colleagues (2018) that the availability of attention is an important mechanism underlying the production effect. In their study, they found that fluctuating simultaneous background noise during encoding eliminated the production effect by reducing available attention typically used to enhance the processing of words read aloud. It may be, however, that the volume of the noise in their study was too loud, as it was intentionally loud enough to mask the participant's voice, and this exceeded a participant's processing capacity, resulting in catastrophic interference. In our design, however, this is less of a concern. Participants had to process and evaluate a second stream of information heard through speakers at a lower volume that did not mask their own voice during 'read aloud' trials. Other evidence in support of attention's role in the production effect is mixed: a study showed that those with attention deficit hyperactivity disorder (ADHD) differentially benefited from production (Mama & Icht, 2019). Production's benefit was weakest for those with unmedicated ADHD, stronger for those on medication, and strongest in healthy controls. This suggests that production was less effective in those with difficulty directing attention; however, the presence of any production effect, even in those with unmedicated ADHD, suggests a limited role of attention. Consistent with our results, a small amount of attention appears sufficient to produce the benefit. Additionally, it is possible that the participants with ADHD approached the task differently than controls, perhaps being less motivated, as those with ADHD often struggle with tasks that are not engaging or that they find under-stimulating (American Psychiatric Association, 2022). However, we employed a fully within-subjects design to control for such individual differences, further eliminating the possibility of these influences.

Another possibility suggested by Fawcett and colleagues (2026) is a reorienting effect from reading words aloud. Specifically, producing words aloud during encoding may direct attention towards the target word, making it more memorable than those silently read. However, our results are at odds with this conclusion as production provided a benefit to memory even under DA. Fawcett et al. (2026) used pupillometry as a measure of arousal to serve as a proxy measure of attention while producing and silently reading words. Pupillometry is used as a measure of the phasic firing of the locus coeruleus (LC), which is used as an index of momentary changes in attention or cognitive load (Sirois & Brisson, 2014). The pupillary response to greater cognitive demands is strongly linked to the activation of the LC (Laeng et al., 2012; Samuels & Szabadi, 2008). The LC, a subcortical structure located within the brainstem, has been shown to play a pivotal role in the noradrenergic system across the brain (Aston-Jones & Cohen, 2005; Laeng et al., 2012; Sara, 2009). That is, the LC has a large influence on states of arousal, as it is involved in stress responses and the sleep-wake cycle (Swift et al., 2018; Valentino & Van Bockstaele, 2008). As such, pupillometry measures arousal, serving as a proxy measure of attention.

Fawcett and colleagues (2026) found greater pupil dilation for aloud than silent words, suggesting that an initial attention-focusing effect results from preparing to articulate on aloud trials. This evidence supports the interpretation that the benefit to produced items under DA conditions could also result from a momentary attention reorienting effect. Future studies should aim to replicate their work and examine whether this holds within a divided attention paradigm. Fawcett et al (2026) only examined encoding under full attention, and so the proposed benefit of reorienting may only be necessary to articulate, while production's benefit may still arise from other mechanisms (Fawcett et al., 2023; MacLeod et al., 2010; MacLeod & Bodner, 2017). Since pupillometry measures arousal, and the authors' evidence suggested increased arousal to produced words, other measures should also

be examined. This would help to assess a potential arousal-based account of the production effect. While this is not addressed within my thesis, Experiment 2 involved participants wearing two devices that are reliable measures of arousal: heart rate and galvanic skin response (Giannakakis et al., 2022). Future work could assess whether either measure of arousal also captures this proposed reorienting of attention for articulation, based on enhanced arousal during production trials.

To date, the literature contains mixed evidence specifying the role of attention in accounting for the production effect. Some suggest that producing allows for great attention at encoding relative to silently reading (Fawcett et al., 2026; Mama et al., 2018; Mama & Icht, 2019; Ozubko, Hourihan, et al., 2012), but these results are unclear on whether attention enhances the encoding process in the production effect, or if the act of reading newly presented words aloud forces one to read before being able to verbalize the word itself. Given the findings presented in this thesis and the mixed support for the need for attention, it is likely that attention plays only a limited role in accounting for the production effect. If only a moment is required to encode an unknown, unpredictable word that will be presented, then a minuscule amount of attention needed to articulate the word is likely not driving the production benefit.

A limitation of Experiment 1 is potential motor confounds. While participants were audio recorded and a compliance check for adherence to task instructions was conducted, it can not be conclusively ruled out that participants were possibly mouthing the words on silent trials. While mouthing still benefits memory on recognition tests, albeit less effectively (Forrin et al., 2012), there is no existing evidence suggesting this affects recall. Furthermore, if some participants mouthed silently read words during encoding, it likely had a limited effect on memory performance, as a production effect was still observed in Experiment 1. In Experiment 2, I was physically present during the study to ensure participants adhered to task instructions, therefore the possibility of not

following instructions was minimized. Another limitation is that memory performance was low in both experiments. Notably, however, the means reported here are not the lowest in the literature on the production effect (Jones & Pyc, 2014; Jonker et al., 2014). Mean total recall was 5.21 words in Experiment 1 and 5.77 words in Experiment 2, while past published work has reported mean total recall as low as 4.52 words (Jonker et al., 2014) and 5.1 words (Jones & Pyc, 2014). Thus, the means reported here are not outside the range reported in past work. Given this, I would expect that the results reported here would replicate if longer word lists were used to elevate overall memory performance.

4.2 The importance of multi-modal representations

The leading mechanism explaining the production effect is distinctiveness, whereby articulating information aloud relative to silently reading is thought to generate additional cognitive processing and recruitment of motor and auditory components within the brain (Bailey et al., 2021; MacLeod et al., 2010; MacLeod & Bodner, 2017; Nakamura et al., 2023). We found that the production effect was resilient under divided attention. This evidence suggests that these additional components operate without the need for dedicated attentional resources. These results are aligned with predictions from a multimodal account of encoding (Engelkamp & Zimmer, 1989; Fawcett et al., 2012; Kinjo & Snodgrass, 2000; Wammes et al., 2019; Zormpa et al., 2019), whereby engaging in multiple sensory modalities or cognitive processes creates additional representations that enhance later memory. Production has been shown to elicit greater activation of the primary sensorimotor and auditory cortex associated with articulation and auditory processing, respectively, compared to silently reading items (Bailey et al., 2021; Nakamura et al., 2023). The additional neural processing generated by producing items could aid encoding by facilitating diverse representations, preserving

retention. The results presented here align with this theory and with existing evidence that multi-modal encoding enhances memory (Wammes et al., 2019).

It is important to note that the current findings represent a null interaction in both experiments. However, given our large sample size in Experiment 1, within-subjects manipulation, and a priori power calculations, it is safe to say we had sufficient power to detect a significant interaction should one exist. We replicated this finding in Experiment 2, and Bayesian analyses provided moderate evidence in favour of no interaction in both experiments. The consistent lack of such interaction suggests that attention plays a limited role in the production effect: otherwise, memory for read-aloud and read-silently items under DA would have differed if attention were driving this effect. Production's consistent benefit to memory under DA conditions demonstrates the usefulness of recruiting different cortical regions to facilitate the encoding process, especially when memory deficits are to be expected.

4.3 Encoding-based strength representation in memory

The goal of ESRM was to create a more biologically plausible model of the production effect and compare its data to that of humans under full and divided attention. By using Nengo (Eliasmith, 2015; Eliasmith & Anderson, 2003), we implemented the first iteration of a model of the production effect derived from generating multiple representations in memory that strengthen the trace, increasing the likelihood of recall. The results revealed that ESRM simulated human data of the production effect quite well under full attention. Consistent with predictions of multimodal encoding (Wammes et al., 2019), generating more representations of information during encoding benefited memory. ESRM strengthened the representations of stimuli, improving memory for "produced" words relative to "silently read" words. To our surprise, using ESRM, the magnitude of the production effect was significantly smaller when encoding under divided attention relative to full

attention. Currently, in ESRM, the parameter we set for attention is 0.60, out of a possible 1.0. This parameter is a weight set on the target's representation between population ensembles during the encoding process, inducing a loss of the representation. One way to optimize the attention parameter would be to run 50 trials of ESRM for each parameter weight ranging from 0.61 to 0.70. We could then systematically test which parameter most closely matches the human data. Further optimization of other parameters, such as the reinforcement factor and decay rate, could be conducted to determine which implementation best simulates human data. This would involve many iterations of ESRM, where only one parameter is altered in small increments, at each level of the other parameters, until the model is optimized.

While ESRM was used to simulate the production effect, it is not inherently specific to it. ESRM and the strengthening manipulation can be applied to other encoding strategies, such as enactment (Engelkamp & Zimmer, 1989) and drawing (Wammes et al., 2016). Future iterations of ESRM should enhance its biological plausibility.. Specifically, adding components associated with auditory and motoric processing would broaden the model's capacity to represent different cortical regions in the brain, yielding a more neurologically accurate simulation of production, or other encoding techniques during encoding (Bailey et al., 2021; Nakamura et al., 2023).

A limitation of ESRM is that the implementation of DA was simplistic. We achieved this by destabilizing the neuron representation during encoding. However, ESRM could be improved by making the simulation of DA more faithful to that of humans. Components related to a secondary task during encoding could better simulate the real-life experience of interference due to having to simultaneously complete another task with the target one. Additionally, the implementation of retrieval in ESRM resulted in lower overall output. Retrieval is currently based on a threshold of activation determined by the memory representation's similarity to the dictionary representation, and

silent items may have experienced more "drift" in high-dimensional vector space caused by random noise (Delamare et al., 2024), as their representations have weaker magnitudes. This also may have reduced overall recall under DA. Further work refining the model's threshold for recall would be needed. Furthermore, a direct comparison to other models such as MINERVA 2 (Jamieson et al., 2016) or the Revised Feature Model (Saint-Aubain et al, 2021) would help assess ESRM's effectiveness. Based on the results reported here, I would expect similar findings across models, such that read-aloud words would be better remembered than words read silently.

Our findings suggest that our Nengo-based ESRM model, and spiking neural networks more broadly, can successfully model the effectiveness of encoding techniques under full attention. Furthermore, ESRM can be iterated upon for different encoding strategies in the future, making it a versatile option for memory researchers interested in computational neuroscience approaches. This work highlights the importance of applying computational modelling within a neuroscience perspective, as it can drive a deeper understanding of how cognitive theories apply in the brain, and bridges cognitive-behavioural and neuroscience approaches, generating greater insight into the processes underlying encoding.

4.4 Conclusion

The resilience of the benefit from production under divided attention suggests that attention plays a limited role in accounting for the production effect. While attention may play a limited role, production cannot overcome the global deficit caused by encoding under divided attention. When faced with this deficit, encoding techniques that generate greater recruitment of cortical areas, such as production, appear to still provide a benefit to memory. A spiking neural network model of the production effect was also created, *Encoding-based Strength Representation in Memory (ESRM)*. The model's simulated human data under full attention quite well. However, the implementation of

divided attention in the model altered the magnitude of the benefit. Future work should expand the model in two key directions: improving the simulation of the encoding process of production and enhancing overall biological plausibility. *ESRM* demonstrated the effectiveness of creating multiple representations during encoding to strengthen memory, providing further support for production as a multimodal encoding technique. Adopting a computational approach can provide a unique opportunity to deconstruct and test the assumptions underlying encoding techniques, yielding a deeper knowledge of their mechanisms and revealing new avenues for future research. The findings presented in my Master's thesis highlight the importance of creating diverse representations during encoding, even when encoding under divided attention, to ultimately improve memory performance. Moreover, this thesis suggests that attention serves a limited role in the production effect, as manipulations of attention had a limited influence on its benefit.

References

American Psychiatric Association. (2022). Neurodevelopmental Disorders. In *Diagnostic and Statistical Manual of Mental Disorders* (Fifth Edition, Text Revision (DSM-5-TR)). American Psychiatric Association Publishing. https://doi.org/10.1176/appi.books.9780890425787.x01_Neurodevelopmental_Disorders

Anderson, N. D., Craik, F. I. M., & Naveh-Benjamin, M. (1998). The attentional demands of encoding and retrieval in hunger and older adults: 1. Evidence from divided attention costs. *Psychology and Aging*, *13*(3), 405–423. https://doi.org/10.1037/0882-7974.13.3.405

Anderson, N. D., Iidaka, T., Cabeza, R., Kapur, S., McIntosh, A. R., & Craik, F. I. M. (2000). The effects of divided attention on encoding- and retrieval-related brain activity: A PET study of younger and older adults. *Journal of Cognitive Neuroscience*, *12*(5), 775–792. https://doi.org/10.1162/089892900562598

Aston-Jones, G., & Cohen, J. D. (2005). An integrative theory of locus coeruleus -norepinephrine function: Adaptive gain and optimal performance. *Annual Review of Neuroscience*, *28*(1), 403–450. https://doi.org/10.1146/annurev.neuro.28.061604.135709

Baddeley, A. (2000). The episodic buffer: A new component of working memory? *Trends in Cognitive Sciences*, *4*(11), 417–423. https://doi.org/10.1016/S1364-6613(00)01538-2

Baddeley, A., Lewis, V., Eldridge, M., & Thomson, N. (1984). Attention and retrieval from long-term memory. *Journal of Experimental Psychology. General*, *113 (4)*, 518–540. https://doi.org/10.1037/0096-3445.113.4.518

Bailey, L. M., Bodner, G. E., Matheson, H. E., Stewart, B. M., Roddick, K., O'Neil, K., Simmons, M., Lambert, A. M., Krigolson, O. E., Newman, A. J., & Fawcett, J. M. (2021). Neural

correlates of the production effect: An fMRI study. *Brain and Cognition*, *152*, 105757. https://doi.org/10.1016/j.bandc.2021.105757

Balota, D. A., Yap, M. J., Hutchison, K. A., Cortese, M. J., Kessler, B., Loftis, B., Neely, J. H., Nelson, D. L., Simpson, G. B., & Treiman, R. (2007). The English Lexicon Project. *Behavior Research Methods*, *39*(3), 445–459. https://doi.org/10.3758/BF03193014

Bekolay, T., Bergstra, J., Hunsberger, E., DeWolf, T., Stewart, T. C., Rasmussen, D., Choo, X., Voelker, A. R., & Eliasmith, C. (2014). Nengo: A Python tool for building large-scale functional brain models. *Frontiers in Neuroinformatics*, *7*. https://doi.org/10.3389/fninf.2013.00048

Brooks, D. N., & Baddeley, A. D. (1976). What can amnesic patients learn? *Neuropsychologia*, *14*, 111–122.

Buchsbaum, B. R., Moscovitch, M., Tang, K., Ziegler, M., & Craik, F. I. M. (2024). The interactive effects of divided attention and semantic elaboration on associative recognition memory: An fMRI study. *Cerebral Cortex*, *34*(12), bhae464. https://doi.org/10.1093/cercor/bhae464

Cabeza, R., & Moscovitch, M. (2013). Memory systems, processing modes, and components: Functional neuroimaging evidence. *Perspectives on Psychological Science*, *8*(1), 49–55. https://doi.org/10.1177/1745691612469033

Caplan, J. B., & Guitard, D. (2024). A Feature-Space Theory of the Production Effect in Recognition. *Experimental Psychology*, *71*(1), 64–82. https://doi.org/10.1027/1618-3169/a000611

Castel, A. D., & Craik, F. I. M. (2003). The effects of aging and divided attention on memory for item and associative information. *Psychology and Aging*, *18*(4), 873–885. https://doi.org/10.1037/0882-7974.18.4.873

Choo, F.-X., & Eliasmith, C. (2010). *A Spiking Neuron Model of Serial-Order Recall*.

Craik, F. I. M., & Byrd, M. (1982). Aging and cognitive deficits: The role of attentional resources. In *Aging and Cognitive Processes* (pp. 191–211).

Craik, F. I. M., Eftekhari, E., & Binns, M. A. (2018). Effects of divided attention at encoding and retrieval: Further data. *Memory & Cognition*, *46*(8), 1263–1277. https://doi.org/10.3758/s13421-018-0835-3

Craik, F. I. M., Govoni, R., & Naveh-Benjamin, M. (1996). The effects of divided attention on encoding and retrieval processes in human memory. *Journal of Experimental Psychology. General*, *125*(2), 159–180.

Craik, F. I. M., & Lockhart, R. S. (1972). Levels of processing: A framework for memory research. *Journal of Verbal Learning and Verbal Behavior*, *11*(6), 671–684. https://doi.org/10.1016/S0022-5371(72)80001-X

Craik, F. I. M., Luo, L., & Sakuta, Y. (2010). Effects of aging and divided attention on memory for items and their contexts. *Psychology and Aging*, *25*(4), 968–979. https://doi.org/10.1037/a0020276

Craik, F. I. M., Naveh-Benjamin, M., Ishaik, G., & Anderson, N. D. (2000). Divided attention during encoding and retrieval: Differential control effects? *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *26*(6), 1744–1749. https://doi.org/10.1037/0278-7393.26.6.1744

Cyr, V., Poirier, M., Yearsley, J. M., Guitard, D., Harrigan, I., & Saint-Aubin, J. (2022). The production effect over the long term: Modeling distinctiveness using serial positions. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *48*(12), 1797–1820. https://doi.org/10.1037/xlm0001093

Delamare, G., Zaki, Y., Cai, D. J., & Clopath, C. (2024). Drift of neural ensembles driven by slow fluctuations of intrinsic excitability. *eLife*, *12*, RP88053. https://doi.org/10.7554/eLife.88053

Ebbinghaus, H. (1885). *Über das Gedächtnis*.

Eliasmith, C. (2015). *How to build a brain: A neural architecture for biological cognition*. Oxford University Press.

Eliasmith, C., & Anderson, C. H. (2003). *Neural engineering: Computation, representation, and dynamics in neurobiological systems*. MIT Press.

Eliasmith, C., Stewart, T. C., Choo, X., Bekolay, T., DeWolf, T., Tang, Y., & Rasmussen, D. (2012). A Large-Scale Model of the Functioning Brain. *Science*, *338*(6111), 1202–1205. https://doi.org/10.1126/science.1225266

Engelkamp, J., & Zimmer, H. D. (1989). Memory for action events: A new field of research. *Psychological Research*, *51*(4), 153–157. https://doi.org/10.1007/BF00309142

Faul, F., Erdfelder, E., Lang, A.-G., & Buchner, A. (2007). G*Power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behavior Research Methods*, *39*(2), 175–191. https://doi.org/10.3758/BF03193146

Fawcett, J. M. (2013). The production effect benefits performance in between-subject designs: A meta-analysis. *Acta Psychologica*, *142*(1), 1–5. https://doi.org/10.1016/j.actpsy.2012.10.001

Fawcett, J. M., Baldwin, M. M., Whitridge, J. W., Swab, M., Malayang, K., Hiscock, B., Drakes, D. H., & Willoughby, H. V. (2023). Production improves recognition and reduces intrusions in between-subject designs: An updated meta-analysis. *Canadian Journal of Experimental Psychology / Revue Canadienne de Psychologie Expérimentale*, *77*(1), 35–44. https://doi.org/10.1037/cep0000302

Fawcett, J. M., Quinlan, C. K., & Taylor, T. L. (2012). Interplay of the production and picture superiority effects: A signal detection analysis. *Memory*, *20*(7), 655–666. https://doi.org/10.1080/09658211.2012.693510

Fawcett, J. M., Roberts, B. R. T., Willoughby, H. V., Tiller, J. C., Hourihan, K. L., & MacLeod, C. M. (2026). The pupillometric production effect: Evidence for enhanced processing preceding, during, and following production. *Cognition*, *266*, 106326. https://doi.org/10.1016/j.cognition.2025.106326

Fernandes, M. A., & Moscovitch, M. (2000). Divided attention and memory: Evidence of substantial interference effects at retrieval and encoding. *Journal of Experimental Psychology: General*, *129*(2), 155–176. https://doi.org/10.1037/0096-3445.129.2.155

Finkenauer, C., Luminet, O., Gisle, L., El-Ahmadi, A., Van Der Linden, M., & Philippot, P. (1998). Flashbulb memories and the underlying mechanisms of their formation: Toward an emotional-integrative model. *Memory & Cognition*, *26*(3), 516–531. https://doi.org/10.3758/BF03201160

Forrin, N. D., & MacLeod, C. M. (2016). Order information is used to guide recall of long lists: Further evidence for the item-order account. *Canadian Journal of Experimental Psychology / Revue Canadienne de Psychologie Expérimentale*, *70*(2), 125–138. https://doi.org/10.1037/cep0000088

Forrin, N. D., & MacLeod, C. M. (2018). This time it's personal: The memory benefit of hearing oneself. *Memory*, *26*(4), 574–579. https://doi.org/10.1080/09658211.2017.1383434

Forrin, N. D., MacLeod, C. M., & Ozubko, J. D. (2012). Widening the boundaries of the production effect. *Memory & Cognition*, *40*(7), 1046–1055. https://doi.org/10.3758/s13421-012-0210-8

Giannakakis, G., Grigoriadis, D., Giannakaki, K., Simantiraki, O., Roniotis, A., & Tsiknakis, M. (2022). Review on Psychological Stress Detection Using Biosignals. *IEEE Transactions on Affective Computing*, *13*(1), 440–460. https://doi.org/10.1109/TAFFC.2019.2927337

Gosmann, J., Voelker, A. R., & Eliasmith, C. (2017). *A spiking independent accumulator model for winner-take-all computation*. Cognitive Science Society, London.

Greene, N. R., Martin, B. A., & Naveh-Benjamin, M. (2021). The effects of divided attention at encoding and at retrieval on multidimensional source memory. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *47*(11), 1870–1887. https://doi.org/10.1037/xlm0001051

Greene, N. R., & Naveh-Benjamin, M. (2022a). Effects of divided attention at encoding on specific and gist representations in working and long-term memory. *Journal of Memory and Language*, *126*, 104340. https://doi.org/10.1016/j.jml.2022.104340

Greene, N. R., & Naveh-Benjamin, M. (2022b). The effects of divided attention at encoding on specific and gist-based associative episodic memory. *Memory & Cognition*, *50*(1), 59–76. https://doi.org/10.3758/s13421-021-01196-9

Guez, J., & Naveh-Benjamin, M. (2006). Divided attention at encoding and retrieval for once- and thrice-presented items: A micro-level analysis of attentional costs. *European Journal of Cognitive Psychology*, *18*(6), 874–898. https://doi.org/10.1080/09541440500485854

Guez, J., & Naveh-Benjamin, M. (2013). The asymmetrical effects of divided attention on encoding and retrieval processes: A different view based on an interference with the episodic register. *PLoS ONE*, *8*(9), e74447. https://doi.org/10.1371/journal.pone.0074447

Hamann, S. (2001). Cognitive and neural mechanisms of emotional memory. *Trends in Cognitive Sciences*, *5*(9), 394–400. https://doi.org/10.1016/S1364-6613(00)01707-1

Hintzman, D. L. (1984). MINERVA 2: A simulation model of human memory. *Behavior Research Methods, Instruments, &amp Computers*, *16*(2), 96–101. https://doi.org/10.3758/BF03202365

Iidaka, T., Anderson, N. D., Kapur, S., Cabez, R., & Craik, F. I. M. (2000). The effect of divided attention on encoding and retrieval in episodic memory revealed by positron emission

tomography. *Journal of Cognitive Neuroscience*, *12*(2), 267–280. https://doi.org/10.1162/089892900562093

Jamieson, R. K., Mewhort, D. J. K., & Hockley, W. E. (2016). A computational account of the production effect: Still playing twenty questions with nature. *Canadian Journal of Experimental Psychology / Revue Canadienne de Psychologie Expérimentale*, *70*(2), 154–164. https://doi.org/10.1037/cep0000081

Jones, A. C., & Pyc, M. A. (2014). The production effect: Costs and benefits in free recall. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *40*(1), 300–305. https://doi.org/10.1037/a0033337

Jonker, T. R., Levene, M., & MacLeod, C. M. (2014). Testing the item-order account of design effects using the production effect. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *40*(2), 441–448. https://doi.org/10.1037/a0034977

Joshi, S. C., Woodward, J., & Woltering, S. (2023). Cell phone use distracts young adults from academic work with limited benefit to self-regulatory behavior. *Current Psychology*, *42*(31), 27071–27087. https://doi.org/10.1007/s12144-022-03830-4

Kahana, M. J. (2020). Computational models of memory search. *Annual Review of Psychology*, *71*(1), 107–138. https://doi.org/10.1146/annurev-psych-010418-103358

Kahneman, D. (1973). Attention and effort. *Prentice-Hall*.

Kelly, M. O., Ensor, T. M., Lu, X., MacLeod, C. M., & Risko, E. F. (2022). Reducing retrieval time modulates the production effect: Empirical evidence and computational accounts. *Journal of Memory and Language*, *123*, 104299. https://doi.org/10.1016/j.jml.2021.104299

Kelly, M. O., Ensor, T. M., MacLeod, C. M., & Risko, E. F. (2024). The prod eff: Partially producing items moderates the production effect. *Psychonomic Bulletin & Review*, *31*(1), 373–379. https://doi.org/10.3758/s13423-023-02360-9

Kinjo, H., & Snodgrass, J. G. (2000). Does the generation effect occur for pictures? *The American Journal of Psychology*, *113*(1), 95. https://doi.org/10.2307/1423462

Laeng, B., Sirois, S., & Gredebäck, G. (2012). Pupillometry: A Window to the Preconscious? *Perspectives on Psychological Science*, *7*(1), 18–27. https://doi.org/10.1177/1745691611427305

Lin, O. Y. H., & MacLeod, C. M. (2012). Aging and the production effect: A test of the distinctiveness account. *Canadian Journal of Experimental Psychology / Revue Canadienne de Psychologie Expérimentale*, *66*(3), 212–216. https://doi.org/10.1037/a0028309

Lozito, J. P., & Mulligan, N. W. (2006). Exploring the role of attention during memory retrieval: Effects of semantic encoding and divided attention. *Memory & Cognition*, *34*(5), 986–998. https://doi.org/10.3758/BF03193246

Maass, W. (1997). Networks of spiking neurons: The third generation of neural network models. *Neural Networks*, *10*(9), 1659–1671. https://doi.org/10.1016/S0893-6080(97)00011-7

MacLeod, C. M. (2011). I said, you said: The production effect gets personal. *Psychonomic Bulletin & Review*, *18*(6), 1197–1202. https://doi.org/10.3758/s13423-011-0168-8

MacLeod, C. M., & Bodner, G. E. (2017). The production effect in memory. *Current Directions in Psychological Science*, *26*(4), 390–395. https://doi.org/10.1177/0963721417691356

MacLeod, C. M., Gopie, N., Hourihan, K. L., Neary, K. R., & Ozubko, J. D. (2010). The production effect: Delineation of a phenomenon. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *36*(3), 671–685. https://doi.org/10.1037/a0018785

Mama, Y., Fostick, L., & Icht, M. (2018). The impact of different background noises on the Production Effect. *Acta Psychologica*, *185*, 235–242. https://doi.org/10.1016/j.actpsy.2018.03.002

Mama, Y., & Icht, M. (2019). Production effect in adults with ADHD with and without methylphenidate (MPH): Vocalization improves verbal learning. *Journal of the International Neuropsychological Society*, *25*(2), 230–235. https://doi.org/10.1017/S1355617718001017

Marrero, D., Kern, J., & Urrea, C. (2024). A novel robotic controller using neural engineering framework-based spiking neural networks. *Sensors*, *24*(2), 491. https://doi.org/10.3390/s24020491

Melton, A. W. (1970). The situation with respect to the spacing of repetitions and memory. *Journal of Verbal Learning and Verbal Behavior*, *9*(5), 596–606. https://doi.org/10.1016/S0022-5371(70)80107-4

Murdock, B. B. (1965). Effects of a subsidiary task on short-term memory. *British Journal of Psychology*, *56*(4), 413–419. https://doi.org/10.1111/j.2044-8295.1965.tb00983.x

Nakamura, R., Nouchi, R., Yagi, A., Yamaya, N., Ota, M., Ishigooka, M., & Kawashima, R. (2023). Neural representation of a one-week delay in remembering information after production and self-generated elaboration encoding strategy. *Acta Psychologica*, *240*, 104051. https://doi.org/10.1016/j.actpsy.2023.104051

Naveh-Benjamin, M., & Brubaker, M. S. (2019). Are the effects of divided attention on memory encoding processes due to the disruption of deep-level elaborative processes? Evidence from cued- and free-recall tasks. *Journal of Memory and Language*, *106*, 108–117. https://doi.org/10.1016/j.jml.2019.02.007

Naveh-Benjamin, M., Craik, F. I. M., Guez, J., & Kreuger, S. (2005). Divided attention in younger and older adults: Effects of strategy and relatedness on memory performance and secondary task costs. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *31*(3), 520–537. https://doi.org/10.1037/0278-7393.31.3.520

Naveh-Benjamin, M., Craik, F. I. M., Perretta, J. G., & Tonev, S. T. (2000). The effects of divided attention on encoding and retrieval processes: The resiliency of retrieval processes. *The Quartly Journal of Experimental Psychology*, *53A*(3), 609–625.

Naveh-Benjamin, M., Guez, J., & Dori, H. (1998). *Effects of divided attention on encoding and retrieval processes in human memory: Further support for an asymmetry*.

Naveh-Benjamin, M., Guez, J., Hara, Y., Brubaker, M. S., & Lowenschuss-Erlich, I. (2014). The effects of divided attention on encoding processes under incidental and intentional learning instructions: Underlying mechanisms? *Quarterly Journal of Experimental Psychology*, *67*(9), 1682–1696. https://doi.org/10.1080/17470218.2013.867517

Naveh-Benjamin, M., Guez, J., & Sorek, S. (2007). The effects of divided attention on encoding processes in memory: Mapping the locus of interference. *Canadian Journal of Experimental Psychology / Revue Canadienne de Psychologie Expérimentale*, *61*(1), 1–12. https://doi.org/10.1037/cjep2007001

Naveh-Benjamin, M., Kilb, A., & Fisher, T. (2006). Concurrent task effects on memory encoding and retrieval: Further support for an asymmetry. *Memory & Cognition*, *34*(1), 90–101. https://doi.org/10.3758/BF03193389

Ozubko, J. D., Gopie, N., & MacLeod, C. M. (2012). Production benefits both recollection and familiarity. *Memory & Cognition*, *40*(3), 326–338. https://doi.org/10.3758/s13421-011-0165-1

Ozubko, J. D., Hourihan, K. L., & MacLeod, C. M. (2012). Production benefits learning: The production effect endures and improves memory for text. *Memory*, *20*(7), 717–727. https://doi.org/10.1080/09658211.2012.699070

Penzkofer, A., Furlong, P. M., Eliasmith, C., & Bulling, A. (2025). *A Cognitively Plausible Model of Visual Working Memory*.

Prolific. (2026). [Online participant recruitment platform]. https://www.prolific.com

Quintana, D. S. (2017). Statistical considerations for reporting and planning heart rate variability case-control studies. *Psychophysiology*, *54*(3), 344–349. https://doi.org/10.1111/psyp.12798

Rasmussen, D., & Eliasmith, C. (2014). A spiking neural model applied to the study of human performance and cognitive decline on Raven's Advanced Progressive Matrices. *Intelligence*, *42*, 53–82. https://doi.org/10.1016/j.intell.2013.10.003

Richardson-Klavehn, A., & Bjork, R. A. (1988). *Measures of memory*. *39*, 475–543.

Rosenbaum, R. S., Gilboa, A., & Moscovitch, M. (2014). Case studies continue to illuminate the cognitive neuroscience of memory. *Annals of the New York Academy of Sciences*, *1316*(1), 105–133. https://doi.org/10.1111/nyas.12467

Sahakyan, L., & Malmberg, K. J. (2018). Divided attention during encoding causes separate memory traces to be encoded for repeated events. *Journal of Memory and Language*, *101*, 153–161. https://doi.org/10.1016/j.jml.2018.04.004

Saint-Aubin, J., Yearsley, J. M., Poirier, M., Cyr, V., & Guitard, D. (2021). A model of the production effect over the short-term: The cost of relative distinctiveness. *Journal of Memory and Language*, *118*, 104219. https://doi.org/10.1016/j.jml.2021.104219

Samuels, E., & Szabadi, E. (2008). Functional Neuroanatomy of the Noradrenergic Locus Coeruleus: Its Roles in the Regulation of Arousal and Autonomic Function Part I: Principles of Functional Organisation. *Current Neuropharmacology*, *6*(3), 235–253. https://doi.org/10.2174/157015908785777229

Sara, S. J. (2009). The locus coeruleus and noradrenergic modulation of cognition. *Nature Reviews Neuroscience*, *10*(3), 211–223. https://doi.org/10.1038/nrn2573

Sirois, S., & Brisson, J. (2014). Pupillometry. *WIREs Cognitive Science*, *5*(6), 679–692. https://doi.org/10.1002/wcs.1323

Slamecka, N. J., & Graf, P. (1978). The generation effect: Delineation of a phenomenon. *Journal of Experimental Psychology : Human Learning and Memory*, *4*(6), 592–604. https://doi.org/https://doi.org/10.1037/0278-7393.4.6.592

Swift, K. M., Gross, B. A., Frazer, M. A., Bauer, D. S., Clark, K. J. D., Vazey, E. M., Aston-Jones, G., Li, Y., Pickering, A. E., Sara, S. J., & Poe, G. R. (2018). Abnormal Locus Coeruleus Sleep Activity Alters Sleep Signatures of Memory Consolidation and Impairs Place Cell Stability and Spatial Memory. *Current Biology*, *28*(22), 3599-3609.e4. https://doi.org/10.1016/j.cub.2018.09.054

Tsapoitis, P., Chouinard, J., Eliasmith, C., & Fernandas, M. A. (2026a). *Modelling Strength-Based Representations in Memory Using Spiking Neural Networks [conference presentation abstract]*. Cognitive Neuroscience Society, Toronto, ON, Canada.

Tsapoitis, P., Chouinard, J., Eliasmith, C., & Fernandas, M. A. (2026b). *Resilience of the production effect under divided attention: Converging evidence from a spiking neural network [conference presentation abstract]*. The Canadian Society for Brain, Behaviour and Cognitive Science, Toronto, ON, Canada.

Tsapoitis, P., & Fernandes, M. (2026). The limited role of attention on the production effect in memory [Manuscript submitted for publication]. Department of Psychology, University of Waterloo.

Tulving, E. (1972). Episodic and semantic memory. In *Organization of memory* (pp. 381–403). New York: Academic Press.

Valentino, R. J., & Van Bockstaele, E. (2008). Convergent regulation of locus coeruleus activity as an adaptive response to stress. *European Journal of Pharmacology*, *583*(2–3), 194–203. https://doi.org/10.1016/j.ejphar.2007.11.062

Wammes, J. D., & Fernandes, M. A. (2017). The residual protective effects of enactment. *Cognition*, *164*, 87–101. https://doi.org/10.1016/j.cognition.2017.03.015

Wammes, J. D., Jonker, T. R., & Fernandes, M. A. (2019). Drawing improves memory: The importance of multimodal encoding context. *Cognition*, *191*, 103955. https://doi.org/10.1016/j.cognition.2019.04.024

Wammes, J. D., Meade, M. E., & Fernandes, M. A. (2016). The drawing effect: Evidence for reliable and robust memory benefits in free recall. *Quarterly Journal of Experimental Psychology*, *69*(9), 1752–1776. https://doi.org/10.1080/17470218.2015.1094494

Weiskrantz, L., & Warrington, E. K. (1979). Conditioning in amnesic patients. *Neuropsychologia*, *17*(2), 187–194. https://doi.org/10.1016/0028-3932(79)90009-5

Wickens, C. (1980). The structure of attentional resources. In R. Nickerson, *Attention and performance VIII* (1st ed., pp. 239–257). Psychology Press.

Wickens, C. (1984). Processing resources in attention. In R. Parasuraman & R. Davies, *Varieties of attention* (1st ed., pp. 63–101). Academic Press.

Wickens, C. (2021). Attention: Theory, principles, models and applications. *International Journal of Human–Computer Interaction*, *37*(5), 403–417. https://doi.org/10.1080/10447318.2021.1874741

Yamazaki, K., Vo-Ho, V.-K., Bulsara, D., & Le, N. (2022). Spiking Neural Networks and Their Applications: A Review. *Brain Sciences*, *12*(7), 863. https://doi.org/10.3390/brainsci12070863

Zormpa, E., Brehm, L. E., Hoedemaker, R. S., & Meyer, A. S. (2019). The production effect and the generation effect improve memory in picture naming. *Memory*, *27*(3), 340–352. https://doi.org/10.1080/09658211.2018.1510966

Appendix A

Word List Characteristics

Table 5.

Characteristics of Word Stimuli Used in Experiments 1 and 2, from the English Lexicon Project (Balota et al., 2007)

Word	Concreteness	Arousal	Valence
user	3.16	3.21	3.67
heavy	3.37	3.65	4.78
metal	4.87	3.48	5.05
gopher	4.67	3.58	5.37
header	3.93	3.33	5.33
resume	4.00	3.67	4.89
letter	4.70	3.19	5.68
device	3.97	3.42	5.79
expand	3.36	3.30	5.35
carry	4.04	3.47	5.67
weekly	3.28	2.86	5.43
turkey	4.89	3.45	5.90
area	3.72	2.19	5.56
item	4.41	2.90	5.29

lawyer	4.70	3.95	3.94
reset	3.00	3.17	4.65
image	3.85	3.48	5.58
novel	4.21	3.41	5.74
county	4.04	3.40	5.18
double	3.37	3.38	5.78
dozen	4.66	2.95	5.78
copy	3.90	3.15	5.22
second	3.30	3.48	5.23
column	4.48	3.11	5.00
supply	3.43	3.28	5.11
jacket	4.86	3.35	5.86
manual	4.45	3.17	4.95
shadow	4.54	3.10	5.07
static	3.32	3.33	4.41
survey	4.08	3.68	5.55
remote	3.44	3.50	5.42
cable	4.74	3.52	5.90
backup	3.20	3.45	5.85

budget	3.14	3.33	4.56
native	3.03	3.05	5.85
single	3.27	3.85	5.39
liver	4.68	3.27	4.19
senate	3.81	3.63	3.38
domain	3.40	3.36	5.05
handle	4.57	3.48	5.73
people	4.82	3.77	5.70
minute	3.04	3.76	5.50
demo	3.66	3.91	5.65
solid	4.42	2.36	5.65
attend	3.17	3.50	5.40
member	3.07	3.47	5.95
follow	3.26	3.76	4.82
center	3.85	2.62	5.56

Appendix B: Supplementary Material

Experiment 1b

Methods

Participants.

Twenty participants were recruited from the online recruitment platform Prolific (https://www.prolific.com), who completed the study in return for £4.00. Those with recall outputs of zero on the memory or secondary task under FA were excluded from the analysis, resulting in the removal of 3 participants, who received a score of 0 on the secondary task at baseline. The remaining sample of 17 participants is comprised of 52.94% men and 47.06% women, with a mean age of 38.29 years (*SD* = 10.91, range = 22-56), and a mean year of education of 17.12 (*SD* = 3.97, range = 12-25). Participants also indicated proficiency in reading and speaking English. 94.12 % indicated they have high proficiency in reading English, and 5.88% indicated moderate proficiency. Similarly, 88.24% indicated high proficiency in speaking English, with only 11.76% indicating moderate proficiency. Data was collected from October to November 2025.

To ensure the validity of the results from Experiment 1, the target sample size was 20.

Materials.

All materials were the same as in Experiment 1.

Procedure.

The procedure used in Experiment 1b followed the same design as Experiment 1, but the timings of 1b were adjusted to ensure encoding conditions were as similar as possible. Stimuli were set to be presented for 3 seconds with a 0.5-second fixation point under DA, instead of the 3.5-second presentation seen in FA. This adjustment best offset the accruing lag and ensured encoding condition

lengths were within seconds of one another. Due to the nature of the Qualtrics platform, random lag from the server cannot be controlled for.

All procedures were approved by the University of Waterloo's Office of Research Ethics (Protocol #46917).

Results

Memory Performance.

Recall was verified for accuracy and tabulated separately for words read aloud versus silently at encoding. To confirm that the pattern of results observed in Experiment 1 is not a result of timing issues caused by Qualtrics, a 2 (Attention: FA vs. DA) x 2 (Encoding type: silent vs. aloud) repeated measures ANOVA was conducted on the number of correctly recalled words. We replicated our results from Experiment 1, as there was a main effect of Attention such that recall following FA (M = 5.06) was better than following the DA condition at encoding (M =2.18), $F(1, 16) = 69.94$, $p = .011$, $\eta^2_p = .34$[4]. There was also a main effect of Encoding type, such that words read aloud ($M = 2.41$) were better remembered than words read silently ($M = 1.21$), $F(1,16) = 8.32$, $p = .011$, $\eta^2_p = .34$. Critically, there was no significant Attention x Encoding type interaction, $F(1,16) = 0.97$, $p = .340$.

[4] The Shapiro-Wilk test showed a significant departure from normality across conditions ($ps < .001$)

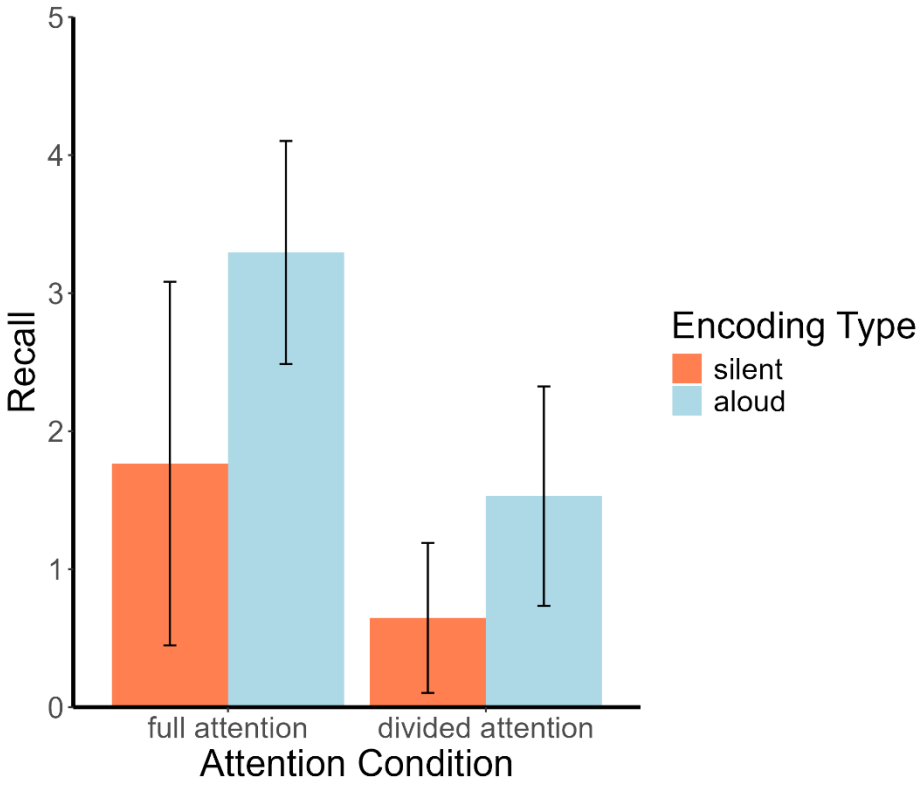
Table 6.

Mean Number (and standard deviation in parentheses) of Words Recalled in each Condition following each Encoding Type in Experiment 1b

	Condition	
	Full	Divided
Encoding type		
Aloud	3.29 (1.57)	1.53 (1.55)
Silent	1.76 (2.56)	0.65 (1.06)
Total recall	5.06 (3.17)	2.18 (2.32)

Figure 6.

Experiment 1b: Memory performance under full and divided attention by encoding type



Note. Error bars represent 95% confidence intervals.

Secondary Task Performance.

To ensure the divided attention manipulation worked as intended, performance on the digit monitoring task under FA was compared to performance under DA using a paired t-test. As expected, performance on the digit monitoring task under FA (M = 54.90%) was significantly better than under DA (M = 19.61%), $t(16) = 4.52$, $SE = 7.81$, $p < .001$, $d = 1.49$.

Discussion

Replicating our findings from Experiment 1, the production effect persisted when production was used as an encoding technique under DA conditions. Consistent with past literature (Bailey et al., 2021; Cyr et al., 2022; Forrin et al., 2012; Jones & Pyc, 2014; MacLeod, 2011; MacLeod et al., 2010), words read aloud were better remembered than words read silently when encoded in both the FA and DA conditions. We again replicated past literature demonstrating DA's known impairment on memory performance when experienced at encoding (Anderson et al., 1998; Craik et al., 1996, 2000, 2018). This confirms that the observed pattern of results in Experiment 1 was not due to faulty timing arising from Qualtrics. The adjustment still replicates our findings from Experiment 1, suggesting the extra seconds gained in Experiment 1 did not have a significant impact on the pattern of our results.