Dynamics of Internal Attention and Internally-Directed Cognition: The Attention-to-Thoughts
(A2T) Model

Iftach Amir, M.A. & Amit Bernstein, Ph.D.*

University of Haifa, Israel

*Corresponding author:

Prof. Amit Bernstein, Ph.D.

Director, Observing Minds Lab

School of Psychological Sciences, University of Haifa

Mount Carmel, Haifa 31905, Israel

Email: abernstein@psy.haifa.ac.il

Lab: www.observingmindslab.com

Phone: +972-4-824-9659 | Fax: +972-4-824-0966

Abstract

The propensity to focus attention inwards is fundamental to human mental life and internally-directed cognition (IDC) (e.g., mindwandering, rumination). Yet, understanding of the mechanisms through which internal attention shapes IDC is limited. We argue that understanding the *dynamics of how internal attention interacts with other cognitive processes* can significantly facilitate our capacity to predict and model (mal)adaptive IDC. We therefore introduce the Attention-to-Thoughts model – a dynamic systems theory and computational model of internal attention in IDC. Through the model we aim to, first, conceptually and computationally define *momentary states* of this dynamic system; second, simulate and predict differential temporal *trajectories* of this dynamic system through which IDC emerge. Through experimental simulations, we explore how Attention-to-Thoughts may be used to better understand how internal attention selection is expressed from moment-to-moment; how internal attention unfolds by documenting how, as a function of contextual demands for focused attention, internal attentional selection iteratively transacts with working-memory and emotion; and, in turn, how maladaptive IDC (e.g., repetitive negative thinking, cognitive dyscontrol) emerges from temporal trajectories of the dynamic system of internal attention. Finally, we highlight key conceptual, computational and methodological directions for the study of internal attention, IDC and related phenomena (e.g., mindfulness).

Introduction

*“And in the naked light I saw,
Ten thousand people maybe more,
People talking without speaking,
People hearing without listening...”*
Sound of Silence, Simon & Garfunkel

Internally-Directed Cognition: Looking in

Our propensity to direct attention inwards – onto our thoughts, memories and feelings – is quintessential to human mental life and conscious experience. We spend as much as ~30-50% with our attention turned inwards, “looking in” (Killingsworth & Gilbert, 2010; Klinger, 1978), often also termed “internally-directed cognition” or “self-generated cognition”, or simply *thinking* (Axelrod et al., 2017). Internally-directed cognition (IDC) is an umbrella term for inter-related mental phenomena such as reflective attention, self-focused or self-directed attention as well as mindwandering, internal processing or mentation, imagery and mental time travel (Axelrod et al., 2017; Chun & Johnson, 2011; Ingram, 1990). IDC is therefore a fundamental characteristic of human mental life and is thought to be functionally important (Klinger, 2013). Critically, internal attention determines what internal information reaches awareness, including the selection of thoughts, memories, images and related internal experiences (Posner, 1994). Accordingly, whereas some of our looking inwards enables adaptive thinking (e.g., goal-setting, problem solving, mental time travel), it can alternatively potentiate maladaptive thinking (e.g., spirals of negative repetitive thinking).

Yet, our understanding of *how*, *when* and *for whom* (mal)adaptive IDC emerges from internal attentional selection, is limited and fragmented. Indeed, theory and research to date has largely focused on the conceptual and empirical characterization of IDC. Progress has been made with respect to characterizing key forms or expressions of IDC (e.g., intentional vs. unintentional mindwandering), essential features of IDC, as well the temporal dynamics of IDC (e.g. how moment-to-moment trains of thought unfold of time) (Andrews-Hanna et al., 2013, 2018; Irving, 2021; Smallwood & Schooler, 2015). Emerging theories have focused on candidate cognitive processes necessary for IDC and the related neural substrates which may subserve various expressions (e.g., task-related vs. -unrelated) and dynamics of IDC (Axelrod et al., 2017; Christoff et al., 2016; McVay & Kane, 2010; Smallwood, 2013a). Building on this theoretical and empirical research, we now must try to understand *how* key cognitive processes interact and give rise to various forms, mal(adaptive) expressions, and temporal dynamics of IDC.

Accordingly, in this paper we introduce the *Attention-to-Thoughts* (A2T) model – a dynamic systems theory and computational model of internal attention in IDC. Specifically, A2T characterizes how internal attention is expressed and iteratively transacts with working memory and emotion, from moment-to-moment in time, as a function of contextual demands on sustained focused attention. A2T thereby accounts for how internally-directed cognitive processes such as (mal)adaptive thinking emerge and dynamically unfold. Subsequently, through computational simulations, we test and demonstrate the theoretical plausibility of A2T and its implications for theories of IDC.

The novelty of A2T beyond extant theory and research entails the conceptualization and modeling of IDC as a dynamic system, its theoretical focus on internal attention in IDC, and critically, the computational formalization of the theory and its implications for simulating the

complex dynamic phenomenon in time. We thus aspire to advance understanding of IDC and its roles in human mental life and (mal)adaptation. We also hope to demonstrate that, as a field, we can use computational formalization of theory to advance our understanding of the complexity and dynamics of mental phenomena in which we are interested.

Manuscript overview

We begin by reviewing extant theory and study of internal attention, working memory, and IDC. We then lay out the potential implications of dynamic systems theory as well as formal computational theory and modeling for the study of IDC. We then describe the A2T model and delineate its components and pathways. We detail the computational model formulations that characterize momentary states of the system, the inter- and trans-action of model components in time, and the temporal trajectories that emerge from these states and interactions. We then contextualize A2T relative to extant theoretical frameworks of IDC. Subsequently, using the A2T computational model, we conduct quantitative simulations that model dynamics of IDC, and thereby help to characterize and account for common forms of maladaptive IDC, including, repetitive thinking, cognitive (dys)control, and interpretation bias. Finally, we conclude by highlighting future directions for A2T and the study of IDC.

External & internal attention

In an ongoing process of selection and modulation, our minds are challenged to process events in our (external) environment as well as the (internal) events within our mind including our thoughts, memories and mental images (Klinger, 1978; Uddin, 2015). Due to the brain's limited processing capacity, not all concurrent external or internal events may be processed – certain information must be *selected* over competing information for preferential processing (*modulation*) (Chun et al., 2010; Desimone & Duncan, 1995) (see Table 1).

External attention is the attentional processing of perceptual-sensory information incoming from various sources external to the mind/brain such as the peripheral nervous system, originating from outside and/or with-in the body (e.g., visual information incoming via the eyes, proprioceptive sensations originating from the muscles). *Internal attention* is the attentional processing of information stored in the mind, whether recalled from long-term or active in working memory (Chun et al., 2010; Dixon et al., 2014; Gazzaley & Nobre, 2012). That is, internal attention biases processing in favor of certain internally generated- or stored- mental representations over other competing internal and external objects or stimuli (Myers et al., 2017). Emerging work indicates that the goal-directed/stimulus-driven systems which govern *external-perceptual* processing may also operate over processing of *internal* events (e.g., memories, thoughts; (Chun et al., 2010; Chun & Johnson, 2011; Dixon et al., 2014; Uddin, 2015; Ziegler et al., 2018).

Executive control processes, such as working memory and response selection, are by definition *internal and goal-directed* processes (Chun et al., 2010). Other forms of cognitive processes and states may be characterized as *internal and stimulus-driven* processes. For example, unwanted memories or involuntary remembering or any interesting memory that “enters consciousness and takes over attentional resources” have been conceptualized as a result of automatic reflexive bottom-up forms of internal attention (Cabeza et al., 2008; van Schie & Anderson, 2017). This interplay between internal goal-directed and stimulus-driven systems is analogous to recent theory seeking to characterize dynamics of spontaneous thought processes including how thought processes such as mindwandering, rumination and goal-directed thoughts arise and change over time (Christoff et al., 2016). Such thought processes are driven by dynamics between varying levels of deliberate (i.e., cognitive control / goal-directed system) and automatic

(i.e., affective and sensory salience / stimulus-driven system) as well as contextual and mnemonic (e.g., working-memory capacity) constraints on thinking (Christoff et al., 2016).

Likewise, *selection history* may be especially meaningful for understanding internal attention and its role in IDC. In the external attention literature, a “selection history” system has been proposed to account for attentional effects such as reward history, priming or (previously learnt) statistical regularities of how relevant and irrelevant information is distributed in the environment (Awh et al., 2012; Theeuwes, 2019). Similarly, internal attention may also be biased to representations that had been previously selected (Theeuwes, 2019). For example, imagine a person who is preoccupied with thoughts regarding an on-going personal crisis or an unresolved problem. In attentional terms, this means that crisis-related thoughts (representations) are selected into WM and awareness, and selection history to such representation begins to form or “accumulate” (Theeuwes, 2019). Internal selection history may bias continued and ongoing internal selection to related thoughts and memories of the crisis (Ehring & Watkins, 2008) thereby maintaining IDC (e.g., negative repetitive thinking) (Everaert et al., 2020).

Table 1. Definitions of key concepts.

TERM	DEFINITION
<i>Attentional selection</i>	The preferential allocation of limited processing resources to certain sources of information over concurrently competing sources
<i>Attentional modulation</i>	The extent of facilitated processing of selected source of information
<i>Internal attention</i>	“Selection and modulation of internally generated information” (p. 77; Chun et al., 2010)
<i>External attention</i>	“Selection and modulation of sensory information” (p. 77, Chun et al., 2010)
<i>Working memory</i>	The limited capacity to store information in the mind in a highly accessible and modular state such that information can be quickly retrieved and manipulated

Working memory & internal attention

Although there has been limited study of *internal* attention per se (Chun et al., 2010; Kiyonaga & Egner, 2013; Nobre et al., 2004), there is extensive cognitive psychology and neuroscience focused on *working memory*. Working memory (WM) refers to the mental capacity to store and manipulate information in the mind (Baddeley, 2011; Myers et al., 2017). WM is inherently *attentional* – in that it is limited in capacity and so entails preferential processing of selected information. Critically, WM is also inherently *internal* – in that the information processed

is independent of external sensory stimulation. Because working memory and internal attention are closely related processes (Kiyonaga & Egner, 2013; Myers et al., 2017; Oberauer, 2009), we use the term *internal attention* to refer to the specific processes of preferential selection and modulation of internal objects. In the present paper, when we use the term *working memory*, we refer mostly to its function in short-term storage and guiding behavior (Myers et al., 2017; Oberauer, 2009). We do so for simplicity and in line with models of WM that emerged from the short-term memory literature and theory distinguishing attentional from other processes (e.g., memory encoding, retrieval or capacity) subserving WM (Baddeley, 2011; Oberauer, 2009).

Internal Attention, Working Memory and Internally-Directed Cognition

Internal attention and WM serve critical functions in IDC. Attentional selection drives the gating or filtering of information that reaches conscious experience (Posner, 1994). As such, attention functions to determine whether the focus of awareness and cognition is directed externally or inwardly (Verschooren et al., 2019) as well as which of the vast number of (external or internal) stimuli are represented in awareness at any given moment (Posner, 1994). That is, from moment-to-moment, attention gates which information reaches WM; and WM serves as the temporary storage mechanism of conscious detail (Bor & Seth, 2012). In this way, internal attention determines the focus of awareness and IDC at each moment; and, by doing so repeatedly, also sustains or shields IDC by suppressing both external source selection (Smallwood, 2013a) and other internal distractors. Accordingly, the capacity for crucial mental tasks, for example planning an important event in the future, requires the ability to (at least temporarily) filter and gate external and internal distractors as well as to maintain and update WM with the (event) relevant information. As such, inability to filter out *external* distractors (e.g., a noisy train station) results in impaired capacity for focusing on important internal goals and processing. This is known

as the perceptual decoupling hypothesis – that the inhibition of perceptual inputs into WM is necessary for temporal continuity of IDC (Smallwood, 2013a; Smallwood & Schooler, 2015). Likewise, the inability to filter and suppress internal distractors, for example associative memories and thoughts, similarly results in inability to sustain contextually important IDC or attention to external stimuli.

In order to account for findings that mindwandering and sustained (external) attention are mutually inhibiting processes, and the corresponding decoupling hypothesis, Smallwood (2013a) proposed the process-occurrence framework – a seminal conceptual model of mindwandering. First, the process-occurrence framework argues that both mindwandering and on-task (external) attention are subserved by similar (shared) cognitive processes – i.e., both phenomena emerge from a general cognitive architecture. Thus, because some cognitive processes resources are domain-general (Baddeley, 2011; Teasdale et al., 1995), mindwandering reduces available shared resources for simultaneous attention to on-going task. Accordingly, the process-occurrence framework highlights the importance of such a general cognitive architecture in IDC, and critically, the importance of distinguishing between the processes/phenomena (e.g., mindwandering, sustained on-task attention) that emerge from the interacting components and processes of the cognitive architecture that subserves these phenomena.

Advancing theory through a dynamic systems perspective

We argue that our capacity to predict and model (mal)adaptive IDC may be significantly facilitated through understanding the *how internal attention interacts with other cognitive processes* that together form a dynamic system which subserves (mal)adaptive IDC. First, **complexity in dynamic systems** arises from multiple reciprocal inter- and trans-actions between the system's components/processes (Kelso, 1995; Lewis, 2005). These include reciprocal

interactions between internal attentional selection, working memory, mnemonic and emotional factors as well as contextual demands on attention (Axelrod et al., 2017; Dixon et al., 2014). For example, internal and external attention gate the information entering WM, yet the contents or activated representations in WM also guide internal and external attentional selection (Hollingworth & Luck, 2009; Nobre & Stokes, 2019). Similarly, attention amplifies perceived emotional experience (similar to how external attention increases perceptual vividness; (Mrkva et al., 2019)). In turn, emotional states amplify attentional selection by facilitating processing of- or disrupting on-going task and reorienting to- emotionally relevant information (Öhman et al., 2001; Smallwood et al., 2009; Vuilleumier et al., 2003).

Second, not only do these processes have complex inter- and trans- actions in any given moment, but these complex interactions are recursive – they unfold dynamically from moment-to-moment in time. A **complex dynamic system** emerges from these circular causalities in time (Kelso, 1995; Lewis, 2005). The states of each process in the current moment are determined by the systematic interactions between those states in the previous moment(s) which then influence the state of each process in the next moment(s) – repeatedly over time (see Figure 1B).

Furthermore, this complexity in time may also subserve **dynamics of (mal)adaptive internally-directed cognitive processes** – most notably, the temporal stability or variability of thought content. For example, while goal-directed thinking and mindwandering are both expressions of IDC (Christoff et al., 2016), they are characteristically different in terms of stability/variability of thought content in time (Andrews-Hanna et al., 2018). Goal-directed thinking is characterized by constrained internal attention to goal/task-relevant information in a purposeful, organized manner, whereas mindwandering is characterized by goal/task-irrelevant fluctuations in thought content that is processed in a more spontaneous, less deliberate way.

Temporal epochs of underlying narrowed scope of internal attention (e.g., when selection is constrained to representations associated to content in WM) subserve periods of temporal *stability* in thought content (Whitmer & Gotlib, 2013). For example, when a thought or memory leads to a thematically related thought or memory, conscious (stream of) thought may be experienced as coherent (R. Epstein, 2000). Likewise, moments in which internal selection is not constrained (or fails to constrain) to information associated with contents in awareness (or WM) are more likely to lead to spontaneous shift in thematic content of thought. Such moments subserve higher-order episodes of temporal *variability* in thought content such as episodes of task-unrelated thoughts (when there is an on-going task to attend to) or mindwandering (when there is no urgent task to attend to) (Axelrod et al., 2017; Christoff et al., 2016; Ellamil et al., 2016; Engen & Anderson, 2018).

Importantly, these dynamics of (mal)adaptive IDC (i.e., temporal stability or variability of thought content) emerge from the temporal patterns of recursive circular causality and thereby can be understood as self-organizing. In dynamic systems, self-organization helps to explain how wholes emerge from parts (or what we refer to as underlying processes) (Kelso, 1995). Accordingly, a dynamic systems perspective may help to explain how different expressions of IDC emerge from the interaction of underlying processes including attention, memory, affective processes and contextual demands (Axelrod et al., 2017; Christoff et al., 2016; Smallwood, 2013a). This emergent systemic self-organizational property of dynamic systems is theoretically significant because it does not require an extra-systemic homunculus to account for IDC. Likewise, this dynamic systems perspective helps to explain how the same system that gives rise to adaptive IDC can also readily give rise to maladaptive thinking process; as well as helps to characterize the specific conditions in which – how, when, and for whom – maladaptation in IDC is likely to occur.

Advancing theory through formal computational modeling

Furthermore, we propose that **formal computational modeling** may be particularly instrumental in advancing understanding of internal attention in (mal)adaptive IDC (J. M. Epstein, 2008; Grahek et al., 2021). Moreover, formal computational modelling may be *necessary* for dealing with- and understanding- the complexity of the dynamic system subserving IDC (see (J. M. Epstein, 2008; Farrell & Lewandowsky, 2010; Lewis, 2005) for reviews). Formal computational models are designed to formalize and computationally implement and quantify theory by translating the key principles of a theory into computational rules and/or equations (Borsboom et al., 2021). Critically, ‘formal’ computational models should not be confused with ‘data’ computational models (Borsboom et al., 2021). Data models are designed to process, test, statistically fit and understand *empirical* data (e.g. regression models, SEM, network models, (Haslbeck et al., 2019; Heathcote et al., 2015)¹. Our focus here is on formal computational models.

First, the development of computational models – the theory formalization process – reciprocally and iteratively facilitates the development of the theory behind the model by necessitating that all or most assumptions or key parameters of a theory are explicit (Borsboom et al., 2021; Epstein, 2008; Grahek et al., 2021) (e.g., are causal relations between system components (non)linear?). Second, by permitting mathematical manipulations of key parameters and their inter-actions in the dynamic system, computational simulations can provide novel and more precise understanding of, and predictions about, the phenomena of interest than conceptual theory alone (Huys et al., 2016; Scheel, 2022). Such benefits include the capacity to run computational simulations of the model, and thereby quantify and visualize momentary states as well as temporal trajectories of the dynamic system under various theoretical scenarios/parametric

¹ There are certain cases wherein formal and data models highly overlap, such as evidence accumulation models or reinforcement learning models (Gershman, 2016; Heathcote et al., 2018).

conditions (e.g., context, initial states or parameters). In turn, computational modeling enables formal simulations testing how complex systems unfold in time (Borsboom et al., 2021; Epstein, 2008). Critically, such simulations allow for exploring whether a proposed formal theory (e.g. A2T) provides a *plausible explanation* of the phenomena of interest (i.e., primary explanada (van Rooij & Baggio, 2021); e.g. repetitive negative thinking). Finally, formalized models permit the comparison of simulated and observed experimental effects and results (i.e., secondary explanada; see Borsboom et al., 2021; van Rooij & Baggio, 2021). This facilitates examination of the explanatory scope and empirical verisimilitude of the model and theory (Borsboom et al., 2021; J. M. Epstein, 2008; van Vugt & van der Velde, 2018).

Attention-to-Thoughts Model

“All entities move and nothing remains still.” – Heraclitus.

Thus, we propose the A2T model – a conceptual and computational dynamic systems model of internal attention in IDC. Through the model we aim to, first, conceptually and computationally define *momentary states* of this dynamic system of attention, thought and emotion; and, second, we aim to simulate and predict differential *trajectories* of this dynamic system. To do so, the A2T model characterizes how internal attention affects and iteratively transacts with working-memory and affect processes, in time, as a function of contextual demands for sustained focused attention.

The model thus focuses on two explanatory levels. First, **momentary states in context** – how the components of the model causally inter- and trans-act in each moment in time (temporal resolution: seconds). The results of these inter- and trans-actions in time determine each of the following states of the system components: (1) the current internal attention selection likelihood or “bias” to attend to specific representations (e.g., negative vs. neutral representations), (2) the

current representations active in WM, and (3) the current affective state (e.g., degree of momentary negative affect). Critically, each *momentary state* (Time t) is influenced by the previous (Time $t-1$), and affects the subsequent (Time $t+1$), momentary state. That is, each momentary state is causally “linked” to its previous and subsequent states, creating a temporal “chain” or vector of momentary states of the system.

Accordingly, the second level of explanation focuses on temporal dynamics or **trajectories** – how momentary states of the dynamic system unfold in time and content, from moment-to-moment (temporal resolution: minutes, hours). Critically, the likelihood and frequency of specific trajectories constitute individual differences in key aspects of IDC (e.g., mindwandering, repetitive thinking, cognitive dyscontrol) that emerge from the moment-to-moment unfolding of momentary states or underlying processes.

Utilizing A2T, we sought to characterize each of the following: (1) how internal attention selection is expressed from moment-to-moment; (2) how internal attention drives and iteratively transacts with WM, affective states, and how such components of the dynamic system feedback onto- and thereby influence- internal attentional selection of thought content; (3) how high and low contextual demands for focused attention to task-relevant information may moderate relations of internal attention, WM and affect; and (4) how individual differences in the magnitude of influence – between WM, affect and internal attention – impact emergent trajectories of the system. Furthermore, by addressing these questions using the A2T model, we demonstrate how dynamic temporal patterns of the system may subserve the emergence of (mal)adaptive IDC. Finally, we use A2T to conduct a series of experimental simulations to test and illustrate how the dynamic internal attentional system, under different contextual demands and individual difference

parametric conditions, may subserve (mal)adaptive IDC and thereby may contribute to mental health.

Figure 1. Overview of the model. *S* = Stochastic/random effects on selection. Figure 1A illustrates the *momentary state in context* of the model. Path *a* reflects cognitive control, path *c* reflects emotional reactivity and path *e* reflects cognitive reactivity. Figure 1B illustrates how the model unfolds in time.

Table 2. Definitions of A2T key terms and model components.

<i>TERM</i>	<i>CATEGORY</i>	<i>SCALE</i>	<i>DEFINITION</i>
<i>Context</i>	System component	Seconds	Degree that current context demands goal-directed focused attention.
<i>Internal Attentional Selection</i>	System component	Seconds	Momentary probability of internal selection given previous state
<i>Representations in WM</i>	System component	Seconds	Representations momentarily stored and accessible in working memory
<i>Affect</i>	System component	Seconds	The momentary the subjectively experienced hedonic tone (degree of positive and negative affect)
<i>Momentary state in context</i>	Emergent characteristic	Seconds	Momentary constellation of the components of model – i.e., momentary context, momentary affective state, momentary representations stored in working memory)
<i>Trajectory</i>	Emergent characteristic	Minute(s)	States in context in time
<i>Vulnerability</i>	Emergent characteristic	Days, months, years	Chronicity of trajectory or states in time, over longer time epics and across contexts

Model synopsis

First, the proposed A2T model characterizes the dynamic, inter- and trans-actions, from moment-to-moment in time, of four key cognitive-affective components. These components constitute the repeated momentary process of selectively attending to internal representations into working-memory, such as verbal thoughts and memories (Alderson-Day & Fernyhough, 2015;

Andrews-hanna et al., 2014; Dixon et al., 2014; Kanske et al., 2011), and their influence on affective state (LeDoux & Brown, 2017). The model components are: (1) *Contextual Demand*: Degree that context demands goal-directed focused attention ranging from high-demand task-oriented states to low-demand mind-wandering states; (2) *Internal Attentional Selection*: Selection of internal mental representation(s) for preferential processing and thereby access to working memory; (3) *Representations in Working Memory*: Representations momentarily active in working memory; and (4) *Affect*: The momentary subjective hedonic tone of experience (degree of positive and negative affect). Each component has a distinct function and process (see Table 2). Yet, from their myriad constellations of simple interactions over time (Kelso, 1995) emerge the various expressions of IDC (Smallwood, 2013b).

Figure 2. Illustration of selection of internal content. Figure 1A visualizes the competition by several objects. Figure 1B visualizes how competition out-come can be represented as likelihood distributions.

Model components

First, *internal attentional selection* is at the functional center of the proposed dynamic system subserving IDC and accordingly at the center of the A2T model. At each moment in time, various sources for internal information, such as stimulus-driven spontaneous associative thoughts and memories as well as goal-directed thoughts, compete for processing². The selection determines

² Computational approaches have helped to advance theories of (external) attention, and in cases where different theories converge to similar predictions, to then clarify theoretical differences in underlying processes and computations (e.g., percept vs. exemplar similarity estimation or signal-over-noise detection) (see Logan, 2004 for a

what internal information receives processing priority from the limited capacity in working memory (see Figure 2A). Significant for theory formalization and its computational modeling (see *Computational Formulations* below), we assume here that thoughts are “temporally discrete elements – a ‘chain’ rather than a ‘stream.’” (R. Epstein, 2000, pg. 553).

Thus, assuming that each thought reflects a discrete entity, selection can be based on any number of dimensions reflecting the “features” of thought content (e.g., degrees of emotionally-associated valence, self-referentiality, temporal orientation, etc.; see Andrews-Hanna et al., 2013)). For simplicity, to illustrate the model, in this paper we focus on (degree of) negative valence as the key dimension on which selection is based³. The momentary state of internal attentional selection is represented, and may be formalized, as a probability distribution biasing selection in favor of certain representations over others in any given moment (see Figure 2B). Critically, in each moment this selection probability distribution changes as a function of momentary states of the other components (their mechanism of influence is explained below). An additional source of influence on selection are stochastic/random factors such as random neural (system) noise (Buzsáki, 2006; Logan, 2004; Shadlen & Newsome, 1994; van Vugt & van der Velde, 2018). This randomness is essential to ensure a degree of *flexibility over time* such that the system does not become “stuck” indefinitely in a certain (biased likelihood) state due to internal feedback loops without an intervening stochastic event (see *Common temporal trajectories* section below).

review). Such theories are based on the rich history of psychophysics research and accordingly focus on external attention (Chun et al., 2010). A2T focuses on internal attention *in IDC*, and integrates other components into a dynamic system subserving IDC, rather than focus solely on attentional processes (Smith & Sewell, 2013). Previous theories nevertheless influenced conceptualizations in A2T – most notably executive control driven attentional weights for biasing and optimizing selection, and the inclusion of noise/stochastic processes (Logan, 2004).

³ However, the features/dimension on which selection is based can be changed when applying the model to specific topics of interest.

Second, the contents or *representations in working memory* are the momentary outcomes of internal selection. These include mental experiences such as verbal thoughts (internal speech), internal imagery and associative memories (Alderson-Day & Fernyhough, 2015; Oberauer & Hein, 2012). These representations are stored in-, and as such subject to, the constraints of- short-term memory and accordingly ‘exist’ for short periods of time (until decaying or reattended/selected) (Baddeley, 2011)⁴. During these time periods, these representations have brief (i.e., phasic) influence over likelihoods of selection (internal attentional selection component) by biasing likelihoods in favor of content-congruent internal representations (Hollingworth & Luck, 2009; Smallwood, 2013a), similar to the biasing effects of selection history on external attention (Awh et al., 2012). See Figure 1A.

Notably, the A2T model functionally distinguishes between internal attention and WM processes. As such, A2T attributes the process of selection history to WM, although it is typically discussed as an attentional process (see Awh et al., 2012)). For A2T implementation, we adapted a more limited definition of selection history based primarily on (inter-trial) priming studies (Anderson et al., 2021). Accordingly, here, *history* is equated or implemented as short-term memory. This also implies that for selection history to occur, at least in A2T, the underlying representation (specific “history”) must be active in WM. Future developments of A2T can incorporate “longer term” learning histories (e.g. reward history; (Anderson et al., 2021).

Third, the **affect** component reflects the consequence(s) of the representation in working memory on current negative affective state (i.e., the more negative representations in WM trigger more negative affect; (Engen & Anderson, 2018; Ruby et al., 2013; Siemer, 2005)). Like the *representations in working memory* component of the model, affect has phasic influence over

⁴ For computational/simulation purposes we view this component as a repeatedly updating first-in-first-out storage device containing the last 5 selected representations/objects.

likelihoods of selection by biasing selection in favor of affect-congruent internal representations. This is assumed to occur through spreading activation along a shared associative network between the current affect tone and long-term memory representations (e.g., negative affect increases activation levels of memories associated with negative affective experience) (Eich, 1995; Williams et al., 2007).

Figure 3. Illustration of the effects of contextual demands for focused attention on selection of task relevant and irrelevant information.

The fourth component, *contextual demands for focused attention*, reflects the degree to which a person, at each moment in time, is under (external or internal) demands to selectively attend to specific information (Buetti & Lleras, 2016; Lavie, 1995; Smallwood, 2013a) (see Figure 4). For example, external contextual high-demands for focused attention may be participating in a cognitively demanding experiment; an internal high-demand may occur when a person tries to recall important details from a specific autobiographical memory. We thus refer to high-demand contexts as task-oriented states and low-demand contexts as mindwandering states (Christoff et al., 2016). Within the model, greater demand is translated into greater constraints on the momentary attentional selection bias to negative representations (i.e., more contextual demands reduces internal selection bias driven by the current emotional state of the system) (Christoff et al., 2016; Whitmer & Gotlib, 2013). The less contextual demands, i.e., more mindwandering state, the less bias selection in favor of particular representations.

Accordingly, in the model, the contextual demand component has two (computational) functions. First, contextual demand delineates what information is contextually- (i.e., task-) relevant (Buetti & Lleras, 2016). This is similar to the functions, in external attention, of top-down signaling of features or task sets (Corbetta & Shulman, 2002; Logan, 2004). For example, contextually-relevant information may be recalling a shopping list (wherein information is emotionally-neutral). Alternately, imagining an upcoming confrontation with an unpleasant co-worker (wherein certain context-relevant information is emotionally evocative). Second, contextual demand additionally functions to indirectly moderate (attenuate) the influences of representations in WM and affect components on internal attentional selection. The degree of attenuation increases as greater contextual demands for focused attention increase (Smallwood & Schooler, 2015).

Model paths: Feed-forward & Feed-back

The components of the system are linked through a number of feedforward (see Figure 1 paths *a*, *b* and *c*) and feedback paths (*d* and *e*). For simplicity, the strengths of causal links are assumed to be constant between people, except for two important paths we believe are crucial for accounting for individual differences – (affective) *reactivity to representations in WM* (path *c*) and (attentional) *reactivity to affective state* (path *e*). These paths are crucial to understanding why certain trajectories are likely to occur more frequently in certain individuals relative to others (see *Common temporal trajectories* below). Accordingly, the paths of reactivity to representations in WM (path *c*) and reactivity to affective state (path *e*) are the only two elements in the model that may vary between individuals in their relative causal strength. As such, the causal strength of these paths or processes are not predicted by the model, rather, between-person variability in these paths are moderated by factors extraneous to the system (Fried & Cramer, 2017). As such, individual differences in these paths are crucial for generalizing and applying the model to fields of research in which core questions and interests deal with between-person variability – for example, individual differences in cognitive vulnerabilities to depression and anxiety (see *Accounting for Maladaptive Internally-Directed Cognition* below).

First, *affective reactivity to representations in WM* (path *c*) or “emotional reactivity” refers to the change in emotional state and its intensity (peak amplitude) in response to emotional information (Davidson, 1998). Reactivity to representations in WM is an important individual differences factor in mental health, as persons high on repetitive thinking, depression or anxiety show increased negative emotional response when instructed to direct attention to negative *internal* experiences (mostly through experimental manipulations such as, “Think how you feel inside.”; Nolen-Hoeksema, Wisco, & Lyubomirsky, 2008; Watkins, 2008). In the proposed A2T

model, reactivity to representations in WM is reflected in the effect of cognitive representations in WM on affect (see Path *c* in Figure 1A). Accordingly, when an emotionally associated representation is selected into WM it activates a corresponding affect state (affective/emotional reaction). The “higher” an individual is on reactivity to representations in WM, the stronger the negative representations in WM trigger a momentary negative affect.

Second, *cognitive reactivity to affective state* (path *e*) or “cognitive reactivity”, refers to the magnitude of increase in probability of negative cognitions (thoughts) in response to negative affect (Scher et al., 2005). For example, in both experimental and naturalistic settings, depressed mood has been shown to increase the likelihood of recalling negative memories (i.e., mood-congruent memory) (Teasdale & Barnard, 1993). In the model, cognitive reactivity to affective state is reflected in the influence of affect on the internal attention selection likelihoods in favor of affect-congruent representations (Figure 1A Path *e*). For example, the greater momentary negative affect, the greater internal attentional selection will be biased to negative representations.

Computational Formulations

Momentary States of the System

As detailed above, *internal attentional selection* is at the functional hub of A2T. Momentary states of each component converge onto internal attentional selection – determining the likelihood of attending to a negative representation state of the internal attention component at Time *t*. To reiterate, here we illustrate the role of internal attention in IDC using an A2T model which focuses on attention to negative versus neutral thoughts. Accordingly, selection likelihoods are based on the “feature” or dimension of (degree of) negatively valenced representations. Notably, the model can be applied to other (potentially multiple) features/dimensions of interest (e.g., self-referentiality, chronic goal relevance).

Computationally, the likelihood of attending to negative representations is drawn from an exgaussian distribution whose parameters (mean, variance and exponential rate; see Table 3) change, from moment-to-moment, as a function of the state of different system components. The *mean* parameter is determined by information from contextual demands of what is task-relevant information, and more specifically, the degree (from 0 to 1) to which emotionally negative or neutral information is task-relevant. For example, the mean parameter will be .5 when modelling an individual trying to recall a list with equal number (50%/50%) of emotionally neutral and negative words. The *variance* parameter represents the stochastic element of internal attentional selection, such that the greater the stochastic element, the less the selection likelihood distribution constrains around the mean. Finally, the *exponential rate* (tau) parameter reflects the degree of momentary selection bias to negative representations. Rate is determined by the momentary interaction of representations in WM, affect and contextual demands (see Equation 1 below). Essentially, as rate (i.e., negative bias) increases, the distribution accordingly biases/shifts towards overall greater likelihood of attending to negative representations (see Figure 4).

Table 3. Parameters for the ex-gaussian distribution of likelihood of attending to negative representations.

<i>Parameter</i>	<i>Meaning</i>
<i>Mean</i> (<i>mu</i> ; μ)	Proportion to which negative information is context-/task- relevant. The more the current task/context requires prioritizing negative representations, the distribution center accordingly shifts to “higher” selective bias.
<i>Variance</i> (<i>sigma</i> ; σ)	Degree of stochastic element of internal attention. As the stochastic element increases, the wider the distribution becomes, and so selection likelihood randomly varies more from moment-to-moment.
<i>Exponential rate</i> (<i>tau</i> ; τ)	Degree of bias to negative information. Integrates the states of representations in WM and affect (Time t-1) and contextual demands (Time t). As tau increases, the distribution shifts more toward higher negatively biased selection likelihoods.

Figure 4. A) Illustration of change of ex-gaussian distribution as a function of tau values. As tau increases (i.e., exponential rate), the more the distribution is skewed to higher levels of selective bias to negative representations. **B)** Illustration of computational procedure of determining tau/selection bias at Time t . In brief, first the states of contextual demands (Time t), representations in WM (Time $t-1$) and affect (Time $t-1$) are integrated using formula to determine the tau parameter (part I) together with the mean and variance (part II). From this distribution function a single value is randomly sampled (part III). This likelihood value determines the selection likelihood of attending to a negative representation at Time t . Finally, in simulations of the model, to constrain values between 0 and 1, this selection likelihood is converted with tangent hyperbolic function with 0 imputed for values < 0 . Based on this selection likelihood value an “uneven coin-toss” is simulated to decide whether a negative or neutral representation is selected/entered into WM.

Momentary states: Selection bias (exponential rate / tau)

The mean and variance parameters reflect typically stable factors (e.g., context is usually stable over short periods of time) and, as such, do not vary from moment-to-moment. In contrast, the rate parameter, representing selection bias, is most subject to temporal changes because it is determined by the momentary states of the system components. As such, the rate parameter is central to understanding how the model trajectories unfold over time. This selection bias (exponential rate, tau) can be represented as a heuristic formula (Equation 1):

$$Selection\ bias_{i,t} = tau = \frac{Representations\ in\ WM_{i,t-1} + (Affect_{t-1} \times Reactivity\ to\ Affect_i)}{2 + (Context_{i,t}^2)}$$

where i represents the individual person/model, t the specific moment in time. Accordingly, *selection bias* is a value between 0 (no bias to negative stimuli) to 5 (complete bias to negative representations) and is determined by values of the following elements: (a) the product of *affect_{t-1}* and *reactivity to affective state*, and (b) the sum valence of *representations in WM_{t-1}*⁵. The average of these two elements is divided by (c) *Context_t*, the demand for focused attention at that moment in time. *Context* is squared and placed in the denominator to reflect the strong constraining influence of contextual demands on internal attentional processes (i.e., the higher the contextual demands for focused attention the less influence for non-context related biasing factors such as affect).

⁵ As described in *Model components* section, the Representations in WM component is computationally implemented a short-term storage of 5 representations. Where neutral representations have a value of 0 and negative representations a value of 1.

Momentary states: Affect

The degree of momentary subjective negative *affect* is determined by the affective valence of representations active in working memory (which is determined by internal attentional selection) and reactivity to representations in WM. This can also be represented in a heuristic formula (Equation 2):

$$Affect_{i,t-1} = \frac{Reactivity\ to}{representations\ in\ WM_i} \times \frac{WM}{representation_{i,t-1}}$$

Momentary states: Representation selection

After the selection likelihood distribution has been determined by the parameters (mean, variance, tau) a single value at *Time t* (*Selection likelihood_t*) is sampled from the exgaussian selection likelihood distribution. Finally, in simulations of the model, to constrain values between 0 and 1, this value is converted using the tangent hyperbolic function with 0 imputed for values < 0. Based on this final selection likelihood_t value an “uneven coin-toss” is simulated to decide whether a negative or neutral representation is selected/entered into WM. This simulates how, from any number of different representations competing for selection into WM, a single representation is selected, and this selection outcome is influenced by the momentary bias of the internal attentional selection component.

Inter- and Trans-action of model components in time

These heuristic equations help to illustrate how each contextualized momentary state of the system (a) converges on internal attention and thereby a Selection likelihood value at time *t*, (b) how this selection likelihood is influenced by the moment state values of *representations in WM*

and *affect* at *Time t-1*, and (c) how *representations in WM* and *affect* (at *Time t*) are influenced by the probabilistic outcome of selection likelihoods of the *internal attention* component at *Time t*. This formalization of model components' inter- and trans-actions, from moment-to-moment in time, facilitates modeling of the system's temporal dynamics (see Figure 1B). For example, while *affect* at *Time t* is determined by the representations in WM at that moment in time, *affect* also influences internal attention at *Time t+1* which, in turn, will determine representations in WM and thereby *affect* at *Time t+1* and so on. Accordingly, to understand the current state of the system, at any moment in time, it is essential to understand the preceding state(s). Consequently, by computationally linking together a series of preceding and subsequent states (i.e., momentary state in context at *Time 1* to *t*), a dynamic trajectory (i.e., a "greater whole") emerges representing the unfolding of attention, thought and affect over time, as detailed below.

Temporal trajectories from sequential momentary states

A central function of the A2T model is its capacity to characterize and make predictions about how one momentary state in context leads to the (likely) next momentary state, and so on, emerging over time as a *trajectory*. As illustrated above, the dynamic trajectories of the system are a function of the moment-to-moment values of each model element, and critically, the inter- and trans-actional feedback (paths *d* and *e*) between the components and inter-component paths within the system in time. Accordingly, one constellation of initial values of the components is more likely to lead to a specific trajectory than other constellations of initial values. For example, an initial state of low contextual demands, concurrently with a negative affect state, is more likely to lead to a trajectory of repeated negative content in WM and negative affect (i.e., repetitive negative thinking) than would an initial state of high contextual demands with a neutral affect state. Thus, from different initial momentary states in context (i.e., momentary constellations of the

components within the system), we are also able to characterize more and less adaptive cognitive process trajectories.

For example, trajectories may be characterized by greater stability or, conversely, variability in thought content (i.e., content of representations in WM and related on-/off- task thought) and related fluctuations in affect. Stability is reflected in temporal sequences of thematically similar/related thought content (e.g., a series of task-related thoughts). Temporal variability reflects the opposite – sequences of thoughts that are thematically unrelated to each other (e.g., frequent shifts in thought content such as between task- related/unrelated thoughts). The degree to which stability or variability is (mal)adaptive is context dependent (Watkins, 2008). For example, in some situations (e.g., a chess game), stability may be more adaptive. In other contexts (e.g., when trying to brain-storm), variability may be more adaptive. However, trajectories of high stability or variability may also be maladaptive, especially when such trajectories become chronic or so habituated that they are insensitive to contextual demand (Christoff et al., 2016).

Attention-to-Thoughts and alternate frameworks of Internally-Directed Cognition

A2T is an explanatory formal model (Borsboom et al., 2021; J. M. Epstein, 2008; Grahek et al., 2021; van Rooij & Baggio, 2021). It provides an explanation – through a system of computational principles – of how various expressions of IDC emerge. Descriptively, A2T converges with previous theories of IDC, such as the process-occurrence framework (Smallwood, 2013a), control failure (McVay & Kane, 2010) and dynamics of spontaneous thought (Christoff et al., 2016). Indeed, A2T implicates similar cognitive processes as the process-occurrence and control failure frameworks, including attention, WM and contextual demands. Furthermore, A2T incorporates the roles of deliberate and automatic constraints (i.e., in A2T contextual demands and

reactivity pathways, respectively) in determining the dynamics of IDC. One critical advancement of A2T is its computational formalization. This results in more explicit assumptions and mechanistic principles and facilitates direct and rigorous examination of the empirical verisimilitude of the theory and model (Borsboom et al., 2021; Muthukrishna & Henrich, 2019; van Rooij & Baggio, 2021).

Another key contribution of A2T to frameworks of IDC is its dynamic systems perspective and, perhaps most notably, the property of circular causality and its implications for (mal)adaptive expressions of IDC. For example, rather than asking whether attentional control influences mindwandering or mindwandering influences attentional control (McVay & Kane, 2010; Seli et al., 2018; Smallwood & Schooler, 2015), circular causality allows both processes to function as cause and effect. Importantly, A2T implicates internal attention as the systemic hub of this circular causality by integrating previous (representations in WM, affect) and current (contextual demands) component states, and then, with a degree of stochasticity (Kelso, 1995), determines the following (*Time $t+1$*) state of the system. Notably, these recursive circular processes of the dynamic system furthermore enable the emergence of self-organizing trajectories of IDC (e.g., periods of sustained on-task attention, repetitive negative thinking).

A2T thereby builds on extant theory and frameworks of IDC by offering a unified explanatory framework for the emergence of various forms of adaptive and maladaptive IDC. Finally, as further developed below, the computational formalization of A2T permits contrasts of findings from model simulations relative to theory, empirical observations and experimental findings related to IDC (e.g., reduced mindwandering under increased task-demands).

Simulations of Attention-to-Thoughts: Modeling Dynamics of Internally-Directed Cognition

We conducted a series of simulation experiments using A2T. Broadly, we sought to explore how temporal trajectories emerge from momentary states of the model processes as a function of changes in contextual demands for focused attention as well as the valence of context-relevant information (i.e., to what degree is task-relevant information also negatively valenced). Such simulations may be useful in a number of ways: to better understand (and visualize) how temporal trajectories of the dynamic system emerge and unfold; to better characterize the momentary and temporal inter- and trans-action of system processes (e.g., attention and affect); to examine whether proposed A2T model formalization sufficiently characterizes all or most important assumptions or parameters of the theory and, as needed, to refine the A2T model; as well to examine the explanatory scope of the theory and model by contrasting simulation findings to observed empirical phenomena and specific experimental findings – and thereby an empirical validation process of the theory and formal model (Borsboom et al., 2021).

Simulation Procedure

In each simulation, we compute the values of each of the four model components, in each moment in time, based on the values of the other components at that- and previous- moments in time (see Figure 1 and 5 and formulas above). Because we are focused on the temporal dynamics of IDC, and the momentary states of the cognitive-affective processes that sub-serve these phenomena, simulations were run over a 5-minute time period with a resolution (i.e., discrete time/data points) of 1 second. In each simulation the initial starting points (Time 0) are identical and we manipulate only the starting values of the relevant factors/components according that simulation's goal. For example, when examining the role of degree of contextual demands for

focused attention, we accordingly run two simulations – one with high demand for sustained focused attention and one in which demand is low. The simulation outcomes are longitudinal data – moment-to-moment values of internal attentional selection likelihoods, representations in WM (i.e., thought content in awareness), degree of negative affect, as well as the temporal features (stability, variability) of the trajectories in these processes over the simulated 5-min period. See Figure 5 below for a visual illustration and details on the simulation algorithm and procedure. The simulation code in MATLAB is available at: <https://github.com/iftachamir/AttentionToThoughts>.

The effects of high contextual demand for sustained focused attention on temporal trajectories

High contextual demand to focus on neutral information: Sustaining focused attention on neutral information

The ability to focus attention on an on-going task is crucial for adaptive functioning – from mundane tasks such as planning dinner to recalling first aid procedures during an emergency. Such contexts of high-demand for focused attention impose strong constraints on internal attentional selection likelihoods. As demonstrated heuristically in Equation 1, the greater the value of the contextual demand denominator, the less “weight” or influence there is for affect or representations in WM (i.e., Equation 1 numerator) on internal attention selection likelihoods. Accordingly, under high contextual demands for sustained focused attention, a task-oriented state and subsequent trajectory initiates and is maintained until contextual demands for sustained focused attention decreases. For example, trying to recall the author and name of a paper to cite requires that internal attention be constrained to associated information in long-term memory, until the required information is retrieved.

Figure 5A illustrates a simulation of how selection bias and negative affect are maintained at a low value when high contextual demands for sustained focused attention on neutral information are high. Moreover, because selection likelihoods are drawn from an exgaussian distribution (and thus even when the distribution mean is 0 there is still some part of the distribution above 0) there is still a (low) probability for selection of negative representations. As such, there are time points in which negative representations are randomly selected. Accordingly, when this random selection occurs sequentially (see Figure 5A ~190 second mark) there is an increase in the values of both attentional and affective components. Importantly, however, this rise is temporary as the tonic, sustained, effect of contextual demands eventually out-competes “random” or low probability events (Buetti & Lleras, 2016). This simulation illustrates how the system is indeed able to maintain focused attention – i.e., suppress emotionally-evocative but task-irrelevant thoughts – when the contextual demands are high. Finally, these simulation findings (see also below *The effects of low contextual demands*) are aligned with empirical findings showing that subjective reports of mindwandering decrease as a function of task difficulty (Seli et al., 2018) as well as with corresponding Attentional Resources (Smallwood & Schooler, 2006) hypotheses and findings.

Figure 5. Simulated values in time (5 minutes) of Internal Attention and Affect components. Red line = degree of negative affect at each moment in time. Black line = selection bias – the likelihood of selectively attending to negative representations. Importantly, the selection bias is a *likelihood but not necessarily outcome* – i.e., even under high bias there is a small likelihood for neutral representation to be selected. Accordingly, dots represent the valence of the *outcome* of selection in each time point. Red dot = Selected *negative* representation into WM. Blue dot = Selected *neutral* representation. In Figure 6A the contextual demands is set to high (= 4) and in 6B to low (= 2). In both simulations reactivity to- affect and to-representations in WM (= -.25), as well as initial attention (= .5) and affect are set to moderate (= 1).

High-demand context and stochastic nature of internal attentional selection: Random lapses in sustained attention

Lapses in sustained attention, even for people with high levels of attentional control, occur (infrequently) under demands for focused attention. In the A2T characterization of IDC, lapses in sustained attention are expressed as occurrences wherein task-unrelated thoughts are selected (over task-related thoughts). Accordingly, in A2T, such lapses occur in part due to the partially stochastic nature of the internal attentional selection component of the model— wherein selection is represented as a probability and so, occasionally, low probability events occur. These infrequent lapses are reflected visually in the random (yet infrequent) selection of negative task-unrelated representations (red dots) in Figure 5A. Consequently, a task-unrelated representation in WM may bias selection in favor of (current WM) content-related but task-unrelated thoughts, increasing the likelihood of mindwandering. Yet, mindwandering is likely to dissipate quickly due to the sustained biasing effect of contextual demands in favor of task-related information (see Figure 5A).

Unlike other components in the system, contextual demand for focused attention receives no inputs from other system components. It influences the system's momentary state through its influence on internal attentional selection. Yet, it is not influenced by the previous momentary state (see Figure 1). This is more aligned with attentional resources theoretical accounts (Smallwood & Schooler, 2006) but not theories positing that executive/attentional control is amplified as a reaction to (meta-awareness of) task-unrelated thoughts (see McVay & Kane, 2010; Smallwood & Schooler, 2006). In contrast, in A2T, sustained contextual demand is sufficient for the dynamic system, over time, to self -correct or -organize. Accordingly, the alternative *reactive*

executive-control account predicts that task- or contextually- unrelated thoughts will increase the likelihood of a subsequent (*Time t+1*) on task thoughts. A2T, however, predicts that task-unrelated thoughts increase the likelihood of a subsequent task-*unrelated* thought (see Figure 5A ~180 seconds and Figure 9A). Finally, in A2T, return to “on-task thinking” emerges from self-organization rather than from homunculi control processes, such as via extra-systemic mechanisms of meta-awareness or monitoring (McVay & Kane, 2010; Smallwood & Schooler, 2006).

High-demand context to focus on negatively valenced information: Sustaining attention to emotionally-negatively valenced information

When task-related information is *negatively-valenced*, for example when trying to recall important information from a traumatic experience/memory or when planning for a stressful event, contextual demands bias selection in-favor of task-relevant information which, in this case, is also negatively valenced. Once the first cycle of the system is initiated, and *negative- and task-relevant* representations are selected into WM, these negative representations in WM (in addition to contextual demands) will bias subsequent selection in favor of negative- as well as task-relevant-representations. Accordingly, such negative representations in WM should also trigger negative affect. This may then further bias subsequent selection in favor of negatively valenced – affect-congruent – information competing for internal selection. When task-relevant information may be inter-mixed with *negative and neutral* information, such as memorizing a list of mixed negative and neutral words or reflecting on negative and neutral thoughts, this ultimately creates a selection conflict between the contextual demand and affect-driven biases. For optimal performance on a task, attention should be equally (non-preferentially) distributed between all task-relevant information (in this example both negative and neutral words). While the contextual demands bias task-*related* content, negative affect will also increase the likelihood of negative task-*unrelated*

content. Therefore, emotionally-valenced representations in WM, even if task-related, increase the likelihood for off-task thoughts and impair task performance (Welhaf et al., 2019). Figure 6 simulates a situation wherein contextually task-relevant information is 50% negative and 50% neutral. This simulation illustrates how, in-line with contextual demands, attentional selection bias (black line) fluctuates around .5 and the contents of working memory (blue and red dots) similarly randomly alternate between negative and neutral.

High context / 50% task relevant negative information

Figure 6. Simulated values when task-relevant information are both neutral and negatively valenced – e.g., recalling a list of mixed negative and neutral words. Relative to Figure 5A, the frequency of negative thoughts (red dots) as well as mean selection bias and negative affect, are higher. All initial component values are equal to those used for Figure 5A.

The effects of low contextual demand for sustained focused attention on temporal trajectories

In the absence of immediate task demands, the human brain continues to show coordinated and orchestrated neural activity (Raichle et al., 2001). These findings, alongside concurrent introspective reports of mindwandering (Christoff et al., 2009), show that IDC occurs, and

potentially increases, during periods of low contextual demands (Seli et al., 2018). In A2T, contexts of low demand for focused attention do not impose constraints on selection likelihoods. Indeed, when there is no ‘current task’, the context does not bias selection in favor of task-related information. As such, the mind is free to wander (Smallwood & Andrews-Hanna, 2013) including to (task-unrelated) personally-relevant chronic goals or unresolved problems (Klinger et al., 2018). In this context, the representations in WM, affect as well as stochastic element of internal attention have greater weight in influencing selection. The contents of WM influence selection such that current representations in WM (*Time t*) bias subsequent (*Time t+1*) selection in favor of content-congruent information. Over time, this should result in a higher probability for a series of repeated selection of content-related representations into WM. This is in-line with the phenomenological experience of relative stability of streams of thought (R. Epstein, 2000). However, the stochastic element also impacts selection such that at random occasions *unrelated* thought-content (to that at *Time t-1*) is selected – switching the ‘theme’ of stream of thought (Christoff et al., 2016; James, 1890). Consequently, under low contextual demands for sustained attention on a task and emotionally-neutral representations held in WM, A2T predicts that the stream of thought contents in awareness should be relatively stable (in terms of perceived relation between content from moment-to-moment) with largely random intervals between changes in the content of those representations (see Figure 5B for visualised simulation).

This property of the system also helps demonstrate the dynamic system’s capacity for explaining stability in chains-of-thought through self-organization. Such self-organization occurs, critically, during low demand contexts (e.g., mindwandering) and without the need for extra-systemic homunculi control, as well as during high contextual demands (i.e., on-task thoughts, constructive thinking (Watkins, 2008)).

Interactions of low contextual demand for focused attention and affect.

As described above (see *Model components*), affect also influences selection of internal content by biasing selection in favor of affect-congruent thought content. Therefore, when negative affect is triggered (*Time t*), it biases subsequent (*Time t+1*) selection in favor of (negative) affect-congruent representations (e.g., negative thoughts about oneself). If a negative representation is selected into WM (*Time t+1*), then this may further bias selection of negative affect congruent representations, potentially resulting in a spiral of repetitive negative thinking driven by the feedback from representations in WM and affect into selection and so on (Whitmer & Gotlib, 2013) (see ~90sec timepoint in Figure 5B). Here again, the stochastic element has an important and potentially adaptive function. In this type of low-demand context, a negative thought-affect spiral may only be exited – meaning that the self-sustaining feedback loop may be disrupted/stopped – due to random selection of non-negative thought content which terminates the current cycle of repetitive negative thinking. Alternately a change in contextual demands may also lead to an exit from the self-sustaining state of the system (see *High-demand context* above).

Accounting For Maladaptive Internally-Directed Cognition Using A2T

A2T may have a variety of applications and implications for better understanding and accounting for a variety of forms of IDC, such as dynamics of spontaneous thought, the temporal relations between context, cognition and emotion, and individual differences in mindwandering and cognitive control (Axelrod et al., 2017; McVay & Kane, 2012; Pessoa, 2008; Schweizer & Dalgleish, 2016). Likewise, and critically, comparing and contrasting A2T model simulation findings to key empirical phenomena and empirical findings provides a powerful process of examination and potential validation of the theory and model (Borsboom et al., 2021; J. M. Epstein, 2008). Here, we focus on the application of A2T to account for the emergence of- and individual

differences in- maladaptive IDC implicated in the development and maintenance of prevalent forms of mental health problems (Hong & Cheung, 2014; Mansell & McEvoy, 2017; Marchetti et al., 2016) (see Figure 7 for illustration).

Common forms of maladaptive IDC include negative thinking, rumination and worry (Borkovec et al., 1983; Ehring & Behar, n.d.; Ehring & Watkins, 2008; Nolen-Hoeksema & Morrow, 1991), emotion (dys)regulation (Sheppes et al., 2015), cognitive fusion and reactivity (Bernstein et al., 2015), cognitive biases such as interpretation bias (Everaert et al., 2014, 2020) and impairments in cognitive control secondary to negative emotional information in working memory (Grahek et al., 2018; Joormann & Gotlib, 2008) or dyscontrol over episodic memory (Engen & Anderson, 2018; Hitchcock et al., 2018). These forms of maladaptive cognition are characteristically *internal* (focus on thought content and thinking styles), *temporal* (how thought content and style is expressed over time), *affective* (how thoughts invoke affect and vice-versa) and *selective* (e.g., why only specific content becomes repetitive or difficult to disengage from) (Amir et al., 2021; Fox et al., 2018; Harvey et al., 2004; Koster et al., 2011; Nolen-Hoeksema et al., 2008; Siemer, 2005). Accordingly, exploring how the dynamic system of internal attention may subserve these common forms of maladaptive IDC may help illustrate potential applications and implications of the A2T model; and, in turn, provide empirical validation of the theory and model by contrasting simulation findings from A2T to empirical and experimental observations of (mal)adaptive IDC such as negative repetitive thinking, cognitive (dys)control, and interpretation bias (Borsboom et al., 2021; Grahek et al., 2021).

Figure 7. Examples of the role of internal attention in various forms of higher-order (mal)adaptive internally-directed cognition implicated in mental health. The text in the overlap between internal attention (center) and each form of internally-directed cognition (outer circles) delineates the attentionally-driven lower-order processes theorized to subserve each higher-order internally-directed thinking process.

Repetitive negative thinking

Repetitive negative thinking has been conceptualized as a style or process of thinking characterized by negative and repetitive thoughts which are experienced as intrusive and difficult to disengage from (Ehring et al., 2011; Ehring & Watkins, 2008). Repetitive negative thinking, as well as related processes of rumination and worry, predicts negative outcomes including momentary negative emotions and, over time, the onset of depression as well as post-traumatic stress and generalized anxiety disorders (Hirsch et al., 2018; Watkins, 2008).

Repetitive negative thinking in A2T.

In A2T, repetitive negative thinking will be initiated, typically, when a negative representation (thought) is selected into WM in a state characterized by low contextual-demands for sustained focused attention. This representation then triggers or increases negative affect. Consequently, both the representation and affective state bias subsequent selection in favor of content- and affect- congruent thoughts (e.g., “Bad things always happen to me.”). This then triggers the same process of selection in favor of negative content and so the same process repeats itself through feedforward (Figure 1A paths *b* and *c*) and feedback (paths *d* and *e*) between internal attentional selection, representations in WM and affective state. Here, the stochastic element in internal attentional selection is functionally critical. Indeed, the stochastic element enables ‘random exits’ from repetitive negative thinking – selection of non-negative content breaking or attenuating the feedback loop (see Figure 8B time point ~240sec). Without a random element the model becomes overly rigid, determining that once a RNT state initiates it cannot terminate (except when contextual demands change and focused attention to task-relevant information is required).

Individual differences in RNT. As described above, the strengths of causal links between contextual demands, representations in WM and internal attentional selection (paths *a* and *d*;

Figure 1A) are assumed to be constant between people. The exception to these are two important paths we believe are crucial for accounting for individual differences, especially when modelling individual differences in maladaptive thinking and maladaptive trajectory likelihoods – (affective) *reactivity to representations in WM* (path *c*) and (attentional) *reactivity to affective state* (path *e*). Critically, these two paths constitute the closed feedback loop from WM onto affect and then back onto internal attentional selection. Therefore, individuals with higher levels of reactivity have a stronger feedback loop, increasing the likelihood of a self-sustaining state of biased selection of negative representations and heightened negative affect. Figure 8 illustrates simulated differences between models/individuals with moderate (Figure 8A) and high (Figure 8B) reactivity to representations in WM and to affective state. As can be seen, higher reactivity levels increase both (a) the frequency of entering- and (b) average duration of- states of repeated selection of negative content into WM and related increase in negative affect. Interestingly, research has shown that repetitive negative thinking depletes WM resources (i.e., capacity) and accordingly hypothesised that (internal) attention subserves this effect (Curci et al., 2013; Hayes et al., 2008). A2T's closed feedback loop between internal attention and WM and affect, and the simulations demonstrating its impact on frequency and duration of repetitive negative thinking, may help to explain and account for these effects of repetitive negative thinking on WM capacity.

Figure 8. Simulated differences between cognitive and emotional reactivity level (Moderate = 0, High = .25). Contextual demand for sustained focused attention is set to low (= 2). All other initial component values are equal to those used for Figure 5A. RNT = Repetitive negative thinking.

Summary: Repetitive Negative Thinking in A2T

Critically, A2T predicts that RNT is most likely to emerge under conditions of low contextual demands for focused attention (Seli et al., 2018). A2T also illustrates how the phenomenon of RNT may be occasionally experienced by more or less any person, and not likely a byproduct of malfunction or disorder per se. Furthermore and importantly, A2T also provides a formal theoretical account for individual differences in the frequency and duration of RNT episodes; and predicts that these differences are a function of reactivity to thought content and (negative) affective states (Smallwood et al., 2009). A2T thus provides a dynamic systems account for how the process of RNT may emerge from the temporal interactions of low-level cognitive-affective processes. The model also explains why, once negative affect is activated, it is difficult to interrupt this process. In general, these predictions are in-line with research showing that RNT both influences- and influenced by- negative affect (Curci et al., 2013; Poerio et al., 2013; Ruby et al., 2013) and may be expected to function as transdiagnostic process that cuts across emotional disorders (Ehring & Behar, n.d.; Ehring & Watkins, 2008).

Cognitive (dys)control

Cognitive control refers to the ability to flexibly adapt cognition and behavior to current goals, often used interchangeably with executive control and executive functions (Grahek et al., 2018). Cognitive control accordingly entails various cognitive abilities including inhibiting prepotent or dominant responses and updating and shifting between contents of WM. Cognitive control deficits have been observed in mood disorders and accordingly play central roles in cognitive models of depression and anxiety (Eysenck, Derakshan, Santos, & Calvo, 2007; Grahek et al., 2018). However, it is not clear whether this deficit is specific to control over emotional

information or is domain-general (i.e., neutral) (Grahek et al., 2018; Zetsche, Bürkner, & Schulze, 2018).

Cognitive (dys)control in A2T.

Cognitive control and the component of contextual demands for focused attention are closely related. Both serve the same function – prioritizing the processing of task-relevant over irrelevant information (Buetti & Lleras, 2016; Seli et al., 2018). More precisely, we conceptualize cognitive control as a dynamic behavior which emerges from the moment-to-moment competition between the effort to maintain attention on task-related information vs. the capturing of attention by salient but task-irrelevant information. Accordingly, in A2T, cognitive control is conceptualized as the moment-to-moment competition (or differential influences) between the effects of contextual demands vs. the effects of representations in WM and affect on internal selection likelihoods (see also Wegner, 1994; Wegner, Erber, & Zanakos, 1993). This means that successful control is a state in which the contextual demands component out-weighs/influences other factors, and vice-versa with respect to control failure (Awh et al., 2012). For example, following a highly arousing but task-irrelevant spontaneous memory (e.g., a car accident), the prepotent response is to continue analyzing information related to that memory (e.g., other memories from the event) (Klinger, 2013; McVay & Kane, 2013). However, the contextual demands signal may be strong enough to bias selection to task-relevant-, and memory event unrelated-, information driving a state of cognitive control (McVay & Kane, 2013).

Furthermore, A2T assumes that the influence of contextual demands on focused attention, relative to other components of the model, should be more stable and persist over longer time periods. Whereas thoughts (representations in WM) and their influence decay in seconds, due to constraints of short-term memory, contextual demands for sustained attention should persist for

longer time periods. For example, the instructions and motivation to optimally perform on a demanding task is likely to remain the same for the duration of the task. The facilitation or interference of stimulus-driven signals (representations in WM and affect), rather than the momentary ability to exert focused attention (the sustained cognitive control/inhibition over distracting information), is what changes from moment-to-moment. Thus, momentary changes in cognitive control are **due to changes in stimulus-driven signals rather than fluctuations in goal-directed signaling** (McVay & Kane, 2012). This may seem trivial, but often in the cognitive control literature, if cognitive control fluctuations are not due to stimulus-driven fluctuations, then failures must be attributed to a sub-component of cognitive control – i.e., a “homunculus” control component (Baddeley, 2011; Everaert, Grahek, & Koster, 2017). The proposed A2T model enables examining the stability of cognitive control (or conversely failures) as frequency of momentary states of attention directed towards/away from task irrelevant information (i.e., task-unrelated thoughts) – as a function of the different states in context and individual differences of low and high reactivity. Importantly, A2T provides a conceptualization and computational operationalization of cognitive control without an extraneous/homunculus control mechanism (Hazy, Frank, & O’Reilly, 2007). Temporal fluctuations in (dys)control emerge from the complex temporal interactions of the low-level components of the A2T model, as well as the inherent stochasticity in internal attention selection and individual differences in feedback paths representing cognitive and affective reactivity.

Individual differences in cognitive (dys)control. In addition to contextual demands, the momentary changes in selection bias likelihoods are also determined by affect, representations in WM and reactivity paths, as well as the stochastic element of internal selection. Figure 9A illustrates how a simulated model with high reactivity has random elevations or spikes in selection

likelihood of bias to negative task-unrelated representations, even under high contextual demands for focused attention. Moreover, the model predicts that when the *task-relevant information is negatively-valenced* and inevitably selected into WM, such information/representation in WM increases the probability of subsequent selections of *affect-congruent but potentially task-irrelevant* information (McVay & Kane, 2013). This likely leads to greater frequency of cognitive control failures in the form of attending to task-unrelated thoughts. This prediction is in-line with a number of observed phenomenon, such as the Emotional Stroop effect, wherein the naming of emotional, versus neutral, words is slowed (Williams et al., 1996). A2T provides an alternative, task-unrelated thoughts-based account, of the effect (cf. conflict-based account of Stroop effects) (Algom et al., 2004). Likewise, these A2T predictions are also in line with findings of increased task-unrelated thoughts and impaired external attention performance following (task-embedded) personal concern cues (McVay & Kane, 2013).

The ability to sustain attention on task-related information, in the presence of emotionally evocative task-relevant information, is crucial for functioning in various situations. For example, being able to focus in the presence of stressors, such as performing well during stressful interviews. A more extreme example are ‘first responders’ who need to focus in the presence of potentially traumatic scenes. Figure 9B illustrates how high reactivity, together with negatively-valenced task-relevant information, increases the selection bias to negative representations (as the context requires) but has a stronger impact on variability and mean negative affect. As such, individual differences in strength of critical paths – from representation in WM to affect and from affect to internal attentional selection – help to explain previously observed deficits in cognitive control over negatively valenced information in individuals vulnerable to depression and anxiety (Grahek et al., 2018; Hertel, 1997; LeMoult & Gotlib, 2018; Schweizer et al., 2019).

Accordingly, A2T diverges from theories that propose domain-general, rather than affect-specific-, impairment in cognitive control in depression or anxiety (Grahek et al., 2018; Joormann & Gotlib, 2010). Indeed, there is mixed evidence regarding the presence and temporal stability (e.g., during major episodes, remission, etc.) of these impairments in externally-directed cognition (Keller et al., 2019; LeMoult & Gotlib, 2018). Furthermore, evidence for domain-general impairment is even weaker in WM tasks (i.e., more internal- than external- directed cognition) (LeMoult & Gotlib, 2018). Critically, control failure effects in WM tasks are largest when attention is not entirely constrained to the task – i.e., in A2T terms, when contextual demands are low, and so feedback paths of cognitive and affective reactivity have greater relative influence on internal attentional selection (see *The effects of low contextual demands* and *Repetitive negative thinking* sections above) (LeMoult & Gotlib, 2018).

Summary: Cognitive (Dys)control in A2T

The A2T conceptualization of cognitive (dys)control and computational simulations offer a number of insights. For example, when studying the interactions of cognition and emotion on cognitive (dys)control, aggregating performance across time (e.g. across an entire task or task-block) may fail to capture the key signal/effects (Algom et al., 2004). Rather, it may be more conceptually accurate to make hypotheses and empirical tests on the momentary temporal level – e.g., to examine momentary affective changes as both antecedents (predictors) and consequences (outcome) of momentary control failures and vice-versa (Ruby et al., 2013; Ruimi et al., 2018; Smallwood & Schooler, 2015).

Figure 9. Simulation of trajectories under high-contextual demands ($= 4$) and high emotional and cognitive reactivity ($= .25$). In Figure 10A all task-relevant information is neutrally valenced. In Figure 10B, half the information is negatively valenced (e.g., memorizing a list of mixed negative and neutral words).

Interpretation bias

Interpretation bias is the tendency to interpret ambiguous information as negative. Such biases are associated with depression and anxiety as well as other forms of cognitive biases (e.g., memory bias; (Everaert et al., 2014)) and vulnerabilities (e.g., repetitive negative thinking; (Everaert et al., 2020; Hirsch et al., 2018)). Accordingly, interpretation bias is a primary target for many psychological treatments for depression and anxiety as well as emerging cognitive training methodologies (Everaert et al., 2017; Hirsch et al., 2018). Notably, a core feature of interpretation bias is the preferential selection of one interpretation over competing resolutions to ambiguous information (Gernsbacher & Faust, 1991).

Interpretation bias in A2T

The process of interpretation bias is, by definition, triggered by information that is ambiguous or may be alternatively interpreted. Various interpretations of such an ambiguous situation and subsequent thoughts compete for selection (Everaert, 2021). In A2T, the specific interpretation selected (e.g., negative, positive or neutral) is determined by the selection likelihoods (at *Time t*) influenced by the immediately preceding state of the system – such as the active representations in WM and affective state (at *Time t-1*). For example, imagine a person arriving at a social event and greeted by the host who has an ambiguous non-verbal expression (e.g., facial expression, body posture). If the person arrived with negative expectations (in the form of negative thoughts/content in WM) and/or in a negative mood, this then increases the likelihood that negative interpretation is selected for further processing (Davey et al., 2006), i.e., entering WM and reaching awareness. That is, people with *active* negative expectations/beliefs are more likely to demonstrate negative interpretation biases. This prediction is, however, in contrast to current perspectives on the roles of priming (whether conscious or unconscious, and conceptually

similar to path d in the Figure 1A) and affect as outcomes rather than causes of biased interpretations ((Mathews, 2012); but see (Halberstadt, Niedenthal, & Kushner, 1995) for evidence on the effects of affect on interpretation bias). To reconcile this disparity, we again highlight that the model emphasizes the transaction that unfolds from moment-to-moment in time (see Fig 1B) between attention, WM and affect – i.e., they are reciprocal and circular causes- *and* outcomes- of one another in time. These A2T predictions are in line with recent findings (Everaert, 2021) and emerging theory regarding the interacting roles of multiple cognitive (attention, WM) biases in driving interpretation biases (Everaert et al., 2020).

A2T and Maladaptive Internally-Directed Cognition: Summary

A2T offers a single, unified explanatory framework for the emergence of various forms of (mal)adaptive IDC including common forms of maladaptive thinking. A2T delivers a computational account and basis to simulate the theorized dynamic system underlying IDC. Thus, A2T not only *describes* what internally-directed cognitive processes may become dysregulated but also provides a *computational* framework for how dysregulation emerges from what is also a normative/adaptive system. This enables quantifying trajectories of the A2T model under key differential conditions (i.e., contextual and individual differences factors) and comparing to empirically observed phenomena of interest.

Future directions

This paper lays out our initial efforts to use the A2T model to better understand the role of internal attention in (mal)adaptive IDC. Future work applying, testing, and further developing A2T could focus on a number of key questions and directions. First, A2T may help generate more refined hypotheses and quantitative predictions regarding the function of internal attention in IDC (Borsboom et al., 2021; Grahek et al., 2021; van Rooij & Baggio, 2021). A2T's computational

framework enables simulating specific contexts and individual differences and their interactions. In turn, such simulations enable testing the overlap between simulated and empirically observed phenomena including behavior (van Vugt & van der Velde, 2018). Such computational approaches have been utilized in research fields such as decision making (Daw et al., 2006) and external attention (Logan, 2004) and helped refine related theories through an iterative process of (mis)matching theoretical predictions, simulated data and observed behavior (Muthukrishna & Henrich, 2019). Using A2T, this type of computational approach may serve to iteratively refine theory and our understanding of internal attention and (mal)adaptive IDC in the coming years.

It is therefore important to reiterate that A2T is a *formal* model that adopts dynamic systems approach; but is not a *data* model. A2T provides specific predictions/hypotheses about the behaviour of IDC under different contexts and individual differences; but is not specifically designed for parametric fitting to experimental data. While this may be possible given well-matching data (e.g., high temporal resolution experiential momentary assessments) it was not the aim when developing A2T. Accordingly, support for A2T is currently limited to simulations demonstrating previously empirically observed effects and behaviours (e.g., high mindwandering under low contextual demands), and A2T's significant value lies in its potential for providing theoretically plausible (van Rooij & Baggio, 2021) common framework for various expressions of (mal)adaptive IDC.

A second inter-related future direction for theory and A2T model development is the examination, refinement and further elaboration of specific model components and pathways. For example, in this report and instantiation of A2T, the proposed computational formulation assumes that WM storage capacity (of 5 items) is similar across individuals. However, there are meaningful differences between individuals in their WM capacity (Kane et al., 2007). Furthermore, such

differences in capacity have been theoretically and empirically linked to individual differences in key processes such as attentional control and emotion regulation (Coifman et al., 2019; Kane et al., 2007). Future work may further specify individual differences in A2T's WM component to simulate and test their salutary and/or maladaptive effects on trajectories of the dynamic system (Welhaf et al., 2019). Furthermore, for conceptual and computational application and simplicity, we separated internal attentional and WM into selection and short-term storage functions, respectively. However, internal attention and WM are highly inter-related processes (see *Working memory & internal attention* section). Future work may thus incorporate more elaborate rules for how these processes interact and accordingly produce more elaborate simulation events. For example, we adopt a “winner takes all” approach for the filtering/gatekeeping function of internal attention into WM. However, A2T may be modified for attenuator accounts (Treisman, 1964; Yantis & Johnston, 1990) of how internal attentional selection passes information on to working-memory. Furthermore, although we focused here on *negative* affect in this first instantiation of A2T, *positive* affect and related working memory representations may also be readily integrated into the model.

Likewise, future A2T development may explore factors or intervention strategies that modulate inter-component pathways, in particular those that contribute to or determine individual differences in (affective) *reactivity to representations in WM* and (attentional) *reactivity to affective state*. This is important in order to account for not only individual differences in the strength these model (reactivity) pathways but also to help account for individual differences in IDC that emerge from the model (e.g. vulnerability for maladaptive IDC). A great deal of work points to promising extraneous factors such as genetic heritability (Smoller et al., 2019) for maladaptive thinking styles (du Pont et al., 2019) and learning history such as exposure to adverse

life events (Mansueto et al., 2021; Masten, 2001). Such individual difference factors can be formally incorporated into A2T and modeled as critical determinants of the strength of these model (reactivity) pathways. A similar approach can be adopted to explore how various intervention approaches may modulate – inhibit or activate – the strength of these pathways to impact reactivity and thereby the emergence of (mal)adaptive IDC.

Third, A2T model components and pathways could also be adapted so as to be applied to a variety of additional phenomena characterised by IDC that unfold in time. For example, A2T may be applied to model variability in moment-to-moment focus of attention during mindfulness meditation. Mindfulness meditation is a practice in which attention is effortfully directed to the person's internal experience in the present moment. Interestingly, in such a practice, the term “internal” is typically defined in a broader sense than we adopt here and includes attention to interoceptive and bodily sensations (Dixon et al., 2014; Lutz et al., 2015). For example, in focused attention meditation, a common practice entails “anchoring” attention to some sensory-perceptual object such as one's breath (Lutz et al., 2015). To better understand how attention unfolds during such mindfulness practices, A2T may be used to model and simulate how internal attention drifts to thoughts and feelings (i.e., effects of affect and stochasticity of internal attentional selection) as well as volitional orienting attention back to one's breath sensations (i.e., effects of contextual demands for focused attention) over the course of mindfulness meditation (Hadash et al., 2021; Hadash & Bernstein, 2019). To permit such applications, A2T may be generalized in a number of ways, such as by adding interoceptive- and sensation-based information as competing objects for selective attention; or by accounting for meta-cognitive monitoring processes such as meta-awareness by integrating present moment processes in awareness (e.g. thinking, feeling, hearing) as competing objects for selection into WM (Bernstein et al., 2015; Dunne et al., 2019; Ruimi et

al., 2018; Smallwood, 2013a). Interestingly, meta-awareness may itself be conceived as an emergent form of IDC and accounted for by A2T. From the perspective of A2T, meta-awareness emerges from repeated internal attentional selection of present moment processes (e.g. thinking) in awareness, as opposed to the contents (e.g. thought content) of awareness (Bernstein et al., 2015). Such applications of A2T may be able to provide a computational account for the emergence of meta-awareness and its effects (e.g., disengaging from mindwandering) and in turn mindfulness meditation (Hadash et al., 2021; Hadash & Bernstein, 2019; Smallwood & Schooler, 2015).

Fourth, A2T may help us in thinking about how we conceptualize and formulate phenomena of interest, what important questions should be addressed, and accordingly what methodologies should be developed to answer these questions (Muthukrishna & Henrich, 2019). One key methodological challenge facing the study of IDC is the capacity for controlled experimental study and measurement of internal attentional processes (Amir et al., 2021; M. Posner, 2016). Whereas the methodological paradigm used to measure and quantify external attention allow for experimental control over the content, timing and location of external (e.g., visual) stimuli, such control has been largely enigmatic for the study of internal events (e.g., thoughts) (Amir et al., 2021; M. Posner, 2016). WM tasks enable objective measurement of the processing of internal information, but lack the capacity to sufficiently disentangle storage and attentional processes (Atkinson et al., 2018; Baddeley, 2011). For example, Amir, Ruimi and Bernstein (2021) developed the Simulated Thoughts Paradigm to deliver idiographic stimuli that simulate the *content* and the *experience* of one's own verbal thoughts; and then embed these simulated thought stimuli in established attentional tasks so as to quantify internal attentional processes (e.g., internal selective attention bias, attentional disengagement from thoughts). We

believe that similar methods designed to deliver experimental control over phenomenologically-valid stimuli that simulate internal experiences (e.g., imagery, autobiographical memories) may be critical to advance the study of internal attention broadly and utility of A2T more specifically (see also Engen & Anderson, 2018; Nobre & Stokes, 2019).

A related methodological challenge facing the study of IDC relates to the temporal resolution of measurement methods used to quantify attention, working memory and emotion. Indeed, typical current behavioral methodologies are not designed to quantify dynamic processes with high temporal resolution, but rely on aggregated estimates of such processes by collapsing across repeated measures (e.g., trial-level) data (Zvielli et al., 2015) or rely on less intensive measurement epochs (Smallwood & Schooler, 2015). Yet, A2T and simulations illustrate the importance of low-level moment-to-moment processes in understanding (mal)adaptive IDC. Accordingly, one future direction may focus on measuring and quantifying processes of interest, such as attention and working memory, as dynamic processes from moment-to-moment in time (e.g., trial-to-trial, continuous real-time) (Amir et al., 2016, 2021; Schwartz & Stone, 2007). Such efforts may also be facilitated by integration of continuous real-time multi-modal measurement technologies (e.g., eye-movement, pupil dilation, peripheral psychophysiology, electrophysiology, real-time functioning imaging technologies). A second approach to this challenge could explore down-scaling of A2T simulation data to quantify ‘meta’-parameters (e.g., aggregated mean selection bias, aggregated mean negative affect, proportion of task-unrelated to task-related thoughts) – to better match the lower temporal scale of common current repeated-measures behavioral methods (Ruby et al., 2013). For example, A2T simulation data may be aggregated (e.g., mean, variability) over longer (e.g., 10-minute) temporal epochs (e.g., see Figure 8A & B). This approach could, for example, enable estimates of the aggregated probability/frequency and

duration of IDC processes, such as mindwandering episodes, as a function of context demands and individual differences in reactivity. Such meta-parameters could then be more directly contrasted with, for example, intensive experience sampling data (e.g., thought probes over a 10 minute epoch) (Smallwood & Schooler, 2015; Welhaf et al., 2019) or cognitive-experimental behavioral task data (e.g., aggregated attention bias estimates over a 10 minute epoch).

Summary

In summary, Attention-to-Thoughts (A2T) is a dynamic systems and computational model of internal attention in (mal)adaptive IDC. A2T implicates internal attention at the functional center of a dynamic system of inter- and trans-acting cognitive and affective processes subserving IDC. Critically, A2T reflects the dynamic temporal nature of IDC through the conceptualization and computational formalization of the interactions of system components in time. Simulations over time of the model help to demonstrate how various forms of IDC (e.g., mindwandering, stream of thought) emerge from moment-to-moment interaction of A2T system components. A2T may also help to understand how various forms of maladaptive IDC (e.g., repetitive negative thinking) and thereby mental health problems emerge from the very same system that also subserves adaptive cognition. We hope that A2T may contribute to growing field-wide interest in internal attention as well as the promise and significance of research that seeks to conceptually and computationally reflect the dynamic complexity of mental phenomena that characterize human mental life.

Conflicts of Interest statement

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