Modeling the Dynamics of Goal Pursuit: A Scoping Review of Computational Approaches

Abstract

Computational modeling offers substantial promise for advancing goal pursuit theory by translating verbal psychological theories into more precise, testable mathematical formulations. However, the current integration of computational methods into goal pursuit research remains limited and fragmented, with no existing reviews synthesizing its applications. We conducted a systematic scoping review mapping computational models of goal pursuit, theoretical and methodological trends and identifying avenues for future research. We identified 23 peer-reviewed studies employing computational methods using empirical data. Studies developed models drawing on a diverse range of theories and cognitive architectures, including control theory (n = 14), social cognitive theory (n = 7), expectancy-value frameworks (n = 7), and adaptive control of thought—rational (n = 2). Models primarily aimed to understand performance (n = 9), goal prioritization (n = 9), motivation underlying goal selection (n = 3), and goal revision (n = 2). Methodologically, most studies used laboratory experiments (n = 18), though some incorporated longitudinal datasets from field studies (n = 6). Significant theoretical gaps exist regarding real-world goal pursuit, goal flexibility processes, and intersections between goal pursuit dynamics and mental health. Future research should focus on developing integrative computational frameworks capturing inherent dynamic and adaptive complexities of goal pursuit.

Keywords: Computational modeling, goal pursuit, self-regulation, dynamic processes, scoping review

Acknowledgement of Funding:

The author(s) received no financial support for the research, authorship, and / or publication of this article.

Public Significance statement:

This review looks at studies that have used computational models to understand how people strive for their goals. We show that such modeling can help improve theories and address confusing ideas. It can also deepen our understanding of how to predict performance, and how people choose which goals to focus on, adjust their goals when needed, and how their motivation affects which goals they pick. We suggest that future research should use this modeling to explore how people know when to change or abandon their goals, and how emotions and mental health affect goal pursuit, so that we can design better ways to help people reach their goals.

Modeling the Dynamics of Goal Pursuit: A Scoping Review of Computational Approaches

Goal pursuit is a fundamental psychological process that underpins performance, mental health, and a sense of meaning across various life domains, including health, professional success, relationships, and broader personal aspirations (Brandstätter & Bernecker, 2022; DeYoung, 2015; Vervaeke & Mastropietro, 2024). Although considerable progress has been made in developing theoretical frameworks to explain and predict goal pursuit, capturing its inherently dynamic and adaptive nature remains a significant challenge. The complexity of investigating goal pursuit arises, in part, from its multifaceted nature, encompassing processes such as goal setting or selection, feedback and evaluation processes, decision-making in prioritizing multiple goals, consideration of underlying motivational factors, and the dynamic revision of goals based on evolving circumstances and personal experiences.

In this paper, we describe computational modeling (i.e., using mathematical models to represent, predict, and understand psychological phenomena) as a promising approach to addressing these challenges (Vancouver, 2005; Vancouver et al., 2005). Specifically, we argue that computational modeling advances scientific research by compelling researchers to precisely define constructs and simulate predictions, thereby making explicit both the expected outcomes of a theory and the conditions under which a particular formalization would be supported, challenged, revised, or rejected. These attributes are necessary for advancement of the study of goal pursuit. Goal pursuit is a topic of interest across many areas including social (Louro et al., 2007), cognitive (Alister et al., 2024), educational (Lee, 2016), sport (Healy et al., 2020) and organizational psychology (Vancouver et al., 2010), neuroscience (Carlson & Crockett, 2018), health (Sezer et al., 2025), marketing (Zhu et al., 2019), machine learning (Agarwal et al., 2019), and robotics (Teimoori & Savkin, 2010). Computational modeling can therefore contribute to goal pursuit research across these fields by strengthening construct precision, clarifying theory-derived predictions, and supporting cumulative theoretical development.

Our review aims to provide an overview of existing applications of computational modeling in goal pursuit and make recommendations for future research. We believe this review is necessary for two reasons. First, while goal pursuit is a widely studied topic, computational approaches within this field are relatively underused, and many researchers interested in goal pursuit are unfamiliar with computational modeling. Modeling papers are often rather technical, making interpretation difficult for those goal pursuit researchers without strong mathematical training. This review is designed to gently introduce readers to concepts of computational modeling with the aim of making this method more widely accessible. The second reason we believe this review is necessary is because the interdisciplinary nature of goal pursuit means that several different computational approaches have been used, but no review has synthesized this (limited) body of work. This review, therefore, will attempt to consolidate these approaches and provide an overview of the key methods and frameworks, and how these modeling efforts have contributed to our understanding of goal pursuit to date. For a reader unfamiliar with computational methods, the value of this review is in seeing how existing approaches collectively formalize and test goal pursuit theory. Briefly, we aim to explore what areas of goal pursuit have been studied using computational methods, identify how such methods have advanced knowledge in goal pursuit, and identify future opportunities for using these methods in goal pursuit research. Before doing so, we provide a brief overview of both goal pursuit and computational modeling.

Overview and Challenges in Goal Pursuit

In this section, we provide a brief overview of goal pursuit and define its key concepts. We summarize common questions or issues the extant research typically addresses and highlight key barriers to theorizing.

Goals are commonly defined as cognitive representations of desired states that a person is committed to attaining or maintaining (Austin & Vancouver, 1996; Ecker, 2024; Milyavskaya & Werner, 2018). The goal construct is complex and broad (Carver & Scheier, 1998), as humans pursue goals in many domains, and specific aspects of the goal construct vary significantly from one goal to another (Austin & Vancouver, 1996). For example, goals can vary in content (i.e., the specific state or outcome an individual seeks to approach or avoid), characteristics (e.g., importance, difficulty, or specificity), and source (e.g., internally or externally imposed). Goal pursuit, in turn, refers to the process through which individuals act, monitor progress, and adjust behavior in relation to goals, including by moving toward desired states, and away from undesired states (Carver & Scheier, 1998; Milyavskaya & Werner, 2018). For the purposes of this review, a central defining lens through which we view such goal pursuit is in terms of whether individuals represented a goal, can receive or infer information about goal progress, and have repeated opportunities to adjust effort, performance, prioritization, or motivation for goals over time. This scope includes both bounded goals pursued over relatively brief or specific time periods (e.g., during laboratory sessions), and longer-term or ongoing goals maintained, adjusted, or disengaged from over extended periods of time such as weeks, months, or even years (Brandstätter & Bernecker, 2022; Milyavskaya & Werner, 2018; Milyavskaya & Werner, 2025)

Although research on goal pursuit tackles a multitude of questions, many can be loosely placed into four categories: (1) issues arising from balancing multiple goals and the need to prioritize resources between them (Neal et al., 2017); (2) the influence of motivation in determining the goals we select and persist in pursuing (Ntoumanis & Sedikides, 2018); (3) the processes underpinning how we revise our goals (Brandstätter & Bernecker, 2022), and (4) factors or processes related to predicting goal progress or performance (Vancouver et al., 2005). *Goal prioritization* involves the decision-making process in allocating limited resources, such as time and cognitive effort, among multiple competing goals. This process is frequently influenced by urgency, deadlines, and perceived value or risk associated with each goal (Ballard, Vancouver, et al., 2018; Vancouver et al., 2010). *Goal motives* are the underlying reasons or driving forces behind goal selection and pursuit, and are broadly split into intrinsic or extrinsic motives (Sezer et al., 2024). *Goal revision* involves the adjustment or recalibration of goals, which can occur proactively or reactively in response to new information, feedback, and shifting priorities or contexts (Gee et al., 2018). Finally, *goal progress or performance* reflects the degree to which an individual progresses towards, or achieves their intended goal outcomes, and is influenced by factors such as goal difficulty, motivation, and feedback processes (Vancouver et al., 2005). A multitude of theories exist purporting to explain these complex issues, but formulating more precise predictions requires further development, refinement, assimilation, and potentially rejection of some existing theories.

Theoretical development in goal pursuit is impeded by two central barriers. The first is limited prediction precision, particularly when theories describe dynamic processes. Verbal theories, while useful for conceptual understanding, frequently provide qualitative predictions that limit their explanatory and predictive power. This problem is not unique to goal pursuit; long-standing critiques of psychological theory have argued that when theories generate verbal predictions, many different empirical findings can appear consistent with the same theory (Broers, 2021; Meehl, 1978; Yarkoni & Westfall, 2017). To use simplified examples, a verbal theory might predict that people prioritize goals more as deadlines approach (Ballard, Vancouver, et al., 2018; Steel & König, 2006). Yet, such statements do not specify precisely when or how quickly this change in prioritization occurs, how it varies between individuals, nor its boundary conditions. Similarly, a theory may suggest that increased perceived goal difficulty raise effort requirements (Richter et al., 2016), but this assertion remains ambiguous without specifying how goal difficulty quantitatively changes effort requirements—for instance, whether it increases linearly or follows a non-linear pattern, whereby it rapidly increases initially before plateauing. Such ambiguity significantly limits our capacity to empirically test, falsify, or refine theoretical predictions (Farrell & Lewandowsky, 2018).

The second major barrier is limited construct precision. The literature is often characterized by vague and inconsistent definitions of fundamental concepts, such as "goal value" "valence," or "goal difficulty". For instance, goal value has been variously defined as the anticipated reward, subjective importance, or even accumulated effort toward achieving a goal (Ballard, Farrell, et al., 2018; Biner, 1987) toward achieving a goal. Thus, the problem is not only that constructs are sometimes imprecisely defined, but also that different studies may define the same construct in precise but non-equivalent ways. These inconsistencies complicate meaningful comparisons across studies, obstruct rigorous theoretical testing, and hinder progress toward more comprehensive, integrative theories (Farrell & Lewandowsky, 2018).

Role and Overview of Computational Modeling

Computational modeling has emerged as a valuable methodology that directly addresses these barriers. Unlike verbal theories, computational models translate psychological concepts into more precise mathematical formulations, reducing ambiguity and enabling clearer communication of theoretical assumptions (Guest & Martin, 2021). These formalizations offer several advantages that have been discussed extensively in the broader literature (Crüwell et al., 2019; Csaszar, 2019; Guest & Martin, 2021; van Rooij & Baggio, 2021).

The first advantage is that computational models clarify the meaning of constructs by specifying their relations in explicit quantitative terms. For example, many theories of goal pursuit incorporate the concept of "expectancy," defined as a *goal's difficulty* or *the likelihood of achieving a goal* (e.g., Louro et al., 2007). However, such representations leave important questions unanswered: What specific factors determine the probability of success? How does this probability change over time as progress is made and deadlines approach? A computational approach resolves these ambiguities by forcing researchers to define constructs more precisely. For instance, in one of the earliest formalizations of expectancy, Vancouver and Schmidt (2010) mathematically operationalized expectancy as the discrepancy between the *time available* to achieve a goal and the *time required* to achieve it. This formulation was simple, but *unambiguous*, enabling empirically testable quantitative predictions. Crucially, this definition provided essential building blocks for the development of more sophisticated formalizations, accounting for a wider range of scenarios (Ballard, Yeo, Loft, et al., 2016).

A second advantage of formalizing theories with computational models is their ability to generate explicit quantitative predictions. Although conventional statistical models or machine learning can generate out-of-sample predictions, computational modeling particularly offers the opportunity to generate theory-driven or mechanistic predictions: Given initial conditions and parameter values, computational models simulate new data directly from theory. The model specifies how variables evolve (including any stochastic components), yielding simulated trials, time series, or choice sequences. These are not "made up" arbitrarily; rather, they follow from the theory's stated mechanisms. As a result, models do more than describe relations in observed data, they show *how* and *why* a trend or prediction emerges from precisely specified principles. By generating new data, computational models provide a direct test of whether a theory's explicit assumptions can reproduce observed phenomena.

Computational modeling does not eliminate researcher degrees of freedom but arguably complement traditional approaches to theory testing. Traditional applications of statistical methods to verbal theories require multiple layers of interpretation, translating prose into hypotheses, mapping those to tests, and deciding what patterns count as support or refutation, with each adding ambiguity. Modeling reduces ambiguity at *some* layers by forcing explicit, executable specifications, but it still involves choices about how constructs are operationalized (e.g., treating expectancy as the discrepancy between time available and time required), which can be narrow. Consequently, determining whether data supports a theory is not straightforward; it depends on the validity of the chosen operationalizations and the relative performance of alternative specifications. The comparative advantage of computational modeling is transparency and testability. Assumptions are explicit, and alternative operationalizations can be systematically tested via model comparison. In this way, modeling complements traditional approaches rather than replacing them. By triangulating across simulations, model fitting and comparison, and conventional statistical tests, researchers can distinguish claims about the underlying theory from claims about a particular implementation.

Vancouver and Purl (2017) provided a compelling example of the value of computational modeling in clarifying complex theoretical debates by comparing data generated directly from computational models with empirical data. Specifically, their work addressed contradictory predictions from control theory (Powers, 1973) and social cognitive theory (Bandura & Locke, 2003) regarding the role of self-efficacy in performance. Using computational simulations, Vancouver and Purl's simulations indicated that in ambiguous-feedback contexts, a model positing a negative effect of self-efficacy on performance provided the best fit to the data, outperforming alternatives candidate models (Schmidt & DeShon, 2010). Although non-computational studies based on social-cognitive theory have already identified conditions under which self-efficacy beliefs (e.g., Bandura, 1982, 1997) may not be uniformly or positively related to performance, computational models offered a way to formalise an account of how such effects might emerge dynamically and reconcile contrasting perspectives. Notably, Vancouver and Purl (2017) simulated a model and compared predictions with data but did not statistically fit models to the data. Models may be benchmarked using non-statistical approaches, such as demonstrating a model's sufficiency to reproduce qualitatively different behavior through model simulation (Navarro, 2019; Wilson & Collins, 2019). Alternatively, this comparison is often achieved through *model fitting*, where statistical techniques are used to estimate parameter values that result in the best fit between the model's predictions and the empirical data. Model fitting also enables comparisons between multiple plausible candidate models representing different theories or alternative models within the same theory. Such comparisons enable researchers to quantitatively assess which model provides the best explanation of the observed phenomena, which is important for theory falsification.

A third advantage of computational models is that their parameters can be meaningful by representing a psychological construct (e.g., bias, subjective value, temporal discounting) or environmental constraints (e.g., deadlines, penalties, rewards, time). Therefore, computational models are often used as *measurement tools.* Specifically, researchers will often compare parameter values across experimental conditions to evaluate how experimental manipulations affect that psychological construct. For example, Alister et al. (2024) incorporated a "deadline sensitivity" parameter into their model, to examine how cognitive load affects how people attend to goal deadlines. This parameter quantified the degree to which participants prioritized deadlines over other goal-related factors, such as subjective value or expectancy. By estimating this parameter across different within-subject conditions, Alister et al. demonstrated that participants were more sensitive to deadlines when cognitive load was high, compared to when it was low. This illustrates how computational models provide a structured way to infer latent cognitive mechanisms from behavior. However, parameter estimates should not be treated as direct or context-free measures of psychological constructs. Their interpretation depends on the model architecture, task structure, and potentially comparison with plausible alternative models. For example, a parameter interpreted as deadline sensitivity or subjective value may partly reflect the specific incentives, feedback, time constraints, or response options embedded in the task. Thus, computational models can improve construct precision, but the psychological meaning of any parameter remains tied to the context in which it is estimated.

So far, we have discussed how comparing a model to human data allows researchers to quantitatively evaluate theories and measure psychological constructs. However, computational modeling is valuable even in the absence of direct empirical data. This is particularly important in psychological research, where 'ideal' datasets are often unattainable due to practical or ethical constraints. For example, computational models of cultural evolution have been crucial for theorizing how human societies have developed complex cognitive capacities—such as goal setting—through the gradual evolution of cultural norms, language, and cooperation (Steels, 2011). Additionally, computational models can guide empirical research by identifying the most informative data to collect. By simulating competing theories, researchers can determine the key predictions that distinguish those theories and design experiments that directly test them (Ballard et al., 2021).

While in this paper we advocate for the use of computational modeling more frequently, we wish to clarify that non-computational approaches have been, and will continue to be, valuable for advancing our understanding of goal pursuit. We recognize that not all research questions can be easily formalized into mathematical equations, and we owe much of our progress in the field to date to non-computational approaches. Further, like any scientific tool, computational modeling can be misused and there are many debates within the field of computational modeling about how it should best be implemented (e.g., Navarro, 2019; Szollosi et al., 2023). Regardless, we believe that computational modeling holds many advantages for improving theories of goal pursuit.

Rationale / aims for scoping review

Despite the potential of computational modeling, its applications are limited in goal pursuit research. A key reason is that dominant theories—such as goal-setting theory, self-determination theory, and self-regulation—are still primarily verbal frameworks. These theories rely heavily on constructs articulated in broad, abstract language (e.g., “autonomy,” “goal value,” “discrepancy reduction”) without clear operational specifications or formalized relations between constructs, thus, limiting opportunities to apply computational approaches.

The perception of computational methods as complex and inaccessible is also a notable barrier to their uptake (Farrell & Lewandowsky, 2018). Accessible introductions to the technical aspects of computational modeling, including examples that model goal-pursuit and decision-making processes, are available (Ballard et al., 2024; Ballard et al., 2021; Calder et al., 2018; Knight et al., 2023). Growing recognition of the opportunities and the need to synthesize such applications has spurred reviews across psychological domains, including health behavior change

(Perski et al., 2024), psychopathology (Zavlis et al., 2025), emotions (Ojha et al., 2021), and anxiety (Yamamori & Robinson, 2023). However, no work to date has systematically reviewed and consolidated applications of computational modeling to goal pursuit. Unlike existing goal pursuit reviews, which synthesize verbal theory, or computational tutorials, which teach the technical application of computational methods, our review charts how verbal theories of goal pursuit have actually been rendered as working, testable models. Addressing this gap through non-technical reviews, such as ours, can significantly enhance the uptake and application of computational methods in the goal pursuit literature, thereby accelerating theoretical and empirical advancements. Specifically, we will address the following questions:

- What areas of goal pursuit have been studied using computational methods?
- How have such methods advanced knowledge and addressed current debates within the goal pursuit literature to date?
- What future opportunities exist for using computational methods in goal pursuit and how could such opportunities advance psychological research in general?

Methods

Our scoping review follows the updated methodological guidance for scoping review protocols (PRISMA-ScR; Peters et al., 2020; Pollock et al., 2021). The review process consists of the following steps: (1) developing research questions and objectives; (2) protocol development; (3) developing study eligibility criteria and search strategy; (4) searching for and selecting evidence; (5) extracting and analyzing evidence; (6) presenting results; and (7) summarizing the evidence. Our review protocol was pre-registered on the Open Science Framework (https://osf.io/k36g8/?view_only=8ef581fa9b304e6689475c5afcef2856).

Inclusion/Exclusion Criteria

We included articles that met the following criteria: (1) described a computational model of human goal pursuit; (2) involved experimental tasks (e.g., laboratory studies or empirical data collected in field studies); (3) were written in English; and (4) were published in a peer-reviewed journal. We excluded studies focused primarily on specific cognitive, learning, neural, spatial, or motor processes unless they modeled human goal pursuit more broadly according to the criteria below.

We included studies that modeled experimental tasks, provided they met the following criteria: (a) the task entailed a quantitative performance goal (e.g., performance on a task over time); (b) participants (i.e., goal pursuers) could track their progress toward their goal (exceptions included if progress ambiguity was a feature of the study); and (c) the task included multiple measures of progress and effort, performance, or motivation during goal pursuit (e.g., the proportion of decisions favoring one action over another). These criteria were essential for studying goal pursuit rather than isolated decision-making activities. We included studies with empirical data and computational models because this dual criterion offers an intuitive, pragmatic frame of reference for readers and allows us to demonstrate most directly how modelling can formalize theory and represent human goal pursuit. We also included studies that fit models to experimental datasets described in other articles (i.e., secondary analyses), provided the model specification and model fits were reported in the focal paper. For examples of excluded articles with supporting rationale, see the Supplementary Material.

Search Strategy

We searched the following databases: PsycInfo, PsycArticles, Medline, EMBASE, Academic Search Complete, Web of Science, Scopus, PubMed, ScienceDirect, and ProQuest. The databases were selected for their relevance to the field of psychology. In certain instances, we refined our search to specific categories within psychology (e.g., Web of Science, ScienceDirect) and decision sciences (e.g., ScienceDirect). Grey literature was not included, including conference proceedings, dissertations, and unpublished manuscripts. The full search strategy is provided in Open Science Framework. While our search terms were consistent across databases, their formatting and presentation had to be adapted to ensure accurate searches. We completed the search on February 16, 2024, and included all articles from the inception of each database to that date. We conducted an updated search on August 6th, 2025.

Screening

We adopted a two-stage iterative approach to study selection (Levac et al., 2010). First, all identified studies were uploaded to Covidence (2024), where duplicates were automatically removed, with manual adjustments made by the authors as necessary. Both screeners (TB1 and MA) independently screened the titles and abstracts of all articles to identify those potentially meeting the inclusion criteria. They then met to discuss and refine the eligibility criteria as needed and to resolve any disagreements before moving on to the full-text screening. In the second stage, both screeners independently conducted full-text screenings to determine whether the potential articles met all inclusion and exclusion criteria. Following this process, they met again to resolve any disagreements. If disagreements persisted, the research team consulted with co-authors NN and TB2 for resolution. We chose not to blind the papers, as several of the papers were authored by TB2 or colleagues of TB2 and MA, making true blinding impossible. Following double screening, TB1 manually searched references of included articles for additional papers meeting study criteria and presented candidates to MA for review.

Data Charting

Given the qualitative nature of the extracted information, identical results from double coding are unlikely. Instead, our approach aimed to ensure comprehensive coverage of relevant information presented in the included articles. To achieve this, we followed the recommendations by (Nussbaumer-Streit et al., 2023) regarding the use of a second coder for Rapid Reviews. Two coders (TB1 and MA) extracted data from 20% of the articles to validate the extraction procedure. Given agreement in this context is difficult to quantify, we do not report agreement rates. We used this process to refine our extraction methods, identify additional criteria for extraction, and train the primary coder (TB1) to ensure complete and accurate data extraction. We communicated any changes to the extraction protocol to our co-authors (NN and TB2) via email. For instance, during our double coding process, we observed substantial variation in how papers described their computational approaches. This led us to add additional extraction categories to capture details such as model simulation approaches, parameter estimation methods, model comparison techniques, and the interpretation of parameter estimates. Additionally, we chose not to extract equations from the included studies due to the significant variability in how equations were presented (e.g., some studies provided all relevant equations, while others offered few or none). Our final extraction categories included: (1) study information; (2) goal pursuit information (i.e., motivating theories and relevant goal pursuit constructs); (3) experimental data collection methods (i.e., descriptions of participant samples and empirical / experimental tasks); (4) computational methods (i.e., a verbal description of the formal model(s) and the modelling approach); and (5) author contributions and future research recommendations (reported in Table 2). A basic description of each category and its corresponding extraction criteria is provided on our Open Science Framework page. All searching, screening, inclusion / exclusion decisions, data charting, and analyses were conducted by the authors, who take full responsibility for the content.

Results

Literature Search

A total of 1228 records were identified for the title and abstract screening, of which 57 full texts were screened. An additional five articles were identified through hand-searching reference lists and author expertise, and two articles from the updated search in August 2025. We included 23 articles in this review (see Figure 1).

[INSERT FIGURE 1 HERE]

Study Characteristics

Studies were published between 2005 and 2025. See Table 1 for an overview, including the goal pursuit theory or model(s) underpinning each study, empirical data collection methods, and the computational modeling methods employed. For interested readers, we provide the full extraction table, including extensive descriptions of each study on Open Science Framework.

[INSERT TABLE 1 HERE]

Goal Pursuit Theories and Models

The reviewed studies were grounded in a diverse range of goal pursuit and self-regulation theories, as well as concepts from decision-making and motivation literatures. The most frequently reported theories and models were control theory (Carver & Scheier, 1998; Powers, 1973), typically perceptual control theory (Powers, 1973), the multiple goal pursuit model (MGPM, n = 7; Vancouver et al., 2010), social cognitive theory (SCT, n = 7; Bandura, 1986), expectancy-value theory (Kanfer, 1990; Vroom, 1964), goal setting theory (Locke & Latham, 1990), and approach-avoidance motivation theory (n = 4; Elliot & Covington, 2001). Three studies employed motivation theories, including goal-directed motivation concepts (*n* = 1; Ballard et al., 2022), self-determination theory (*n* = 1; Ryan & Deci, 2000), and achievement, affiliation, and power motivation theories (*n* = 1; Heckhausen & Heckhausen, 2008). We reflect on the most reported theories and models in the Overview of Findings below.

Experimental Paradigms

Most studies (18 of 23, or 78%) involved laboratory-based tasks. Eight of these studies required goal prioritization or trade-offs, particularly under time constraints (Alister et al., 2024; Ballard, Vancouver, et al., 2018; Ballard, Yeo, Loft, et al., 2016; Gee et al., 2018; Ott et al., 2020; Prystawski et al., 2022; Vancouver et al., 2010; Vancouver et al., 2014). The tasks were represented as games, such as an "alien planet protection" game, requiring participants to choose which of two planets (i.e., goals) to defend (i.e., prioritize), over iterative phases across trials (Alister et al., 2024). Three studies employed the SimNurse task (Scherbaum & Vancouver, 2010; Vancouver, 2005; Vancouver & Scherbaum, 2008), which simulated creating nursing schedules and required participants to optimize cost efficiency. Other studies employed tasks such as anagram-solving, ring-toss, or roulette games, and prisoner's dilemma experiments (Merrick & Shafi, 2011; Vancouver & Purl, 2017). Two studies (Corgnet et al., 2018; Zhou et al., 2019) featured tasks involving team management or group coordination, simulating goal attainment within social (e.g., work or leadership) contexts, such as a catering team. One study (Aenugu & O'Doherty, 2025) used a suit-matching task to explore goal overpersistence due to accrued progress.

Additionally, six studies collected field study data —such as longitudinal datasets or real-world behavioral goals—to examine goal pursuit processes over extended periods (Ballard et al., 2022; Banerjee et al., 2024; Pirolli, 2016; Pirolli et al., 2017; Vancouver et al., 2018; Zhang et al., 2019), ranging from 28 days (Pirolli, 2016; Pirolli et al., 2017) to 48 months (Vancouver et al., 2018). For example, Pirolli (2016) and Pirolli et al. (2017) used data from mobile health application-based studies where participants tracked daily goal success of self-selected health goals (e.g., healthy eating, walking). Ballard et al. (2022) complemented laboratory tasks with National Basketball Association data. These studies provided insights into real-world dynamics of goal setting, motivation change, and performance.

Computational Modeling Approaches

Ten studies described developing a particular computational model. Typically, each of these models extended previously developed computational models. For example, Scherbaum and Vancouver (2010) extended the computational model reported in Vancouver et al. (2005) and Vancouver and Scherbaum (2008). Four studies developed and compared two competing models (Neal et al., 2022; Vancouver et al., 2005; Vancouver & Scherbaum, 2008; Vancouver et al., 2018). For example, Vancouver et al. (2005) compared models representing two control theory approaches. Nine studies developed multiple models, allowing for testing competing explanations of goal pursuit processes.

A substantial subset of studies (*n* = 7) explicitly used or extended the Multiple Goal Pursuit Model (MGPM; Vancouver et al., 2010), a formalization of goal pursuit that integrates expectancy-value theory, control theory, and dynamic decision-making processes in prioritizing between two (or potentially more) goals under varying conditions. These MGPM-based studies typically focused on resource allocation, effort prioritization, or decision-making under constraints, and often fitted multiple variants of the model to assess competing explanations for goal prioritization and adaptation (e.g., Ballard et al., 2016; Alister et al., 2024). Three studies extended perceptual control theory, predominantly focusing on the role of the regulation of perception in performance contexts. Two studies employed the ACT-R cognitive architecture (e.g., Pirolli, 2016; Pirolli et al., 2017), which formally implements memory activation, decay, and reinforcement as explicit process-level mechanisms within a modular, neurocognitively plausible system.

Several models were ‘standalone’, meaning they did not explicitly extend any other model in our included studies. For example, Prystawski et al. (2022) and Ott et al. (2020) formalized decision-making under resource constraints, similar to Alister et al. (2024), but developed distinct classes of models grounded in different theories such as resource-rational analysis and bounded optimality, rather than building on the MGPM. Other studies drew on previous modeling but formalized different theories. For example, Zhang et al. (2019) developed a dynamic model formalizing self-determination theory to simulate transitions between intrinsic and extrinsic goals in response to supervisor behaviors. Although it referenced prior models included in this review (e.g., Ballard, Yeo, Loft, et al., 2016), it did not explicitly extend those models.

Computational modeling studies typically evaluate model–data correspondence in two ways. Some simulate behavior with parameters set *a priori* without using empirical data (e.g., theory- or protocol-based values), and the resulting behavior is compared qualitatively to observations. This approach is often used to ascertain whether the computational model can re-produce a particular effect that has been shown in previous research (Vancouver et al., 2018). Others estimate parameters from empirical data to quantify fit between model and data, which is often used to systematically compare competing models. In our pool of studies, the majority of studies conducted model fitting, using frequentist methods (e.g., Pirolli et al., 2017), Bayesian individual-level (e.g., Prystawski et al., 2022), or hierarchical methods (e.g., Ballard, Vancouver, et al., 2018). A smaller subset relied on simulations without data-based parameter estimation (e.g., Merrick & Shafi, 2011; Vancouver, 2005; Vancouver & Purl, 2017).

Studies varied markedly in their interpretation of parameters, that is, the process of inferring the values of psychologically meaningful variables (e.g., urgency sensitivity, deadline weighting) in individual or group (e.g., condition) terms. We classified studies into three levels: individual only, group / condition only, and hierarchical (individual and group / condition). Most studies (14 of 23) used individual-level estimation, where parameters were estimated separately for each participant. This approach captures within-person cognitive and motivational dynamics and allows for the identification of qualitatively distinct goal pursuit strategies across individuals. Within this level, studies used either frequentist (n = 8) or Bayesian (n = 6) individual estimation methods. Four studies (e.g., Corgnet et al., 2018, Vancouver et al., 2020) estimated parameters based on group-level averages or summary statistics. This approach risks masking individual differences and can yield misleading inferences if the population is heterogeneous. As has been noted in the modeling literature, sample aggregate patterns may not reflect any individual's behavior (Heathcote et al., 2000), otherwise known as Simpson's Paradox. Finally, five studies employed hierarchical parameter estimation approaches, which model both individual- and group-level variability simultaneously, typically via hierarchical Bayesian methods (e.g., Ballard, Vancouver, et al., 2018; Alister et al., 2024; Prystawski et al., 2022; Ballard et al., 2022). These methods offer a principled compromise, allowing partial pooling across participants to improve parameter estimates while still capturing individual differences. Potential drawbacks of these methods include longer computation time and complications in parameter interpretation, since it can be difficult to know whether observed effects reflect true individual differences or are partly shaped by group-level patterns.

[INSERT TABLE 1 HERE]

Thematic Overview of Findings from Computational Models of Goal Pursuit

Having explored the type of models and implementation methods used in the included studies, we now examine the findings this research has produced. Computational models in our review investigated four primary aspects of goal pursuit: performance, goal prioritization, goal motives, and goal revision. We describe the issues these models attempted to address and discuss their key findings in terms of potential contributions to our understanding of goal pursuit.

Performance

Performance studies (n = 9; Banerjee et al., 2024; Corgnet et al., 2018; Neal et al., 2022; Pirolli, 2016; Pirolli et al., 2017; Vancouver & Purl, 2017; Vancouver et al., 2005; Vancouver & Scherbaum, 2008; Vancouver et al., 2018) examined how factors such as goal levels, self-efficacy, feedback processes and affect influence or relate to goal success. In six studies, performance was defined in terms of an externally prescribed goal (e.g., performance on a laboratory task, or in terms of one's work), and in two studies (Pirolli, 2016; Pirolli et al., 2017) performance was measured in terms of personally selected health behavior goals (e.g., physical activity, nutrition). In one study, participants' daily step goals were manipulated as part of an intervention (Banerjee et al., 2024). The included studies addressed four performance-focused themes in goal pursuit: (1) perception–action dynamics in self-regulation; (2) the contribution of self-efficacy to performance; (3) prediction of real-world health behavior, and (4) how affect changes during goal pursuit.

Perception—Action Dynamics in Self-Regulation. A core question in goal pursuit research is whether performance is governed by the regulation of perceptions through action, or by the direct energization of action by higher-level goals. In essence, is action a result of attempting to align our perceptions with our goals, or do goals directly increase behavior? The earliest computational model of goal pursuit we identified (Vancouver et al., 2005) sought to explain the "goal-level effect", an observed empirical phenomenon whereby more challenging goals tend to lead to better performance (Locke & Latham, 1990). The authors tested two cybernetic models—Powers' perceptual control theory (Powers, 1973) and Klein's (1989) comparator control theory—to clarify *how* challenging goals improve performance outcomes. Powers' (1973) perceptual control theory posited that *action* is driven by discrepancies between goals and perceptions, not by the *absolute level* of the goal itself. By contrast, Klein's (1989) comparator control theory proposed that goal level exerts a direct motivational influence: higher (more difficult) goals energize behavior directly, in addition to any discrepancy between perceptions and goals.

In simple terms, Powers' account suggests effort rises when a goal (e.g., "climb a mountain") is distant, but diminishes as one nears or reaches the summit (i.e., the discrepancy decreases). Klein's account predicts that effort remains elevated directly because the mountain (i.e., the goal) is high (i.e., in absolute terms), regardless of the size of the remaining gap (i.e., discrepancy). Using a scheduling task, SimNurse, Vancouver et al., (2005) demonstrated that Powers' perceptual control theory-derived model provided a more accurate and parsimonious explanation, better matching empirical data. In contrast, Klein's comparator control theory-derived model produced nonsensical behavior, unless the goal—output weight (i.e., direct link between goal and behavior) was nearly zero. Extending this work, Vancouver and Scherbaum (2008) formalized three competing models to test whether individuals primarily regulate perceptions or actions when pursuing goals. Across diverse cognitive tasks with informative feedback, the model that regulated perceptions best captured performance. Taken together, and consistent with the earlier argument in this section, these findings again support Powers' perceptual control theory:

performance is governed by the regulation of perceptions through action rather than by direct energization from goal level.

The Contribution of Self-Efficacy to Performance. Building on the prior theme—that people regulate perceptions via action—Vancouver and Purl (2017) explored when self-efficacy sustains effort (and by extension, performance) versus when it undermines it, particularly under ambiguous feedback conditions that weaken discrepancy signals. To explore this issue, Vancouver and Purl integrated aspects of control theory and SCT (Bandura, 1989). Control theory suggests high self-efficacy may decrease effort if goal progress judgements are inaccurate (i.e., they do not reflect genuine progress), whereas SCT positions self-efficacy as central to sustaining effort and resilience. Vancouver and Purl's integrative computational approach revealed insights consistent with both theories, demonstrating how high self-efficacy could both support and reduce effort, depending on feedback ambiguity. This study also illustrated how computational models effectively integrate and clarify competing psychological perspectives, refining our understanding of goal pursuit in complex environments.

Representing verbal psychological theories in computational models enables researchers to test the predictions these theories make, and in some cases, identify untenable or counterintuitive predictions based on verbal theory alone. Locke's integrated model of work motivation (Locke & Latham, 2004) is a static model, even though the model depicts a feedback loop from performance back to self-efficacy. Vancouver et al. (2018) set out to translate this nonformal theory into formal computational models, first static, then dynamic, to evaluate its internal coherence and uncover predictions that are otherwise difficult to anticipate as processes evolve over time. The static model was able to reproduce goal setting effects but revealed points where the informal theory lacked specificity (e.g., assigned goals constrained personal goals more than they "energized" them). This meant that the static model required revisions, a reconsideration of prior interpretations, or a modified architecture. The authors reformulated the model in dynamic terms, by introducing negative feedback processes (such that effort adjusts to the gap between one's goal and current performance) and by closing the model feedback loop so that performance influences self-efficacy over time.

By treating self-efficacy as a belief (i.e., a variable with memory), and by 'fading' the effect of assigned goal difficulty on self-efficacy as experience accumulates, this dynamic architecture highlighted redundant aspects of the static model (e.g., "commitment"). It also generated predictions that matched Latham and Baldes (1975) 48-month longitudinal field study of logging truck load data. Although the static model could replicate short-term goal setting effects, only the full dynamic model revealed counterintuitive predictions, such as instances where higher self-efficacy led to reduced effort and lower performance. These surprising outcomes emerged from the model's treatment of motivation as being driven by perceived discrepancies and would have likely remained obscured without the application of dynamic computational modeling. Moreover, the results indicated that even the dynamic integrated model of work motivation (Locke & Latham, 2004) was limited by its narrow, single-goal focus, restricting its ability to account for complex, real world motivational processes involving multiple simultaneous goals.

A different lens on self-efficacy and performance comes from Pirolli (2016), which primary involved expanding on the role of memory in self-efficacy as a dynamic state. Employing the adaptive control of thought-rational (ACT-R) cognitive architecture (Anderson, 2009) to examine how self-efficacy influences daily behavioral goal success, the authors explored similar processes to Vancouver and Purl (2017) and Vancouver et al., (2020). Pirolli identified that mobile health applications (such as ACT-R–Dstress) provide day-by-day records of what people do, but most theories do not make accurate day-level predictions. He closed that gap by treating self-efficacy as a memory state that strengthens with recent successes and fades with time, and by drawing on guided enactive mastery (i.e., setting progressively challenging-yet-achievable goals to build self-efficacy over time). Using DStress, a 28-day mobile health application delivering daily exercise or meditation goals, Pirolli calibrated each day's goal difficulty to each participant to provide guided mastery experiences. Concretely, daily self-efficacy was retrieved from memory for similar past goal episodes, with recent, similar successes weighted more and faded with time. Intended effort and related variables were modeled the same way. This allowed simulations in which memory activation, reinforcement/utility learning, and decay shaped day-to-day adherence. Results showed that the ACT-R model tracked the day-by-day adherence patterns, and reproduced three key regularities seen in the daily records: (1) success was more likely when there had been more prior days of success (frequency); (2) success was less likely the longer it had been since the last successful day (i.e., due to lag / forgetting); and (3) success was more likely when the last successful day had involved a step-up to a harder level (stress from a larger increase in difficulty).

Prediction of Real-World Health Behavior. A third theme under the goal performance aspect asks whether models can forecast day-to-day success on real-world goals. Pirolli (2016)—already covered under the self-efficacy theme — showed, in brief, that an ACT-R-DStress account can capture daily adherence by treating self-efficacy as a memory-based internal state that updates with success and decays with time. Extending that approach Pirolli et al. (2017) modeled implementation intentions ("if–then" plans) and demonstrated that brief text reminders improved adherence by keeping those plans active in memory, thereby counteracting natural decay. Both papers targeted single health behaviors and used a cognitive-architecture lens to link micro-mechanisms (e.g., memory activation and reinforcement) to next-day behavioral success; they modeled processes similar to Vancouver and Purl's but did not extend or share MGPM's architecture. Banerjee et al. (2024) also predicted daily behavioral success (e.g., meeting step goals in the *Just Walk* intervention) but from a process-oriented perspective, grounded in SCT (Bandura, 1986) and fluid dynamics/engineering control (Martín et al., 2020). Treating behavior as a dynamic system shaped by goals, rewards, self-efficacy, and context, Banerjee et al estimated idiographic, person-specific parameters and showed that goal attainment interacts over time with both psychological states and environmental inputs (e.g., temperature). By identifying idiosyncratic drivers of behavior, their models provided a foundation for iterative intervention development and a basis for adaptive, personalized adjustments to sustain engagement. Insights from individual models may inform ongoing, real-time refinement of adaptive, personalized strategies to sustain daily behavioral goal engagement.

How Affect Changes During Performance Goal Pursuit. A fourth theme in performance-focused modeling explores how affect (i.e., a person's feelings at a moment in time) changes as they work towards performance goals. Neal et al. (2022) compared two accounts: (1) Carver and Scheier's non-formal control theory (Carver & Scheier, 1998); and (2) core affect theory (Russell, 1980). Both theories drew on the circumplex model, which represents affect along two dimensions: pleasure (i.e., pleasant vs. unpleasant states) and activation (i.e., high vs. low states). However, the theories differed in terms of how they predicted changes along these dimensions during performance goal pursuit. Carver and Scheier (1998) predicted that affect results from comparing the current rate of progress of a goal with the rate required to hit the deadline (i.e., the "velocity discrepancy"). That comparison is felt as affect. Carver and Scheier predicted that approach and avoidance goal progress lead to different changes in affect. With approach goals, better progress shifted affect from unpleasant, low activation (dejection) to pleasant, high activation (elation). With avoidance goals, better progress shifted affect from unpleasant, high activation (anxiety) to pleasant, low activation (calmness). By contrast, the core affect account (Russell, 1980) predicted that improved goal progress directly increased pleasure, whereas increased task demands elevated activation. Neal and colleagues developed two models operationalizing both accounts and predicted changes from velocity discrepancy and task demand. Results favored the core affect account overall. When progress improved, pleasure increased; changes in task demand primarily changed activation; and activation also often dropped when goal progress was good ("coasting"). However, coasting was also consistent with the broader control-theory idea that people reduced effort when ahead.

In summary, the reviewed performance-focused computational models have advanced knowledge by enabling more precise, quantitative tests of competing theoretical accounts (e.g., differentiating perceptual vs. action regulation in control theory), revealing counterintuitive effects that static or purely verbal models would have likely missed (e.g., high self-efficacy sometimes reduces effort), and unpacking the dynamic cognitive and affective mechanisms underlying behavior (e.g., memory decay in implementation intentions, affect change during goal pursuit). Unlike conventional analyses, these models directly simulate time-varying processes and feedback loops, allowing researchers to identify the specific conditions under which performance is enhanced or impaired, and also to reconcile or refine competing psychological perspectives.

Goal Prioritization

We rarely pursue goals in isolation; instead, we regularly solve the dilemma of which of multiple competing goals to prioritize with our time, attention, and resources, at any given moment. Goal prioritization studies (n = 9; Aenugu & O'Doherty, 2025; Alister et al., 2024; Ballard, Vancouver, et al., 2018; Ballard, Yeo, Loft, et al., 2016; Ott et al., 2020; Prystawski et al., 2022; Vancouver et al., 2010; Vancouver et al., 2014; Zhou et al., 2019) have examined the decision-making process involved in allocating time, resources, or effort towards two or more competing goals. Five studies developed the MGPM (Alister et al., 2024; Ballard, Vancouver, et al., 2018; Ballard, Yeo, Loft, et al., 2016; Vancouver et al., 2010; Vancouver et al., 2014); see below for more details. Prystawski et al. (2022) and Ott et al. (2020) explored heuristic and forward planning in decision making in multiple goal contexts. Zhou et al. (2019) developed a model of interpersonal goal coordination (i.e., how leaders allocate resources and attention to multiple subordinates in work contexts). Aenugu and O'Doherty (2025) explored psychological momentum as a mechanism underpinning maladaptive persistence during multiple goal pursuit. Thematically, these studies address four broad goal prioritization issues: (1) prioritizing among multiple goals under varying conditions (urgency, deadlines, value, approach vs. avoidance); (2) computation costs and strategy choice in goal prioritization; (3) interpersonal coordination of goal priorities; and (4) over-persistence driven by accrued progress.

Prioritizing Among Multiple Goals Under Varying Conditions. The MGPM, first developed by Vancouver et al. (2010), is the first model to model goal prioritization dilemmas, attempting to explain how relative goal discrepancies (i.e., two goals' respective distance from completion) affect resource allocation. The MGPM integrates expectancy-value principles with control theory mechanisms—such as feedback loops, discrepancy monitoring, and resource constraints—to explain how individuals dynamically shift attention and effort among multiple competing goals. Such shifts result in behavior that may appear inconsistent (e.g., withdrawing effort from a previously prioritized goal), yet reflect rational adjustments based on momentary discrepancies, urgency, and resource limitations. From a meta-theoretic perspective, Vancouver et al (2010) rendered decision-making using control theory architecture, affirming it as a dynamic theory in the process. Vancouver et al. (2014) extended the MGPM by integrating learning mechanisms with its control-theoretic framework. This extension addressed prior limitations, allowing the model to explain variability in effort allocation over time. Vancouver et al (2014) demonstrated the overlap between the underlying control-theoretic architecture of supervised learning models, and control theory. Thus, across these two papers, the authors demonstrated that decision making *and* learning processes were variants of goal pursuit processes, which could not be accomplished without the formality of computational modeling.

The psychological framing of goals, such as whether they are framed in terms of desired states (i.e., approach goals) or undesired states (i.e., avoidance goals), adds further complexity to goal prioritization, as allocating effort to one goal detracts from effort and progress towards another. Further developing the MGPM, Ballard, Yeo, Loft, et al. (2016) integrated motivation theories with decision-making principles, specifically drawing on decision field theory (Busemeyer & Townsend, 1993) and extended the model to account for both approach and avoidance goals. These modifications aligned the MGPM with evidence accumulation models widely used in decision-making research (Roe et al., 2001), and enabled the MGPM to represent how individuals accumulate preference strength over time when deciding which goal to prioritize. The decision field theory extension enabled the model to capture dynamic constructs like speed–accuracy tradeoffs and temporal fluctuations in goal prioritization. The extension to incorporate approach *and* avoidance goals enabled the MGPM to test the prediction that people will switch to prioritize avoidance goals as risk increases or deadlines approach. Ballard et al.'s (2016) simulations demonstrated how individuals dynamically evaluate incentives, deadlines, and perceived difficulties when pursuing multiple concurrent goals, and clarified how perceptions of risk and approach—avoidance tendencies shape goal prioritization.

Another critical layer of complexity in multiple goal pursuit is that two or more goals may be due at different time points and therefore, the dynamic value of applying effort toward each goal will vary. How do people allocate resources under varying goal deadlines? By introducing temporal discounting, Ballard, Vancouver, et al. (2018) further extended the MGPM to account for how people vary in their strategic allocation of effort when pursuing multiple goals under different deadlines. Consistent with prevailing theory, participants in multiple experiments typically prioritized goals with the most urgent deadline. The best model explaining participants' decisions assumed that goal valence was determined by time pressure rather than distance. These findings suggest that the expected utility of a given goal was subject to temporal discounting, such that individuals treat goals as more valuable as their deadline draws nearer.

Computation Costs and Strategy Choice in Goal Prioritization. Decisions to prioritize one goal over another are subject to the computational costs of decision-making, and the necessity to adopt strategies that mitigate these costs while preserving effective goal prioritization. How do we select between goals under conditions that limit our cognitive capacity to make fully informed 'optimal' or 'rational' decisions? Most recently, Alister et al. (2024) expanded the MGPM by examining the impact of cognitive capacity on goal prioritization under cognitive load. Their simulations revealed that limited cognitive resources drive individuals toward heuristic-based strategies, simplifying complex prioritization decisions. This study highlighted an essential boundary condition of the MGPM and showed that cognitive capacity critically influences goal prioritization strategies. It also provided insights into how and why simpler heuristic-based decisions emerge under conditions of cognitive load.

Stepping back, the issue is not only how people prioritize goals but what counts as a "rational" decision once computation itself is costly. Deviations from ideal planning can be rational trade-offs, an idea made explicit in complementary modeling research drawing on resource-rational models. Prystawski et al. (2022) utilized a resource-rational approach to model goal pursuit, emphasizing cognitive constraints such as limited attention and planning capacities. A resource-rational approach proposes that people behave rationally to the extent that the benefits of doing so outweigh the cognitive costs required to calculate 'optimal' outcomes. This approach is important because it explains systematic deviations from rationality and highlights the value of computational models, which are necessary to formally assess both how rational a behavior is and how those deviations scale with computational demands. Using simulated microworld tasks, Prystawski et al (2022) demonstrated that resource-rational models better captured human goal pursuit behaviors than models assuming unbounded rationality. Similarly, Ott et al. (2020) explored how individuals dynamically balance costly forward planning with simpler heuristic strategies when pursuing multiple goals. Employing a sequential decision-making task with two potential goals, they found participants initially relied on heuristics, preferring either parallel or sequential goal approaches. This heuristic reliance initially led to suboptimal performance compared to optimal planning agents. However, as participants moved closer to goal achievement, their decision-making became increasingly near optimal, incorporating more forward planning. These findings indicate that humans flexibly integrate heuristic and planning strategies, modulating their approach based on goal proximity, to manage cognitive resources efficiently.

Interpersonal Coordination of Goal Priorities. Goal prioritization also operates interpersonally, not just at the individual level. Work leaders must distribute limited attention and effort across people as well as tasks, with feedback at both team and individual levels. Zhou et al. (2019) explored goal prioritization within action teams from a leadership perspective. Their computational model examined how leaders dynamically allocate attention and effort among multiple subordinates using simple, dynamic, general processes grounded in discrepancy perceptions, adapting their strategies based on discrepancies between overall team progress and individual performance. This work highlighted how interpersonal dynamics and hierarchical relationships influence prioritization decisions, particularly in contexts where disturbances (e.g., external setbacks) and varying deadlines occur frequently.

Over-persistence Driven by Accrued Progress. Pursuing goals over time requires commitment, but in some situations, we fail to recognize opportunities to pursue new goals. Traditionally, appeals to "sunk costs" or the costs of task switching have explained this phenomenon, but there are also situations where the experience of psychological momentum, based on perceptions of previous accumulated goal progress, shape our decision to persist. To explore this phenomenon, Aenugu and O'Doherty (2025) drew on reinforcement learning and a momentum-based account of persistence in temporally extended goals, which was inspired by the physical sciences. These authors formalized momentum as the product of accrued goal progress and the current rate of reinforcement, such that goals with very high levels of accrued progress may nonetheless be favored even when there is low likelihood of further effort being rewarded. The experimental tasks used to explore this proposition involved suit-matching card games which required participants to choose between prospective goals (high future value) and retrospective goals (lower future value but with accumulated past progress). Via developing multiple models, the authors tested whether a momentum-based account could explain participant persistence in the experiment. The momentum-based account predicts that once people have made progress toward a goal, they will tend to continue working on it, not because they have already invested resources (i.e., sunk costs), or because task switching is costly, but because it is psychologically difficult to disengage. The latter is due to a phenomenon the authors coined retrospective bias, that is, the overweighting of past goals due to accumulated progress. This study represents precursor work in understanding the mechanisms that underpin persistent but nonetheless non-optimal goal pursuit.

Collectively, these studies have progressively expanded the theoretical and empirical capabilities of computational models of goal pursuit, clarifying and deepening our understanding of how individuals manage complex, competing demands in diverse goal pursuit scenarios. Computational models of goal prioritization have formalized how people dynamically allocate effort across competing goals under varying constraints, capturing trade-offs between speed and accuracy, planning and heuristics, and short- and long-term task value—patterns that verbal or static (i.e., traditional) approaches could not specify or test with comparable precision.

Goal Motives

Three studies (Ballard et al., 2022; Merrick & Shafi, 2011; Zhang et al., 2019) explored issues specifically related to the motives—or the 'why'—of goal pursuit, and how these affect specific processes such as goal selection or goal transformation. Ballard et al. (2022) contributed a unified computational framework—the GOAL architecture—to describe how motivation rises and falls as people pursue goals over time. Rather than proposing a new motive, this framework formalizes how three familiar drivers—how far you are from the goal (distance), how soon the deadline is (time), and how fast you must progress to succeed (required rate)—jointly shape prioritization for both approach and avoidance goals. By instantiating rival theories within one model and testing them on laboratory tasks (and a naturalistic National Basketball Association dataset), the work of Ballard et al. suggests that people's choices are best explained by combined influence of distance and required rate, with time exerting a secondary but meaningful role. This modeling clarifies how motivation changes over time as people pursue a goal.

Merrick and Shafi (2011) developed computational models of three core motivational constructs: achievement (Atkinson, 1957), affiliation, and power (Heckhausen & Heckhausen, 2008). They showed that different motivational profiles led to distinct goal-selection behaviors in artificial agents, mirroring patterns of human behavior. For instance, achievement-oriented agents targeted moderately challenging goals, affiliation-driven agents favored low-risk goals to minimize conflict, and power-motivated agents preferred goals offering greater control or dominance. Simulations validated human-like behaviors in iterative games, underscoring the effectiveness of incorporating motivational theories into computational models for aiding our understanding of goal-selection patterns.

Zhang et al. (2019) applied self-determination theory (SDT)(Ryan & Deci, 2000) to develop a dynamic computational model that examined how intrinsic (e.g., health, self-acceptance, affiliation) and extrinsic (e.g., financial success and social recognition) work-related goals change according to employees' perceptions of their environments, especially their supervisor's behavior. These authors demonstrated that autonomy-supportive supervisor environments promoted intrinsic goals by fulfilling basic psychological needs postulated by SDT (i.e., autonomy, competence, and relatedness), whereas controlling environments increased extrinsic goals through frustration of these three needs. Zhang et al.'s simulations further revealed that transitioning from a controlling to an autonomy-supportive supervisory setting could encourage shifts from extrinsic to intrinsic goals over time.

In summary, computational models of goal motives have extended our understanding beyond non-computational approaches by formalizing how underlying motivational profiles and social-contextual factors shape goal selection over time. These models not only simulate theoretically derived patterns in artificial agents that mirror human behavior but also capture dynamic shifts in goals in response to changing environmental conditions.

Goal Revision

A ubiquitous challenge in goal pursuit is determining when to revise one's goals. None of the previously described models, for example, explain how we create new goal discrepancies once we achieve, or make progress towards goals. Scherbaum and Vancouver (2010) addressed a key critique (see Bandura & Locke, 2003) of control theories, that is, negative feedback loops, central to these, cannot explain why individuals increase their goals and create positive goal discrepancies. Expanding upon previous computational models (Vancouver et al., 2005; Vancouver & Scherbaum, 2008), and utilizing the same nursing simulation (i.e., SimNurse) task, Scherbaum and Vancouver integrated goal hierarchies and efficiency in goal pursuit to explain positive discrepancy generation. While traditional hierarchical models lacked a clear mechanism linking efficiency improvements to upward goal revisions, these authors' simulations demonstrated that efficiency gains (i.e., by making nursing schedules cheaper over time in the SimNurse task) naturally led to raising goal levels. When efficiency reduces discrepancy, we raise goals to recreate a positive goal discrepancy.

However, there are also situations when we recognize that we need to revise our goals by reducing them, such as when a goal is too difficult to be realistic, or risky. Gee et al. (2018) developed a computational model detailing cognitive mechanisms behind goal revision, emphasizing how past experiences and risk preferences influence goal adjustments. Gee et al. proposed that anchor future goals on past performance and then adjust them according to their risk tolerance, which is influenced by whether the goals emphasize approaching gains or avoiding losses. In an air traffic control simulation task these authors developed, avoidance-oriented individuals consistently adopted more conservative goals compared to approach-oriented counterparts. Personality traits, notably neuroticism, moderated these effects, with highly neurotic individuals being particularly sensitive to avoidance framing. These results highlight the dynamic interplay between personal traits and situational framing in shaping goal revision processes.

In summary, computational models of goal revision have advanced our understanding beyond non-computational approaches by formalizing the mechanisms through which efficiency gains, past performance, risk preferences, and personality traits shape goal adjustments over time. These models capture dynamic interactive effects that verbal theories could only describe qualitatively, enabling more precise tests of how and when individuals revise their goals.

Discussion

Our scoping review aimed to provide an overview of current use of computational modeling in goal pursuit research and to offer suggestions for future applications. The included studies directly addressed diverse theoretical calls in the literature. For example, recommendations to reconcile conflicting explanations between control theory and SCT regarding perception and action in self-regulation (Vancouver et al., 2005; Vancouver & Scherbaum, 2008), and to deepen understanding of self-efficacy's influence on performance using competing theoretical frameworks (Vancouver & Purl, 2017), have led to further refinements of Vancouver et al. (2005) perceptual control theory model. Similarly, another significant line of research has pursued extensions to the MGPM (Alister et al., 2024; Ballard, Vancouver, et al., 2018; Ballard, Yeo, Loft, et al., 2016; Vancouver et al., 2010; Vancouver et al., 2014), by integrating elements such as learning processes, cognitive biases, decision-making under uncertainty, and resource or cognitive constraints, as well as by accounting for both approach and avoidance goals. Overall, these examples illustrate how computational modeling in goal pursuit may substantially contribute to iterative theoretical refinement and advancement.

Avenues for Future Research

Below, we summarize the primary study authors' explicit recommendations for future research, shown in Table 2. We synthesize these recommendations into two categories: (1) general recommendations, and (2) specific author recommendations. Drawing on our appraisal of the included literature, we also identify four broad directions for future research, summarized in Table 3. The recommendations are poised to leverage computational modeling to address contemporary debates regarding the nature of goal pursuit in 'real world' contexts, adaptive flexibility in goal pursuit, and the role of emotions and mental health in goal pursuit and flexibility.

[INSERT TABLE 2 AND 3 HERE]

Modeling 'Real World' Goal Pursuit

Most studies reviewed here utilized artificial experimental tasks (e.g., nursing schedule simulations or goal prioritization games), which, while valuable for isolating key processes, offer limited ecological validity. For instance, understanding how people balance multiple goals in an experimental game differs from how university students prioritize multiple assignments and personal goals over the course of several semesters. Several authors have recommended applying computational models to such realistic goal pursuit contexts (e.g., Pirolli, 2016; Prystawski et al., 2022; Vancouver et al., 2018). We strongly support this direction, as doing so would address contemporary debates regarding the nature of goal pursuit in the complexity of 'real world' situations and provide support for the utility of computational modeling to inform interventions (Perski et al., 2024) to change ecologically valid goal pursuit and related outcomes. We suggest that future research should consider the following features pertinent to real world goal pursuit: (1)

fluctuating emotions during goal pursuit; (2) interruptions and distractions (e.g., unplanned meetings, urgent emails) and interpersonal demands (e.g., maintaining romantic relationships alongside performance career goals); (3) uncertain or shifting time constraints (e.g., changing deadlines, unexpected delays) and (4) goals with ambiguous or evolving success criteria (e.g., unclear "completion" criteria). These features routinely force priority shifts, pauses and restarts (Mayer & Freund, 2025), and goal revision, so models that include them will better explain behavior outside the lab.

We recommend such future research endeavors draw on intensive longitudinal datasets, such as diary studies (ecological momentary assessments). For instance, researchers could gather data over the course of a semester/semesters, from university students reporting goals and salient characteristics of their goals, which have been identified as important in more controlled experimental settings (e.g., expectancy and value, sensitivity to goal performance discrepancy). These data sources can provide insight into how people engage in goal pursuit across time, contexts, and life domains. Crucially, we suggest that subjective perceptions of progress, difficulty, and value—rather than purely objective performance metrics—should be central to these models, as they more closely mirror how individuals evaluate and adapt their goals in real-world contexts (Riddell et al., 2023). Finally, and relatedly, we advocate for the development of computational models that can inform real-time, adaptive interventions in naturalistic settings (Nahum-Shani et al., 2015). This will allow us to precisely anticipate how people may pursue goals in certain goal pursuit situations. For example, models could identify specific patterns of declining motivation or escalating conflict between goals, trigging context-sensitive recommendations (e.g., strategic disengagement, or adapting strategies for goal pursuit, which we discuss further below). These real-world applications underscore the potential of computational modeling, not only to explain goal pursuit, but also to directly support it in applied settings.

Modeling Flexible Goal Pursuit

Goal pursuit is inherently dynamic, requiring individuals to adapt not only their actions, but often their goals and values, in response to changing circumstances. Existing computational models offer insight into how individuals revise goals over time, and how over-persistence may be accounted for as a product of momentum (Aenugu & O'Doherty, 2025). Yet, emerging literature increasingly highlights goal flexibility—broadly, the capacity to adapt one's goals—as critical for sustained, healthy goal pursuit (Brandstätter & Bernecker, 2022; Kappes & Schattke, 2022; Ntoumanis & Sedikides, 2018; Scholer et al., 2024). Contemporary issues raise concerns regarding when, how, and to what extent change in goal pursuit is adaptive in different circumstances, and whether we should treat "flexible goal pursuit" as specific behavior (e.g., disengaging from a specific unattainable goal, and creating a new goal)(Brandstätter & Bernecker, 2022), or as dispositional tendencies (Wrosch et al., 2003). We advocate for computational modeling to be leveraged explicitly to investigate how, when, and why people change during goal pursuit. This includes modeling flexibility across at least three levels:

(1) The goal itself: whether and when people disengage from existing goals, and re-engage with alternative or revised goals (Wrosch & Scheier, 2020). Modeling these dynamics can help identify temporal or contextual thresholds (e.g., after repeated failure or diminished feedback) that trigger goal abandonment or switching.

(2) Strategies for goal pursuit: how individuals modify their approach while holding the same goal constant. For instance, when do people shift from effortful planning to heuristic shortcuts, or adopt different goal prioritization strategies? Existing work (e.g.,

Alister et al., 2024) models different strategies; we recommend future work explores *how* and *when* people change their strategies for goal pursuit.

(3) Interpretations of goal value or alignment with broader personal values: how perceived importance, relevance, or alignment with overarching personal values changes over time. This subjective layer is central to goal persistence or change, and computational models can formalize this dynamic valuation process.

Combined, these levels could help us understand under what conditions this change in goal pursuit would be adaptive. We suggest that advancing models of goal flexibility will be essential for identifying rigidity-related vulnerabilities that may underlie psychological distress, which we discuss further in the following section.

Understanding the Role of Mental Health and Emotions in Goal Pursuit

While existing computational modeling studies provide valuable insights into goal management mechanisms by focusing on goal-related variables such as progress, prioritization, and attainment, there is less focus on the role of mental health and emotion as precursors and outcomes of goal pursuit. Neal et al. (2022) explored how affect (i.e., basic, fundamental experiences of pleasant—unpleasantness and activation) reflects change in goal progress, but specific emotions (i.e., specific and intense mental and physical states like anger; Barrett et al., 2007; Ekman, 1992) and psychological states (e.g., optimism, depressed mood or anxiety) also influence the process and outcomes of goal pursuit behavior (Neal et al., 2017). The potential adaptive or maladaptive function of emotions in the context of goal pursuit remains subject to debate. Frameworks such as affect-as-information theory (Schwarz & Clore, 1983, 2003), and their goal pursuit specific applications (Orehek et al., 2011), and broaden-and-build theory of positive emotions (Fredrickson, 2004), make predictions about how positive and negative emotions facilitate or hinder goal persistence and flexibility, and shape decision-making. These predictions have been tested in non-computational experimental, daily diary, and ecological momentary assessment studies (e.g., Kingsbury & Bernard, 2023; Louro et al., 2007). Modelling them computationally could refine our understanding of *how* such affective states interact with goal pursuit processes over time.

At a broader level, effective goal pursuit promotes a sense of purpose, meaning, positive affect, and resilience in the face of setbacks. Conversely, maladaptive goal pursuit or persistent goal failure can precipitate, or be precipitated by, psychological distress or disorders. Contemporary definitions of psychopathology increasingly highlight persistent goal failure as a defining feature of mental disorder (DeYoung & Krueger, 2023). For instance, depression may facilitate goal disengagement without subsequent meaningful goal re-engagement (Verschuren & Douilliez, 2022). Anxiety may reflect a chronic tendency to frame goals in avoidance rather than approach terms, thereby systematically undermining access to positive effects of approach goal striving (Dickson, 2006). What we presently do not understand is the mechanism underpinning these effects. Computational approaches complement traditional longitudinal and statistical approaches, by simulating within-person dynamics over time, enabling researchers to generate and test fine-grained mechanistic hypotheses. Examples of such hypotheses are how momentary shifts in mood influence the likelihood of goal disengagement, or how persistent mental health symptoms such as anxiety modulate threshold sensitivity for switching between approach or avoidance goal strategies. Such integrative models hold significant potential for informing targeted interventions (Perski et al., 2024) by identifying at-risk moments during goal pursuit—points at which promoting goal flexibility, for instance, might interrupt maladaptive cycles of persistent failure and escalating psychological distress.

A Meta-Theoretical Perspective for Goal Pursuit: Complex Dynamical Systems

A recurring feature of the studies reviewed here is that goal pursuit unfolds over time, is sensitive to context, and often produces behavior that is nonlinear and history dependent. These are the defining features of complex dynamical systems (CDS), a framework for understanding psychological phenomena as something that emerge over time from many interacting parts, rather than as the sum of separate, independent causes (Gernigon, Den Hartigh, et al., 2024). From this perspective, goal pursuit would be self-organizing, and patterns such as persistence, disengagement, or goal switching emerge from interactions among feedback, affect, self-efficacy, goals, opportunities, and contextual constraints. These patterns may also settle into attractor states, or relatively stable configurations that the system tends to return to and resist moving away from. Several findings in our review fit this picture. Goal revision and over-persistence (Aenugu & O'Doherty, 2025) are clearly history-dependent accounts of how momentum makes it difficult for people to pull away from some goals, even when continued effort is no longer likely to lead to progress. The context- sensitive and non-proportional effect of self-efficacy on performance (Vancouver & Purl, 2017) and the way goal prioritization oscillates between goals as deadlines near (Ballard, Vancouver, et al., 2018; Ballard, Yeo, Neal, et al., 2016) are similarly characteristic of CDS. CDS thus offer a principled common language for phenomena that our review treats under separate headings.

At the same time, a CDS framing clarifies an important distinction: not every computational model of goal pursuit instantiates CDS principles. Gernigon, Altamore, et al. (2024) separate two kinds of dynamics. In a component-dominant model, behavior arises from a fixed set of parts and their causal relations; such a model may influence feedback loops or temporal updating without necessarily modeling self-organization, attractor dynamics, nonlinearity, or crosstimescale influences. In an interaction-dominant model, by contrast, a global pattern self-organizes and constraints the components that produce it. Only the latter is a CDS model in the strict sense. The distinction affects how predictable a system's behavior is. Component-dominant models, such as a straightforward negative feedback loop, are in principle predictable. Emergent behavior, such as how a person disengages from one goal and forms another, is not straightforwardly predictable. Rather than following a predictable next step in a sequence, they may replace the abandoned goal with a different one that still serves the same underlying value or higher-order goal, a pattern that resembles settling into an attractor state. Such behavior seems more interaction-dominant, and less easily predicted from the components alone.

By this criterion, most models we reviewed (grounded in control theory, evidence accumulation, or reinforcement learning) are not CDS models in the strict sense, even though the phenomena they address are CDS-consistent. Existing computational work on intrinsically motivated goal selection (Ten et al., 2021) and goal-embedded social networks (Westaby & Parr, 2019) illustrates possible directions for goal pursuit work via explicit CDS lens. Engaging goal pursuit through an explicit CDS lens, future research could explore how goal states emerge, stabilize, and reorganize over time, and how fluctuations in context, feedback, or other personal factors (e.g., affect, self-efficacy) influence these goal states, would represent a substantive new direction for the field.

Empirical Paradigms and Methodological Recommendations

In addition to theoretical contributions, several primary study authors offered recommendations aimed at refining and extending computational approaches to goal pursuit, which we highlight in this section. A consistent recommendation across studies was to construct and compare *multiple* computational models to test competing theoretical accounts (e.g., Vancouver et al., 2014), and to systematically 'prune' or refine existing theories (e.g., Vancouver et al., 2018) in order to identify and retain only theoretically necessary components.

Several authors emphasized the importance of modeling dynamic strategy shifts during goal pursuit, particularly how individuals flexibly adapt their approach in response to change constraints or opportunities (Alister et al., 2024; Ott et al., 2020; Prystawski et al., 2022). As discussed above, such modeling can capture transitions between heuristic or planning-based strategies, or between different goal prioritization tendencies. In some cases, authors suggested employing dynamic programming (i.e., a method that breaks a step-by-step decision into smaller steps and works backward to find the best path) to identify and simulate optimal decision-making trajectories under specific environmental constraints.

To better capture individual and subgroup variability, some studies recommend the use of hierarchical Bayesian modeling (e.g., Ballard, Vancouver, et al., 2018), which only three included studies employed. This approach allows researchers to estimate parameters at both the individual and group level simultaneously, improving the precision of estimates while accounting for shared structure across participants. Such models are particularly useful for identifying general patterns of goal pursuit while still capturing meaningful differences in individual behavior (e.g., differences in sensitivity to urgency or time pressure; see Alister et al., 2024).

Other methodological suggestions include expanding the construct space used in computational modeling research. For example, Zhang et al. (2019) recommended investigating how contextual factors alter the negative effects of performance goals, while Merrick and Shafi (2011) recommended incorporating a broader range of motive profiles—including curiosity, harm avoidance, play, and understanding—beyond the more commonly modeled achievement, affiliation, and power motives.

Practical Benefits of Incorporating Computational Models into Psychological Research

Computational modeling has traditionally remained at the periphery of psychological research: embracing it could offer several practical advantages. As discussed throughout this review, one core benefit is that computational models force theoretical precision by requiring formal specification of constructs and processes. This enhances conceptual clarity and allows for direct simulation of theoretical predictions. Importantly, computational modeling can complement mainstream empirical methods—rather than replacing them—by generating hypotheses that can be tested using traditional designs (e.g., experimental manipulations, longitudinal surveys), while also offering tools to evaluate which constructs are most central to observed outcomes. In addition, computational modeling can strengthen reproducibility by making assumptions, parameters, and update rules explicit in code, enabling exact reanalysis, preregistered simulations, and direct checks on whether findings follow from the model rather than analytic 'flexibility'. It can also reduce theory fragmentation by translating verbal accounts into a shared formal language, exposing equivalences, conflicts, and boundary conditions, and allowing cumulative model comparison across datasets. Notably, while none of the included studies claimed to falsify existing theory in psychology, several identified conditions in which specific theories provide more consistent accounts of empirical data. Importantly, a reader may perceive limitations in existing computational models. For instance, they might argue that expectancy updating (Gee et al., 2018) varies across individuals owing to differing attributional reasoning (e.g., attributing a poor result to bad luck versus to lack of ability). However, such competing accounts can be expressed within existing modeling frameworks and tested against empirical data. For example, one could compare one model where expectancy updating depends only on prior expectation and performance discrepancy, and another where updating also depends on attributional appraisals such as luck, effort, or ability. This is a core strength of computational modelling: it allows alternative psychological processes to be formalised and compared without requiring researchers to start from scratch. Computational modelling does not require researchers to ignore attributional processes. Instead, it requires the role of such processes to be specified explicitly enough that their implications can be tested.

A particularly promising application lies in the design of interventions to improve self-regulation. Computational models can simulate the effects of intervening at different stages of the goal pursuit process (e.g., enhancing feedback sensitivity, adjusting goal difficulty, or modifying strategy selection rules). By identifying the most impactful intervention points in simulations, researchers can optimize empirical testing and reduce the trial-and-error involved in behavioral intervention development (Banerjee et al., 2024). This has direct implications not only for mental health, as discussed earlier, but also for broader self-regulatory challenges in education, health, and work settings.

Lastly, we suggest that computational models may also play an important role in the growing human-AI collaboration (Gomez et al., 2025), particularly in adaptive systems that support real-time decision-making. For instance, computational modeling of dynamic goal pursuit in real world contexts could help identify key, at-risk moments to intervene, drawing on an understanding of both an individual's fluctuating state (e.g., positive and negative affect; perceptions of goal pursuit), but also their cognitive, motivational, and dispositional profiles (e.g., personality traits). By embedding such models into digital coaching tools, this information could be used to dynamically and adaptively recommend tailored strategies (e.g., goal adjustment, goal prioritization strategies, or brief coping strategies) to optimize goal pursuit and mitigate mental health symptomatology.

In brief, all aforementioned practical benefits highlight the value of embedding computational modeling within the broader methodological toolkit of psychology—both as a tool for theory refinement and as a bridge between psychological science and scalable, data-driven applications.

Limitations

We acknowledge several limitations in this review. First, a substantial proportion of the included studies originate from a small cluster of collaborators, particularly early models of perceptual control theory (Vancouver et al., 2005; Vancouver & Scherbaum, 2008) and the MGPM (Ballard, Yeo, Loft, et al., 2016; Vancouver et al., 2010). This reflects the foundational contributions of Jeffrey Vancouver and colleagues but also indicates that computational modeling has not yet been widely represented in published goal pursuit research. That so few groups have formalized goal pursuit theory into models meeting our criteria is itself informative: it indicates a field at an early stage of formalization, and suggests that translating verbal theory into working models is demanding, which is precisely why a synthesis mapping of what has been done is useful to researchers considering this approach. Importantly, although many studies were published by the same researchers, they addressed contrasting theoretical perspectives (for example, control theory and core affect theory; Neal et al., 2022).

Second, our inclusion criteria specifically focused on studies integrating computational modeling with empirical data. This allows us to evaluate how models explain observed human goal pursuit but excluded purely theoretical or simulation-based studies. Such work (e.g., Analytis et al., 2019) can offer important insights into potential goal pursuit dynamics, and should be considered in future reviews. Our criteria also excluded adjacent computational literatures that use goal-related language but did not meet our operational criteria for computational models of human goal pursuit. Briefly, our criteria were consequential for excluding studies focused specifically on reinforcement learning, normative models, or spatial goal pursuit models. Reinforcement learning is a rapidly expanding space, and some researchers likely would suggest this would contribute to the coverage of the interdisciplinarity of this work. We excluded this work because our focus is on how computational modeling can be used to instantiate psychological theory, rather than the application of generic machine learning models. However, at least some of this work has been synthesized in previous and recent narrative reviews, so we encourage readers to explore this literature elsewhere. These reviews explore goal pursuit and learning (Molinaro & Collins, 2023), motivation (O'Reilly, 2020), goal selection (De Martino & Cortese, 2023), and neural mechanisms underpinning motivated decision-making (Yee, 2024). What differentiates our review is its explicit specification of selection criteria relating to broader goal-pursuit processes involving quantitative performance goals, trackable progress, and repeated measures of progress, effort, performance, or motivation, as well as its detailed description of the process used to identify papers for inclusion.

Third, defining the scope of a “computational model” remains challenging. Our primary interest was in formal, parameterized models of human goal pursuit that support model experimentation, such as varying parameter values or estimating parameters from data to evaluate predicted behavior. Some included studies could reasonably be described as statistical models rather than computational models (e.g., Ballard et al., 2022). This distinction reflects our broader inclusion logic, which focused on whether models were used to formalize and evaluate psychological theory about human goal pursuit. We retained these cases because they illustrate the overlap between computational and statistical modeling, particularly when models represent dynamic goal pursuit processes. Future reviews may benefit from a more precise operational definition of computational modeling.

Fourth, although our review encourages computational modeling to refine verbal theory, we described the models, theories, and findings primarily in verbal terms. This reflects our aim to provide a non-technical introduction to computational modeling in goal pursuit for a diverse psychological readership. However, this accessibility limits how fully we can convey each model's formal structure and implementation. Readers are therefore encouraged to consult the original sources to fully comprehend the nature and implication of each study.

Conclusion

Overall, computational modeling presents a promising methodological approach for deepening our understanding of goal pursuit. By addressing ongoing theoretical debates, employing refined methodological practices, and extending research into ecologically valid, real-world contexts, future studies have the potential to significantly advance both theoretical knowledge and practical applications, ultimately supporting effective goal striving and human well-being in goal pursuit.

References

Aenugu, S., & O'Doherty, J. P. (2025). Building momentum: A computational account of persistence toward long-term goals. *PLOS Computational Biology*, *21*(5), e1013054. https://doi.org/10.1371/journal.pcbi.1013054

Agarwal, R., Liang, C., Schuurmans, D., & Norouzi, M. (2019). Learning to generalize from sparse and underspecified rewards. International conference on machine learning,

Alister, M., Herbert, S. L., Sewell, D. K., Neal, A., & Ballard, T. (2024). The impact of cognitive resource constraints on goal prioritization. *Cognitive Psychology*, *148*, 101618. https://doi.org/10.1016/j.cogpsych.2023.101618

Analytis, P. P., Wu, C. M., & Gelastopoulos, A. (2019). Make-or-break: Chasing risky goals or settling for safe rewards? *Cognitive Science*, *43*(7), e12743. https://doi.org/https://doi.org/10.1111/cogs.12743

Anderson, J. R. (2009). *How can the human mind occur in the physical universe?* Oxford University Press. https://doi.org/10.1093/acprof:oso/9780195324259.001.0001

Atkinson, J. W. (1957). Motivational determinants of risk-taking behavior. *Psychological Review*, *64*(6), 359–372. https://doi.org/10.1037/h0043445

Austin, J. T., & Vancouver, J. B. (1996). Goal constructs in psychology: Structure, process, and content. *Psychological Bulletin*, *120*(3), 338–375. https://doi.org/10.1037/0033-2909.120.3.338

Ballard, T., Farrell, S., & Neal, A. (2018). Quantifying the psychological value of goal achievement. *Psychonomic Bulletin & Review*, *25*(3), 1184–1192. https://doi.org/10.3758/s13423-017-1329-1

Ballard, T., Neal, A., Farrell, S., Lloyd, E., Lim, J., & Heathcote, A. (2022). A general architecture for modeling the dynamics of goal-directed motivation and decision-making. *Psychological Review*, *129*(1), 146. https://doi.org/10.1037/rev0000324

Ballard, T., Neal, A., & Palada, H. (2024). Fitting computational models to data: A tutorial. In J. B. Vancouver, M. Wang, & J. M. Weinhardt (Eds.), *Computational modeling for industrial-organizational psychologists.* (pp. 1–1). Routledge. https://doi.org/10.4324/9781003388852

Ballard, T., Palada, H., Griffin, M., & Neal, A. (2021). An integrated approach to testing dynamic, multilevel theory: Using computational models to connect theory, model, and data. *Organizational Research Methods*, *24*(2), 251–284. https://doi.org/10.1177/1094428119881209

Ballard, T., Vancouver, J. B., & Neal, A. (2018). On the pursuit of multiple goals with different deadlines. *Journal of Applied Psychology*, *103*(11), 1242–1264. https://doi.org/10.1037/apl0000304

Ballard, T., Yeo, G., Loft, S., Vancouver, J. B., & Neal, A. (2016). An integrative formal model of motivation and decision making: The MGPM*. *Journal of Applied Psychology*, *101*(9), 1240–1265. https://doi.org/10.1037/apl0000121

Ballard, T., Yeo, G., Neal, A., & Farrell, S. (2016). Departures from optimality when pursuing multiple approach or avoidance goals. *Journal of Applied Psychology*, *101*(7), 1056–1066.

Bandura, A. (1982). Self-efficacy mechanism in human agency. *American Psychologist*, *37*(2), 122.

Bandura, A. (1986). Social foundations of thought and action. *Englewood Cliffs, NJ*, *1986*(23-28), 2.

Bandura, A. (1989). Regulation of cognitive processes through perceived self-efficacy. *Developmental Psychology*, *25*(5), 729–735. https://doi.org/10.1037/0012-1649.25.5.729

Bandura, A. (1997). *Self-efficacy : The exercise of control*. W. H. Freeman.

Bandura, A., & Locke, E. A. (2003). Negative self-efficacy and goal effects revisited. *Journal of Applied Psychology*, *88*(1), 87. https://doi.org/10.1037/0021-9010.88.1.87

Banerjee, S., Rachael, T. K., Rivera, D. E., & Hekler, E. (2024). Predicting goal attainment in process-oriented behavioral interventions using a data-driven system identification approach. *Journal of Process Control*, *139*, 103242. https://doi.org/10.1016/j.jprocont.2024.103242

Barrett, L. F., Mesquita, B., Ochsner, K. N., & Gross, J. J. (2007). The experience of emotion. *Annual Reviews in Psychology*, *58*(1), 373–403. https://doi.org/10.1146/annurev.psych.58.110405.085709

Biner, P. M. (1987). Effects of difficulty and goal value on goal valence. *Journal of Research in Personality*, *21*(3), 395–404. https://doi.org/10.1016/0092-6566(87)90020-1https://doi.org/10.1016/0092-6566(87)90020-1

Brandstätter, V., & Bernecker, K. (2022). Persistence and disengagement in personal goal pursuit. *Annual Review of Psychology*, *73*, 271–299. https://doi.org/10.1146/annurev-psych-020821-110710

Broers, N. J. (2021). When the numbers do not add up: The practical limits of stochastologicals for soft psychology. *Perspectives on Psychological Science*, *16*(4), 698–706. https://doi.org/10.1177/1745691620970557

Busemeyer, J. R., & Townsend, J. T. (1993). Decision field theory: a dynamic-cognitive approach to decision making in an uncertain environment. *Psychol Rev*, *100*(3), 432–459. https://doi.org/10.1037/0033-295x.100.3.432

Calder, M., Craig, C., Culley, D., de Cani, R., Donnelly, C. A., Douglas, R., Edmonds, B., Gascoigne, J., Gilbert, N., Hargrove, C., Hinds, D., Lane, D. C., Mitchell, D., Pavey, G., Robertson, D., Rosewell, B., Sherwin, S., Walport, M., & Wilson, A. (2018). Computational modelling for decision-making: where, why, what, who and how. *Royal Society Open Science*, *5*(6), 172096. https://doi.org/10.1098/rsos.172096

Carlson, R. W., & Crockett, M. J. (2018). The lateral prefrontal cortex and moral goal pursuit. *Current Opinion in Psychology*, *24*, 77–82. https://doi.org/10.1016/j.copsyc.2018.09.007

Carver, C. S., & Scheier, M. F. (1998). *On the self-regulation of behavior*. Cambridge University Press. https://doi.org/10.1017/CBO9781139174794

Corgnet, B., Gómez-Miñambres, J., & Hernán-Gonzalez, R. (2018). Goal setting in the principal–agent model: Weak incentives for strong performance. *Games and Economic Behavior*, *109*, 311–326. https://doi.org/10.1016/j.geb.2017.12.017

Crüwell, S., Stefan, A. M., & Evans, N. J. (2019). Robust standards in cognitive science. *Computational Brain & Behavior*, *2*(3), 255–265. https://doi.org/10.1007/s42113-019-00049-8

Csaszar, F. (2019). Certum Quod Factum : How Formal Models Contribute to the Theoretical and Empirical Robustness of Organization Theory. *Journal of Management*, *46*(7), 1289–1301. https://doi.org/10.1177/0149206319889129

De Martino, B., & Cortese, A. (2023). Goals, usefulness and abstraction in value-based choice. *Trends in Cognitive Sciences*, *27*(1), 65–80. https://doi.org/10.1016/j.tics.2022.11.001

DeYoung, C. G. (2015). Cybernetic big five theory. *Journal of Research in Personality*, *56*, 33–58. https://doi.org/10.1016/j.jrp.2014.07.004

DeYoung, C. G., & Krueger, R. F. (2023). A cybernetic perspective on the nature of psychopathology: Transcending conceptions of mental illness as statistical deviance and brain disease. *Journal of Psychopathology and Clinical Science*, *132*, 228–237. https://doi.org/10.1037/abn0000541

Dickson, J. M. (2006). Perceived consequences underlying approach goals and avoidance goals in relation to anxiety. *Personality and Individual Differences*, *41*(8), 1527–1538. https://doi.org/10.1016/j.paid.2006.06.005

Ecker, Y. (2024). The unseen pillar of behavior: A review of maintenance goals. *Social and Personality Psychology Compass*, *18*(9), e70003. https://doi.org/10.1111/spc3.70003

Ekman, P. (1992). Are there basic emotions? *Psychological Review*, *99*(3), 550–553. https://doi.org/10.1037/0033-295X.99.3.550

Elliot, A. J., & Covington, M. V. (2001). Approach and avoidance motivation. *Educational Psychology Review*, *13*(2), 73–92. https://doi.org/10.1023/A:1009009018235

Farrell, S., & Lewandowsky, S. (2018). *Computational modeling of cognition and behavior*. Cambridge University Press. https://doi.org/10.1017/CBO9781316272503

Fredrickson, B. L. (2004). The broaden–and–build theory of positive emotions. *Philosophical Transactions of the Royal Society of London. Series B: Biological Sciences*, *359*(1449), 1367–1377. https://doi.org/10.1098/rstb.2004.1512

Gee, P., Neal, A., & Vancouver, J. B. (2018). A formal model of goal revision in approach and avoidance contexts. *Organizational Behavior and Human Decision Processes*, *146*, 51–61. https://doi.org/10.1016/j.obhdp.2018.03.002

Gernigon, C., Altamore, R., Vallacher, R., Geert, P., & Den Hartigh, R. (2024). Almost, but not quite there: Research into the emergence of higher-order motivated behavior should fully embrace the dynamic systems approach. *Behavioral and Brain Sciences*, *48*(e34). https://doi.org/10.31234/osf.io/rt6wj

Gernigon, C., Den Hartigh, R., Vallacher, R., & Geert, P. (2024). How the complexity of psychological processes reframes the issue of reproducibility in psychological science. *Perspectives on Psychological Science*, *19*(6), 952–977. https://doi.org/10.31234/osf.io/nbfwe

Gomez, C., Cho, S. M., Ke, S., Huang, C.-M., & Unberath, M. (2025). Human-AI collaboration is not very collaborative yet: a taxonomy of interaction patterns in AI-assisted decision making from a systematic review. *Frontiers in Computer Science*, *6*, 1521066. https://doi.org/10.3389/fcomp.2024.1521066

Guest, O., & Martin, A. (2021). How computational modeling can force theory building in psychological science. *Perspectives on Psychological Science*, *16*(4), 789–802. https://doi.org/10.31234/osf.io/rybh9

Healy, L. C., Ntoumanis, N., & Arthur, C. A. (2020). Goal motives and well-bbbeing in student-athletes: A person-centered approach. *Journal of sport & exercise psychology*, *42*(6), 433–442. https://doi.org/10.1123/jsep.2019-0125

Heathcote, A., Brown, S., & Mewhort, D. J. (2000). The power law repealed: The case for an exponential law of practice. *Psychonomic Bulletin & Review*, *7*(2), 185–207. https://doi.org/10.3758/BF03212979

Heckhausen, J., & Heckhausen, H. (2008). *Motivation and action: Introduction and overview* (2nd ed.). Cambridge University Press. https://doi.org/10.1017/CBO9780511499821.002

Kanfer, R. (1990). Motivation theory and industrial and organizational psychology. In *Handbook of industrial and organizational psychology* (Vol. 1, pp. 75–130).

Kappes, C., & Schattke, K. (2022). You have to let go sometimes: Advances in understanding goal disengagement. *Motivation and Emotion*, *46*(6), 735–751. https://doi.org/10.1007/s11031-022-09980-z

Kingsbury, C., & Bernard, P. (2023). Dynamic patterns of personality states, affects and goal pursuit before and during an exercise intervention: a series of N-of-1 trials combined with ecological momentary assessments. *Health Psychology Bulletin*, *7*(1), 27–43. https://doi.org/10.5334/hpb.43

Klein, H. J. (1989). An integrated control theory model of work motivation. *Academy of Management Review*, *14*(2), 150–172. https://doi.org/10.5465/AMR.1989.4282072

Knight, E., Neal, A., Palada, H., & Ballard, T. (2023). A tutorial on bayesian modeling of change across time, individuals, and groups. *Computational Brain & Behavior*, *6*(4), 697–718. https://doi.org/10.1007/s42113-023-00173-6

Latham, G. P., & Baldes, J. J. (1975). The "practical significance" of Locke's theory of goal setting. *Journal of Applied Psychology*, *60*(1), 122. https://doi.org/10.1037/h0076354

Lee, H. (2016). Which feedback is more effective for pursuing multiple goals of differing importance? The interaction effects of goal importance and performance feedback type on self-regulation and task achievement. *Educational Psychology*, *36*(2), 297–322. https://doi.org/10.1080/01443410.2014.995596

Levac, D., Colquhoun, H., & O'Brien, K. K. (2010). Scoping studies: advancing the methodology. *Implementation Science*, *5*(69), 1–9. https://doi.org/10.1186/1748-5908-5-69

Locke, E. A., & Latham, G. P. (1990). *A theory of goal setting & task performance*. Prentice-Hall, Inc. https://doi.org/10.2307/258875

Locke, E. A., & Latham, G. P. (2004). What should we do about motivation theory? Six recommendations for the twenty-first century. *Academy of Management Review*, *29*(3), 388–403. https://doi.org/10.2307/20159050

Louro, M. J., Pieters, R., & Zeelenberg, M. (2007). Dynamics of multiple-goal pursuit. *Journal of Personality and Social Psychology*, *93*(2), 174–193. https://doi.org/10.1037/0022-3514.93.2.174

Martín, C. A., Rivera, D. E., Hekler, E. B., Riley, W. T., Buman, M. P., Adams, M. A., & Magann, A. B. (2020). Development of a Control-Oriented Model of Social Cognitive Theory for Optimized mHealth Behavioral Interventions. *IEEE Transactions on Control Systems Technology*, *28*(2), 331–346. https://doi.org/10.1109/TCST.2018.2873538

Mayer, Z., & Freund, A. M. (2025). To let go for now or for good? Goal shelving and goal disengagement across adulthood. *Psychology and Aging*, *40*(4), 391–412. https://doi.org/10.1037/pag0000892

Meehl, P. E. (1978). Theoretical risks and tabular asterisks: Sir Karl, Sir Ronald, and the slow progress of soft psychology. *Journal of consulting and clinical Psychology*, *46*(4), 806–834. https://doi.org/10.1037/0022-006X.46.4.806

Merrick, K. E., & Shafi, K. (2011). Achievement, affiliation, and power: Motive profiles for artificial agents. *Adaptive Behavior*, *19*(1), 40–62. https://doi.org/10.1177/1059712310395953

Milyavskaya, M., & Werner, K. (2018). Goal pursuit: Current state of affairs and directions for future research. *Canadian Psychology*, *59*(2), 163–175. https://doi.org/10.1037/cap0000147

Milyavskaya, M., & Werner, K. M. (2025). An integrative model of goal pursuit. *Advances in Motivation Science*. https://doi.org/10.31234/osf.io/qydpv

Molinaro, G., & Collins, A. G. E. (2023). A goal-centric outlook on learning. *Trends in Cognitive Sciences*, *27*(12), 1150–1164. https://doi.org/10.1016/j.tics.2023.08.011

Nahum-Shani, I., Hekler, E. B., & Spruijt-Metz, D. (2015). Building health behavior models to guide the development of just-in-time adaptive interventions: A pragmatic framework. *Health Psychology*, *34S*(0), 1209–1219. https://doi.org/10.1037/hea0000306

Navarro, D. J. (2019). Between the devil and the deep blue sea: Tensions between scientific judgement and statistical model selection. *Computational Brain & Behavior*, *2*(1), 28–34. https://doi.org/10.1007/s42113-018-0019-z

Neal, A., Ballard, T., & Vancouver, J. B. (2017). Dynamic self-regulation and multiple-goal pursuit. *Annual Review of Organizational Psychology and Organizational Behavior*, *4*(1), 401–423. https://doi.org/10.1146/annurev-orgpsych-032516-113156

Neal, A., Gee, P., Ballard, T., Vancouver, J. B., Yeo, G., Chandra, V., & Ambrose, L. (2022). Changes in affect during the pursuit of performance goals. *Emotion*, *23*(5), 1472–1491. https://doi.org/10.1037/emo0001164

Ntoumanis, N., & Sedikides, C. (2018). Holding on to the goal or letting it go and moving on? A tripartite model of goal striving. *Current Directions in Psychological Science*, *27*(5), 363–368. https://doi.org/10.1177/0963721418770455

Nussbaumer-Streit, B., Sommer, I., Hamel, C., Devane, D., Noel-Storr, A., Puljak, L., Trivella, M., & Gartlehner, G. (2023). Rapid reviews methods series: Guidance on team considerations, study selection, data extraction and risk of bias assessment. *BMJ Evidence-Based Medicine*, *28*(6), 418–423. https://doi.org/10.1136/bmjebm-2022-112185

O'Reilly, R. C. (2020). Unraveling the mysteries of motivation. *Trends in Cognitive Sciences*, *24*(6), 425–434. https://doi.org/10.1016/j.tics.2020.03.001

Ojha, S., Vitale, J., & Williams, M.-A. (2021). Computational emotion models: A thematic review. *International Journal of Social Robotics*, *13*(6), 1253–1279. https://doi.org/10.1007/s12369-020-00713-1

Orehek, E., Bessarabova, E., Chen, X., & Kruglanski, A. W. (2011). Positive affect as informational feedback in goal pursuit. *Motivation and Emotion*, *35*(1), 44–51. https://doi.org/10.1007/s11031-010-9197-2

Ott, F., Marković, D., Strobel, A., & Kiebel, S. J. (2020). Dynamic integration of forward planning and heuristic preferences during multiple goal pursuit. *PLOS Computational Biology*, *16*(2), e1007685. https://doi.org/10.1371/journal.pcbi.1007685

Perski, O., Copeland, A., Allen, J., Pavel, M., Rivera, D. E., Hekler, E., Hankonen, N., & Chevance, G. (2024). The iterative development and refinement of health psychology theories through formal, dynamical systems modelling: a scoping review and initial expert-derived 'best practice'recommendations. *Health Psychology Review*, *19*(1), 1–44. https://doi.org/10.1080/17437199.2024.2400977

Peters, M. D. J., Marnie, C., Tricco, A. C., Pollock, D., Munn, Z., Alexander, L., McInerney, P., Godfrey, C. M., & Khalil, H. (2020). Updated methodological guidance for the conduct of scoping reviews. *JBI Evidence Synthesis*, *18*(10). https://doi.org/10.11124/JBIES-20-00167

Pirolli, P. (2016). A computational cognitive model of self-efficacy and daily adherence in mHealth. *Translational Behavioral Medicine*, *6*(4), 496–508. https://doi.org/10.1007/s13142-016-0391-y

Pirolli, P., Mohan, S., Venkatakrishnan, A., Nelson, L., Silva, M., & Springer, A. (2017). Implementation intention and reminder effects on behavior change in a mobile health system: a predictive cognitive model. *Journal of Medical Internet Research*, *19*(11), e397. https://doi.org/10.2196/jmir.8217

Pollock, D., Davies, E. L., Peters, M. D. J., Tricco, A. C., Alexander, L., McInerney, P., Godfrey, C. M., Khalil, H., & Munn, Z. (2021). Undertaking a scoping review: A practical guide for nursing and midwifery students, clinicians, researchers, and academics. *Journal of Advanced Nursing*, *77*(4), 2102–2113. https://doi.org/https://doi.org/10.1111/jan.14743

Powers, W. T. (1973). *Behavior: The control of perception*. Aldine.

Prystawski, B., Mohnert, F., Tošić, M., & Lieder, F. (2022). Resource-rational models of human goal pursuit. *Topics in Cognitive Science*, *14*(3), 528–549. https://doi.org/10.1111/tops.12562

Richter, M., Gendolla, G., & Wright, R. (2016). Three decades of research on motivational intensity theory: What we have learned about effort and what we still don't know. In A. J. Elliot (Ed.), *Advances in Motivation Science* (Vol. 3, pp. 149–186). https://doi.org/10.1016/bs.adms.2016.02.001

Riddell, H., Lamont, W., Lombard, M., Paduano, S., Maltagliati, S., Gucciardi, D. F., & Ntoumanis, N. (2023). Autonomous motivation promotes goal attainment through the conscious investment of effort, but mental contrasting with implementation intentions makes goal striving easier. *The Journal of Social Psychology*, 1–14. https://doi.org/10.1080/00224545.2022.2163610

Roe, R. M., Busemeyer, J. R., & Townsend, J. T. (2001). Multialternative decision field theory: A dynamic connectionst model of decision making. *Psychological Review*, *108*(2), 370. https://doi.org/10.1037/0033-295X.108.2.370

Russell, J. A. (1980). A circumplex model of affect. *Journal of Personality and Social Psychology*, *39*(6), 1161–1178. https://doi.org/https://doi.org/10.1037/h0077714

Ryan, R. M., & Deci, E. L. (2000). Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. *American Psychologist*, *55*(1), 68–78. https://doi.org/10.1037/0003-066X.55.1.68

Scherbaum, C. A., & Vancouver, J. B. (2010). If we produce discrepancies, then how? Testing a computational process model of positive goal revision. *Journal of Applied Social Psychology*, *40*(9), 2201–2231. https://doi.org/10.1111/j.1559-1816.2010.00656.x

Schmidt, A. M., & DeShon, R. P. (2010). The moderating effects of performance ambiguity on the relationship between self-efficacy and performance. *Journal of Applied Psychology*, *95*(3), 572. https://doi.org/10.1037/a0018289

Scholer, A. A., Hubley, C., & Fujita, K. (2024). A multiple-goal framework for exploring goal disengagement. *Nature Reviews Psychology*, *3*(11), 741–753. https://doi.org/10.1038/s44159-024-00363-4

Schwarz, N., & Clore, G. L. (1983). Mood, misattribution, and judgments of well-being: Informative and directive functions of affective states. *Journal of Personality and Social Psychology*, *45*(3), 513–523. https://doi.org/10.1037/0022-3514.45.3.513

Schwarz, N., & Clore, G. L. (2003). Mood as information: 20 years later. *Psychological Inquiry*, *14*(3-4), 296–303. https://doi.org/10.1080/1047840X.2003.9682896

Sezer, B., Gucciardi, D. F., Ntoumanis, N., & Riddell, H. (2025). Investigating the role of goal motives in predicting bedtime procrastination using a daily diary study design: a registered report. *Psychology & Health*, 1–24. https://doi.org/10.1080/08870446.2025.2458871

Sezer, B., Riddell, H., Gucciardi, F., Sheldon, K., Sedikides, C., Vasconcellos, D., Jackson, B., Thøgersen-Ntoumani, C., & Ntoumanis, N. (2024). Goal motives, approach/avoidance appraisals, psychological needs, and well-being: A aystematic review and meta-analysis. *Motivation Science*, *11*(3), 259–276. https://doi.org/10.1037/mot0000366

Steel, P., & König, C. J. (2006). Integrating theories of motivation. *Academy of Management Review*, *31*(4), 889–913. https://doi.org/10.2307/20159257

Steels, L. (2011). Modeling the cultural evolution of language. *Physics of Life Reviews*, *8*(4), 339–356. https://doi.org/https://doi.org/10.1016/j.plrev.2011.10.014

Szollosi, A., Donkin, C., & Newell, B. R. (2023). Toward nonprobabilistic explanations of learning and decision-making. *Psychological Review*, *130*(2), 546–568. https://doi.org/10.1037/rev0000355

Teimoori, H., & Savkin, A. V. (2010). A biologically inspired method for robot navigation in a cluttered environment. *Robotica*, *28*(5), 637–648. https://doi.org/10.1017/S0263574709990294

Ten, A., Kaushik, P., Oudeyer, P.-Y., & Gottlieb, J. (2021). Humans monitor learning progress in curiosity-driven exploration. *Nature Communications*, *12*(1), 5972. https://doi.org/10.1038/s41467-021-26196-w

van Rooij, I., & Baggio, G. (2021). Theory before the test: How to build high-verisimilitude explanatory theories in psychological science. *Perspectives on Psychological Science*, *16*(4), 682–697. https://doi.org/10.1177/1745691620970604

Vancouver, J. B. (2005). The depth of history and explanation as benefit and bane for psychological control theories. *Journal of Applied Psychology*, *90*(1), 38–52. https://doi.org/10.1037/0021-9010.90.1.38

Vancouver, J. B., & Purl, J. D. (2017). A computational model of self-efficacy's various effects on performance: Moving the debate forward. *Journal of Applied Psychology*, *102*(4), 599. https://doi.org/10.1037/apl0000177

Vancouver, J. B., Putka, D. J., & Scherbaum, C. A. (2005). Testing a computational model of the goal-level effect: An example of a neglected methodology. *Organizational Research Methods*, *8*(1), 100–127. https://doi.org/10.1177/1094428104271998

Vancouver, J. B., & Scherbaum, C. A. (2008). Do we self-regulate actions or perceptions?A test of two computational models. *Computational and Mathematical Organization Theory*, *14*(1), 1–22. https://doi.org/10.1007/s10588-008-9021-7

Vancouver, J. B., Wang, M., & Li, X. (2018). Translating informal theories into formal theories: The case of the dynamic computational model of the integrated model of work motivation. *Organizational Research Methods*, *23*(2), 238–274. https://doi.org/10.1177/1094428118780308

Vancouver, J. B., Weinhardt, J. M., & Schmidt, A. M. (2010). A formal, computational theory of multiple-goal pursuit: Integrating goal-choice and goal-striving processes. *Journal of Applied Psychology*, *95*(6), 985–1008. https://doi.org/10.1037/a0020628

Vancouver, J. B., Weinhardt, J. M., & Vigo, R. (2014). Change one can believe in: Adding learning to computational models of self-regulation. *Organizational Behavior and Human Decision Processes*, *124*(1), 56–74. https://doi.org/10.1016/j.obhdp.2013.12.002

Verschuren, A., & Douilliez, C. (2022). Goal disengagement and goal reengagement: Associations with depression, anxiety, and satisfaction with life. *Canadian Journal of Behavioural Science / Revue canadienne des sciences du comportement*, *56*(2). https://doi.org/10.1037/cbs0000360

Vervaeke, J., & Mastropietro, C. (2024). *Awakening from the Meaning Crisis: Part One*. Story Grid Publishing LLC.

Vroom, V. H. (1964). *Work and motivation*.

Westaby, J., & Parr, A. (2019). Network goal analysis of social and organizational systems: Testing dynamic network theory in complex social networks. *The Journal of Applied Behavioral Science*, *56*, 002188631988149. https://doi.org/10.1177/0021886319881496

Wilson, R. C., & Collins, A. G. E. (2019). Ten simple rules for the computational modeling of behavioral data. *eLife*, *8*, e49547. https://doi.org/10.7554/eLife.49547

Wrosch, C., & Scheier, M. F. (2020). Adaptive self-regulation, subjective well-being, and physical health: The importance of goal adjustment capacities. In *Advances in Motivation Science* (Vol. 7, pp. 199–238). Elsevier. https://doi.org/10.1016/bs.adms.2019.07.001

Wrosch, C., Scheier, M. F., Miller, G. E., Schulz, R., & Carver, C. S. (2003). Adaptive self-regulation of unattainable goals: Goal disengagement, goal reengagement, and subjective well-being. *Personality and Social Psychology Bulletin*, *29*(12), 1494–1508. https://doi.org/10.1177/0146167203256921

Yamamori, Y., & Robinson, O. J. (2023). Computational perspectives on human fear and anxiety. *Neuroscience & Biobehavioral Reviews*, *144*, 104959. https://doi.org/10.1016/j.neubiorev.2022.104959

Yarkoni, T., & Westfall, J. (2017). Choosing prediction over explanation in psychology: Lessons from machine learning. *Perspectives on Psychological Science*, *12*(6), 1100–1122. https://doi.org/doi:10.1177/1745691617693393

Yee, D. M. (2024). Neural and computational mechanisms of motivation and decision-making. *Journal of Cognitive Neuroscience*, *36*(12), 2822–2830.

Zavlis, O., Story, G., Friedrich, C., Fonagy, P., & Moutoussis, M. (2025). A systematic review of computational modeling of interpersonal dynamics in psychopathology. *Nature Mental Health*, *3*(8), 932–942. https://doi.org/10.1038/s44220-025-00465-9

Zhang, Y., Zhang, J., Forest, J., & Chen, Z. (2019). A dynamic computational model of employees goal transformation: Using self-determination theory. *Motivation and Emotion*, *43*, 447–460. https://doi.org/10.1007/s11031-019-09753-1

Zhou, L., Wang, M., & Vancouver, J. B. (2019). A formal model of leadership goal striving: Development of core process mechanisms and extensions to action team context. *Journal of Applied Psychology*, *104*(3), 388–410. https://doi.org/10.1037/apl0000370

Zhu, M., Bagchi, R., & Hock, S. J. (2019). The mere deadline effect: Why more time might sabotage goal pursuit. *Journal of Consumer Research*, *45*(5), 1068–1084. https://doi.org/10.1093/jcr/ucy030

Figure 1.
PRISMA Flow Chart.

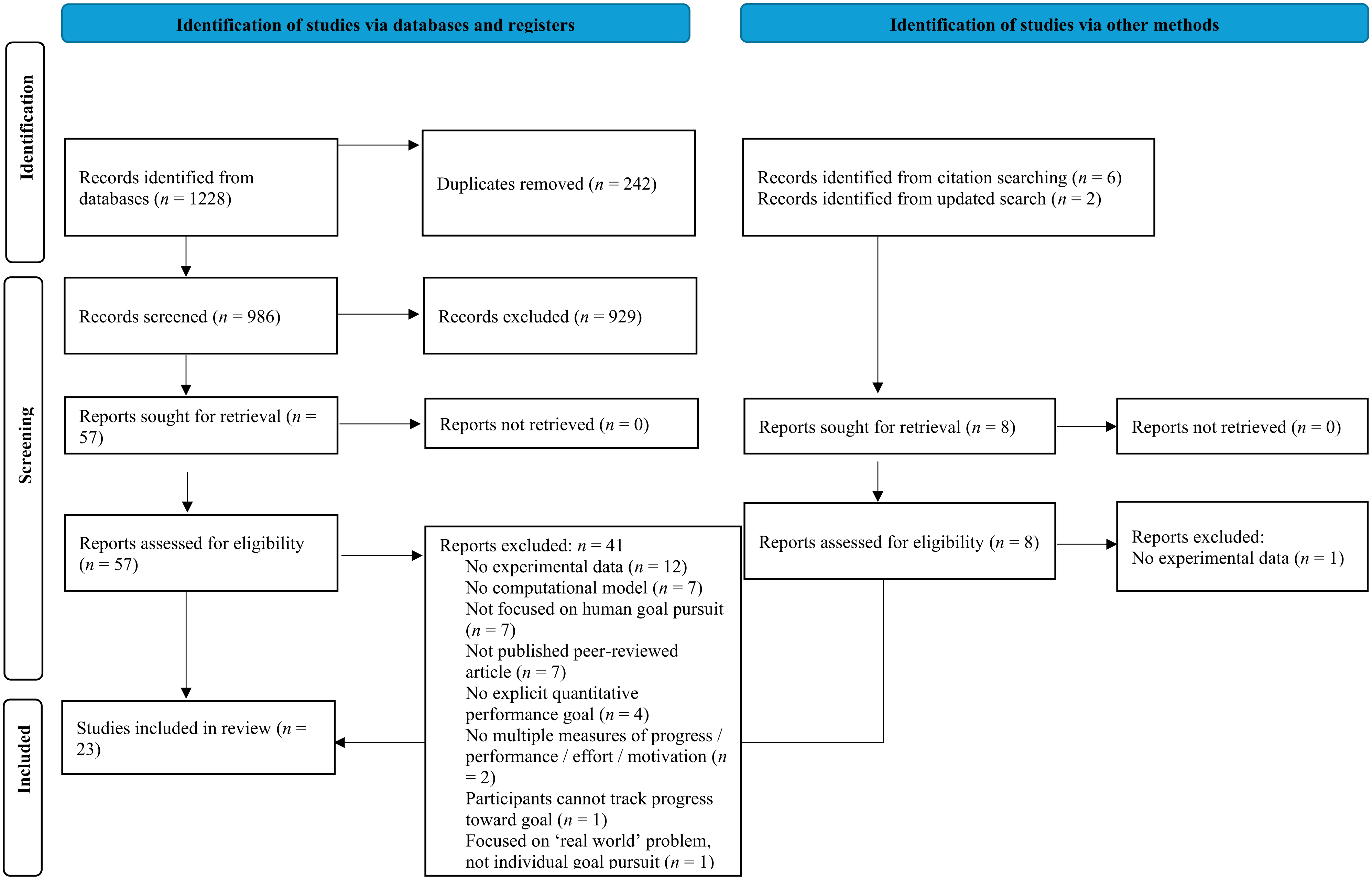

Table 1.

Overview of Included Studies

Domain	Study	Goal Pursuit Theory / Model(s)	Goal Pursuit Focus	Experimental Task / Approach	Model Simulation Approach
Performance	Vancouver et al. (2005)	Control theory (perceptual control theory); goal-level effect	Meet scheduling cost goals.	Utilized "SimNurse", a task involving scheduling nurses in an intensive care unit. Participants revised schedules to meet specific cost goals, with goal levels (i.e., cost goals) manipulated during the experiment.	Simulate two competing models, reflecting (1) perceptual control theory; and (2) comparator control theory.
	Vancouver and Scherbaum (2008)	Control theory (perceptual control theory); social-cognitive theory	Meet scheduling cost goals.	Employed SimNurse task described in Vancouver et al., (2005), but manipulated goal level and initial costs of schedules, to test whether what was regulated (i.e., actions or perceptions) was based on discrepancies between initial cost and goal.	Simulated two models, representing competing perception-focused vs action-focused self-regulation accounts.
	Pirolli (2016)	Goal setting theory; social cognitive theory; theory of planned behavior; attributional theory of performance; ACT-R theory	Daily behavioral goal success.	Utilized data reported by Konrad et al. (2015) on DStress, a web and mobile platform for automated goal coaching. Adult participants were assigned to one of three groups: (1) an adaptive group, where goal difficulty adjusted to performance, (2) an easy-fixed group, with gradual difficulty increases, or (3) a difficult-fixed group, with rapid difficulty increases. The adaptive group achieved significantly higher daily goal success.	Simulated one model, the ACT-R DStress architecture predicting daily behavioral goal success.
	Vancouver and Purl (2017)	Multiple goal pursuit model, control theory (perceptual control theory); social cognitive theory	Influence of self-efficacy on performance.	Utilized data reported by Schmidt and DeShon (2010). Schmidt and DeShon (2010) studied anagram-solving performance, measured by the percentage of correct answers. Participants received either high-ambiguity feedback (i.e., participants were only told if their answer was correct) or low-ambiguity feedback (i.e., participants were given the total number of possible anagrams and their progress in each trial).	Simulated one model, an MGPM-based hybrid integrating perceptual control theory and social cognitive theory.
	Pirolli et al. (2017)	ACT-R theory; implementation intentions; memory; social cognitive theory; self-efficacy theory	Daily behavioral goal success.	The authors examined how implementation intentions and reminders affect daily goal success using a mobile Health application. Participants chose a health goal (eating slowly, walking, or eating more vegetables) and were split into two groups: with or without reminders. The reminder group was further divided by frequency (high vs. low) and timing (massed vs. clustered).	Simulated one model, an ACT-R implementation-intention model of daily behavioral goal success
	Corgnet et al. (2018)	Principle-agent framework; goal setting; reference-	Productivity in terms of correctly	Participants were assigned to either a principal or agent role. Principals offered contracts with monetary incentives and optional wage-irrelevant goals. Agents performed	Simulated one model, a principal–agent framework with monetary and non-monetary incentives

		dependent utility theory; contract theory	completed matrices.	effort-based tasks (summing large matrices) and could switch to internet browsing. Goal setting boosted productivity, even with weaker monetary incentives.	
	Vancouver et al. (2018)	Integrative model of work motivation; social cognitive theory; goal setting theory; expectancy-value theory	Percentage of truck load relative to capacity.	Using longitudinal data from Latham and Baldes (1975), the study examined how goal setting affected logging truck performance. Setting challenging goals (94% capacity) increased the average truck load from 60% over 48 months.	Simulated two models, a static and a dynamic instantiation of Locke's integrated work-motivation model.
	Neal et al. (2022)	Core affect theory; control theory	Performance (i.e., affect dynamics during performance goal pursuit)	Three lab experiments used a farm-simulation in which participants repeatedly prioritized between two goals while the authors manipulated starting distance and time to deadline: 1a varied starting distance; 1b fixed starting distance (90 cm) and varied deadline; 1c crossed distance and deadline with fewer decision stages; goal type (approach crops vs. avoidance weeds) was within-person. Study 2 applied the same framework to a naturalistic dataset from professional basketball, modeling coaches' resource allocation via number of starters on court per minute as a function of score difference and time remaining across preseason, regular season, and playoff games.	Simulated two models instantiating assumptions derived from control theory and core affect theory.
	Banerjee et al. (2024)	Social cognitive theory; fluid analogy; engineering control systems	Goal attainment in daily step count	Participants in the *Just Walk* program, an 80-day daily walking intervention for sedentary adults, received daily step (i.e., physical activity) goals and point-based rewards through wearable devices. These goals varied in a pattern that appeared random to participants but were deliberately structured to provide variation required to identify how different inputs affect behavior over time.	Simulated one model, fit as participant-specific variants to capture idiographic differences.
Goal prioritization	Vancouver et al. (2010)	Multiple goal pursuit model; expectancy-value theory; temporal motivation theory; Vancouver's dynamic process theory of self-regulation	Task allocation under varying deadlines.	Participants created schedules of classes for students in two schools, with goals set for each school, and an experimental condition manipulating the incentives available for each school. The task was difficult, but not impossible, to meet both goals within the time available. External events affected the state of progress.	Simulated multiple models, including an MGPM tailored to Schmidt & DeShon (2007) and comparison models for model–data fit and parameter identification
	Vancouver et al. (2014)	Social cognitive theory; control theory (perceptual control theory); multiple goal pursuit model	Efficient resource / time allocation because of learning processes.	Used empirical data from two studies (Schmidt and DeShon, 2007; DeShon and Rench, 2009). In Study 1, participants manage two tasks, switching between them based on perceived urgency or incentives. In Study 2, participants chose between three options (seek food, seek drink, or do nothing), in a task simulating managing hunger and thirst.	Simulated one model, the MGPM with supervised learning, cross-validated on two datasets.

Ballard, Yeo, Loft, et al. (2016)	Multiple goal pursuit model; expectancy value theory; decision field theory; control theory; approach-avoidance motivation	Resource allocation under varying levels of risk, time pressure.	Participants made repeated decisions regarding which of multiple goals to prioritize over others in conditions varying based on risk (i.e., how uncertain goals were in terms of their outcomes), and time sensitivity (i.e., the amount of time remaining to achieve specific goals). Participants also faced scenarios involving both approach and avoidance dynamics.	Simulated four models, an MGPM–Decision Field Theory extension, the original MGPM, and two simpler alternatives.
Ballard, Vancouver, et al. (2018)	Multiple goal pursuit model; temporal motivation theory; expectancy-value theory; control theory (perceptual control theory); approach-avoidance motivation	Resource allocation when pursuing goals with different deadlines.	Four experiments used a farm simulation task where participants managed two crops with different deadlines. The experiments varied conditions: (1) deadline and starting distance, (2) the same factors but with constant time pressure, (3) deadline, distance, and time pressure manipulated separately, and (4) all factors manipulated together.	Simulated four models, MGPM variants capturing goal prioritization under differing experimental conditions.
Zhou et al. (2019)	Control theory (perceptual control theory)	Time / resource allocation in leadership contexts.	The task required participants to role-play as team leaders ("head chef") managing four subordinates in a catering team. Their goal was to complete all tasks on time. The study manipulated deadlines, disturbances, and task interdependence, key factors in the motivating theory.	Simulated multiple models, a process-oriented self-regulation model of leader–subordinate dynamics plus alternatives varying complexity and fit.
Ott et al. (2020)	Heuristics; decision-making models; planning	Heuristic and planning-based decision-making strategies.	Participants completed a task requiring them to switch between forward planning and heuristic decision-making while pursuing two goals. Participants were presented with offers to increase or trade points between two goals, and had to accept or reject offers, influencing progress on one or both goals.	Simulated multiple models representing heuristic strategies contrasted with a full forward-planning optimal agent.
Prystawski et al. (2022)	Bounded rationality; resource-rational analysis; control theory; reinforcement learning theories; planning; heuristics	Heuristic and planning-based decision-making strategies.	Participants engaged in a farming task within a Simulated Micro World. Participants allocate resources to meet targets over several rounds, and received instructional videos explaining the task, objectives, and methods for manipulating task variables.	Simulated four models, an optimal decision-making model and three resource-rational variants (limited planning, limited attention, combined).
Alister et al. (2024)	Multiple goal pursuit model; expectancy-value theory; evidence accumulation; decision field theory; heuristics; cognitive constraints; control theory; approach-avoidance motivation	Resource / time allocation under cognitive load and resource constraints	Two experiments were conducted. In Experiment 1, participants played an “alien shield-building game,” choosing which of two planets to protect under different time and resource constraints. Experiment 2 added a cognitive challenge with an n-back task, requiring them to recall stimulus colors across trials.	Simulated five models, the Standard MGPM, Speed/Accuracy Trade-off, Deadline Heuristic, Expectancy Heuristic, and Valence Heuristic.

	Aenugu and O'Doherty (2025)	Momentum; reinforcement learning theories	Over-persistence in temporally extended goals	Four experiments were conducted, employing a suit-matching card game. Participants could, under varying conditions, persist on retrospective goals (i.e., goals with past progress) or prospective goals (i.e., goals with higher probability of progress). This paradigm distinguishes momentum from sunk costs and task switching costs, as participants did not lose or quit progress by task switching.	Simulated five models: momentum, persistence, perturbed prospection, hybrid, and a simpler reinforcement-learning benchmark.
Goal revision	Scherbaum and Vancouver (2010)	Control theory (perceptual control theory); social-cognitive theory; goal hierarchies	Positive goal discrepancy production)	Utilized SimNurse task described in Vancouver et al., (2005). Participants also reported their goal levels for task variables every 4th schedule. To illustrate that discrepancy production would be the result of increased efficiency, the authors manipulated the cost of a shift, without informing participants of this manipulation.	Simulated one model, a SimNurse variant incorporating positive goal-discrepancy production.
	Gee et al. (2018)	Control theory (perceptual control theory); expectancy-value theory; interactionist theories of personality; approach-avoidance motivation; prospect theory	Approach / avoidance contexts	Utilized an Air Traffic Control simulation task where participants monitored aircraft pairs and classified them as in "conflict" or "not in conflict". Participant goal framing varied between conditions, framed as either approach (e.g., "Aim for 6 or more correct decisions), or avoidance (e.g., "Limit errors to 4 or fewer) goals. These goals were revised across trials to demonstrate within-person variation in goal revision across approach and avoidance contexts.	Simulated one model, a goal-revision process account spanning approach and avoidance contexts.
Goal motives	Merrick and Shafi (2011)	Atkinson's risk-taking model; goal setting theory; affiliation motivation; power motivation; achievement motivation	Goal selection because of varying affiliation, achievement, and power motive profiles	The authors replicated data from three experiments on goal selection: (1) ring toss (Atkinson & Litwin, 1960), (2) roulette (McClelland & Watson, 1973), and (3) prisoner's dilemma (Li et al., 2010). Across tasks the authors manipulated probability of success (ring toss), incentive structure (roulette), and payoff threat (prisoner's dilemma), and assessed correspondence to human goal selection.	Simulated three models representing core motive systems for achievement, affiliation, and power combined into reflex-agent profiles.
	Zhang et al. (2019)	Self-determination theory; goal content theory; control theory	Goal motive change (i.e., transformation from extrinsic to intrinsic goals)	Implemented a three-wave field design (N=128) in Chinese firms, with employee reports of supervisor autonomy support/control at Time 1, basic need satisfaction and frustration at Time 2 (~3 months later), and intrinsic/extrinsic work-goal content at Time 3 (~6 months from baseline). Utilized data to examine how employees' goal motives transform over time because of supervisors' autonomy-supportive and controlling behavior.	Simulated one model, a dynamic account of evolving goal motives under perceived supervisory support vs control.
	Ballard et al. (2022)	GOAL architecture, control theory, expectancy-value theory, goal-directed motivation (distance,	Goal selection because of varying goal-directed motivation	Study 1 used a simplified blackjack task in which card sequences were scripted to create runs of wins and losses, manipulating velocity discrepancy within-person while participants pursued approach or avoidance goals and reported affect repeatedly. Study 2 used a medium-fidelity	Simulated six mode variants, formalizing how motivational drivers instantiating goal distance, time, and rate-of-progress, affect goal selection decisions.

	time, and rate-of-progress)	air traffic control simulation with between-subjects goal framing and self-set goals; task demand varied naturally as successive waves of aircraft entered and exited the sector.	

Table 2

Synthesis of Primary Study Authors' Recommendations for Future Research

Study / Authors	General Recommendations	Specific Recommendations
Merrick and Shafi (2011); Pirolli (2016); Prystawski et al. (2022); Vancouver et al. (2018)	Improve Computational Model Validity and Realism	- Validate computational models through interaction with real behavior change - Improve accuracy of goal choice/value functions. - Use richer empirical data for setting realistic model parameters.
Ballard, Vancouver, et al. (2018); Scherbaum and Vancouver (2010); Vancouver et al. (2005); Vancouver et al. (2010)	Integration of Individual Differences	- Incorporate individual values and personality to enhance model generalizability. - Include measurable traits like impulsiveness or self-efficacy to explain behavioral variations.
Alister et al. (2024); Merrick and Shafi (2011); Ott et al. (2020); Prystawski et al. (2022); Vancouver and Purl (2017)	Dynamic and Adaptive Modeling	- Allow computational models to flexibly shift strategies during goal pursuit. - Adapt models to accommodate changes in goal importance and task complexity. - Introduce adaptive planning horizons (e.g., planning a few steps ahead in goal pursuit, or decomposing tasks into smaller subtasks) for better modeling of foresight.
Gee et al. (2018); Vancouver et al. (2014)	Long-term and Extended Goal Pursuit Research	- Investigate motivational processes over extended periods. - Explore changes in risk preferences over longer durations. - Manipulate expectations about progress or delays across prolonged tasks.
Corgnet et al. (2018); Vancouver et al. (2014); Zhou et al. (2019)	Social, Cultural, and Organizational Contexts	- Extend computational models to team processes or cultural interactions. - Examine incentives and leadership structures in complex organizational settings. - Include subordinate competencies and leadership monitoring frequencies.
Zhang et al. (2019)	Improvement of Measurement Tools and Constructs	- Develop goal-content scales specific to workplace contexts rather than adapting general-life scales. - Study goal dimensions beyond simple intrinsic/extrinsic classifications.
Alister et al. (2024); Ballard, Yeo, Loft, et al. (2016); Ott et al. (2020); Vancouver et al. (2005); Vancouver et al. (2010); Banerjee et al. 2024; Neal et al. (2022)	Testing and Comparison of Alternative Modeling Approaches	- Construct competing models of chance or random behavior in goal pursuit as potential alternative explanations for observed findings. - Use dynamic programming to define optimal goal prioritization strategies. - Employ hierarchical Bayesian methods to better represent individual and subgroup differences. - Explore alternative decision-making algorithms to improve computational efficiency - Incorporate models addressing different aspects of goal pursuit (e.g., core affect model with MGPM)
Alister et al. (2024); Ballard, Yeo, Loft, et al. (2016); Neal et al. (2022); Scherbaum and Vancouver (2010); Vancouver and Purl (2017); Vancouver et al. (2010)	Integration of Emotional and Cognitive Variables	- Examine emotional influences (e.g., negative affect, optimism/pessimism) on strategy selection. - Incorporate attention and learning elements into models. - Investigate the role of cognitive biases, such as perceptual distortions or forecasting errors. - Incorporate fatigue into modeling of goal pursuit processes over time (e.g., affecting decision-making, depleting energy, lowering activation)
Ballard et al. (2022); Ballard, Vancouver, et al. (2018); Gee et al. (2018); Neal et al. (2022)	Expansion into Avoidance Goals and Other Goal Types / More than Two Goals	- Research how avoidance goals differ from approach goals, especially under pressure or constraints. - Test motivational patterns involving cumulative or slower feedback loops with different goal frames.

		- Expand modeling beyond approach / avoidance / performance goals, such as extend modeling to account for ambiguous goals (i.e., where concept, level, and timing of success are unclear). - Expand modeling to account for multiple goal pursuit with more than two focal goals
Scherbaum and Vancouver (2010); Vancouver and Purl (2017); Vancouver and Scherbaum (2008); Vancouver et al. (2018)	Clarification and Refinement of Theoretical Constructs	- Clarify the theoretical constructs underlying self-regulation models, such as perceptions vs. actions. - Improve the representation of task ambiguity, by incorporating factors such as dominant responses (i.e., from activation theory).

Table 3

Our Recommendations for Advancing Computational Modeling of Goal Pursuit

Theme	Recommendation	Design	Model focus
Modeling 'Real World' Goal Pursuit	Apply models to realistic goal pursuit contexts with fluctuating emotions, interruptions and distractions, interpersonal demands, uncertain or shifting time constraints, and multiple goals with ambiguous or evolving success criteria.	Naturalistic settings (e.g., semester-long study of university students).	Ecological validity; multiple interacting goals.
	Draw on intensive longitudinal datasets (e.g., diary studies, ecological momentary assessments) across semester(s).	EMA/diary with repeated reports of goals characteristics (e.g., value, sensitivity to goal performance discrepancy).	Within-person change across time, contexts, and life domains.
	Center subjective perceptions of progress, difficulty, and value rather than purely objective performance metrics.	Repeated subjective ratings aligned to ongoing goal episodes.	Perceived progress and value as drivers of adaptation.
	Develop models that can inform real-time, adaptive interventions in naturalistic settings.	Just-in-time adaptive interventions.	Detection of declining motivation and escalating conflict between goals; context-sensitive recommendations.
Modeling Flexible Goal Pursuit	Model when people disengage from unattainable or low-value goals and re-engage with alternative or revised goals; identify temporal or contextual thresholds.	Intensive longitudinal designs with event markers for failure/feedback.	Disengagement/re-engagement thresholds; momentum effects in over-persistence.
	Model strategy changes while holding the same goal constant (e.g., shifting between effortful planning and heuristic shortcuts; goal prioritization strategies).	Tasks and EMA capturing strategy use under cognitive load and time pressure.	Strategy selection and switching policies.
	Model dynamic interpretations of goal value and underlying values (importance, relevance, alignment) over time.	Repeated valuation and values-alignment measures.	Formalization of changing goal value.
Understanding the Role of Mental Health and Emotions in Goal Pursuit	Integrate mental health and emotions as precursors and outcomes of goal pursuit; test predictions from affect-as-information theory and broaden-and-build theory.	Experience sampling of affect linked to goal episodes.	How positive and negative emotions facilitate or hinder persistence and flexibility.
	Simulate within-person dynamics to generate mechanistic hypotheses (e.g., how momentary shifts in mood influence likelihood of goal disengagement; how anxiety modulates threshold sensitivity for switching between approach or avoidance strategies).	EMA with computational simulations of state-dependent transitions.	Mood-linked disengagement; approach/avoidance switching thresholds.
	Use integrative models to identify at-risk moments during goal pursuit where promoting goal flexibility may interrupt maladaptive cycles of persistent failure and escalating psychological distress.	Just-in-time adaptive interventions triggered by modeled risk.	Targeted intervention timing and tailoring.