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ORIGINAL PAPER

Advancing Self-Determination Theory via computational modelling: the case of competence and optimal challenge

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Abstract
Computational modelling is a powerful tool to specify psychological theories and conduct model-based empirical research. Yet it has seen little use in Self-Determination Theory (SDT), one of the most successful theories of human motivation. Here, we use two basic SDT constructs, competence and optimal challenge, to demonstrate how computational modelling can benefit theory building and practical application for SDT. Drawing on conceptual analysis and a toy model, we identify three plausible intensional facets of verbal competence definitions that unevenly align with operationalisations and propositions on optimal challenge. We then show how computational modelling, inspired by the AI field of computational intrinsic motivation, can help inform the refinement of these and other constructs, provide point-precise predictions, complement cognition-level mechanistic accounts of competence, refine practical guidance, and support implementation in digital task and goal-setting applications.

Keywords Self-Determination Theory · Competence · Optimal challenge · Computational modelling · Theory crisis

Introduction

Self-Determination Theory (SDT) (Ryan & Deci, 2017) is one of the most widely studied and applied theories of human motivation and well-being to date, shaped and supported by over more than forty years of active research (Ryan et al., 2022). It has equally focused on systematic theory building – carefully refining and extending constructs and propositions “brick by brick” (Ryan & Deci, 2019) – and practical application through theory-guided interventions (Ryan & Vansteenkiste, 2023) in many domains such as education, parenting, healthcare and sport (see Ryan et al., 2022, for a selection of meta-analyses on these domains). A large evidence base supports that interventions and conditions that satisfy people’s basic psychological needs for autonomy, competence, and relatedness enhance intrinsic motivation, enjoyment, learning, behavior change, performance, wellness, psychological growth, and sustained behavior change (Ryan et al., 2022).

This article argues for computational modelling as a timely addition to the SDT research toolkit to advance both continued theory-building and practical application.

As part of the current “theory crisis”, numerous psychological researchers have called for more formal and, specifically, computational modelling of psychological theories (Devezer & Buzbas, 2023; Guest & Martin, 2021; Muthukrishna & Henrich, 2019; Oberauer & Lewandowsky, 2019; Robinaugh et al., 2021; Sanbonmatsu et al., 2025; van Rooij & Baggio, 2021). They broadly follow a line of argument going back at least to Meehl (1967, 1978, 1990): contemporary psychological theories are commonly articulated verbally. While verbal theorizing is an essential part of theory and its construction (Robinaugh et al., 2021; van Rooij & Blokpoel, 2020), it also retains inevitable interpretive

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ambiguity, as compared to mathematically expressed theory in many natural sciences. For instance, verbal theories often only allow directional hypotheses (of the form 'x will correlate positively with y') rather than quantitative point predictions (of the form 'x = y+b'). This renders theory-based empirical research less informative than it could be.

The widely prescribed remedy is formal, and more specifically, computational modelling (for introductory tutorials, see Farrell & Lewandowsky, 2018; Smaldino, 2020; van Rooij & Blokpoel, 2020). To formally model a theory means to articulate its verbal propositions as formal logic, mathematical equations, or computational models – algorithmic embodiments of theory that can be executed by computers. Psychological computational modelling typically starts by theoretically specifying a particular mental function or capacity that one wants to explain (Grahek et al., 2021; van Rooij & Baggio, 2021). It then aims to articulate mechanisms of representations and algorithms that could plausibly produce this function. By 'running the model' – calculating outcomes, running computer simulations – we can observe how a theory actually behaves' under a wide range of circumstances and assess its relative fit with human data (Farrell & Lewandowsky, 2018).

Turning theories into computational models can also increase their practical utility (Sanbonmatsu et al., 2025). For instance, more and more digital applications in education, productivity, health, or entertainment automatically adapt their content and interfaces (Jaquero et al., 2008; Oulasvirta et al., 2018; Yu et al., 2021) to optimise for some user behaviour or experience, such as intrinsic motivation (Peters & Calvo, 2023). Such intelligent user interfaces necessarily require and embody *some* computational model of how their stimuli affect psychological states – i.e., of pertinent psychological theory (Deterding & Cutting, 2023; Marsella et al., 2010).

Of course, verbal theory can already make effective and useful predictions about a wide range of human experience, behavior, and their antecedents; integrate and guide research programs; and generate effective practical interventions. In fact, there is some debate whether computational modelling is necessary or sufficient to reign in the ambiguity of verbal theory (Oude Maatman, 2021; Grahek et al., 2021), or whether the inherent complexity and situatedness of psychological phenomena puts hard bounds on how much psychology can ever take the form of a set of mathematical equations (Sanbonmatsu et al., 2025). Yet there is broad agreement that computational modelling brings a wide range of epistemical and practical benefits – even among critics of the very idea of a "theory crisis" (Sanbonmatsu et al., 2025, see also Farrell and Lewandowsky, 2018; Grahek et al., 2021; van Rooij and Baggio, 2021).

Now calls for computational modelling (and the connected theory crisis) are a now decades-long *general* discourse in psychology. They don't probe whether and how they apply to SDT. The closest is a recent, hotly debated *Behavioral and Brain Sciences* target article by Murayama and Jach (2024), which holds that we should "unpack the black box" of motivation constructs like competence by replacing them with models of "how motivated behavior is *realized* through mental computational processes". While Murayama and Jach (2024) evoke pertinent arguments from computational cognitive science (see Sect. 2.3), they engage "computation" as a particular level of analysis of the human mind, not *computational models* of this or other levels; nor do they demonstrate the benefits of such modelling to SDT. And while SDT has begun to engage with the theory crisis (Ryan & Vansteenkiste, 2023, pp. 4–5; Ryan et al., 2022, p. 836), this has so far not touched computational modelling as maybe *the* major call to action in the debate. Researchers like Vancouver and Weinhardt have championed computational models to study system dynamics of motivation (Vancouver et al., 2010, 2020), which has been picked up in SDT with models of intrinsic to extrinsic goal transformation (Zhang et al., 2019) or the interaction of situational and global levels of motivation (Ferreira Chame et al., 2019). But it is fair to say that computational modelling has not found wide adoption in the SDT community yet.

Therefore, we here want to make a concrete case to fellow SDT researchers for how computational modelling can benefit SDT in particular. Specifically, we use the worked example of competence and optimal challenge as articulated in Cognitive Evaluation Theory (CET) (Ryan & Deci, 2017, pp. 123–157) to demonstrate (a) how present definitions and propositions retain verbal ambiguity in ways that matter, and (b) how computational modelling can foster their specification and thus advance SDT.

We begin with a conceptual analysis of core SDT texts to identify three opportunities for formal specification. First, competence definitions across the long history of SDT research entail at least three different facets that need not co-occur and have been unevenly operationalised: effectance, capacity growth, and task performance (Sect. 2.1). Second, we use a simple mathematical model to illustrate that SDT propositions on optimal challenge are only coherent under some facets of competence (Sect. 2.2). Third, revisiting the debate around Murayama and Jach (2024), we highlight how model-centric, cognition-level explanations (as common in computational cognitive science) present a complementary addition to SDT's present multi-level account of the link between competence and challenge (Sect. 2.3).

In Sect. 3, we then go on to articulate four concrete benefits from computationally modelling competence-challenge links. These illustrate more general ways in which modelling can make SDT even more precise, transparent, and useful: providing model-centric, cognition-level explanations; deriving point-precise predictions, especially where researcher intuition would struggle; offering new, complementary forms of construct validation and study design; and enabling practical implementation in computational systems. We point to the field of competence-based computational intrinsic motivation in AI as an opportune starting point for such modelling.

We close by connecting our worked example with wider debates in cognitive science and AI on modelling intrinsic motivation.

How competence and optimal challenge are defined in current SDT

To determine how competence and optimal challenge are presently verbally defined, we conducted a conceptual analysis (Machado & Silva, 2007) of the corpus of landmark monographs and collections by Ryan and Deci, which their forewords self-identify as then-definitive articulations of SDT (Deci & Ryan, 1985, Ryan & Deci, 2002; 2017, see Box 2.1).[1] We then compared these definitions with a corpus of major domain-general (sub)scales designed to measure felt competence (see Box 2.2), as well as exemplary empirical studies identified in relevant reviews or meta-analyses. We analyse definitions of optimal challenge and propositions on the competence-challenge link in the same corpus. We explicitly limit our analysis to competence and optimal challenge, bracketing SDT's many theorised interactions of competence, e.g., with autonomy, vitality, or psychological growth (Ryan & Deci, 2017, p. 85). Each warrants separate treatment.

[1] We found no expanded or revised definitional language on competence in the more recent *Oxford Handbook of Self-Determination Theory* (Ryan, 2023).

Methodologically, conceptual analysis is concerned with clarifying words, concepts, or definitions thereof, that is, explicating their *extension* or the set of phenomena they are used to refer to, and their *intension* or the necessary and sufficient qualities or properties that are used to jointly identify each phenomenon as an instance of this concept (Gupta & Mackereth, 2023; see also Brun, 2016). To do this, we will extensively quote language from the above-described corpus; this may be less familiar to some psychological readers, but is standing practice in analytic, documentary, or qualitative methods to evidence one's claims about what a text says (Mantzavinos, 2014).

Crucially, these quotations are not supposed to critique individual researchers. On the contrary, as has been pointed out throughout the literature (Robinaugh et al., 2021; Sanbonmatsu et al., 2025), *any* verbal theory *necessarily*, *as verbal theory*, retains interpretive latitude, even if they take construct development and validation as seriously as SDT has. Moreover, the very fact that SDT has organically grown through a large research community over decades can be seen to increase the likelihood that different researchers at different times come to different interpretations, which may then require future integration efforts to identify and resolve.

Box 2.1: Verbal definitions of competence in Self-Determination Theory

Intrinsic Motivation and Self-Determination in Human Behavior (1985)

The 1985 book defines competence only implicitly via intrinsic motivation: "*Intrinsic motivation* is based in the innate, organismic needs for competence and self-determination. It energizes a wide variety of behaviors and psychological processes for which the primary rewards are the experiences of effectance and autonomy." [emphasis in original] (Deci & Ryan, 1985, p. 31)

Handbook of Self-Determination Research (2002)

"*Competence* refers to feeling effective in one's ongoing interactions with the social environment and experiencing opportunities to exercise and express one's capacities . The need for competence leads people to seek challenges that are optimal for their capacities and to persistently attempt to maintain and enhance those skills and capacities through activity. Competence, then, is not an attained skill or capability, but rather is a felt sense of confidence and effectance in action." [emphasis in original] (Ryan & Deci, 2002, p. 7)

Self-Determination Theory: Basic Psychological Needs in Motivation, Development, and Wellness (2017)

"*Competence* refers to feeling effective in one's interactions with the social environment—that is, experiencing opportunities and support for the exercise, expansion, and expression of one's capacities and talents. Where individuals are prevented from developing skills, understanding, or mastery, the competence need will be unmet." [emphasis in original] (Ryan & Deci, 2017, p. 86)

Box 2.2: Competence scales in common domain-general SDT questionnaires

Among the many SDT questionnaires that entail a scale for felt competence (Center for Self-Determination Theory, 2024), we here present the subset that are domain-general and in wide use. We exclude the Perceived Competence Scale (PCS): despite its general title, the PCS only exists in domain-specific variants (Williams & Deci, 1996). An "(R)" indicates reverse scoring.

Intrinsic Motivation Inventory (IMI) (Ryan, 1982)

1. I think I am pretty good at this activity.
2. I think I did pretty well at this activity, compared to other students.
3. After working at this activity for a while, I felt pretty competent.
4. I am satisfied with my performance at this task.
5. I was pretty skilled at this activity.
6. This was an activity that I couldn't do very well. (R)

Basic Psychological Need Satisfaction and Frustration Scale (BPNSFS) (Chen et al., 2015)

1. I feel confident that I can do things well.
2. I feel capable at what I do.
3. I feel competent to achieve my goals.
4. I feel I can successfully complete difficult tasks.

Basic Psychological Need Satisfaction Scale (BPNSS) (Gagné, 2003)

1. Often, I do not feel very competent. (R)
2. People I know tell me I am good at what I do.
3. I have been able to learn interesting new skills recently.
4. Most days I feel a sense of accomplishment from what I do.
5. In my life I do not get much of a chance to show how capable I am. (R)
6. I often do not feel very capable. (R)

At least three facets of competence

Across core texts, we find at least three separable intensional facets of competence, still retained in the most recent definition (Ryan & Deci, 2017, p. 86):

- **Effectance (C1)** or observing that one's action causes consequences, which can be unintended.
- **Task performance (C2)** or observing that one performs (a) well at an intended task, (b) to an extent that requires a certain skill or skill level.
- **Capacity growth (C3)** or observing gain in the (a) range and/or (b) strength of one's skills.

By differentiating these facets in the following, we firstly just wish to make explicit what many SDT researchers take as given: that basic needs such as competence point to broad, multi-faceted experiences that can be engendered in different ways. Our conceptual analysis does not disprove the extensive validation work of SDT scales nor the large body of theory-congruent findings using them, nor say anything about what competence as a latent construct or real phenomenon 'really' is. All we show here, to prepare our case for how a dialogue between verbal theory and computational modelling can sharpen constructs and their operationalisation, is that *as verbal texts*, the analysed definitions and scales entail plausible different meanings.

Effectance (C1)

Just as Ryan and Deci (2017, pp. 112–119) consistently identify R. W. White's (1959; 1963) work as foundational for SDT, they equate competence with *effectance (C1)* or "experiences of effectance" (Deci & Ryan, 1985, p. 27), as proposed by White:

> White referred to the energy behind this activity as effectance motivation and to the corresponding affect as the feeling of *efficacy*. Because the capacity is called competence, the motivational counterpart is often called competence motivation as well as effectance motivation. [italics in original] (Deci & Ryan, 1985, p. 27)

The 2002 definition similarly anchors competence in "a felt sense of effectance in action" (Ryan & Deci, 2002, p. 7). In 2017, Ryan and Deci still equate competence and effectance – "the needs for competence (i.e., effectance)" (p. 188) – and directly reference White in the course: "efficacy, that is, 'the satisfaction that comes with producing effects' (White, 1963, p. 185)" (p. 95).

White (1963, p. 33) saw effectance as prototypically manifesting in and motivating exploratory movement and object play. Specifically, he defined effectance as "a feeling of efficacy of doing something, of being active or effective, of having an influence on something" arising from observing action-consequence links (White, 1963, p. 35). He emphasised that effectance is *not* tied to achieving an intended outcome, or its difficulty: "the feeling does not have to be connected with the achievement of a particular intended result" because "with exploratory behavior, results cannot be anticipated" (White, 1963, p. 35). Just observing that one's exploratory action has an attributable effect on the world, even if unexpected and unintended, suffices to feel effectance. However, White *did* expressly tie effectance to some form of *novelty* in observed action-effect links:

> effectance motivation is aroused by difference-in-sameness. This leads to variability and novelty of response, and interest is best sustained when the resulting action affects the stimulus so as to produce

> further difference-in-sameness. [E]ffectance motivation subsides when a situation has been explored to the point that it no longer presents new possibilities. (White, 1959, p. 332)

Deci and Ryan (1985, p. 27) acknowledge this:

> With each new acquisition of a skill there is some room for playful exercising of that skill, but boredom soon sets in when one merely exercises the same skill over and over.

In short, core SDT texts expressly equate competence with "experiences of effectance" (Deci & Ryan, 1985, p. 27) in explicit reference to White. Yet several of White's intensions of effectance – *novel*, intended *and unintended action-outcome contingencies* – are not consistently operationalised across common, domain-general SDT scales or experimental designs. Many competence scale items reference particular tasks or goals, which imply an intended outcome, e.g., "I feel competent to achieve my goals" (BPNSFS). Conversely, at face value, current scales (Box 2.2) do not capture effectance in the sense of our actions causing observable consequences. Novelty is similarly not captured by most scales, with the notable exception of one Basic Psychological Need Satisfaction Scale (BPNSS) item: "I have been able to learn interesting new skills recently" – though this item targets *skills*, not action-consequence links. As for experimental manipulations, many SDT studies on competence give participants predetermined tasks to attain (e.g., solving puzzles), hence create situations where participants arguably *intend* to bring about particular outcomes (solving the puzzle), and do not intentionally manipulate (or manipulation-check) novelty (see, e.g., the studies reviewed in Ryan & Deci, 2017, pp. 152–154; Fong et al., 2015; Schmierbach et al., 2024). This shows a first verbal ambiguity in present definitions, resulting in uneven operationalisation: does competence entail effectance as novel, intended and unintended action-outcome contingencies?

Task performance (C2)

The arguable main thrust of competence definitions and operationalisations is *task performance: observing that one performs an intended activity or task to some standard, specifically, a standard that requires a certain level of skill*. In definitions, this is entailed in "feeling effective in one's interactions" (where "effective" commonly means "producing a decided, decisive, or desired effect"). It is abundant in operational definitions via self-report items:

IMI:

- I think I am pretty good at this activity.
- I think I did pretty well at this activity.
- I am satisfied with my performance at this task.
- I was pretty skilled at this activity.
- This was an activity that I couldn't do very well. (R)

BPNSFS:

- I feel confident that I can do things well.
- I feel capable at what I do.
- I feel competent to achieve my goals.
- I feel I can successfully complete difficult tasks.

BPNSS:

- I often do not feel very capable. (R)

While this facet is unquestionably core to competence definition and operationalisation, note that it retains some internal ambiguity: we can arguably be "satisfied with [our] performance at this task" without necessarily engaging "difficult tasks," or us "being pretty skilled" at it. In other words, we can perform a task to some standard (*C2.a*), and we can perform to a standard that requires a certain, non-trivial skill or skill level (*C2.b*). This may seem like a distinction without a difference, but experiencing competence even over attaining very easy tasks (*C2.a*) goes against the SDT proposition of optimal challenge (see below).

Capacity growth (C3)

The third intensional facet is *capacity growth: observing gain in the range or strength of available skills*: '[the] expansion of one's capacities and talents. Where individuals are prevented from developing skills, understanding, or mastery, the competence need will be unmet." (Ryan & Deci, 2017, p. 86) One ambiguity here is whether extending or expanding talents refers to the range of different skills one commands (*C3.a*, e.g., chopping and blanching vegetables), or the strength of one or more given skills (*C3.b*, e.g., how good we are at chopping vegetables).

While clearly emphasised in definitions and surrounding explication, *capacity growth* is noticeably absent in current self-report scales. To the best of our knowledge, it is only featured in the following BPNSS item: "I have been able to learn interesting new skills recently." Further, our spot checks on experimental paradigms on competence and feedback or challenge reported in relevant reviews (Fong et al., 2015, 2019) suggest that experimental paradigms do not consistently manipulation-check for induced capacity growth (e.g., performing repeat performance measures to check for performance gains over time). Relevant systematic and meta-analyses in SDT research on competence and performance similarly explore whether competence need satisfaction enhances performance, but frequently do not explore the alternative direction implicit in competence as capacity growth, namely whether perceived performance gains in turn enhance competence need satisfaction (Cerasoli et al., 2014, 2016).

Why specifying facets matters

Of course, broad, multi-faceted constructs are commonplace in psychology and not as such problematic. For instance, facets can be analytically separable semantic intensions that are not practically separable in empirical extension. Or, regardless of face value semantics, people's response behaviour on competence scale items might be fully expressive of competence as a latent construct. Different facets may be operative in different contexts or at different levels of generality. The large volume of theory-congruent findings using current scales and paradigms in SDT suggests their broad operational functionality.

We don't deny that. However, if the analytic facets we make out were all empirical, we can envisage plausible scenarios where they need not coincide: we can feel and enjoy that we caused change (*C1*) without performing well (*C2*), as the positive experience impacts of juicy feedback in video games demonstrates (Kao et al., 2024). We can feel that we perform well at a task (*C2*) without growing our skill in the course (*C3*), as evidence on high reported competence satisfaction under assured success suggests (Deterding & Cutting, 2023; Lomas et al., 2013; Schmierbach et al., 2014). Vice versa, we can feel that we grew our skills while repeatedly failing at an intended task (*C3*)—consider the case of players of very difficult "Soulslike" video games reporting that they experience motivating learning gains in the process of repeatedly failing and dying (Petralito et al., 2017).

Therefore, the fact that current scales and paradigms capture meaningful, real patterns around competence as task performance (*C2*) does not escape the issue of potential incomplete construct coverage (Clark & Watson, 2019), which can induce unwanted yet hard to detect measurement error and blind spots. E.g., we may overlook or falsely reject effectance-focused interventions because they don't show significant effects on a task performance-centred questionnaire. For the same reason, we may underestimate the relative importance of capacity growth or observe a false negative in a context where it matters more to competence satisfaction than task performance. Finally, when it comes to optimal challenge, SDT propositions actually do not fit all potential facets equally well.

Optimal challenge

Informed by prior work on flow theory and optimal incongruity, SDT posits "optimal challenge" (Deci & Ryan, 1985, pp. 32–34, 58–63, 123–125, 221–223; Ryan & Deci, 2002, p. 7; Ryan & Deci, 2017, pp. 152–53) as a core antecedent of both competence-motivated behaviour and competence need satisfaction: "when people are intrinsically motivated, they will tend to select optimal challenges, and the experience of feeling competent when volitionally undertaking such tasks is what sustains intrinsic motivation over time" (Ryan & Deci, 2017, p. 153).

So what constitutes an optimal challenge? Beyond "neither too easy nor too difficult" (Deci & Ryan, 1985, p. 33), the answer differs between and within SDT texts. It is suggested that "challenge is something that requires stretching one's abilities, trying something new" (Deci & Ryan, 1985, p. 33), to the point that intrinsically motivated people's "preferred challenge on achievement-related tasks has a difficulty level greater than 50:50" (i.e., a less than 50% chance of succeeding) (Deci & Ryan, 1985, p. 223). Other texts characterise optimal challenge as "being regularly in a zone of mastery," such that people "succeed at the vast majority of tasks they undertake" (Ryan & Deci, 2017, p. 153), because people would otherwise not experience regular positive competence feedback.

The current definition seems to attempt to bridge this tension:

> Within SDT, then, optimal challenge means facing demands that most often one can master, rather than ones that are continuously at the leading edge of one's capabilities. That type of high difficulty challenge should, however, be an intermittent element, in which case it can enhance and heighten intrinsic motivation. (Ryan & Deci, 2017, p. 153)

Opportunities for clarifying optimal challenge

We note two immediate opportunities for clarifying ambiguity. First, the present definition could be more explicit about the functional referent of optimality, i.e. answering the question, "optimal *for what*?" We can infer from context that optimality likely refers to the growth of capacities and functioning: Since "intrinsic motivation is a growth function," (Deci & Ryan, 1985, p. 123) it should logically steer people to "stretch existing capacities or skills" (Ryan & Deci, 2017, p. 152), in line with competence as capacity growth: "the most compelling feeling of effectance comes from exercising and enhancing skills or abilities" (Ryan & Deci, 2017, pp. 152–3).

Second, the present definition could be further specified to guide plausible operationalisations, auxiliary hypotheses, and quantified point estimates. For experimental and intervention designers, it provokes questions such as: How frequent and on what time scale is “most often”? What counts as “master[ing]” a task or “the leading edge”? What is the optimal “intermittent” frequency? How should challenge be measured: as a single causal consequence (like win rates), as the ratio of two values, like skill and difficulty (e.g., “Elo” ratings of two Chess opponents)? Should we measure it moment to moment or as a post-hoc aggregate? The definition and surrounding text do not specify, and maybe for that reason, a recent meta-analysis found the ways different studies measured and calculated challenge simply “too heterogeneous to meaningfully aggregate” (Fong et al., 2015, p. 13). Also, as Deterding and Cutting (2023, p. 24) note, although results of their large-scale pre-registered test of challenge in games at face value contradicted some SDT-derived hypotheses, the theory was “not well-specified enough to allow severe testing,” because one could always post-hoc claim that their chosen operationalisation did not embody the theory, or that their difficulty conditions did not in fact include optimal and non-optimal challenge levels.

Coherence of competence facets with optimal challenge

In addition to these opportunities for clarification, closer analysis shows that not all of the three intensional facets in current competence definitions are coherent with SDT’s account of optimal challenge – specifically, the arguably most operationalised facet, task performance (C2), is also the least compatible.

If “feeling effective” (in the sense of effectance (C1) or task performance (C2.a)) satisfies our need for competence and is afforded by positive feedback on task outcomes or performance (Ryan & Deci, 2017, pp. 153–155), then *inter alia*, people should be intrinsically motivated to seek tasks with the *lowest possible* challenge that therefore maximise likely task performance, likely resultant positive competence feedback, and thus, competence need satisfaction. Yet that seems to contradict the core proposition that we seek and enjoy *learning*-optimal challenges: “Situations in which people have well mastered a skill are thus ones that would yield high rates of success but would not typically provide opportunities for growth... The positive feelings that come from overlearned mastery are not intrinsic satisfactions” (Ryan & Deci, 2017, p. 152–153).

This contradiction is repeated in empirical evidence: When it comes to post-hoc self-reported competence *satisfaction*, there is no evidence that “negative feedback on an activity that stretches people’s abilities may actually serve to challenge and thus motivate” (Ryan & Deci, 2017, p. 156) – which Ryan and Deci acknowledge to be a puzzling finding. Rather, recent evidence suggests that competence satisfaction (as measured with current scales) *increases* consistently as challenge *decreases* (Deterding & Cutting, 2023; Lomas et al., 2013; Schmierbach et al., 2014). As the same time, in voluntary settings, people do frequently choose and persist at highly challenging tasks, despite repeated failure and resultant copious negative competence feedback (Petralito et al., 2017). SDT posits such observations of spontaneous challenge-seeking as evidence for competence-motivated behaviour (Deci & Ryan, 1985; Ryan & Deci, 2017).

This incoherence could be resolved if competence need satisfaction arises from dynamic capacity growth, not (or not just) absolute task performance, assuming learnable tasks. To illustrate, take the following simple formal model of competence as task performance (C2.a, equation 1) and capacity growth (C3.b, equation 2) for a learnable task with “task-inherent feedback” (Ryan & Deci, 2017, p. 164), i.e., one where participants can directly and accurately assess how well they do at each attempt. Under competence as task performance, competence need satisfaction at the present point ($C(t) \in [0, 1]$) equates to objective task performance at the present attempt, here expressed as a normalised degree of success ($s(t) \in [0, 1]$). Under capacity growth, present competence satisfaction ($C(t)$) equates to the delta in success between present ($s(t)$) and previous attempt ($s(t-1)$): the more one improves between attempts, the higher. We model task challenge (β) for a given person as their success degree on the first task attempt ($s(0)$): the less they succeeded on first attempt, the more challenging the task for them.

$$C(t) = s(t) \tag{1}$$

$$C(t) = s(t) - s(t-1) \tag{2}$$

Learning through practice in many tasks describes a negative exponential function, with initial rapid gains diminishing over repeated attempts (Evans et al., 2018). Following Evans et al. (2018), we here assume a simple delayed exponential function of learning (L) as improvement in task performance (Eq. 3), where α' is mean asymptotic performance, β the amount by which initial performance is slower than the asymptote, r is the rate of learning, t the number of repetitions, and τ a delay parameter:

$$L = \alpha' + \beta \frac{\tau + 1}{\tau + e^{rt}} \tag{3}$$

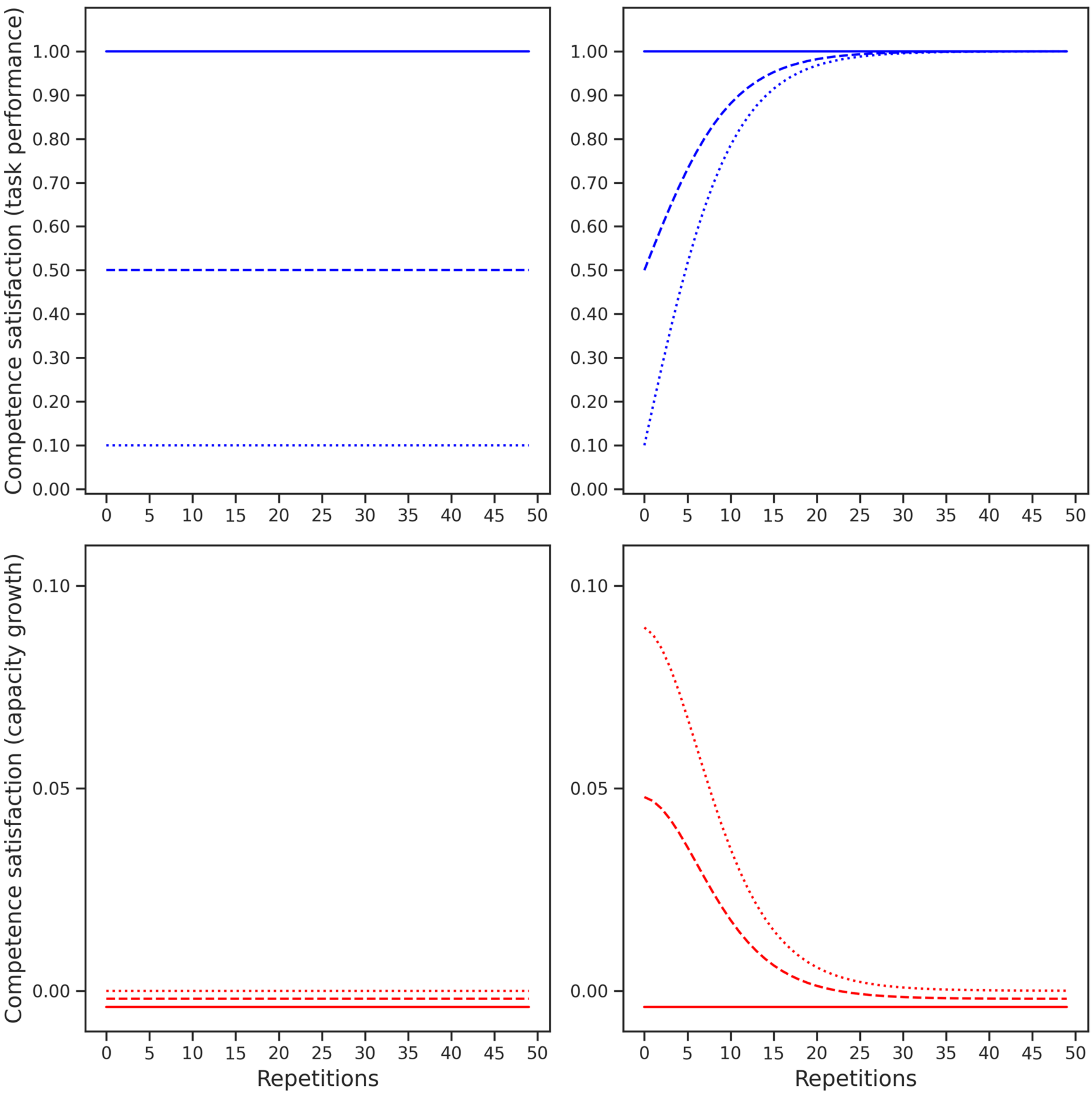

Fig. 1 Competence need satisfaction as task performance (top) and capacity growth (bottom) without (left) and with (right) learning for different initial success degrees β: dotted line = 0.1 (very challenging), dashed line = 0.5 (moderately challenging), solid line = 1.0 (not challenging). Values are slightly offset in bottom graphs to show otherwise overlapping lines

Based on this model, Fig. 1 plots competence satisfaction for three tasks: very easy ($\beta = 1$), moderately difficult ($\beta = 0.5$), and very hard ($\beta = 0.1$), using standard parameters $\alpha' = 1, \tau = 1, r = 0.2$ (from Evans et al., 2018). We see that no matter the circumstance, if competence need satisfaction equates task performance (top two graphs), the *least* challenging task always yields the most competence satisfaction. Meanwhile under capacity growth, people feel no competence satisfaction if they do not learn (bottom left graph), regardless of task challenge. If people learn with each attempt (bottom right graph), then the more challenging the task, the more capacity growth (and resultant felt competence satisfaction) a person experiences at each attempt, assuming an equal rate of learning across tasks. However, since capacity growth per subsequent attempt rapidly diminishes, after only a few repetitions, it would generate more competence satisfaction to switch to an equally challenging, but less practised task (e.g. from $\beta = .5$ at repetition $t = 15$ to another $\beta = .5$ at repetition $t = 0$). That is, modelling competence as capacity growth, a person intentionally maximising competence satisfaction would choose the *most* challenging learnable task available, and never a fully mastered task; alternative available tasks would become more competence-satisfying the moment learning gains at the present task diminish below possible gains offered by an alternative, leading them to switch to more challenging tasks once they promise more learning gains.

This simple model demonstrates several important points: (1) *Different plausible intensional* facets of competence in present definitions generate *different empirical* predictions when formally specified. (2) Each modelled facet makes predictions that fit one group of theoretical propositions and empirical findings and contradict another. (3) Among the modelled conditions, only capacity growth under learning (C3.b, bottom right graph) fits SDT's wider claim that the need for competence directs organisms toward increasing their capacities (Deci & Ryan, 2000, p. 252). (4) Different practical guidance arises from different facets: Capacity growth proposes to pick the hardest task with immediate learning gains for, e.g., learners or athletes, while task performance implies avoiding exposure to easier tasks, as leaners would find them more motivating, despite slower learning gains.

The apparent contradiction with empirical studies showing *in*creasing competence satisfaction under *de*creasing challenge could be explained by the fact that, as shown in Sect. 2.1, popular self-report scales at face value predominantly capture task performance (C2.a), *not* capacity growth (C3.b). It is plausible that this tension has persisted in the SDT literature because different studies employed operationalisations of different facets of the assumed same "competence" construct: early studies of optimal challenge manipulated and measured task difficulty, task choice and time on task, therein construing and measuring competence as capacity growth (Deci & Ryan, 1985, pp. 221–223). Meanwhile, studies on task feedback manipulated and measured task feedback and self-reported felt competence, therein construing competence as task performance (Ryan & Deci, 2017, p. 154). Both bodies of literature were seen to support the same theory because the competence construct and its relation to challenge was not specified sufficiently to surface the inherent contradiction.

There are of course other plausible explanations (e.g., different bodies of work using different tasks). Readers may rightfully challenge any and all assumptions in our model. For instance, formalising competence satisfaction as *task performance relative to a standard that requires a certain level of skill* (C2.b) might yield different results than 'pure' task performance (C2.a.), closer to propositions of, e.g., Atkinson's original theory of achievement motivation (cited in Deci & Ryan, 1985, pp. 218–221). Similarly, one may argue that formalising competence as entailing task performance *and* capacity growth might produce plausible results that align with empirical findings. Any such critique only strengthens our point that formally modelling verbal propositions makes their potentially diverging implications apparent; in cyclical dialogue with verbal theories, it gives us a new rigorous tool to identify which articulation of constructs and propositions actually produces all explananda we are interested in.

Kinds and levels of explanation

The third aspect of how SDT specifies competence brings us back to the most forceful (and contested) recent proposal to engage competence as computation, put forward by Murayama and Jach (2024). In our view, the ensuing debate (Sheldon and Ryan, 2025; Elliot and Sommet, 2025; Murayama and Jach, 2025) surfaces differences or mutual misunderstanding over what it means for psychological theory to *explain*, and what we refer to with *levels of explanation*.

Kinds and levels of explanation in SDT

SDT presents itself as a metatheory that inductively develops and integrates new constructs and relations within a guiding organismic frame (Ryan & Vansteenkiste, 2023). It explicitly strives toward a *consilient*, multi-level account that seeks "*convergent evidence* [...] from biological, behavioral, phenomenological, and clinical inquiries. [...] SDT's organismic view posits that descriptions of human functioning at all levels of analysis can, and in principle should, be integrated" (Ryan & Vansteenkiste, 2023, p. 10, see also Sheldon & Ryan, 2025). SDT positions psychological processes as the often "regnant level of explanation" (Ryan & Deci, 2004). That is, for most everyday human endeavours, phenomenologically accessible intentions and experiences are the analytic level most practically relevant to successfully predict and intervene. Neurobiological processes by contrast are positioned as "mechanism without reductionism" (Ryan & Vansteenkiste, 2023, p. 12): they can help refine theorised processes, but do little to directly explain or predict intentional behaviour.

Kinds and levels of explanation in computational psychology and cognitive science

This view shares much ground with current mechanistic, model-centric conceptions of scientific explanation in psychology or cognitive science (Marraffa & Paternoster, 2013; Bechtel, 2009; Devezer & Buzbas, 2023; van Dongen et al., 2024), which Murayama and Jach (2024) evoke. Both they and SDT appeal to *multi-level accounts* and consilience across levels. Both appeal to *mechanisms* as accounts of how constituent parts work together to produce to-be-explained phenomena and empirical data patterns (Bechtel, 2009).

One divergence relates to what counts as a sufficient explanation. Theory construction involves articulating verbal theory that makes sense of explananda like competence as an organismic propensity, guides the accrual of convergent empirical data patterns, and is refined in dialogue with such data (Borsboom et al., 2021; van Rooij & Baggio, 2021). However, for model-centric or productive accounts, a scientific explanation *also* needs to verbally specify mechanisms that produce explananda; explicate verbal mechanisms into formal models; and then run these formal models to show that they actually produce to-be-explained data patterns (Devezer and Buzbas, 2023; Devezer, 2023; van Dongen et al., 2024). When Murayama and Jach (2024) demand to specify "how motivated behavior is *realized* through mental computational processes", intentionally or not, they are evoking this epistemic standard. We see this as gap for productive future work: deriving and running mechanistic formal models to test whether SDT *explains* target phenomena also by the epistemic standards of model-centric conceptions of explanation.

A second divergence concerns levels of explanation. Computational cognitive science commonly draws on Marr's (1982, pp. 19–29) three analytic *levels of explanation*: to understand any complex information-processing system (such as human cognition), we need to account for it on at least three mutually coherent and linked levels: (1) *computational theory* (what goal does this accomplish under what situational constraints?), (2) *representation and algorithm* (what informational inputs are represented and computed how to realise this function?), and (3) *implementation* (what physical substrates execute this computation how?). For human minds, we can speak of (1) organismic function of situated behaviour, (2) cognition, and (3) neurology.[2] Effects at each level can be more or less strongly emergent and, in principle, be realised by multiple different mechanisms at the 'lower' level (Bickle, 2020). Still, knowledge about each level constrains and informs possible mechanisms 'upward' and 'downward' (Bechtel, 2009). Thus, model-centric computational cognitive accounts similarly appeal to a form of "mechanism without reductionism" (Ryan & Vansteenkiste, 2023, p. 12).

From their point of view, to explain competence and how it links to optimal challenge, we need to specify mutually consilient mechanistic (and formal) models of (1) functional behaviour under relevant constraints as well as the underpinning (2) cognitive and (3) neural mechanisms. SDT undoubtedly articulates the (1) organismic function, and is making strides to collect convergent (3) neuroscientific evidence (Lee, 2023) – e.g., finding the activation of two brain regions during curiosity- and competence satisfaction-inducing tasks (Lee & Reeve, 2017).

However, we think it is fair to say that SDT has yet to provide a mechanistic, let alone model-centric explanation at the level of (2) cognition, understood as representation and algorithm. The closest we found is Deci's information-processing framework (Deci, 1980, pp. 49–69, Deci & Ryan, 1985, pp. 229–242), which offers a verbal and diagrammatic sketch of intrinsically motivated behaviour as initiated by "awareness of potential satisfaction" (Deci & Ryan, 1985, p. 231) of a need from attaining a particular goal state, which results in goal selection and a Test-Operate-Test-Exit loop until the goal and/or need satisfaction are attained. Unfortunately, the framework has remained a sketch; later literature has not formally modelled, adopted, or tested it; and recent representations of SDT no longer include it (Ryan, 2023; Ryan & Deci, 2017). In this sense, Murayama and Jach (2024) are right to identify the lack of mechanistic models of competence at the cognition level. But notably, a cognition-level model does not suffice on its own to explain motivated behaviour, nor does it explain away other levels: for Marr (1982), situated behaviour is an equally relevant level of explanation that takes in important factors (like affordances of the environmental niche) and itself warrants modelling, informing and constraining 'top down' possible and plausible models on the cognition level (see also Bechtel, 2009; Wurm et al., 2025). SDT scholars would add that the psychological level of lived experience has a similar relation of mutual informing and constraining (Sheldon & Ryan, 2025): phenomenological experiences of self-determination, intentions, or enjoyment are not decoupled from but manifested in neurological and cognitive processes embedded in a social world (Ryan, 2023; Ryan & Deci, 2004; Ryan & Deci, 2006).

[2] Some of the contention between Murayama and Jach (2024) and critics seem to arise from different pre-understandings of what (hierarchical) levels refer to. SDT researchers may be less familiar with Marr and more familiar with levels in behaviour (molecular/molar or behaviours/goals, e.g., Deci, 1980); goals (from life-long to situational, e.g., Sheldon & Ryan, 2025); generality in intrinsic/extrinsic/amotivation (e.g., Vallerand, 1997); or generality in approach/avoidance orientation, from temperaments to motives to goals (Elliot, 2006; Elliot & Sommet, 2025) These are all levels of organisation *among* behaviour and motivation constructs, orthogonal to Marr's levels. That is, each of these structures of organisation may be studied at the level of function, cognition, and neurology.

What about phenomenal experience?

Indeed, as a "phenomenologically grounded" theory (Ryan & Deci, 2017, p. 23), SDT has given great import to first-person experiences of self-determination. Sceptical readers might therefore argue that SDT definitions of competence specify structures in phenomenological experience (linked to situated behaviour), *not* cognitive mechanisms in the sense of Marr (1982). All definitions anchor competence as "experiences" (Deci & Ryan, 1985, p. 31) or "feeling" (Ryan & Deci, 2002, p. 7, Ryan & Deci, 2017, p. 86), and all self-report scales seek to elicit conscious perceptions.

This makes for a possible critique of our own analysis of competence facets: the *structure* of objective cognitive processes of competence could in principle be disjunct from the *structure* of its subjective experience (articulated in SDT definitions and scales).[3] Yet, if *objective* capacity growth is the distal adaptive function of agents seeking proximal *felt* competence, as SDT holds, then any imperfect alignment (let alone disjunction) between felt and objective competence *inter alia* equates to poor adaptive fitness. It would raise the serious question why we should have evolved to *not* be optimally subjectively sensitive to objective competence gain. Following Marr (1982), particular task constraints in our ecological niche could make particular deviations adaptive—consider the well-studied case of temporal discounting of rewards, which demonstrably optimises fitness under certain social structures and temporal dynamics of reward availability (Lehmann & Rousset, 2012). However, SDT has proffered no such claims. If anything, it consistently posits and tests a close correspondence between objective antecedents like optimal challenge, felt competence, competence need satisfaction, intrinsically motivated behaviour, and underpinning neurological processes (Ryan & Deci, 2017, p. 23). This supports our approach to start with expecting a correspondence between *felt* competence facets and objective conditions. And as we will show, one of the exciting opportunities of computational modelling for SDT is to be able to determine whether a single parsimonious cognitive mechanism can generate the diversity of experiential facets subsumed in competence or other needs.

[3] We note that this does not invalidate our finding that current self-report instruments at face value do not consistently reflect the facets articulated in definitions, since both operate at the level of appraised experience. Also, unlike flow theory, SDT expressly identifies optimal challenge as an *objective* environmental stimulus property (Ryan & Deci, 2017, pp. 152–153). Hence, our observations regarding optimal challenge also remains untouched by this concern.

How computational modelling can advance SDT

The previous sections explicated plausible interpretive latitudes in present verbal definitions and propositions of competence and optimal challenge within SDT; we showed how even just toy modelling can inform and constrain their articulation, and surfaced model-centric cognitive explanations as a growth area.

In the following sections, we will use these to illustrate four ways of how computational modelling can advance SDT.

Providing model-centric and cognition-level explanations

Starting where we left off, computational models can directly 'fill in' the model-centric, cognition-level explanation of competence as an organismic propensity which has so far been largely absent from SDT.

Fortunately, SDT need not start from a blank slate either. Just like Deci (1980, p. 50) took inspiration from then state-of-the-art TOTE models in nascent cognitive and computer science (Miller et al., 1960), SDT today can take inspiration from contemporary artificial intelligence (AI) research, where a growing community has embraced the task of building competence-seeking computational agents. Competence-based intrinsic motivation (CB-IM) forms an entire sub-field of AI research focused on designing and applying computational intrinsic motivation (IM) (Colas et al., 2022, p. 1161; Oudeyer & Kaplan, 2007, pp. 8–10). SDT and CB-IM share a promising amount of ground: both focus on individual agents and model these as inherently active and growth-oriented. Both aim to explain open-ended exploratory behaviour or play. And both agree on autonomous competence gain as the ultimate *function* of competence motivation—evolutionary for SDT, engineering-driven for CB-IM (Baldassarre, 2022, p. 252; Colas et al., 2022; Deci & Ryan, 2000; Vansteenkiste et al., 2023).

Maybe even more importantly, the computational IM and CB-IM literature has, at least historically, directly drawn on SDT to inspire its models (Oudeyer & Kaplan, 2007, p. 8). Its many formalisms (such as predictor performance improvement, Schmidhuber, 2010; learning progress, Oudeyer et al., 2007; or competence progress motivation, Stout & Barto, 2010) therefore stand a good chance of already embodying competence as conceptualised in SDT. These formalisms give concrete specification to the energizing content or 'why' Sheldon and Ryan (2025) found lacking in Murayama and Jach (2024). What's more, these formalisms demonstrably *work* for physical robots and virtual agents to self-directedly develop impressive skill sets with only little or without agent-external reward or guidance (Oudeyer et al., 2007, Pathak et al., 2017). And for most published CB-IM research, code and simulation results can be readily accessed in open access repositories. We direct readers interested in CB-IM to Lintunen et al. (2025), who, building on the present article, identify candidate formalisms for each competence facet outlined above.

Supporting point-precise prediction

Maybe the major refrain of the theory crisis debate is that when verbal theory leaves its propositional content underspecified, hypothesis tests have little power to corroborate, falsify, inform, or select among competing theories (Scheel et al., 2021), since people can plausibly justify different predictions and auxiliary assumptions. In our case, we saw that researchers could and did derive highly divergent operationalisations and predicted values for optimal challenge (Fong et al., 2015).

Computational modelling can help here. Turning theory into a model – equations and code – that actually simulates performance on given tasks forces exhaustive specification that brings out hidden ambiguities and assumptions, and can do so *in advance of* empirical tests (Robinaugh et al., 2021; van Rooij & Baggio, 2021). To construct even our toy model, we needed to specify how learning over time evolves, that capacity growth is a delta to the last attempt, instead of, e.g., an average window of the last x attempts, etc. This also furthers transparent (dis)agreement over theory or derived hypotheses and auxiliary assumptions for study designs: If researchers object that a given model (or study design) does not actually capture verbal theory, this simply allows and tasks them to specify their alternative (Weinhardt & Vancouver, 2012).

Meehl and many after him particularly stressed that formalising theory as equations or computational models allows to make *precise quantified point predictions for any range of conditions*, instead of merely directional hypotheses (Meehl, 1967, 1990; Oberauer & Lewandowsky, 2019; Robinaugh et al., 2021). This makes empirical hypothesis tests more "severe" or informative – a major concern in the current replication crisis (Scheel et al., 2021).

Moreover, computational modelling lets us derive predictions in situations where human (researcher or practitioner) imagination struggles to make accurate inferences from theory (Robinaugh et al., 2021; Weinhardt & Vancouver, 2012). A prime example are *dynamics over time* (see, e.g. Zhang et al., 2019). Take the practical problem in work, sports, learning, or games to determine *when* to switch from one activity or goal to *which* other one to optimise intrinsic motivation. SDT predicts that switching *at some point* from an easy to a more difficult goal will enhance motivation, but not *when exactly*. Formal models let us principally calculate this.

Another case are *complex systems* with interacting components. For instance, SDT suggests that competence satisfaction interacts with ego involvement and autonomy satisfaction (Ryan & Deci, 2017). Once modelled, making precise point predictions how even just these three components interact can rapidly exceed unaided human mental calculation. Or take the question whether observed task performance, capacity growth, and effectance contribute independently and equally to competence satisfaction. A final situation where models augment our ability to make rigorous predictions are emergence and interaction *across levels of organisation* – such as Ferreira Chame et al. (2019) modelling the interaction of situational and global levels of motivation.

New forms of construct validation

Just like computational modelling can help make precise predictions, it can also support construct validation (Fried, 2020; Grahek et al., 2021; Scheel et al., 2021). Of course, many SDT scales for competence have been carefully developed and validated and show good predictive validity for many important outcomes. But as noted (Sect. 2.1.4), the case of competence warrants at least discussing content validity, especially incomplete construct coverage (Clark & Watson, 2019; Fried et al., 2022): at face value, prevalent scales and study designs predominantly operationalise task performance, while verbal definitions entail at least two further plausible facets that align with prior theory (e.g., White, 1963), better fit optimal challenge propositions, and would explain the conflicting evidence on challenge-seeking and competence satisfaction.

Again, we think that existing competence scales *do* capture an important facet of competence. Our conceptual analysis of SDT texts does not disprove prior scale validation work or the large volume of theory-congruent findings using them. We suggest specifically to revisit possible *incomplete* content coverage drawing on the points by Clark and Watson (2019) that if an initial item pool in scale development is too narrow to fully represent a construct, this is often hard to detect let alone redress through later validation procedures: Concurrent validity tests of new and previous scales would reproduce this gap, while factor analyses of internal construct structures would not detect it, nor would tests of criterion validity, provided included and omitted facets all independently contribute to theorized consequences. We think this is beginning to be recognised: While relevant scale references[4] and papers (Chen et al., 2015; Gagné,

[4] Obtained from https://selfdeterminationtheory.org/questionnaires/.

2003; Ryan, 1982) of general competence scales don't indicate concern for different intensional facets in competence, the most recent Basic Needs in Games Scale (Ballou et al., 2024), co-created by Richard Ryan, expressly aims to reflect both task performance and capacity growth facets.

Construct coverage closely relates to the deeper question whether a given construct 'carves nature by its joints,' and connected questions over lexical fallacies (Fiske, 2020), illusory essences (Brick et al., 2021), operational ghosts (Maul, 2017), or, to return to Murayama and Jach (2024), jingle-jangle (Lawson & Robins, 2021): that is, how do we know whether different motivation labels in (English) language or received literature and linked statistical regularities in (English) verbal response behaviour actually correspond with different, unitary, causally real psychological entities? We would like to avoid the operationalist circularity of adjudicating the proper intensional content of competence by 'whatever competence scales measure.'

The standard recommendation is to take construct validation seriously as an iterative process of mutually refining theoretical construct *and* measurement (Clark & Watson, 2019; Maul, 2017), one that explicitly tests phenomena for a common underlying cause (Brick et al., 2021) and triangulates multiple, also non-verbal sources of evidence (Fiske, 2020) across levels of analysis. While there are many traditional validation methods beyond factor analyses (Lawson & Robins, 2021), computational modelling can complement them in at least two new ways (Grahek et al., 2021).

Firstly, it lets us specify and test the precise internal structure of complex, multi-faceted constructs. There are many plausible structures of even just three competence facets, from simple parallel and co-equal aggregates, where each facet suffices on its own to instil, e.g., intrinsic motivation; to graded structures, where some facets are more sensitive to certain antecedents, or more salient for certain consequences; to, e.g., causal network structures (Fried et al., 2022). These possible variations quickly create a large possibility space that is hard to derive quantified predictions for from verbal theory alone, or select between with standard factor analytic means (Fried et al., 2022). Robinaugh et al. (2024) provide an instructive example for how computational modelling can inform such specification: their model of panic disorder explicates which associated symptom plays what (proportional) causal role in an attack and should thus be included in measurement.

Secondly, in the course of construct validation, computational modelling can complement model-centric and cognition-level evidence on construct content, mechanism, and jingle-jangle. Take novelty. White's (1959, p. 322) original formulation of effectance emphasised novelty as an intensional property of effectance, which Ryan and Deci acknowledge and subsume into competence (Deci & Ryan, 1985, pp. 227, 236, Ryan & Deci, 2017, p. 39). Yet recent SDT work proposes novelty-variety as an additional candidate need separate from competence (Bagheri & Milyavskaya, 2020; González-Cutre et al., 2016, 2020), drawing on factor analyses and correlations of various self-report measures.

Here, computational modelling can help determine whether phenomenologically, semantically, or statistically distinct novelty and competence factors at the phenomenological-psychological level necessitate or equate to distinct mechanisms at the cognitive-computational level. Consider that several CB-IM algorithms produce emergent exploratory behaviour that preferentially visits novel states while only pursuing, e.g., learning progress (Oudeyer et al., 2007). Other CB-IM algorithms generate highly organised skill-learning just from being intrinsically rewarded for differentiating more and more *diverse* courses of action (Eysenbach et al., 2019; Lintunen et al., 2024). This suggests that at the cognitive level, a single mechanism can suffice to generate, explain, and predict both competence- *and* novelty-seeking behaviour and interest/enjoyment arising under both. Similarly, one could test whether, e.g., a plausible capacity growth model also parsimoniously generates the explananda we ascribe to effectance, such as preferentially visiting tasks with disproportional input–output relations. Such modelling could similarly help address the present fragmentation of achievement motivation theories (Wigfield et al., 2021) including SDT, seeing whether these can be parsimoniously integrated under one formalism generating their various explananda (Pekrun, 2024).

These two cases illustrate the complementary role of computational modelling in consilient, multi-level construct validation. Experimental work can construct and test situations which people report as feeling novel but not competence-inducing (or vice versa), and see whether both lead to theorised behavioural consequences. Neurology can explore whether behaviourally or phenomenologically distinct circumstances nevertheless involve similar neural pathways. Cognitive computational modelling can test whether some formalised single mechanism can generate observed data patterns under overtly construct-discriminating conditions.

New study designs

In addition to new forms of hypothesis derivation and construct validation, computational modelling also opens new forms of study and analysis design. We can explore the behaviour of a wide range of alternative models of theory in simulation. This lets us plausibility-check theories and their variants against established effects or theoretical axioms, without effortful empirical data collection (van Rooij & Baggio, 2021). Similarly, we can use such exploration to quickly and cheaply discover optimally discriminating experimental conditions under which different models generate the most diverging point predictions.

We can optimise and assess competing model fit with human data over time and conditions through parameter estimation and model comparison methods (Farrell & Lewandowsky, 2018) to systematically refine, select, and integrate theories.[5] E.g., to refine our understanding of how challenge relates to intrinsically motivated behaviour, we can model any facet or combination of facets of competence as well as competing theories such as Atkinson's achievement motivation model (cited in Deci & Ryan, 1985, pp. 218–221). We can then explore in simulation whether any formal specification of any combination of facets produces behaviour that accords with empirical findings and theoretical explananda. Thus, a recent study on free task choice over time in an online game explored a range of alternative computational models and found that a model comprising task performance *plus* capacity growth *plus* uncertainty reduction best fitted the data (Ten et al., 2021a).

Of course, psychology and SDT are no stranger to multi-factorial models and model fitting using statistical techniques like regression. The difference is that these techniques typically fit a conceptual model to *one* specific data set to *retrospectively* calculate, e.g. coefficients. Computational modelling in contrast allows *prospective*, quantified predictions and determining their fit with a wide range of data sets. This eases cumulative progress at the granular level of the formal model: study by study, we can revise the formalism to improve overall fit with all data sets (see Evans et al. (2018) for an example).

Another new opportunity arises from CB-IM models as functioning AI implementations: we can test whether virtual or robotic agents equipped with some formalism of competence produces learning gains under a wide range of plausible environments, and which formalism learns faster, deeper, wider – or more human-like. This is nicely exemplified by Burda et al. (2019), who compared the behaviour of models on 54 different digital environments. They shows one new path to rapid and stringent testing of plausibility and generalisability. Burda et al. (2019) illustrate another benefit of kickstarting formalisation from prior CB-IM work: its community has developed and is developing a 'canon' of shared evaluation environments, akin to standard experimental tasks.

Finally, CB-IM models have been implemented in so-called procedural content generation systems for games (Guckelsberger et al., 2017). This can be leveraged to create universes of systematically varied stimuli, exposing participants to precisely controlled hypervariate combinations of stimuli in a way that would be cost-prohibitive in material lab setups. These computation-centred experimental designs can support metastudies (Baribault et al., 2018) that allow to systematically and efficiently explore, e.g., the generalisability limits of a theory.

Enabling scalable practical implementation via computational systems

SDT rightfully prides itself in generating effective advice for practitioners such as educators, coaches, managers, or designers on how to intrinsically motivate their clienteles (Ryan & Vansteenkiste, 2023). One widely recognised practical challenge is to identify tasks and goals for each individual that keep them intrinsically motivated, and ideally, sequences of such tasks or goals whose difficulty follows their growing abilities. SDT researchers have derived and tested specific behaviour change techniques and behavioural interventions to enhance need satisfaction, where "provide optimal challenge" (Ahmadi et al., 2023; Gillison et al., 2019) features prominently. In direct interpersonal interaction (e.g., tutor-tutee), skilled practitioners can effectively follow such guidance to, e.g., monitor signs of tutee boredom or frustration and switch to tasks which they believe from past experience will offer a more fitting difficulty (Ahmadi et al., 2023).

Computational modelling can strengthen such practice support in several ways. First, models allow to articulate and validate *quantified* practical guidance, which can be especially useful where reported experience is unreliable. Spaced learning is a great example where behavioural and neurological studies in conversation with computational models helped refine precise and actionable guidance on how to space out, e.g., vocabulary rehearsal to maximise retention (Smolen et al., 2016). The same could be achieved for task difficulty. E.g., evidence-based models of optimal challenge would allow us to tell teachers that an X% success rate is optimal for intrinsic motivation and learning, or that optimal task-switching should occur when trial-on-trial performance improvement drops below Y%.

The second and maybe most important benefit is that computational models are de facto needed for computational systems. In modern society, task and goal allocation increasingly occur at scale, predefined, and/or drawing on a large pool of possible, also new and unfamiliar tasks or goals: take textbooks or MOOCs with test banks for serving large numbers of large classes across the world; company-wide performance targets for job roles; fitness apps; crowd work platforms; or digital games. Here, flexible, in-the-moment

[5] Another useful paradigm enabled by modelling is ablation studies, common in research on complex CB-IM models (e.g. Colas et al., 2019); here, the performance of model versions stripped by one or more of its core features is compared, thus isolating the contributions of each feature.

observation and adaptation by human tutors is impossible or impractical.

In response, more and more task/goal-setting is augmented by or offloaded into software systems that allow automatic individual adaptation at scale. The popular language learning app *Duolingo* for instance generates personalised curricula of tasks with point-precise estimates of learning- and motivation-optimal difficulty (Bicknell et al., 2023). The same logic operates in adaptive goal-setting systems in health behaviour change applications (Baretta et al., 2019) or in task allocation systems in crowdsourcing or citizen science (Sarkar & Cooper, 2021). In education, intelligent tutoring or curriculum and learning task optimisation systems similarly automatically generate, select, or adapt learning tasks, goals, and guidance to present a just-right level of challenge (Mousavinasab et al., 2021; Pandarova et al., 2019). In digital games, automated playtesting systems use AI players to play game levels to test whether their difficulty is "balanced" (Albaghajati & Ahmed, 2020). Dynamic difficulty adjustment systems, AI directors, adaptive AI opponents, and matchmaking systems all detect or predict a player's current skill and then select opponents, opponent actions, or features that present an assumed competence-optimal challenge level (Graepel & Herbrich, 2006; Mortazavi et al., 2024; Paraschos & Koulouriotis, 2023). Experience-driven procedural content generation systems (Yannakakis & Togelius, 2011) similarly generate whole game levels that are predicted to present optimal challenges to a player.

All these are *computational* task/goal-setting systems that therefore need *computable* specifications of SDT on the link between competence and optimal challenge and how to operationalise it in objectively observable task properties and user behaviour.[6] At present, SDT doesn't provide such computable formalisms. It therefore leaves a vast possibility space of plausible and conflicting computational implementations for designers and engineers, possibly resulting in misrepresentation of the theory and thus decreased effectiveness of its application. Computationally modelling competence and challenge not only directly addresses this growing practical need: where real-life systems implement state-of-the-art research models, they can provide vast, granular data sets that can in turn refine theory.

[6] These systems don't work on repeated self-reports of, e.g., perceived difficulty or need satisfaction, as this would quickly overburden users. Even if they did, they still would need quantified, computable guidance on what perceived difficulty is optimal, what level of need satisfaction maximally possible, and by how much to adjust difficulty based on self-report numbers.

Conclusions and outlook

With this article, we hope to have persuaded SDT researchers of the potential of computational modelling. To do so, we used the worked example of competence and optimal challenge. Through conceptual analysis and toy modelling, we found that competence definitions over the long history of SDT's development entail at least three plausible intensional facets (effectance, task performance, capacity growth) which can generate contradicting predictions. Of them, face value analysis suggests that only task performance may be consistently operationalized in our sample of common self-report scales and experimental paradigms. We gave examples like computational models of panic disorder to show how modelling can help determine and validate the internal structure of such a potentially multi-faceted competence construct.

Using our toy model of optimal challenge, we demonstrated how computational modelling furthers transparent and detailed specification to surface ambiguities and diverging assumptions in verbal theory. We showed that competence need satisfaction as task performance is logically maximised under *minimal* challenge, while competence as capacity growth is maximised under *high* challenge. This incoherence may have been occluded by the verbal ambiguity of the optimal challenge construct.

We also argued that computational cognitive science and psychology add complementary conceptions and levels of explanation to SDT's multi-level account of human motivation. They position a *cognitive level* of subpersonal information representation and processing in addition to behavioural, psychological, and neurological levels more familiar in SDT, and a notion of explanation that entails explicating formal models that demonstrably *produce* to-be-explained data patterns. Here, computational modelling can offer useful triangulating, non-linguistic evidence at the cognition level on construct validation and integration – e.g., testing whether one formalised cognitive mechanism suffices to predict and generate phenomenally or behavioural different explananda, like competence and its facets, or competence and novelty-diversity. We pointed to lost beginnings of such a cognition-level account in Deci's information-theoretic sketch of self-determined behaviour (Deci, 1980). More importantly, we identified the AI field of competence-based intrinsic motivation (CB-IM) as an ideal starting point for computational models of competence: it has spent decades developing computational formalisms for artificial agents that self-directedly learn and explore, originally inspired by SDT. This argument is made very concrete by Lintunen et al. (2025), who have mapped the identified facets of competence to CB-IM models.

Finally, we presented an array of powerful new forms of prediction, study design, and analysis enabled by computational modelling, together with practical benefits: Models enable quantitative point predictions for more theory-discriminating hypothesis tests, granular practical guidance, and for temporal, complex, and multi-level processes where human imagination may struggle to predict theory behaviour. They let us conduct model fitting in a way that allows prospective prediction of factor contributions and interactions and cumulative refinement over numerous data sets. Finally, the growing list of automated systems for task/goal-setting manifests a present and growing practical need for computable models of challenge and competence in SDT.

More substantively, we found that specifying competence as *capacity growth* fits propositions on optimal challenge; the distal evolutionary and developmental function of competence motivation claimed in SDT; and aligns with White's (1963) original dynamic notion of effectance as novelty in caused effects. There is a growing body of work in cognitive science suggesting that people orient toward, are sensitive to, and enjoy such *learning progress* (Gottlieb & Oudeyer, 2018; Poli et al., 2022; Sayalı et al., 2023; Ten et al., 2021a, 2021b). Capacity growth or learning progress are inherently *dynamic* and *relational* constructs that involve some comparison of prior and posterior states. Such dynamic models, some have argued, can explain the motivational appeal of seemingly *non*-optimal challenges as well (Deterding et al., 2022). And they fit emerging evidence on the attenuating role of expectations in the salience of need thwarting and satisfaction (Ballou & Deterding, 2023). We therefore see a promising direction for future SDT in more explicitly considering capacity growth in measures, study paradigms, formal models, and tested interventions.

Competence and optimal challenge offered an ideal case study for our argument. But they are just a start. As others before us have shown, computational modelling can fruitfully advance many aspects of SDT across many levels of explanation (Ferreira Chame et al., 2019; Zhang et al., 2019). Theory development and practical guidance around SDT's mini-theories can benefit from point-precise predictions around *how much*, *how often*, *when*, *over what duration*. Imagine we could predict, test, and instruct *how frequently* and *over what time period* interventions should occur to optimally support the internalisation of health-promoting behaviours (following organismic integration theory (Ryan & Deci, 2017)). We see other basic needs and constructs as the next immediate opportunity after competence. Social motives for instance are just beginning to be studied by CB-IM scholars (e.g., Guckelsberger, 2020, p. 150ff.). For autonomy (and perceived locus of causality), the neuroscientific literature on sense of agency meanwhile offers inspiring (neuro)computational mechanisms, although focused more on the immediate action level (Haggard, 2017; Legaspi et al., 2019; Wen & Imamizu, 2022). But these are really just beginnings.

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Declarations

Conflict of interest S.D. declares that the work has no relation with his past position and work at Amazon UK Services Ltd., and was conducted independent of a past paid consultancy for King.com Ltd. The other authors have nothing to declare.

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