

From Compliance to Motivation: Building AI Systems Around Autonomy, Competence, and Relatedness

Front Matter

Abstract

Organizations increasingly deploy AI to improve performance, standardize decision-making, and scale talent processes. Yet many AI-enabled performance systems replicate the same control-heavy logic that has long limited traditional performance management: they optimize for compliance, short-term output, and measurable activity—often at the expense of sustainable motivation, learning, creativity, and retention. Research in Self-Determination Theory (SDT) shows that human motivation quality (autonomous vs. controlled) is shaped by social context—especially whether work environments support the basic psychological needs for autonomy, competence, and relatedness. When these needs are supported, people show higher-quality motivation, stronger well-being, and more durable performance. When these needs are thwarted, extrinsic pressure can “work” in the moment but frequently yields disengagement, burnout, and turnover risk. [1]

This whitepaper synthesizes SDT research and adjacent evidence (including MIT- and HBR-published management guidance) into a privacy-first product blueprint for AI-enabled motivation systems. It translates SDT mechanisms into concrete product components—personalized growth dashboards, mastery loops, and social recognition systems—paired with validated measurement of intrinsic/autonomous motivation and experiment-ready causal validation designs. The central thesis is that AI systems should be designed less as evaluators and more as autonomy-supportive “growth infrastructure,” with explicit guardrails against surveillance and coercion. [2]

Executive Summary

SDT—developed by Edward L. Deci[3] and Richard M. Ryan[4]—distinguishes **motivation quality**: people can act autonomously (because work is interesting or personally meaningful) or under control (because of pressure, contingent rewards, or fear of judgment). In workplaces, the most scalable lever is not “more incentives,” but the design of contexts that support autonomy, competence, and relatedness—the three needs SDT identifies as essential for optimal functioning and high-quality motivation. [5]

Traditional performance systems fail not primarily because measurement is impossible, but because many implementations are **need-thwarting by design**: annual appraisal cycles concentrate evaluation, amplify power asymmetries, and attach status or pay to outcome metrics in ways that can invite gaming, reduce learning orientation, and weaken intrinsic/autonomous motivation. HBR has documented a broad shift away from annual reviews toward more frequent, development-focused check-ins—framed as a move from

accountability to learning—highlighting dissatisfaction with legacy appraisal designs at scale. [6]

Modern work amplifies the importance of autonomy. Hybrid-work randomized trials show that granting flexibility (e.g., two WFH days/week) can improve job satisfaction and reduce quit rates substantially while leaving performance and promotion outcomes unchanged (in that setting), underscoring a practical autonomy–retention pathway when implemented without punitive monitoring. [7]

Product translation (RUDY AI): This whitepaper specifies three SDT-aligned product primitives—(1) personalized growth dashboards, (2) mastery loops, and (3) social recognition systems—implemented with privacy-first data minimization and dignity-by-design governance. The core product job is to raise the **probability of autonomous motivation** for strategically important behaviors (learning, collaboration, innovation, customer problem-solving), not to intensify control. Each feature is paired with validated measurement instruments (e.g., MWMS, WEIMS, BPNSFS) and experiment designs (cluster A/B tests, stepped-wedge rollouts) to link psychological constructs to business KPIs (engagement, performance quality, retention). [8]

Foundations and Evidence

Literature Review

SDT provides a research-grounded account of how environments can **facilitate or undermine intrinsic motivation** and internalization. In SDT’s classic framing, intrinsic motivation is “catalyzed” under conditions that support competence and autonomy; social-context events such as feedback, rewards, and evaluations can shift perceived locus of causality and change motivation quality. [9]

A major empirical finding relevant to performance systems is that **expected, tangible, contingent rewards** can undermine intrinsic motivation in many settings. A meta-analysis of 128 experiments found that engagement-, completion-, and performance-contingent rewards significantly undermined free-choice measures of intrinsic motivation.[10] This does not imply that compensation is inherently harmful; SDT-based workplace research emphasizes that motivational impact depends on the reward’s **functional significance**—whether it is experienced as informational (supporting competence) or controlling (thwarting autonomy). [11]

Within work contexts, SDT has been used to explain how basic need satisfaction predicts high-quality motivation and downstream outcomes. The workplace-focused review by Marylene Gagné[12] and Edward L. Deci[3] articulated SDT’s relevance to organizational behavior, including job design, leadership, and compensation structures. [13] More recent workplace syntheses reinforce that autonomous motivation is typically linked to adaptive outcomes (e.g., engagement, job satisfaction) and lower distress, while controlled motivation is linked to maladaptive outcomes such as burnout and turnover risk. [14]

Meta-analytic evidence refines the common “intrinsic vs. extrinsic” dichotomy into more decision-useful predictions. A large 40-year meta-analysis found intrinsic motivation to be a medium-to-strong predictor of performance, with intrinsic motivation explaining more unique variance in **quality** of performance while extrinsic incentives better predicted **quantity** of performance; it also found incentive salience can reduce the performance-predictive validity of intrinsic motivation in a crowding-out pattern. [15] Complementary SDT meta-analysis suggests intrinsic motivation is particularly important for well-being and attitudes, while identified regulation (doing work because it is meaningful) can be more predictive of performance and organizational citizenship behaviors—an important nuance for product design, because “autonomy support” often means helping people connect work to personally valued goals, not only making tasks “fun.” [16]

Finally, a well-established workplace mechanism is autonomy-supportive leadership. A workplace meta-analysis of leader autonomy support found strong positive associations with autonomous work motivation and positive work outcomes, and negative associations with distress; it also emphasizes leader behaviors such as acknowledging perspectives and offering choice/meaningful rationale rather than using rewards/sanctions as primary motivators. [17]

Theoretical Framework

SDT’s core causal logic can be expressed as a measurable chain:

Work context → (need support vs. need thwarting) → (need satisfaction/frustration) → (motivation quality: autonomous vs. controlled) → **outcomes** (performance quality, well-being, retention, citizenship behaviors). [18]

Autonomy is not mere independence; it is the experience of volition and self-endorsement in action (owning the “why” and having some control over “how”). [19]

Competence is the experience of effectiveness, growth, and mastery; informational feedback and optimal challenge support it. [20]

Relatedness is feeling respected, connected, and valued in a social context; it is catalyzed by belonging, supportive relationships, and recognition that affirms contribution. [21]

The intrinsic vs. extrinsic distinction becomes operationally important when designing AI systems: - **Controlled motivation** (external or introjected regulation) is associated with pressure and compliance. It can produce short-term action but often carries well-being costs and can degrade learning and creativity under evaluative pressure. [22]

- **Autonomous motivation** includes intrinsic motivation and well-internalized extrinsic motivation (identified/integrated). It supports persistence, higher-quality performance, and healthier functioning—especially in complex, creative, or relational tasks where quality matters. [23]

Two modern-work implications are especially consequential for AI-enabled performance systems:

First, autonomy is not optional in hybrid contexts. A randomized trial of hybrid work at Trip.com[24] found improved job satisfaction and reduced quit rates by about one-third, while performance grades and promotions were not adversely affected in that setting—evidence that autonomy-supportive policy can move retention without obvious performance trade-offs when implemented credibly. [25]

Second, measurement and “people analytics” can easily become need-thwarting. MIT researchers argue that ethical employee-data use should center on dignity—ensuring data use helps employees achieve goals and receive appropriate recognition, while acknowledging that employee-data use can also produce negative outcomes when it treats employees as objects to be managed. [26] A critical review of people analytics warns that applying efficiency-driven analytics logic to humans carries significant risks and ethical perils, particularly as learning algorithms expand analytical power. [27] These findings are aligned with HBR’s warnings that workplace surveillance erodes trust and can create ethical and managerial dilemmas. [28]

Productization

Productization

RUDY AI is specified here as a privacy-first “motivation infrastructure” that helps organizations shift from compliance systems (measurement → ranking → pressure) toward motivation systems (need support → learning → contribution). The design requirement is to make SDT constructs **computable and actionable** without collapsing into surveillance.

The product primitives below map directly to autonomy, competence, and relatedness, while remaining testable against engagement, performance, and retention KPIs.

Personalized growth dashboards

Design intent: Replace “scoreboards” with **self-endorsed growth views** that employees can use to understand progress toward personally meaningful goals and role expectations.

SDT translation - Autonomy support: Dashboard begins with user-chosen goals (or user-edited goals) and explicitly distinguishes “manager-required” objectives from “self-chosen” objectives; it offers meaningful rationale for organizational priorities rather than opaque directives. [29]

- **Competence support:** Emphasize progress-to-mastery signals: skill acquisition, feedback loops, and task clarity. SDT research highlights that competence-supportive feedback is informational and effectance-promoting, not demeaning or controlling. [9]

- **Relatedness support:** Elevated visibility of collaboration, help given/received, and recognition narratives (not just counts). Relatedness is supported when people feel connected and valued, which also aligns with recognition research. [30]

Privacy-first data architecture (non-surveillance) - Default to **voluntary, purpose-labeled data sources:** self-reports (micro-surveys), opt-in learning activity, explicit goal tracking, and employee-controlled reflection notes. [31]

- Prohibit individual “activity surveillance” (keystrokes, random screenshots) as a product default; HBR documents both the rise of such tools and the trust harms associated with surveillance practices. [28]
- Apply “dignity-by-design” rules: data use must demonstrably benefit employees (goal achievement, recognition) and remain legible and contestable, consistent with MIT guidance. [26]

Mastery loops

Design intent: Operationalize competence (and internalization) through structured cycles of challenge, practice, feedback, and reflection tied to real work.

Loop mechanics (measurable, SDT-aligned)

1. **Choose a growth target** (user chooses or edits; manager can suggest). This protects autonomy while enabling alignment. [32]
2. **Micro-challenge** embedded in workflow (one behavioral commitment per week).
3. **Feedback** that is timely and informational (what worked, what to do next), not evaluative ranking. SDT’s cognitive evaluation perspective predicts informational feedback supports competence and can support intrinsic motivation when paired with autonomy. [9]
4. **Reflection** (“what did I learn; what do I want to do differently?”) to support internalization (identified/integrated regulation). Meta-analytic SDT evidence suggests identified regulation can be especially predictive of performance outcomes. [33]
5. **Iteration** with user control over pace and difficulty.

Evidence anchors - Workplace SDT guidance argues that need-supportive job design and managerial climates can enhance motivational quality and support outcomes including retention and wellness. [34]

- A meta-analysis indicates intrinsic motivation is a stronger predictor of **quality** performance, supporting the product decision to emphasize mastery loops for knowledge-work quality rather than only throughput. [15]

Social recognition systems

Design intent: Design recognition that supports relatedness and competence without turning recognition into a gamified status contest that becomes controlling.

SDT translation - Recognition should be framed as **informational appreciation** (“this helped the team/customer; here is the impact”) rather than a scarce reward controlling behavior. SDT explicitly notes that the impact of rewards depends on functional significance and interpersonal context. [35]

- Recognition should preferentially reinforce **prosocial contribution and learning behaviors** (helping, mentoring, documenting) that underlying performance systems often fail to capture.

Implementation patterns - “Reflective recognition” prompts: invite employees to share what they are proud of and why (useful in hybrid settings where invisible work increases). HBR describes reflective recognition as a structured approach to surface meaningful contributions and support engagement. [36]

- Lightweight, frequent recognition: HBR reports that small recognition interventions can improve morale, particularly when organizations have limited budget flexibility. [37]
- Guardrails: do not publicly rank employees by recognition counts; SDT and broader analytics critiques warn that metricizing social signals can shift employees into controlled motivation and gaming. [38]

Measurement, Behavior Change, and KPI Mapping

Measurement of intrinsic motivation

Intrinsic motivation is not directly observable, and SDT research emphasizes that measurement typically uses (a) behavioral persistence under free choice and (b) self-reports of interest/enjoyment; in field settings, self-report and context-sensitive repeated measures are most practical. [9]

For workplace-grade measurement that RUDY AI can operationalize without surveillance, a **triangulated approach** is recommended:

Motivation quality (autonomous vs. controlled) - Use validated work-motivation scales grounded in SDT, such as the **Multidimensional Work Motivation Scale (MWMS)**, designed for cross-cultural organizational use and linking motivation types to outcomes like commitment, performance, and turnover intentions. [39]

- Use the **Work Extrinsic and Intrinsic Motivation Scale (WEIMS)** as an alternative SDT-based measure validated across worker samples, capturing intrinsic motivation and internalization forms (identified/integrated) as well as controlled forms. [40]

Need satisfaction and need frustration - Measure autonomy/competence/relatedness satisfaction and frustration using instruments explicitly designed and validated for these constructs (e.g., BPNSFS and work-specific variants). Cross-cultural validation work includes a six-factor model distinguishing satisfaction and frustration for each need. [41]

Measurement design principles for AI systems - Prefer **short, frequent, opt-in** pulse measures rather than heavy annual surveys; MIT argues employee-data programs should ensure use benefits employees and respects dignity. [26]

- Maintain **measurement separation**: collect motivation/need measures as employee-facing self-insight first, and only aggregate to team/org levels for leadership dashboards unless employees explicitly consent to individual sharing. This reduces surveillance perception and aligns with the perils identified in people analytics reviews. [42]

Behavior change loops

RUDY AI's behavior-change design should not rely on manipulation ("dark patterns"), but on transparent, autonomy-supportive behavior scaffolding.

Two evidence-based behavior system models are particularly useful for translating SDT into digital loops:

- The **COM-B system** (capability, opportunity, motivation) provides a compact diagnostic model: a behavior occurs when individuals have capability and opportunity and sufficient motivation; these components interact dynamically. [43]
- The **Fogg Behavior Model** similarly frames behavior as a product of motivation, ability, and triggers occurring at the same moment—useful for product instrumentation and intervention timing. [44]

SDT-aligned behavior loop (non-coercive) - Autonomy: allow employees to select or customize the target behavior (“what skill / what change matters to me”), with clear rationale when a behavior is organizationally required. [32]

- **Competence:** ensure the behavior is broken into achievable steps and accompanied by informational feedback; SDT predicts competence support enhances intrinsic motivation especially when autonomy is supported. [9]

- **Relatedness:** include optional social supports (peer mentor, buddy system, recognition) that affirm contribution without public ranking. [45]

Critically, SDT-informed HRD work cautions that technology features like “gamification” can be ineffective or even counterproductive if not grounded in basic need support; therefore, behavior loops in RUDY AI should be explicitly audited for autonomy support versus control. [46]

KPI mapping

The goal is to map SDT constructs → measurable psychological mediators → observable behaviors → business outcomes.

Below is an implementation-ready mapping for engagement, performance, and retention.

SDT construct (leading)	Validated measurement options	Proximal product signals (privacy-first)	KPI linkage and expected direction
Autonomy satisfaction	BPNSFS / work-need satisfaction measures [41]	% goals user-edited; frequency of “choice” selections; opt-in usage of coaching tools	↑ engagement, ↑ retention; autonomy-supportive contexts correlate with autonomous motivation and positive outcomes [47]
Competence satisfaction	BPNSFS; mastery-related items in work-need scales [48]	completion of mastery loops; feedback utilization; self-reported mastery confidence	↑ performance quality; intrinsic motivation predicts performance, especially quality [15]
Relatedness satisfaction	BPNSFS; work-relatedness	meaningful recognition events	↑ engagement, ↓ burnout/turnover risk;

SDT construct (leading)	Validated measurement options	Proximal product signals (privacy-first)	KPI linkage and expected direction
	items [41]	(narrative + context); network support opt-ins	leadership and recognition relate to engagement and burnout outcomes [49]
Autonomous motivation (intrinsic + identified/integrated)	MWMS; WEIMS [50]	voluntary participation in growth loops; persistence on goals; proactive help-seeking	↑ well-being and attitudes; identified regulation can be especially predictive of performance and OCB [16]
Controlled motivation	MWMS; WEIMS [51]	“checkbox” completion without reflection; spikes tied to deadlines	Short-term ↑ throughput possible, but ↑ burnout risk and well-being costs [52]
Need frustration	BPNSFS (frustration factors) [53]	opt-in “pressure” pulses; perceived surveillance signals; complaint/appeal rates	↑ turnover risk, ↓ engagement; surveillance erodes trust and can backfire [28]

Two additional KPI anchors help business leaders interpret why SDT-aligned systems are not “soft”: - HBR reports that invasive monitoring often undermines trust, engagement, and creativity—risks that directly threaten performance and retention. [54]
- Hybrid-work causal evidence shows flexibility can reduce quit rates dramatically without measurable performance damage in that trial context, suggesting autonomy-supportive work design can create immediate retention ROI. [25]

Hypotheses and Experimental Validation

Hypotheses + measurable constructs

Each hypothesis links: (feature → SDT mediator → business KPI). Constructs should be measured with validated scales (MWMS/WEIMS/BPNSFS) plus operational metrics, using privacy-preserving aggregation.

H1: Autonomy-supportive choice architecture increases autonomous motivation.

If RUDY AI presents growth actions as user-selectable options with rationale (vs. system-assigned directives), then autonomy satisfaction and autonomous motivation will increase, and controlled motivation will not increase (or will decrease). [55]

Measures: BPNSFS autonomy satisfaction/frustration; MWMS autonomous vs. controlled subscales; weekly opt-in “felt autonomy” item. [56]

H2: Mastery loops increase competence satisfaction and performance quality.

If employees engage in structured mastery loops (micro-challenges + informational feedback + reflection), then competence satisfaction will increase and quality-of-performance indicators will improve more than quantity indicators. [57]

Measures: competence satisfaction (BPNSFS); skill confidence self-report; quality KPIs specific to role (defect rate, customer satisfaction, peer-rated craftsmanship), avoiding surveillance. [58]

H3: Narrative recognition increases relatedness satisfaction and reduces burnout/turnover intention.

If recognition is designed as narrative appreciation tied to impact (not leaderboard points), then relatedness satisfaction and engagement will increase and burnout/turnover intention will decrease. [59]

Measures: relatedness satisfaction (BPNSFS); engagement (validated engagement scale or internal engagement index); burnout proxy; turnover intention (from MWMS/related surveys). [60]

H4: Surveillance-perceived instrumentation increases need frustration and harmful outcomes.

If employees perceive RUDY AI as monitoring/controlling (even with good intentions), then need frustration will increase and trust/engagement will decline; rule-breaking or gaming behaviors may increase. [61]

Measures: BPNSFS frustration; trust items; system “workarounds” rates; qualitative feedback; ethics incident trends. [62]

Experimental design

RUDY AI should be validated via causal designs that respect organizational constraints and protect employees.

Design principles - Prefer **cluster randomization** (team or manager-level) to reduce contamination (coworkers share experiences).

- Pre-register primary endpoints (engagement, performance-quality metric, retention/turnover intention) and specify guardrail metrics (stress, surveillance perception).

- Use intention-to-treat analysis; preserve opt-out rights without penalty (critical for “autonomy support” integrity). [31]

A/B test portfolio 1. Choice architecture test (Autonomy) - *Control:* AI assigns a weekly development task (“Do X this week”).

- *Treatment:* AI offers 3–5 options aligned to the same competency with rationale and allows “none of the above.”

- *Primary outcomes:* autonomy satisfaction; autonomous motivation; engagement. [63]

1. Mastery loop test (Competence)

- 2. *Control:* dashboard shows goals and progress only.

3. *Treatment*: dashboard includes guided micro-challenges, informational feedback prompts, and reflection capture.
4. *Primary outcomes*: competence satisfaction; quality-performance metric; learning behavior persistence. [64]
5. **Recognition design test (Relatedness)**
6. *Control*: recognition via “likes/badges” count only.
7. *Treatment*: narrative recognition with impact tags + optional reflective recognition prompt (employee shares what they’re proud of).
8. *Primary outcomes*: relatedness satisfaction; engagement; burnout proxy; turnover intention. [65]

Quasi-experimental option If full randomization is infeasible, use a **stepped-wedge rollout**: sequentially introduce features across teams, comparing early vs. later adopters while controlling for time trends—especially relevant for organization-wide tools. This should still include explicit monitoring of surveillance perception and dignity harms. [66]

Ethical considerations

A motivation-centered AI system can fail ethically even if its models are accurate, because controlling instrumentation can undermine autonomy, dignity, trust, and well-being—core SDT constructs and business-critical assets.

Non-surveillance as a product principle - Avoid default collection of “what/where/when” continuous monitoring data (e.g., keystrokes, screenshots). HBR documents both the rise of monitoring technologies and the trust harms of surveillance approaches. [28]

- When productivity insight is needed, prefer “interactional monitoring” patterns: human check-ins, shared goals, and employee voice, consistent with HBR guidance that monitoring effects depend on how it is done. [67]

Dignity-by-design governance MIT argues ethical employee-data use should be guided by dignity—ensuring data use helps employees achieve goals and receive recognition—and warns that employee-data use can also harm employees when it becomes objectifying. Practically, this supports product rules like purpose limitation, employee-access rights, and contestability of inferences. [26]

People analytics risk controls A critical review of people analytics identifies serious perils when organizations apply efficiency-driven analytics logic to humans, especially as AI increases analytical power and decision automation. RUDY AI should therefore implement:

- **Data minimization and separation**: keep personalized coaching data private by default; aggregate for leadership.

- **Explainability and appeal**: allow employees to challenge inferences and correct context.
- **No hidden optimization**: prohibit reinforcement strategies that maximize engagement regardless of well-being (a known “metric extraction” failure mode in algorithmic systems). [68]

Avoid “AI as the boss” Research on algorithmic management highlights that algorithmic systems can shift power toward managerial prerogatives, enable surveillance, and deskill roles if deployed chiefly for control. This is directionally incompatible with SDT’s autonomy support mechanism and with hybrid-work trust requirements. [69]

Fairness and inclusion Recognition and performance systems can encode bias when metrics privilege visible work and penalize invisible collaboration. Recognition design should surface hidden work (coaching, documentation, help) and avoid leaderboard dynamics that drive strategic behavior rather than authentic contribution. [70]

References

Baard, P. P., Deci, E. L., & Ryan, R. M. (2004). *Intrinsic Need Satisfaction: A Motivational Basis of Performance and Well-Being in Two Work Settings*. Journal of Applied Social Psychology. [71]

Bloom, N., et al. (2024). *Hybrid working from home improves retention without damaging performance*. Nature. [72]

Bloom, N., Liang, J., Roberts, J., & Ying, Z. J. (2013/2015). *Does Working from Home Work? Evidence from a Chinese Experiment*. NBER Working Paper. [73]

Cappelli, P., & Tavis, A. (2016). *The Performance Management Revolution*. Harvard Business Review. [74]

Chen, B., Vansteenkiste, M., et al. (2015). *Basic psychological need satisfaction, need frustration, and need strength across four cultures*. Motivation and Emotion (includes BPNSFS development/validation). [53]

Cerasoli, C. P., Nicklin, J. M., & Ford, M. T. (2014). *Intrinsic Motivation and Extrinsic Incentives Jointly Predict Performance: A 40-Year Meta-Analysis*. Psychological Bulletin. [75]

Deci, E. L., Koestner, R., & Ryan, R. M. (1999). *A Meta-Analytic Review of Experiments Examining the Effects of Extrinsic Rewards on Intrinsic Motivation*. Psychological Bulletin. [76]

Deci, E. L., Olafsen, A. H., & Ryan, R. M. (2017). *Self-Determination Theory in Work Organizations: The State of a Science*. Annual Review of Organizational Psychology and Organizational Behavior. [77]

Fogg, B. J. (2009). *A Behavior Model for Persuasive Design*. Persuasive '09 (ACM). [44]

Gagné, M., & Deci, E. L. (2005). *Self-determination theory and work motivation*. Journal of Organizational Behavior. [13]

Gagné, M., Forest, J., Vansteenkiste, M., et al. (2015). *The Multidimensional Work Motivation Scale: Validation evidence in seven languages and nine countries*. European Journal of Work and Organizational Psychology. [78]

Giermendl, L. M., Strich, F., Christ, O., Leicht-Deobald, U., & Redzepi, A. (2021/2022). *The dark sides of people analytics: reviewing the perils for organisations and employees*. European Journal of Information Systems. [27]

Hamrick, A. B., et al. (Referenced by HBR tip). *Research: A Better Way to Keep Tabs on Your Remote Workforce*. (HBR adaptation note). [79]

HBR (Buckingham, M., & Goodall, A.). (2015). *Reinventing Performance Management*. Harvard Business Review. [80]

HBR (O’Flaherty, S., Sanders, M. T., & Whillans, A.). (2021). *Research: A Little Recognition Can Provide a Big Morale Boost*. Harvard Business Review. [37]

HBR (Thiel, C., McClean, S., Harvey, J., & Prince, N.). (2024). *Surveilling Employees Erodes Trust — and Puts Managers in a Bind*. Harvard Business Review. [81]

HBR (Thiel, C., Bonner, J. M., Bush, J., Welsh, D., & Garud, N.). (2022). *Monitoring Employees Makes Them More Likely to Break Rules*. Harvard Business Review. [82]

MIT Sloan. (2021). *Use dignity as a guide when collecting data on employees*. MIT Sloan School of Management (Ideas Made to Matter; MIT CISR brief referenced). [26]

MIT Task Force on the Work of the Future. (2019). *The Work of the Future: Shaping Technology and Institutions*. [83]

Michie, S., van Stralen, M. M., & West, R. (2011). *The behaviour change wheel: A new method for characterising and designing behaviour change interventions*. Implementation Science. [43]

Parker, S. K., & Knight, C. (2024/2025). *SMART Work Design model / Design Work to Prevent Burnout* (MIT Sloan Management Review materials: store page + presenter slides). [84]

Rigby, C. S., & Ryan, R. M. (2018). *Self-Determination Theory in Human Resource Development: New Directions and Practical Considerations*. Advances in Developing Human Resources. [46]

Ryan, R. M., & Deci, E. L. (2000). *Self-Determination Theory and the Facilitation of Intrinsic Motivation, Social Development, and Well-Being*. American Psychologist. [85]

Ryan, R. M., & Deci, E. L. (2000). *Intrinsic and Extrinsic Motivations: Classic Definitions and New Directions*. Contemporary Educational Psychology. [86]

Slemp, G. R., Kern, M. L., Patrick, K. J., & Ryan, R. M. (2018). *Leader autonomy support in the workplace: A meta-analytic review*. Motivation and Emotion. [17]

Stanford News. (2024). *Study finds hybrid work benefits companies and employees* (summary of hybrid-work RCT findings). [87]

Tremblay, M. A., Blanchard, C. M., Taylor, S., Pelletier, L. G., & Villeneuve, M. (2009). *Work Extrinsic and Intrinsic Motivation Scale (WEIMS): Its Value for Organizational Psychology Research*. Canadian Journal of Behavioural Science. [40]

Van den Broeck, A., Ferris, D. L., Chang, C.-H., & Rosen, C. C. (2016). *A Review of Self-Determination Theory's Basic Psychological Needs at Work*. Academy of Management Annals. [88]

Van den Broeck, A., Howard, J. L., Van Vaerenbergh, Y., Leroy, H., & Gagné, M. (2021). *Beyond intrinsic and extrinsic motivation: A meta-analysis on SDT's multidimensional conceptualization of work motivation*. Organizational Psychology Review. [33]

[1] [5] [12] [18] [19] [21] [85]

https://selfdeterminationtheory.org/SDT/documents/2000_RyanDeci_SDT.pdf

https://selfdeterminationtheory.org/SDT/documents/2000_RyanDeci_SDT.pdf

[2] [3] [29] [34] [46] https://selfdeterminationtheory.org/wp-content/uploads/2018/05/2018_RigbyRyan_HR.pdf

https://selfdeterminationtheory.org/wp-content/uploads/2018/05/2018_RigbyRyan_HR.pdf

[4] [28] [81] <https://hbr.org/2024/02/surveilling-employees-erodes-trust-and-puts-managers-in-a-bind>

<https://hbr.org/2024/02/surveilling-employees-erodes-trust-and-puts-managers-in-a-bind>

[6] [74] <https://prod-edxapp.edx-cdn.org/assets/courseware/v1/0d740b595eaebe7a8cdd812f86f6760/asset-v1%3AWhartonOnlineProfessionalEd%2BMGMT1x%2B4T2017%2Btype%40asset%2Bblock/Performance-Appraisal-HBR.pdf>

<https://prod-edxapp.edx-cdn.org/assets/courseware/v1/0d740b595eaebe7a8cdd812f86f6760/asset-v1%3AWhartonOnlineProfessionalEd%2BMGMT1x%2B4T2017%2Btype%40asset%2Bblock/Performance-Appraisal-HBR.pdf>

[7] [25] [72] <https://www.nature.com/articles/s41586-024-07500-2>

<https://www.nature.com/articles/s41586-024-07500-2>

[8] [39] [50] [51] [78] https://selfdeterminationtheory.org/wp-content/uploads/2014/04/2015_GagneForestEtAl_MultidimensionalWork.pdf

https://selfdeterminationtheory.org/wp-content/uploads/2014/04/2015_GagneForestEtAl_MultidimensionalWork.pdf

[9] [20] [57] [64] [86]

https://www.selfdeterminationtheory.org/SDT/documents/2000_RyanDeci_IntExtDefs.pdf

https://www.selfdeterminationtheory.org/SDT/documents/2000_RyanDeci_IntExtDefs.pdf

[10] <https://pubmed.ncbi.nlm.nih.gov/10589297/>

<https://pubmed.ncbi.nlm.nih.gov/10589297/>

[11] [14] [22] [23] [24] [35] [38] [52] [77] https://selfdeterminationtheory.org/wp-content/uploads/2017/03/2017_DeciOlafsenRyan_annurev-orgpsych.pdf

https://selfdeterminationtheory.org/wp-content/uploads/2017/03/2017_DeciOlafsenRyan_annurev-orgpsych.pdf

[13]

https://selfdeterminationtheory.org/SDT/documents/2005_GagneDeci_JOB_SDTtheory.pdf

https://selfdeterminationtheory.org/SDT/documents/2005_GagneDeci_JOB_SDTtheory.pdf

[15] [75] https://selfdeterminationtheory.org/wp-content/uploads/2017/06/2014_Cerasoli_Intrinsic.pdf

https://selfdeterminationtheory.org/wp-content/uploads/2017/06/2014_Cerasoli_Intrinsic.pdf

[16] [33] https://selfdeterminationtheory.org/wp-content/uploads/2023/10/2021_VandenBroeckEtAl_Beyond.pdf

https://selfdeterminationtheory.org/wp-content/uploads/2023/10/2021_VandenBroeckEtAl_Beyond.pdf

[17] [32] [47] [55] [63] <https://pmc.ncbi.nlm.nih.gov/articles/PMC6133074/>

<https://pmc.ncbi.nlm.nih.gov/articles/PMC6133074/>

[26] [31] [66] <https://mitsloan.mit.edu/ideas-made-to-matter/use-dignity-a-guide-when-collecting-data-employees>

<https://mitsloan.mit.edu/ideas-made-to-matter/use-dignity-a-guide-when-collecting-data-employees>

[27] [42] [68] <https://www.alexandria.unisg.ch/bitstreams/ae2f994d-4acf-4f91-a0f6-81238e1b3f3e/download>

<https://www.alexandria.unisg.ch/bitstreams/ae2f994d-4acf-4f91-a0f6-81238e1b3f3e/download>

[30] [37] [45] [59] <https://hbr.org/2021/03/research-a-little-recognition-can-provide-a-big-morale-boost>

<https://hbr.org/2021/03/research-a-little-recognition-can-provide-a-big-morale-boost>

[36] [65] [70] <https://hbr.org/2022/10/a-better-way-to-recognize-your-employees>

<https://hbr.org/2022/10/a-better-way-to-recognize-your-employees>

[40]

https://selfdeterminationtheory.org/SDT/documents/2009_TremblayBlanchardetal_CJBS.pdf

https://selfdeterminationtheory.org/SDT/documents/2009_TremblayBlanchardetal_CJBS.pdf

[41] [48] [53] [56] [58] [60] [62] https://selfdeterminationtheory.org/wp-content/uploads/2015/01/2015_ChenVansteenkisteEtAl_BPNS_MOEM.pdf

https://selfdeterminationtheory.org/wp-content/uploads/2015/01/2015_ChenVansteenkisteEtAl_BPNS_MOEM.pdf

[43] <https://pmc.ncbi.nlm.nih.gov/articles/PMC3096582/>

<https://pmc.ncbi.nlm.nih.gov/articles/PMC3096582/>

[44] https://www.demenzemedicinagenerale.net/images/mens-sana/Captology_Fogg_Behavior_Model.pdf

https://www.demenzemedicinagenerale.net/images/mens-sana/Captology_Fogg_Behavior_Model.pdf

[49] <https://journals.plos.org/plosone/article?id=10.1371%2Fjournal.pone.0312951>

<https://journals.plos.org/plosone/article?id=10.1371%2Fjournal.pone.0312951>

[54] [67] [79] <https://hbr.org/tip/2025/02/a-better-way-to-monitor-remote-employees>

<https://hbr.org/tip/2025/02/a-better-way-to-monitor-remote-employees>

[61] [82] <https://hbr.org/2022/06/monitoring-employees-makes-them-more-likely-to-break-rules>

<https://hbr.org/2022/06/monitoring-employees-makes-them-more-likely-to-break-rules>

[69] <https://pages.ischool.utexas.edu/hai-files/files/publications/56/2021-BigDataSociety-AlgorithmicManagement.pdf>

<https://pages.ischool.utexas.edu/hai-files/files/publications/56/2021-BigDataSociety-AlgorithmicManagement.pdf>

[71] https://selfdeterminationtheory.org/SDT/documents/2004_BaardDeciRyan.pdf

https://selfdeterminationtheory.org/SDT/documents/2004_BaardDeciRyan.pdf

[73] https://www.nber.org/system/files/working_papers/w18871/w18871.pdf

https://www.nber.org/system/files/working_papers/w18871/w18871.pdf

[76]

<https://home.ubalt.edu/tmitch/642/articles%20syllabus/Deci%20Koestner%20Ryan%20meta%20IM%20psy%20bull%2099.pdf>

<https://home.ubalt.edu/tmitch/642/articles%20syllabus/Deci%20Koestner%20Ryan%20meta%20IM%20psy%20bull%2099.pdf>

[80] <https://hbr.org/2015/04/reinventing-performance-management>

<https://hbr.org/2015/04/reinventing-performance-management>

[83] <https://web.mit.edu/2.810/www/files/readings/WorkOfTheFuture.pdf>

<https://web.mit.edu/2.810/www/files/readings/WorkOfTheFuture.pdf>

[84] <https://shop.sloanreview.mit.edu/design-work-to-prevent-burnout>

<https://shop.sloanreview.mit.edu/design-work-to-prevent-burnout>

[87] <https://news.stanford.edu/stories/2024/06/hybrid-work-is-a-win-win-win-for-companies-workers>

<https://news.stanford.edu/stories/2024/06/hybrid-work-is-a-win-win-win-for-companies-workers>

[88] https://selfdeterminationtheory.org/wp-content/uploads/2024/01/2016_VandenbroeckFerrisEtAl_a-review-of-self-determination-theory.pdf

https://selfdeterminationtheory.org/wp-content/uploads/2024/01/2016_VandenbroeckFerrisEtAl_a-review-of-self-determination-theory.pdf