Naming emotions in the corporate workplace as a way to measure learnability.

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Abstract

This paper introduces the Naming Emotions Collaborative Prompting (NECP) framework as a conceptual approach to measuring and supporting learnability in the corporate workplace. Grounded in emotional awareness theory, collaborative learning research, and adaptive instructional design, NECP emphasizes the act of naming emotions as a low-cost, privacy-respecting method for enhancing self-regulation and reducing emotional bias in competence assessments. The framework integrates ten parametrized learning environment elements and uses a dual-track system: (1) real-time learner classification into Good, Neutral, or Bad for Learnability states based on competence scores and emotion valence, and (2) longitudinal evaluation of design elements using stable inverse probability weighting (S-IPW). The model dynamically adjusts learning environments and matches learners with complementary profiles to optimize emotional and cognitive conditions for learning. While still theoretical, NECP offers a scalable, evidence-informed method for aligning emotional regulation with workplace learning strategies and provides a foundation for future empirical validation.

Introduction

The corporate workplace operates as a lifelong learning environment characterized by diversity in age, cultural background, and professional roles (Tynjälä, 2008). This diversity, coupled with the constant need for skill development, highlights the importance of learnability—the ability to acquire knowledge continuously, adapt to evolving challenges, and regulate one's own learning in dynamic environments (Hall & Mirvis, 1995; De Grip & van Loo, 2002). Effective learning requires awareness of one's knowledge and limitations (Pellegrino, Chudowsky, & Glaser, 2001), yet emotional bias distorts learnability measurement by affecting self-assessment, motivation, and adaptability. Optimism bias leads to overestimation of abilities, while negativity bias results in underestimation, reducing assessment accuracy (Sharot, 2011; Efklides, 2011). Employees who undertake the assessments are often under the influence of negative past experiences, stress and pressure (Dweck, 2006, Lerner et al., 2015; Tyng et al., 2017).

Despite attempts to reduce distortions in self-evaluation through self-reports, behavioral data, and AI-driven analytics (Cascio & Montealegre, 2016), the role of emotions in metacompetencies such as learnability—where emotional awareness plays a central role—remains under-researched. While emotions are known to influence cognitive flexibility and adaptability (Tyng et al., 2017), limited research explicitly examines how emotional awareness impacts learnability assessments or how targeted strategies can mitigate emotional bias in these evaluations. This paper proposes the Naming

Emotions Collaborative Prompting (NECP) framework as a method for measuring learnability in the corporate workplace. The framework aims to reduce emotional bias while incorporating emotions as a factor that fosters inclusivity. By integrating emotional awareness into assessments, NECP supports collaboration and contributes to the development of a lifelong learning culture in corporate environments.

Literature review

One of the primary obstacles for lifelong learning in the workplace is limited time availability and the workload (Billett, 2001, Tynjälä, 2008), as well, as lack of learning-oriented culture and lack of learning friendly policies (Marsick, V. J., & Watkins, K. E, (2003). Another obstacle stems from the change fatigue (Illeris, 2011) and among older employees the self-efficacy barriers, coming from a belief that younger colleagues are more capable. Additionally, the increasing use of complex technologies like artificial intelligence, machine learning, and automation creates a digital divide where older employees or those with non-technical backgrounds are separated from digital savvy ones and struggle to adapt new technologies (Cascio & Montealegre, 2016). Complexity theory says that intricate challenges emerge from the dynamic interactions of a system's components over time, and the distinct features of such systems can only be understood by analysing how these components interrelate (Manson, 2001). Consequently, understanding and in consequence adapting complex technologies requires breaking them down into smaller, more manageable components, what demands from the employees resilience and adaptability (Mallin, 2019).

To learn in the workplace means to deal with the current workload and to struggle with the time constraints but at the same time it is an opportunity for collaborative learning in a social and interactive environment when learners engage in dialogue and scaffold each other's understanding (Vygotsky, 1978) and knowledge internalization over time (Illeris, 2011). In a long-term perspective employees interacting with their colleagues can curate mentoring relationships (Tynjälä, 2008), establish grounded peer-to-peer learning practices, which contribute to higher engagement and knowledge retention (Eraut, 2004).

However, for collaborative learning to be effective, it requires a clearly defined structure (Dillebourg, 1999). One of the ways to ensure that structure is self-regulation as it provides a framework for learners to set goals, monitor progress, regulate their emotions, and reflect on their learning process (Zimmerman, 2002). Moreover, the socially shared regulation of learning allows learners to co-regulate each other's learning through shared goal setting, monitoring and adaptation. In the lifelong perspective of corporate the self-regulation often serves as an intrinsic motivation factor even when the external incentives are absent (Deci & Ryan, 1985). Self-regulation oftentimes deepens employees' understanding that learning is an ongoing process rather than fixed ability (Dweck, 2006) and helps to assess necessary next steps in the learning process and navigate through change (Efklides, 2011, Zimmerman & Schunk, 2011).

One of the ways to self-regulate is to name the emotions one feels during the work day.
It builds on the theory that emotions are not universal but are socially and linguistically constructed (Barrett, 2017) and naming them using language helps organize thoughts (Vygotsky, 1985) and regulate physiological and behavioral response (Lieberman et al., 2007). The challenge comes from the fact that it is not obvious what emotions are. Ekman identified six fundamental emotions—happiness, sadness, fear, anger, surprise, and disgust—each characterized by distinctive facial expressions and serving evolutionary functions (Ekman, 1992). On the other hand psychoevolutionary theory proposes eight primary emotions, arranged as opposing pairs: joy versus sadness, anger versus fear, trust versus disgust, and surprise versus anticipation (Plutchik, 1980). Another approach building on the Plutchik's approach is a computational study, including sentiment analysis and text-based emotion classification (Gangemi et al., 2023). Research has identified at least seven primary emotional circuits—seeking, fear, rage, lust, care, panic/grief, and play—that are present across all mammals. These neural systems, rooted in subcortical brain regions, are shared among mammals and are responsible for generating fundamental affective states (Panksepp, 1998). However, contemporary interpretations suggest that these neural circuits may be modulated by cognitive processes and environmental influences.

Although the measurement and identification of emotions have become increasingly sophisticated, integrating multiple methodologies such as the Positive and Negative Affect Schedule (PANAS) and the Geneva Emotion Wheel, real-time emotion tracking remains challenging due to its association with increased stress and anxiety (Andalibi, 2023). Similarly, advanced techniques such as facial recognition software like Affectiva and iMotions, as well as natural language processing for sentiment analysis, raise privacy concerns and face technological limitations of measuring accuracy (Marda, 2023). A growing body of research suggests that emotions are more flexible and context-dependent than classical models initially proposed (Barrett, 2017). Flexibility and context-dependent nature of emotions comes from the interaction between internal cognitive load, motivation, past experiences, and external conditions such as social environment and situational triggers (Tyng, Amin, Saad, & Malik, 2017). Moreover, emotional granularity theory states that the ability to distinguish and label emotions with precision, enhances emotion regulation, decision-making, and cognitive flexibility (Barrett, 2017; Kashdan et al., 2015). Consequently, high emotional granularity allows individuals to apply targeted coping strategies, reducing stress and fostering psychological resilience (Kalokerinos et al., 2019). It also mitigates impulsivity, refines social interactions, and strengthens metacognitive processes, all of which contribute to effective learning (Cameron et al., 2013; Lindquist et al., 2015). For example an individual who states, "I feel a mix of excitement and fear before presenting," instead of merely saying, "I'm nervous," demonstrates enhanced cognitive control and self-consciousness that emerges from the dynamic interplay of internal factors and environment, with emotions shaping perception and behavior (Damasio, 1999).

It is important to differentiate that emotion labeling categorizes emotions, while naming emotions verbalizes them for conscious awareness and self-regulation (Lieberman et al., 2007; Barrett, 2017). Both contribute to emotional granularity, metacognition, and emotion regulation, but labeling can occur without explicit verbalization, whereas naming requires conscious expression. Both enhance emotional granularity, improving decision-making, stress regulation, and cognitive flexibility (Kashdan et al., 2015; Cameron et al., 2013). Emotion labeling supports regulation strategies, mitigating stress responses (Gross, 2015), reducing amygdala activation, and enhancing cognitive performance (Lieberman et al., 2007). Additionally, labeling emotions structures experiences, strengthens memory recall (Barrett, 2017), and enhances encoding in long-term memory (Tyng et al., 2017) it supports regulation strategies, mitigating stress responses (Gross, 2015), reducing amygdala activation, and enhancing cognitive performance (Lieberman et al., 2007).

Whereas naming emotions helps reframe challenges and enhance the performance (Gross, 2015), reduce unnecessary tension in teams and improve productivity (Barsade & O'Neill, 2016). Emotional awareness that comes with emotions naming fosters metacognitive control (Efklides, 2011 and helps recognizing emotions as temporary states what strengthens resilience (Dweck & Leggett, 1988). Similarly, the employees in leader roles can contribute to greater trust and collaboration in the team using precise names for the emotions they feel (Grant, 2013). The employees' who can name their emotions such as anxiety or resistance can reframe them in a constructive manner, facilitating adaptation. In essence, recognizing emotions fosters a growth mindset, which is essential for continuous workplace learning. Teams that accurately express emotions experience lower tension and higher levels of creativity, which directly contributes to collaborative learning (Barsade & O'Neill, 2016). Learning in corporate settings involves social interaction and tacit knowledge exchange, both of which are strengthened by emotional awareness (Tynjälä, 2008).

Curiosity, surprise, confusion, interest, and frustration are the epistemic emotions that influence how employees navigate novel situations and adapt to complex tasks (Muis et al., 2015). Research indicates that epistemic emotions significantly impact cognitive engagement and learning behaviors. For instance, curiosity drives learners to seek information actively, while moderate levels of confusion can promote deeper learning by signaling the need to resolve cognitive conflicts (Vogl et al., 2019). Similarly, surprise captures attention and stimulates inquiry, fostering a more engaged learning process, whereas frustration and boredom tend to negatively affect performance and motivation (Vilhunen et al., 2022). Understanding how epistemic emotions shape learning experiences is crucial for designing workplace training interventions that promote effective knowledge retention and problem-solving skills. The study of epistemic emotions often uses experience sampling methods and controlled experiments to analyze learners' emotional responses. Surveys such as the Epistemically Related Emotion Scales (EES) have been validated to measure curiosity, confusion, and surprise in educational contexts (Muis et al., 2015). Nonetheless, the key strength of epistemic emotions research is its recognition that negative emotions are not always detrimental to learning. When effectively managed, emotions such as confusion can enhance cognitive engagement and promote deeper understanding (D'Mello & Graesser, 2012). However, a critical challenge associated with epistemic emotions lies in the balance between beneficial and detrimental confusion. While moderate confusion may enhance active learning, excessive confusion can lead to frustration and disengagement (Vilhunen et al., 2022).

Furthermore, the real-time measurement of epistemic emotions remains complex, as emotional states fluctuate based on contextual and individual factors. Affective computing encompasses systems designed to recognize, interpret, and respond to human emotions using technologies such as facial expression analysis, voice tone recognition, and physiological sensors (Picard, 1997). These systems tailor instructional content based on learners' emotional states, thereby enhancing engagement and motivation. Affective tutoring systems (ATS), a subset of affective computing, employ machine learning algorithms to detect frustration, confusion, or boredom and modify instructional strategies accordingly (Liu et al., 2022). One key advantage of affective computing is its capacity to personalize learning by dynamically adjusting content delivery in response to emotional feedback. For instance, emotion-aware learning platforms can detect if a learner appears overwhelmed and modify the pace of instruction or offer encouragement. Additionally, emotion-adaptive systems can mitigate burnout by monitoring stress indicators and suggesting breaks when necessary (Liu et al., 2022). However, affective computing faces notable challenges concerning accuracy and ethical considerations. Emotion recognition algorithms may misinterpret expressions, leading to incorrect interventions, while continuous monitoring of learners' facial and physiological data raises significant privacy concerns (Liu et al., 2022).

Among methods used for measuring learnability, including self-explanation, retrieval-based assessments, and error-based learning. Encouraging learners to generate explanations enhances understanding and retention by assessing how well they integrate new information. Self-explanation during problem-solving has been shown to improve skill acquisition (Chi et al., 1989). Regular testing not only assesses knowledge but also reinforces learning through the testing effect, as evidenced by improved retention among students who engage in practice testing compared to those who rely solely on studying (Roediger & Karpicke, 2006). Active learning strategies, such as discussions and problem-solving activities, enhance learnability by increasing engagement, with meta-analyses demonstrating higher performance in active learning environments compared to traditional lecture-based instruction (Freeman et al., 2014). In human-computer interaction, learnability is assessed by measuring how quickly users become proficient with new systems, with key metrics including task completion time, error rates, and user satisfaction. Studies evaluating gesture recognition systems have used these measures to track user adaptation (Wobbrock et al., 2007). Measuring cognitive load provides further insights into learnability. Techniques include subjective rating scales, physiological measures such as eye-tracking, and performance-based assessments. The cognitive load scale (Paas et al., 1994) measures mental effort and instructional efficiency. Since different emotions bias perception in distinct ways, emotional states play a crucial role in shaping judgment, decision-making, and learning behaviors. Emotional bias is not limited to anger but extends to fear, sadness, disgust, and happiness, all of which influence cognition and behavior systematically (Lerner, Li, Valdesolo, & Kassam, 2015). While it is possible to mitigate the emotional bias (Greenwald, McGhee, & Schwartz; 1998, Kahneman & Tversky 1979; Frederick 2005; Lerner et al., 2015; Phelps et al., 2000), emotional bias is often deeply ingrained in lifelong experiences (Kahneman, 2011) and can resurface in other contexts (Lai et al., 2016). That is why bias mitigation practices should be continuous and context specific.

Concept

The Naming Emotions Collaborative Prompting (NECP) framework proposes naming emotions as a way to increase emotional awareness and contextually mitigate the bias right before uptaking the competence assessment. Nonetheless, for the framework to yield expected results it should be continuous, and to make it continuous it should be fun, which comes from the engagement and flow, where deep focus and a balance between skill level and challenge create enjoyment (Csikszentmihalyi, 1990), and there is more enjoyment when it is a collaborative experience (Reis, O'Keefe, & Lane, 2016), that is why I propose to use a collaborative chat, that could also serve as a place to extract the tacit knowledge to explicit knowledge (Nonaka & Takeuchi, 1995; Soliman & Vanharanta, 2018). Since, novelty and exploration introduce excitement, making activities more enjoyable (Gopnik, 2020), NECP uses AI agent as a prompter of regular surveys preceded with the emotions assessment. Since playfulness and humor further contribute to well-being by transforming routine tasks into enjoyable experiences (Proyer, 2017), NECP leverages the use of emojis, memes and GIFs as universal method of modern communication (Highfield & Leaver, 2016, Grundlingh, 2017) to further that experience and ease the regularity of the assessments. The AI agent's role is primarily to prompt emotion and competence surveys; it is designed to use memes, emojis, and GIFs to help the employees engage. Additionally, AI agent provides general responses within the limits of a standard large language model but is designed to keep answers concise, between 40-70 characters, to reduce visual fatigue (Baymard Institute, 2022); this brevity aligns with the curiosity gap theory, encouraging learners to ask more questions (von Stumm, Hell, & Chamorro-Premuzic, 2011) and supports first principles thinking, helping them break down complex problems and understand them more effectively (Gillett, 2020). The continuous and emotionally unbiased assessment in the conversational chat allows to use the social interactions toolkit like ConvoKit (Chang, Chiam, Fu, Wang, Zhang, & Danescu-Niculescu-Mizil, 2020)(Eraut, 2004b; Marsick & Watkins, 1990) to introduce learning analytics and identify patterns and the learning gaps (Chen, Chen, & Lin, 2020). Unlike facial recognition, which raises privacy concerns, naming emotions provides a more discreet and self-directed way to measure emotional states (Barrett, 2017; Lieberman et al., 2007). It ensures anonymity, supports self-assessment, and encourages self-mastery over competition by eliminating external comparisons (Dweck, 2006; Deci & Ryan, 1985). The NECP framework distinguishes between negative emotions that impair learning—such as frustration or feeling worse (Ashkanasy & Dorris, 2017)—and those that, when paired with appropriate cognitive challenge, contribute positively to the learning process. Drawing on the productive failure framework, it conceptualizes certain negative emotional states as catalysts for deeper understanding and learnability when they emerge in response to meaningful struggle (Kapur, 2016).

The NECP framework proposes a monthly structured intervention called "emotional gym" that brings together learners in different emotional phases (e.g., frustration and satisfaction), as emotional diversity has been shown to deepen engagement and enhance learning (Isohätälä et al., 2019). The intervention consists of three sequential steps, each followed by an emotion survey. It begins with sharing personal preferences—such as a favorite book or movie—to foster interpersonal connection through self-disclosure, a process shown to build mutual trust and perceived closeness in learning environments (Collins & Miller, 1994). Even when the items shared are unfamiliar to others, the act of sharing itself can trigger the familiarity effect and promote empathy by offering insight into the sharer's values or emotional landscape (Mar, Oatley, & Peterson, 2006; Zajonc, 1968). These interactions contribute to a sense of common ground, supporting engagement and collaboration in learning environments after which learners indicate the predominant emotion they feel.

As part of its structured intervention, in the next step NECP framework introduces quantum theory as a designed frustration factor to simulate emotional and cognitive challenges essential for fostering learnability. Triggers of learning-related frustration, include cognitive overload due to complex or excessive content (Sweller, 1988), ambiguity or unclear instructions (Mayer, 2001), lack of feedback (Hattie & Timperley, 2007), technological disruptions (Sun et al., 2008), mismatches in pacing (Csikszentmihalyi, 1990), unrealistic performance goals (Dweck, 2006), and the demotivating effects of social comparison (Festinger, 1954). Quantum theory, due to its inherent complexity, serves as a valuable context for studying frustration in learning. It requires learners to master abstract conceptual frameworks and advanced mathematical tools such as linear algebra, complex numbers, calculus, differential equations, Fourier analysis, and group theory (Dirac, 1981; Shankar, 1994)—meets these conditions. Re-engaging with previously learned but partially forgotten topics, like calculus, reinforces the cyclical nature of learning and fosters self-awareness. Progressing into more complex material, such as superposition, entanglement, and quantum paradoxes, deepens emotional engagement and supports the development of metacognitive skills by challenging learners to tolerate ambiguity and contradiction. Furthermore, paradoxes like Schrödinger's cat can model the emotional dualities inherent in learning, such as simultaneously experiencing curiosity and confusion or trust and skepticism.

To operationalize these effects, the NECP framework integrates quantum theory as a deliberately structured frustration factor within a time-bound "emotional gym" setting conducted in a collaborative chat. Learners progress through a sequential list of topics, each concluding with an open-ended assessment graded by an AI agent and assigned a percentage score. These scores are intended for peer comparison, introducing social comparison as a targeted frustration trigger to evaluate readiness for advancement and prompt emotional reflection throughout the learning process. This intervention draws on established frustration triggers—such as social comparison, which can reduce learner motivation (Festinger, 1954), and productive failure, which enhances deep learning through cognitive struggle (Kapur, 2016). The structured nature of the activity not only promotes emotional awareness and supports the development of learnability but also enables systematic measurement and modulation of how learners respond to and overcome complex cognitive-emotional challenges over time. As a final step in the "emotional gym" intervention, learners receive support from an AI agent trained in quantum physics, including access to QuantumGPT, which answers up to 200 complex quantum-related questions (Nakaji et al., 2024). In parallel, a standard GPT model fine-tuned on a quantum physics knowledge base assists beginner and intermediate learners through accessible, story-based metaphors designed to explain abstract concepts. For example, when asked "What is Calculus?", the AI agent may respond with a metaphorical narrative to support intuitive understanding and emotional engagement.

Imagine you're driving. The road is curved, the speed changes.
Calculus is the mathematics of that change.
In quantum land, everything flows—nothing stands still.
It tells us how a small ripple here leads to a tidal wave there.

In the relief phase, learners receive reflective prompts that highlight the rarity and value of their acquired understanding—for example, "The estimated number of people who understand what you now know does not exceed X, which is around P% of the world population." This type of perspective-taking supports emotional regulation by encouraging recognition of personal progress. Narrative identity construction, which involves situating individual achievements within a broader life story, helps learners generate meaning and reduce psychological strain (McAdams, 2001). Recognizing the scarcity of one's knowledge further enhances perceived self-worth and reduces dependence on external validation (Cialdini, 2001). Additionally, gratitude-based reflection promotes emotional well-being, resilience, and motivation (Emmons & McCullough, 2003).

Emotions influence learning through both their valence (positive or negative) and activation level (high or low arousal), as described in Russell's (1980) circumplex model of affect. Empirical studies rank positive high-arousal emotions—such as curiosity and interest—as the most beneficial for learning, enhancing motivation, engagement, and cognitive flexibility (Fredrickson, 2001; Pekrun et al., 2002; Tyng et al., 2017). Positive low-arousal emotions, like calmness and contentment, support reflective processing and stress regulation, especially after cognitively demanding tasks (Rowe et al., 2007; Immordino-Yang & Damasio, 2007). Negative high-arousal emotions, such as frustration and confusion, may facilitate learning through productive failure when properly regulated (Kapur, 2016; D'Mello & Graesser, 2012; Pekrun, 2006). In contrast, negative low-arousal emotions, such as boredom or apathy, consistently correlate with disengagement and poor learning outcomes (Pekrun et al., 2010; Tze et al., 2013; Silvia, 2008). The theory that human behavior results from the dynamic interplay between internal states and external conditions. According to field theory, behavior is a function of both the person and the environment (Lewin, 1936). Social cognitive theory emphasizes reciprocal determinism, where personal factors, behavior, and environmental influences shape one another (Bandura, 1986). Similarly, ecological systems theory describes development as influenced by multiple nested environmental systems interacting with individual traits (Bronfenbrenner, 1979). Self-determination theory adds that motivation arises when internal needs are supported by external environments (Deci & Ryan, 2000). These perspectives align with NECP's assumption that learner actions reflect both internal emotional states and external design factors. Naming emotions serves as the connecting element to internal states, as each named emotion approximates an internal experience. Competence assessments reflect the outcome of the interaction between internal and external influences. However, external learning environment design elements remain unlinked unless they are systematically associated with named emotions. The NECP framework fills this gap by tracking and weighting design elements to triangulate internal states, external conditions, and behavioral outcomes in measuring learnability. At each design point, the user names an emotion and completes a competence test. Using the circumplex model, NECP categorizes these emotions by valence and arousal to assess their impact on learning.

Valence, Arousal	Example of Emotion	Assigned Value	Justification
Positive, High	Excitement, Curiosity	0.95	Boosts motivation, attention, memory, and creativity (Fredrickson, 2001; Pekrun et al., 2002; Tyng et al., 2017)
Positive, Low	Calm, Contentment	0.8	Supports consolidation and long-term retention,

			especially after intense effort (Rowe et al., 2007; Immordino-Yang & Damasio, 2007)
Negative, High	Frustration, Confusion	0.65	Can be beneficial if well-regulated (productive failure), but carries overload risk (Kapur, 2016; D'Mello & Graesser, 2012; Pekrun, 2006)
Negative, Low	Boredom, Apathy	0.3	Typically harmful; correlates with disengagement and poor performance (Pekrun et al., 2010; Tze et al., 2013; Silvia, 2008)

Table 1: Emotions division

When it comes to assessment measuring short adaptive quizzes provide an effective means of tracking learning progress while minimizing cognitive load (Kalyuga & Sweller, 2005). In the NECP framework, each design element's contribution to learnability is evaluated using a Naming Emotions (NE) score. This score is calculated by multiplying the learner's competence test result (expressed as a percentage) by an assigned emotional value (e.g., 0.95, 0.8, 0.65, or 0.3), which reflects the quality and presence of named emotions. This approach enables continuous monitoring of both emotional engagement and competence development, allowing the system to adaptively optimize personalized learning environments over time.

*NE = competence test result(%) * emotion named assigned value*

For each learning environment element, the process of validating it looks following:

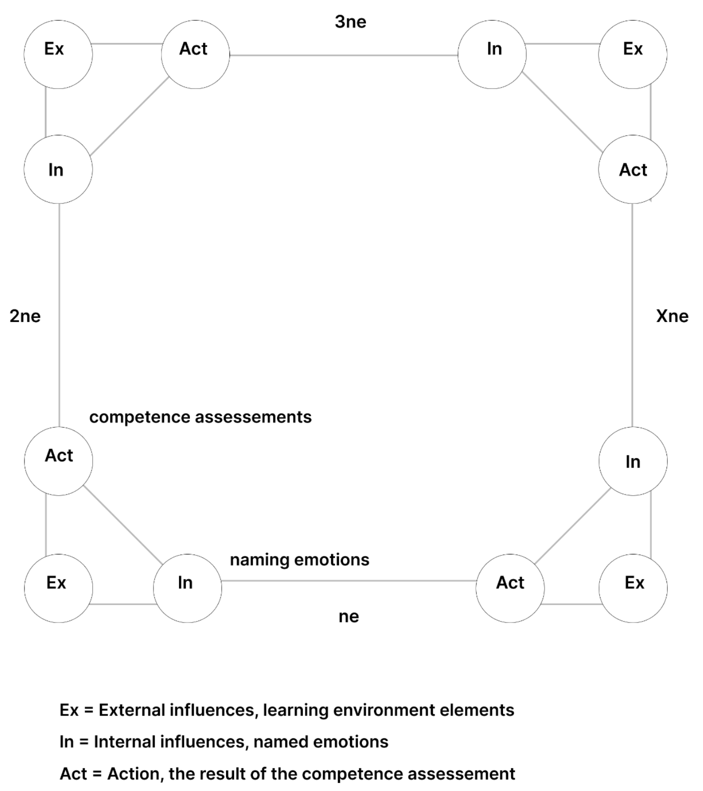

Fig.1: Single element of the learning environment

As data accumulate—the NE score identifies which elements consistently correlate with improved learning outcomes. Effective elements are retained or reinforced, while less effective ones are deprioritized. Below is the list of learning environment elements that are evaluated by the NE score:

1. When a learner names an emotion, this demonstrates emotional awareness, engagement, and readiness for self-reflection, thereby justifying an assigned default value of 1 (Collins & Miller, 1994; Isohätälä et al., 2019).
2. Naming more than one emotion in a single instance indicates higher emotional granularity and the capacity to tolerate emotional complexity, warranting a default value of 1 (Barrett, 2017; McAdams, 2001).
3. Additionally, when learners name positive emotions after previously indicating negative emotions, this reflects emotional growth and adaptability, and thus merits a default value of 1 (Kapur, 2016; Emmons & McCullough, 2003).

4. Conversely, naming negative emotions reveals recognition of challenges and productive cognitive friction, making it valuable for learning progress and therefore also assigned a default value of 1 (Kapur, 2016; Sweller, 1988).
5. Filling out competence surveys within collaborative chat environments ties emotional self-awareness directly to performance assessment, providing essential insights into the relationship between emotions and competencies. This critical link to the learnability measurement process justifies assigning a default value of 1 to survey completion (Festinger, 1954; Hattie & Timperley, 2007).
6. Breaking a pattern of repeatedly naming the same or similar emotions indicates a significant shift in emotional state and increased reflective learning, thereby also supporting a default value of 1 (McAdams, 2001; Emmons & McCullough, 2003).
7. Furthermore, when learners post chunks of knowledge into the collaborative chat, it promotes informal learning through social interaction, aligning with the framework's objective to replicate authentic workplace knowledge sharing scenarios, thus justifying assigning this parameter a default value of 1 (DiMicco et al., 2008).
8. Similarly, active engagement with the AI agent signifies emotional support seeking, metacognitive engagement, and openness to guided reflection, which are essential components of adaptive learning, thus supporting the assignment of a default NE score of 1 (Nakaji et al., 2024).
9. Initiating conversations in the collaborative chat environment signals proactivity, heightened social engagement, and commitment to interpersonal learning, all crucial for supporting ongoing emotional and cognitive development. Hence, this parameter receives a default value of 1 (Isohätälä et al., 2019).
10. Likewise, active contribution to conversations initiated by others enhances social presence, collective problem-solving, and interpersonal learning, thus equally warranting a default value of 1 (Isohätälä et al., 2019).

This is how it looks for the whole learning environment combined of 10 elements that evolves over time based on the NE score and adjusts to the learner's needs:

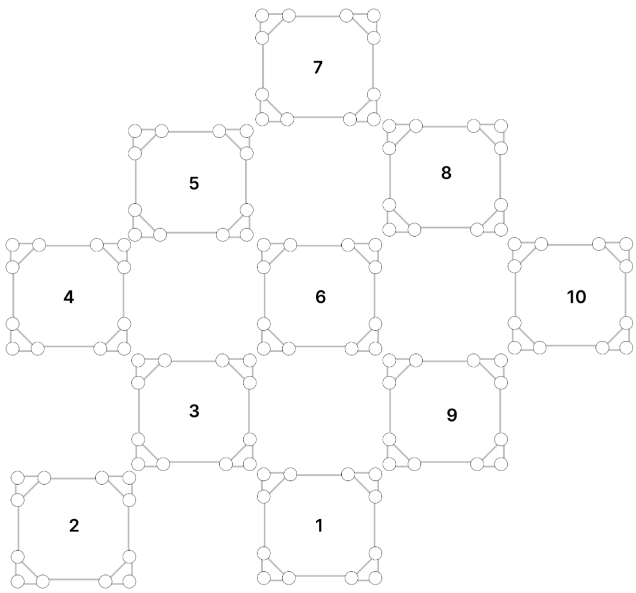

Fig.2: Adaptive learning environment divided into ten elements connected through external factors

The NECP framework uses a dual-track system that distinguishes between (1) the classification of individual learners into learnability states and (2) the longitudinal evaluation of design elements. This structure supports both individual learning progress and continuous optimization of instructional strategies. Initially, NECP assigns binary values (0 or 1) to ten predefined design elements (mentioned above) based on their presumed contribution to learnability. As data accumulates, it adjusts these values to continuous weights in the range [0,1] using Stable Inverse Probability Weighting (S-IPW), which stabilizes variance and reduces overfitting in longitudinal studies (Avagyan & Vansteelandt, 2021). A design element remains in use if it shows a positive correlation with competence improvement over 40–50 assessments, as supported by modeling guidelines (Box & Jenkins, 1976; Chatfield, 2016; Shadish et al., 2002).

Simultaneously, NECP classifies learners into one of three learnability states based on the NE score, which integrates emotional valence (Russell, 1980), competence scores, and engagement with design elements. Learners fall into: Bad for Learnability (B: 0–0.333), Neutral (N: 0.334–0.666), or Good (G:

0.667–1). These thresholds are not empirically validated but are preliminarily informed by early NECP design logic and theoretical clustering patterns, where lower-performing learners tend to score around 0.24, moderate performers cluster around 0.35–0.39, and high performers score ≥0.60. These states guide dynamic peer-matching: learners in G are paired with learners in N or B to promote emotional regulation and collaborative learning (Isohätälä et al., 2019; Barsade & Gibson, 2012). To accelerate profiling, NECP groups learners with similar emotional-competence patterns and generalizes effective configurations across profiles (Kashdan et al., 2015; Zimmerman & Schunk, 2011). In structured environments with low variability, it may only require 20–30 observations to establish reliable weights; in more complex conditions, it needs 40–50 observations (Chatfield, 2016).

Evidence from person-centered and differential susceptibility research supports the existence of complementary learnability profiles. Learners in contrasting emotional states may still demonstrate similar learning behaviors and benefit from collaborative pairing (Putwain et al., 2018; Ellis et al., 2022). Matching learners classified as Good for Learnability (G) with those in a Neutral state (N) fosters emotional regulation, empathy, and peer learning. This strategy aligns with findings that emotionally diverse groups enhance engagement and learning outcomes (Isohätälä et al., 2019; Barsade & Gibson, 2012). These results support NECP's dynamic matching system, which prioritizes emotional and behavioral complementarity over raw performance. As learners' data evolve across time series, group compositions adjust accordingly. For example, Learner @ matches with Learner # in 5 out of 8 observed intervals, demonstrating how NECP adapts matching based on updated emotional and competence data.

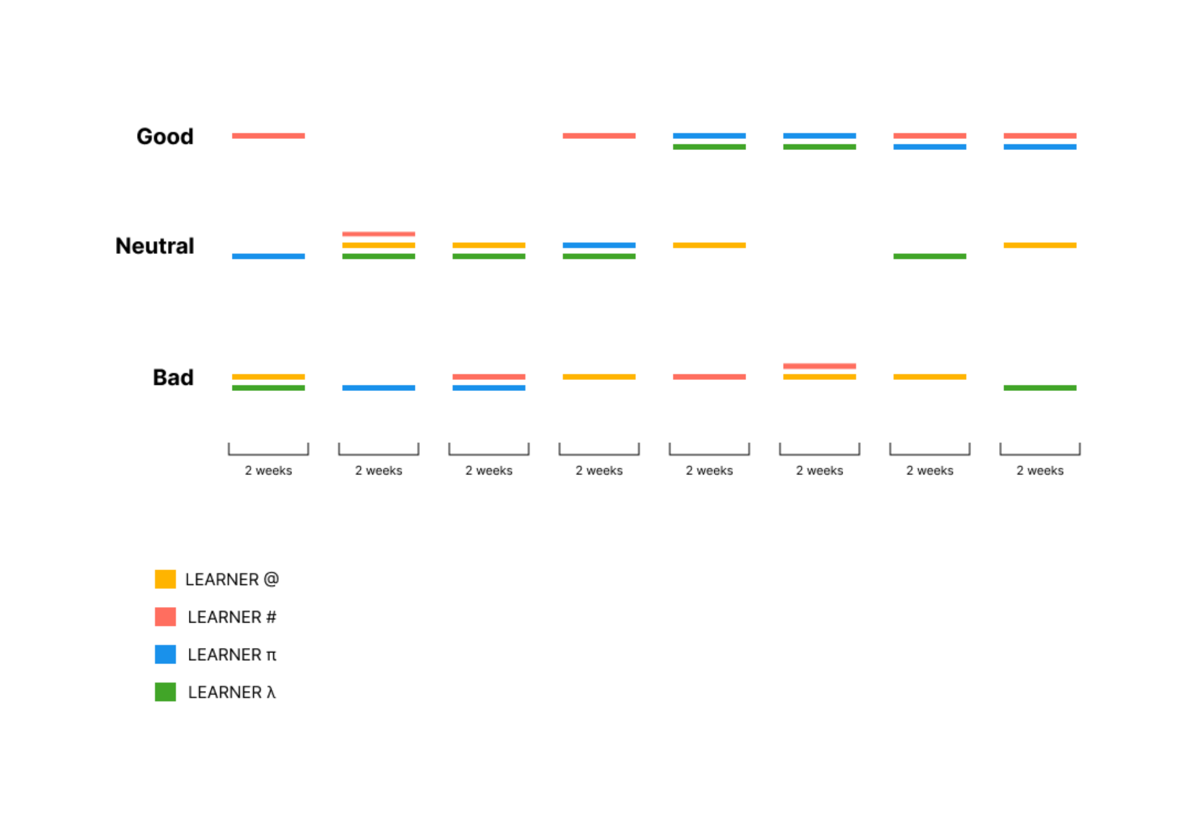

Fig.3: Learnability matching system

Limitations

The primary limitation faced by the NECP framework is the extensive duration currently required—approximately 105 days—to conclusively identify and reject inefficient or inadequate learning environment design elements, and subsequently validate new ones. Optimizing this validation period needs further investigation into the interconnectedness and interrelations among learners' individual learnability profiles. Furthermore, the framework is hugely dependable on competence tests, inconsistent competence tests could skew the measure and negatively affect the matching process, further research on how to address this bias is needed - potentially developing a unified self-assessessment competence methodology for each domain such as structured self-assessment for competence in AI, Encryption etc.

Conclusion

This paper presents NECP (Naming Emotions Collaborative Prompting) as a conceptual framework for measuring and developing learnability within structured workplace learning environments. Grounded in an extensive review of interdisciplinary literature—including emotional regulation, productive failure, corporate learning design, and statistical modeling—NECP offers a novel approach to linking emotional awareness with learning progress. The framework introduces a dual-track structure: (1) dynamic classification of individual learners into Good, Neutral, or Bad for Learnability states based on emotion valence, arousal, and competence scores, and (2) longitudinal evaluation of design elements through stable inverse probability weighting (S-IPW). This separation allows for continuous adaptation of both individual learning paths and systemic instructional strategies.

Although still theoretical, NECP integrates well-established psychological and pedagogical principles with scalable design logic. It emphasizes emotion naming as a low-cost, privacy-conscious proxy for internal states, allowing for precise adjustment of the learning environment without intrusive monitoring. Collaborative matching based on emotional complementarity further supports self-regulation, empathy, and peer learning. Future empirical research is needed to validate NECP's assumptions, refine its classification algorithms, and test its effectiveness in real-world learning settings. If confirmed, the NECP model could offer a practical, adaptable tool for corporate learning environments—and beyond—that balances cognitive challenge with emotional support to foster sustainable, personalized growth.

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