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Attitude and motivation to work in autism rehabilitation operators: Algorithms based on reaction times

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ABSTRACT

Background: Assessing the true motivation and attitudes of rehabilitation professionals working in autism care is crucial for ensuring effective interventions and high-quality support. Traditional self-report tools are limited by social desirability bias, underscoring the need for implicit and computational approaches.
Aims: This exploratory study aims to assess whether reaction-time-based implicit measures, combined with machine learning (ML), can identify latent demotivation and attitudinal inconsistency among rehabilitation professionals.
Methods: Twenty-eight rehabilitation operators and twenty university students participated in the study. Students were assigned to two simulated profiles: satisfied (N = 10) and dissatisfied (N = 10). A custom computerized reaction-time task was developed in which participants were presented with statements and asked to respond "Yes" or "No" by pressing a key on the keyboard. Additionally, three paper-and-pencil tests were administered to assess work motivation, social desirability, and to collect sociodemographic information. The significant variables relating to latency and consistency obtained from the student data were used in the ML analysis (Naïve Bayes and Random Forest) to perform an exploratory classification of the rehabilitation professional sample.
Results: The computerized task, unlike the paper-and-pencil tests, showed statistically significant differences ($p < .005$) between the two profiles of the student sample. Based on the significant variables derived by the student sample, the exploratory model classified seven professionals as dissatisfied, achieving an accuracy of 78 %.
Conclusions: Latency-based implicit measures, when integrated with ML, offer a promising methodological framework for detecting hidden motivational patterns. Results are preliminary and should not be interpreted as diagnostic or predictive; further validation with larger, ecologically valid samples of professionals is required.

1. Introduction

Work-related stress among rehabilitation professionals represents an important concern in healthcare, as it can affect both workers' well-being and the quality of care provided. These professionals are frequently exposed to emotionally demanding situations that can lead to fatigue, reduced motivation, and burnout—a chronic condition of psychological exhaustion, cynicism, and detachment from work (Maslach & Leiter, 2016). Burnout is often associated with job dissatisfaction, high turnover, and diminished quality of care (Hakanen et al., 2006; Maslach & Leiter, 2016; Novack & Dixon, 2019), emphasizing the importance of understanding and preventing motivational decline in those working with vulnerable populations. This issue is particularly relevant in autism rehabilitation, where individuals are highly sensitive to interpersonal dynamics and professionals' attitudes, and rely on stable, predictable, and supportive environments (Corden et al., 2022; Hurt et al., 2013). According to the Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition (DSM-5; American Psychiatric Association, 2013), autism is a neurodevelopmental condition primarily characterized by differences in communication and social interaction, as well as the presence of

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restricted, repetitive, and stereotyped behaviors, interests, or activities. Within a neurodiversity framework, autism is understood as a natural variation in neurodevelopment, with distinctive strengths and support needs (Cherewick & Matergia, 2024); accordingly, autistic individuals display diverse communication styles, sensory regulation, and engagement with interests, with substantial heterogeneity across the spectrum (Anixt et al., 2024). Some individuals may present patterns - e.g., self-injury, externalizing behaviors, and marked sensory responses — that professionals may find challenging to support and that can contribute to heightened emotional strain and occupational stress (Como et al., 2020; Shahid et al., 2024). Persistent exposure to such demands may lead to loss of motivation, reduced empathy, and professional fatigue, ultimately affecting therapeutic relationships and outcomes.

Recent studies suggest that, although rehabilitation and healthcare professionals typically report positive explicit attitudes toward autistic individuals, they may simultaneously hold implicit biases that diverge from their self-reported beliefs (Darazsdi & Bialka, 2023; Dickter et al., 2020; Kelly & Barnes-Holmes, 2013).

These biases are often automatic and unconscious but can subtly shape behavior and communication. In autism care, implicit bias may manifest as lower expectations, microaggressions, or inconsistencies in engagement (Bottema-Beutel et al., 2023; Como et al., 2020), in some cases described as ableist and anti-autistic biases (Darazsdi & Bialka, 2023). It is important to emphasise that such attitudes carry direct clinical consequences: For example, Kelly and Barnes-Holmes (2013) found a negative correlation between the effectiveness of Applied Behavior Analysis (ABA) interventions in autistic children and the presence of therapists' implicit negative attitudes. Additionally, many parents of these children express significant concerns about the negative attitudes of professionals, such as unreliability, high turnover rates, failure to adhere to work schedules, and lack of participation in supervision meetings (Grindle et al., 2009; Hurt et al., 2013; Nastasi et al., 2024).

Collectively, this evidence underscores the need for accurate assessment of both explicit and implicit components of professional motivation and attitude. However, traditional self-report measures are subject to social desirability and self-presentation biases, particularly in professional contexts where maintaining a positive image is socially and occupationally advantageous (Dickter et al., 2020; Ren et al., 2025). In healthcare contexts, this limitation is particularly critical, as workers may consciously or unconsciously mask demotivation or negative attitudes. For this reason, indirect, latency-based methods, such as implicit reaction-time paradigms, can offer valuable alternatives, as they rely on automatic processes less susceptible to conscious control (Greenwald et al., 1998; Verschuere et al., 2011).

In recent years, behavioral research has demonstrated that increased cognitive load during deceptive or inconsistent responding leads to longer reaction times (RT) and higher error rates (Monaro et al., 2017, 2021; Sartori et al., 2018; Vrij et al., 2008). According to Cognitive Load Theory, deception requires greater cognitive effort than telling the truth (Suchotzki et al., 2017). According to Sartori et al. (2018), engaging an individual in a cognitively demanding task - such as responding to unexpected questions, recounting events in reverse chronological order, or performing dual tasks – increases cognitive load for those attempting deception, thereby heightening the likelihood of detecting inconsistent or delayed responses.

In addition to RT, response consistency has been used to assess the reliability of statements (Colwell et al., 2002; Vrij et al., 2016). Consistent responses indicate stable underlying attitudes, whereas inconsistent or delayed answers suggest internal conflict or cognitive strain. This point is particularly interesting because liars can prepare and rehearse a linear story in anticipation of interviews, thereby appearing more coherent. As a result, consistency has been used as a criterion for deception detection in experimental settings (Colwell et al., 2002; Köhnken et al., 1995; Porter & Yuille, 1995).

These principles are already applied in occupational psychology. For instance, the True Response Inconsistency (TRIN) scale of the Minnesota Multiphasic Personality Inventory (Weiss & Weiss, 2010), is based precisely on response consistency across pairs of opposing-content items (Handel et al., 2006), providing an objective indicator of the truthfulness and stability of responses.

Parallel to these methodological advances, machine learning (ML) has gained prominence in behavioral science for modeling complex, non-linear patterns at the individual level (Yarkoni & Westfall, 2017). Unlike traditional statistical approaches, focused on mean group differences, ML algorithms can integrate multiple performance indices—such as reaction time, accuracy, and consistency—to predict latent behavioral states. In deception studies, Monaro et al. (2021) applied ML algorithms to classify liars and truth-tellers with 90 % accuracy, using the Inverse Efficiency Score (IES)—a composite index of speed and accuracy—when responding to unexpected questions. Such results highlight the potential of ML for developing objective behavioral models that capture subtle psychological variability.

Despite these advances and the well-documented limitations of traditional self-report tools, implicit and computational approaches have not yet been systematically applied in the workplace or healthcare context. This represents a significant gap, as these methods could improve the understanding and monitoring of professional motivation, help identify early signs of burnout and disengagement, and ultimately enhance personnel selection and training. Integrating implicit assessments with machine learning may thus provide a robust framework for capturing the hidden motivational processes underlying professional performance.

In particular, drawing on deception-detection paradigms, it may be possible to identify implicit indices of motivational regulation. From this perspective, latency-based measures could serve as indirect indicators of processes such as cognitive load, expressive control, coherence monitoring, and impression management, which may accompany the dissimulation of low or absent motivation.

Building on these premises, the present study aims to evaluate whether reaction-time-based implicit measures, analyzed through ML algorithms, can identify latent demotivation and attitudinal inconsistencies among rehabilitation professionals working in autism care. Specifically, we investigated whether latency and consistency indicators could distinguish genuinely motivated professionals from those exhibiting implicit signs of demotivation—even when explicit self-reports remain positive.

Table 1
Socio-demographic characteristics of the two samples.

Sample	Profile	N	Gender	Age Mean (SD)
Student		20	M= 2, F= 18	23.5 (8.66)
	Satisfied	10	M= 1, F= 9	21.7 (2.58)
	Dissatisfied	10	M= 1, F= 9	25.3 (12.02)
Rehabilitation Operators		28	M= 3, F= 25	39.68 (10.83)

M: Male; F: Female; SD: standard deviation

2. Methods and procedure

2.1. Participants

The recruited participants were volunteers, all over the age of 18 and native Italian speakers. Each participant signed an informed consent form and none received financial compensation. Two populations participated in the study (Table 1):

1. Rehabilitation Operators (N = 28, 3 males and 25 females; mean age 39.68 ± 10.83): This group consisted of rehabilitation professionals working with autistic individuals.
2. Student (N = 20, 2 males and 18 females; mean age: 23.5 ± 8.66): This group consisted of students recruited from the University of L'Aquila, randomly assigned to two profiles:

- o Satisfied Profile (N = 10, 1 male and 9 females; mean age: 21.7 ± 2.58): Students were instructed to identify as satisfied and motivated rehabilitation operators with positive attitudes and a strong sense of efficacy (Hurt et al., 2013; Kazemi et al., 2015; Novack & Dixon, 2019). These students were asked to respond consistently with this profile.
- o Dissatisfied Profile (N = 10; 1 male and 9 females; mean age: 25.3 ± 12.02): Students were instructed to assume the identity of a dissatisfied and demotivated rehabilitation worker with negative attitudes and a low sense of self-efficacy (Hurt et al., 2013; Kazemi et al., 2015; Novack & Dixon, 2019). They were required to perform the computerized task while appearing satisfied and motivated in their work to avoid repercussions and maintain their job.

2.2. Procedure

Each participant individually took part in data collection, conducted in a quiet and distraction-free room. Due to the nature of the study, participants were not informed in advance of the specific content of the administered tests to prevent potential bias, such as social desirability or emotional influences, which could affect response patterns and reaction times (RTs).

Initially, participants were provided with an informational document containing partial details about the study's actual objectives, omitting that the study included implicit detection techniques (RTs, response inconsistency) aimed at assessing the reliability of responses to questions concerning work-related propensity, attitude, and motivation. Given that the procedure and research aim did not pose any emotional or physical harm, all participants were thoroughly debriefed at the end of data collection to clarify and reassure them about the study's purpose. Additionally, they were asked to provide a second consent for the use of the collected data. This informed consent and debriefing process adheres to the guidelines of the Italian Psychological Association (Code of Ethics, Article 2) and the American Psychological Association (APA Ethical Guidelines for Research, Ethical Standards 8.07 and 8.08). No participant withdrew from the study.

The study was conducted following APA ethical standards and was approved by the Internal Review Board of the University of L'Aquila (protocol no. 41769, ID number 09/2022).

2.3. Assessment tools

Each participant completed three paper-and-pencil tests and one custom-designed computerized task to assess work motivation and attitude, with a total duration of approximately 20 min.

2.3.1. Questionnaires

Motivation At Work Scale, Italian Version (MAWS; Galletta et al., 2011): A 13-item scale measuring four key aspects of work motivation based on Self-Determination Theory (SDT): intrinsic, identified, introjected, and external motivation. Participants rated each statement on a 5-point Likert scale (1 =Strongly disagree, 5 =Completely agree) to indicate how well it reflected their reasons for working. Four scores were obtained: Autonomous Motivation, Introjected Motivation, External Motivation, and Total Motivation Score.

Balanced Inventory of Desirable Responding Short Form, Italian Version (BIDR 6; Bobbio & Manganelli, 2011): A 16-item scale assessing social desirability in two dimensions: self-deception and impression management. Participants rated their agreement on a 6-point Likert scale (1 =Strongly disagree, 6 =Strongly agree). The scale provides indices for Self-Deception, representing a tendency to view oneself positively, and Impression Management, indicating a conscious and habitual effort to present a favorable image to others. A Total Social Desirability score was also calculated.

Sociodemographic Questionnaire: This questionnaire included items on demographic information (gender, birth date, nationality, education, hair and eye color) and occupational details (job title, years of experience, weekend work, number of clients, and client clinical characteristics). Participants responded by selecting one or more options when specified.

2.3.2. Computerized task

The task was created and administered using E-Prime® 2.0 software and consisted of 40 control statements and 60 experimental/unexpected statements, paired using the reverse-matching method (each statement α corresponds to its negation -α). Stimuli appeared randomly in the center of the screen. Participants were instructed to press "1" for "Yes" and "0" for "No" on the keyboard. Each stimulus appeared automatically after a response, without requiring any action to proceed to the next question. Participants were asked to respond as quickly as possible without a time limit or feedback on their responses.

The statements were categorized as follows:

- *Control Statements*: 10 pairs of declarative knowledge statements with universally correct answers (e.g., "Rome is the capital of Italy" or "Giraffes have short necks"). Additionally, 10 pairs of statements related to participants' physical, identity, or occupational characteristics were included. Correct answers were determined based on their sociodemographic questionnaire responses (e.g., "My eyes are brown" or "I work on weekends").
- *Unexpected Work-Related Statements*: 30 pairs of experimental statements addressing participants' attitudes, commitment, and emotional involvement in their work with autistic individuals. Some statements were created ad hoc, while others were adapted from the Attitudes to Autism Scale (AAS; Barnes-Holmes et al., 2006) and the Societal Attitudes Towards Autism (SATA; Flood et al., 2013).

All items were reviewed by two independent experts in clinical psychology to ensure content validity and clarity, and the final wording was refined based on expert feedback before data collection.

Statements followed the reverse-matching method. While responses could not be predicted a priori, they were categorized based on “expected responses,” assuming that professionals in this field are motivated and passionate about their work. For instance, participants were expected to answer "Yes" to "I care about my clients' emotional well-being" and "No" to its inverse, "I ignore my clients' emotional well-being."

Participants were unaware of these questions in advance to prevent them from preparing their answers, as preparation can alter response content and reaction time. Studies on deception detection show that planning responses reduces deception indicators. This strategy was used to highlight reaction time differences between those who provided reliable responses about their professional attitudes and those who did not.

The variables analyzed from the computerized task concerned participants' RT and response consistency. Specifically, RT were recorded for both control and unexpected Work-Related Statements,

Table 2
Brief description of the variables investigated in the Computerized Task.

Index	Description	
RT_Yes-Yes_Contr	Reaction time: Expected response Yes – Given response Yes	CONTROL STATEMENTS
RT_Yes-No_Contr	Reaction time: Expected response Yes – Given response No	
RT_No-No_Contr	Reaction time: Expected response No – Given response No	
RT_No-Yes_Contr	Reaction time: Expected response No – Given response Yes	
RT_Contr	Total reaction time	
RT_Contr_right	Average reaction time for correct responses	
RT_Contr_wrong	Average reaction time for incorrect responses	
Choer_Contr	Number of items answered in accordance with the expected response	
Choer_Contr_pair	Number of item pairs in which the subject's responses are consistent	
IES_Contr	Ratio between reaction time and accuracy	
RT_Yes-Yes_Unexp	Reaction time: Expected response Yes – Given response Yes	UNEXPECTED STATEMENTS
RT_Yes-No_Unexp	Reaction time: Expected response Yes – Given response No	
RT_No-No_Unexp	Reaction time: Expected response No – Given response No	
RT_No-Yes_Unexp	Reaction time: Expected response No – Given response Yes	
RT_Unexp	Total reaction time	
RT_Unexp_right	Average reaction time for correct responses	
RT_Unexp_wrong	Average reaction time for incorrect responses	
Choer_Unexp	Number of items answered in accordance with the expected response	
Choer_Unexp_pair	Number of item pairs in which the subject's responses are consistent	
IES_Unexp	Inverse Efficiency Score: Ratio between reaction time and accuracy	

distinguishing between responses that were congruent or incongruent with the expected answer pattern (i.e., expected response Yes - Given response Yes; Expected response Yes - Given response No). Additional indices included the number of consistent responses (both with expected answers and within statement pairs) and the Inverse Efficiency Score (IES), a composite index combining reaction time and accuracy to account for the trade-off between speed and errors (calculated as RT / [1–PE]). RT is the average reaction time to the statements; PE is the error proportion, calculated based on the discrepancy between expected and actual responses. All variables analyzed are shown in detail in Table 2.

2.4. Statistical analysis and machine learning (ML)

The analyses were conducted using IBM SPSS Statistics (2020, version 27), with significance set at $p < 0.05$. A reliability analysis using Cronbach's alpha was performed to assess the internal consistency of the unexpected statements in the computerized task. To compare the socio-demographic characteristics of the samples, means, standard deviations, Fisher's exact test, and the Mann-Whitney test were used. A comparison between the performance on the computerized task and the paper-and-pencil tests across the two student profiles (satisfied vs. dissatisfied) was conducted using the Mann-Whitney test.

Supervised ML procedures were performed using JASP (version 0.17.1.0; JASP Team, 2023). Based on the results obtained from the student sample, a classification analysis (James et al., 2021) was conducted using Naïve Bayes (NB) and Random Forest (RF).

The data were randomly divided into separate subsets to ensure unbiased allocation of cases across training and testing phases. For the NB classification, we split the dataset using 80 % of the observations for the training set (n_{train}=39) and the 20 % for the test set (n_{test}=9 rounding up). The RF underwent a similar procedure using respectively a training set (n_{train}=31), a test set (n_{test}=9), and a validation set (n_{valid}=8). The RF procedures have been optimised according to the out-of-bag (OOB) error performance. Subsequently, a comparison was made between the Rehabilitation Operators classified as satisfied and the Rehabilitation Operators classified as dissatisfied in the indices used as Random Forest features.

3. Results

3.1. Preliminary analysis

The reliability analysis revealed high internal consistency of the items (α=.89), indicating that they reliably represent the construct of work attitude and motivation.

Regarding descriptive analyses, Fisher's exact test was not applied in the comparison of gender between the two profiles of the student sample (satisfied vs dissatisfied) since the frequency distribution between the groups was perfectly identical, making the comparison not significant; furthermore, age was also not statistically different between the two profiles (U=46.5, Z = -.283, p = .789). Comparing the sample of operators and the student sample, no significant differences emerged in gender (p = 1.0), while age was significantly higher in the operators (U=31, Z = -5.23, $p < .001$).

3.2. Behavioral results

In the computerized task, numerous significant differences emerged between the two profiles of the student group (Table 3). In particular, four variables showed a very high statistical significance ($p < .001$): RT_No-No_Unexp (reaction time for unexpected statements where a "No" response was expected and given), RT_Unexp_right (reaction time for correctly answered unexpected statements), RT, and IES for unexpected statements, where the dissatisfied profile had higher scores. No statistically significant differences were found in the paper-and-pencil tests (Table 4).

3.3. Machine learning analysis

Based on previous findings, four significant variables were selected as features to guide the ML analyses (RT_No-No_Unexp; RT_Unexp_right; RT_Unexp and IES_Unexp). The predictive models created using Naïve Bayes and Random Forest classification algorithms demonstrated good accuracy (78 %) in classifying satisfied and dissatisfied profiles. Table 5 reports details about Model Performance Metrics.

Analyzing the crucial metrics to evaluate the performance of a classification model (Accuracy, Precision, Recall, F1-score, Area Under Curve, and Matthews Correlation Coefficient), the Random Forest classification algorithm was selected to guide the comparison between the Rehabilitation Operators classified as satisfied and those classified as dissatisfied. In particular, the Random Forest algorithm has the highest AUC value (0.819; 95 % CI [0.58, 1.00]), indicative of a better discriminating ability of the model; F1-score (0.778; 95 % CI [0.40, 0.97]) is slightly higher than that of the Naïve Bayes (0.738), suggesting better reliability; furthermore, it shows a better balance between Precision and Recall, avoiding bias towards false positives or false negatives.

The Random Forest classifies seven Rehabilitation Professionals as

Table 3
Mann-Whitney test between two profiles of student sample in the Computerized Task.

Variables	Satisfied Students Median (1st-3rd quartile)	Dissatisfied Students Median (1st-3rd quartile)	U	Z	*p-value*	*Effect size**
RT_Yes-Yes_Contr	1.83 (1.52–1.93)	2.39 (1.98–2.86)	16	-2.57	**.01**	**0.68**
RT_Yes-No_Contr	1.95 (1.27–2.60)	2.77 (2.27–4.44)	23	-2.04	**.04**	**0.54**
RT_No-No_Contr	1.90 (1.62–2.22)	2.53 (2.15–3.11)	19	-2.34	**.019**	**0.62**
RT_No-Yes_Contr	2.61 (1.94–5.25)	3.76 (2.86–4.70)	42	-.605	.545	0.16
RT_Yes-Yes_Unexp	2.54 (2.11–3.02)	3.45 (3.12–4.43)	12	2.87	**.004**	**0.76**
RT_Yes-No_Unexp	3.32 (3.11–4.64)	5.36 (4.18–5.84)	17	-2.49	**.013**	**0.66**
RT_No-No_Unexp	2.56 (2.16–3.08)	3.60 (3.28–3.71)	3	-3.55	**<.001**	**0.94**
RT_No-Yes_Unexp	3.41 (2.77–6.47)	4.68 (3.71–6.57)	38	-.907	.364	0.24
RT_Contr	1.93 (1.64–2.38)	2.64 (2.19–3.18)	17	-2.49	**.013**	**0.66**
RT_Unexp	2.65 (2.29–3.31)	3.62 (3.44–4.00)	6	-3.32	**<.001**	**0.88**
RT_Contr_right	1.86 (1.55–2.15)	2.54 (2.07–2.86)	13	-2.79	**.005**	**0.74**
RT_Unexp_right	2.55 (2.19–3.08)	3.55 (3.10–4.02)	7	-3.25	**<.001**	**0.86**
RT_Contr_wrong	2.63 (1.79–4.39)	3.24 (2.52–5.09)	38.5	-.87	.384	0.23
RT_Unexp_wrong	3.43 (2.97–5.23)	4.94 (4.31–6.15)	28	-1.66	.096	0.44
Choer_Contr	36 (33.75–37)	35.5 (34–37.25)	47	-.23	.818	0.06
Choer_Unexp	53.5 (50.50–56)	49.5 (44.75–53.25)	26.5	-1.78	.074	0.47
Choer_Contr_pair	18 (17–18.25)	18.5 (16–19.25)	44.5	-.426	.67	0.11
Choer_Unexp_pair	25.5 (25−28)	27 (25−28)	45.5	-.353	.724	0.09
IES_Contr	1.95 (1.70–2.38)	2.64 (2.24–3.14)	16	-2.57	**.01**	**0.68**
IES_Unexp	2.99 (2.69–3.76)	4.23 (4.09–5.63)	0	-3.78	**<.001**	**1.00**

Significant differences are reported in bold
*rank biserial correlation

Table 4
Mann-Whitney test between two profiles of student sample in paper-and-pencil.

Variables	Satisfied Students Median (1st-3rd quartile)	Dissatisfied Students Median (1st-3rd quartile)	U	Z	*p-value*	*Effect size**
MAWS						
Autonomous Motivation	32 (27−35)	31.5 (24.75–33)	37	-.992	.321	0.26
Introjected Motivation	10 (10−12)	8.5 (6.25–10)	34	-1.22	.222	0.32
External Motivation	7.5 (6–9.25)	8.5 (5.25–12)	44.5	-.419	.676	0.11
Total Motivation Score	49.5 (43.25–52)	49 (31.75–50)	38	-.913	.361	0.24
BIDR						
Self-Deception	31.5 (25.25–33.25)	32 (27.5–36.25)	40	-.758	.448	0.20
Impression Management	30 (22.25–35)	34 (24.25–37.25)	35.5	-1.09	.272	0.29
Total Social Desirability	59.5 (54.25–63.25)	65 (58.25–68)	31	-1.44	.149	0.38

* rank biserial correlation

dissatisfied and twenty-one as satisfied. Comparing the four variables that guided the ML analysis, the dissatisfied Rehabilitation Professionals have significantly higher scores in all four target variables (Table 6).

4. Discussion

The need to accurately measure the attitudes of professionals working in disability and mental health fields has long been emphasized in the literature. Assessing the reliability of professionals' statements regarding their motivation and attitudes toward work can be essential for managing work-related stress and preventing turnover or job abandonment. These factors can significantly impact the lives of people with disabilities and the effectiveness of interventions, especially for autistic individuals, who require stable living environments and personalized interventions (Kaplan, 1982; Kelly & Barnes-Holmes, 2013; Hurt et al., 2013) that are, in many cases, intensive and sustained. Working with autistic individuals often exposes rehabilitation professionals to continuous emotional and behavioral challenges. Over time, these demands can contribute to work-related distress, undermining professionals' effectiveness and their ability to sustain engagement and achieve desired outcomes. While various paper-and-pencil tests exist to assess turnover, burnout, and work motivation, the literature highlights the importance of accurate and precise tools that go beyond self-report measures (Mazza et al., 2021; Kelly & Barnes-Holmes, 2013; Nicholas & Klag, 2020; Pan, 2017).

Unlike explicit measures (e.g., questionnaires), implicit measures appear to capture spontaneous behavior, as demonstrated by reaction-time-based deception detection methods (Monaro et al., 2021; Sartori et al., 2018).

Our study used a customized computerized task based on unexpected questions and inspired by the methodology adopted for the detection of deception (Monaro et al., 2021). The aim was to identify whether rehabilitation professionals working in autism care could provide inconsistent responses about their work attitudes and motivation.

The computerized task analyses revealed highly significant differences between the two student profiles. The dissatisfied students, who were asked to perform the task by impersonating a rehabilitation professional who lies about his / her attitude and work motivation, showed longer reaction times especially in unexpected statements, i.e. those related to commitment, attitude and emotional involvement in their work with autistic individuals. This aligns with Debey et al. (2015), who found that manipulating implicit response results in longer reaction times, as individuals must inhibit their initial truthful response in favor of a deceptive response. Furthermore, also the IES, which combines RT and accuracy, was higher in dissatisfied students, especially in unexpected statements, confirming prior research (Monaro et al., 2021; Melis et al., 2024).

In addition to RT and IES, the computerized task highlighted that

Table 5
Model Performance Metrics of two ML algorithms.

	NAÏVE BAYES			RANDOM FOREST		
	1	2	Average / Total	1	2	Average / Total
Support	6	3	9	6	3	9
Accuracy	0.778	0.778	0.778	0.778	0.778	0.778
Precision (Positive Predictive Value)	0.750	1.000	0.833	0.833	0.667	0.778
Recall (True Positive Rate)	1.000	0.333	0.778	0.833	0.667	0.778
False Positive Rate	0.667	0.000	0.333	0.333	0.167	0.250
False Discovery Rate	0.250	0.000	0.125	0.167	0.333	0.250
F1 Score	0.857	0.500	0.738	0.833	0.667	0.778
Matthews Correlation Coefficient (MCC)	0.500	0.500	0.500	0.500	0.500	0.500
Area Under Curve (AUC)	0.667	0.667	0.667	0.806	0.833	0.819
Negative Predictive Value	1.000	0.750	0.875	0.667	0.833	0.750
True Negative Rate	0.333	1.000	0.667	0.667	0.833	0.750
False Negative Rate	0.000	0.667	0.333	0.167	0.333	0.250
False Omission Rate	0.000	0.250	0.125	0.333	0.167	0.250
Threat Score	1.500	0.500	1.000	1.667	0.667	1.167
Statistical Parity	0.889	0.111	1.000	0.667	0.333	1.000

1 = subjects predicted as satisfied in the test-set; 2 = subject predicted as dissatisfied in the test-set

Table 6
Comparison between operators classified as satisfied and dissatisfied in the critical indices.

Variables	Satisfied Operators Median (1st-3rd quartile)	Dissatisfied Operators Median (1st-3rd quartile)	U	*Z*	*p-value*	*Effect size**
RT_No-No_Unexp	3.51 (2.96–3.87)	4.08 (3.38–4.69)	42	-1.67	.05	0.43
RT_Unexp	3.60 (3.29–4.06)	4.02 (3.96–5.03)	34	-2.09	.018	0.54
RT_Unexp_right	3.39 (3.01–3.71)	3.78 (3.70–4.49)	33	-2.15	.016	0.55
IES_Unexp	4.26 (3.80–4.83)	5.37 (4.66–5.94)	25	-2.57	.004	0.66

Satisfied Operators: Rehabilitation Operators classified as satisfied by Random Forest algorithm.
Dissatisfied Operators: Rehabilitation Operators classified as dissatisfied by Random Forest algorithm.
*rank biserial correlation

dissatisfied students, especially in unexpected statements, showed significantly higher scores also in the total RT in which they provided correct responses, i.e. consistent with those expected (RT_Unexp_right score), in particular negative expected responses (RT_No-No_Unexp score). These results suggest that individuals who attempted to mask their job dissatisfaction were slower in providing consistent responses to statements where a negative response was expected, such as answering “No” to the statement “Working with my clients make me sad”.

Similar findings were observed in the sample of rehabilitation operators, where workers classified as dissatisfied by ML Random Forest algorithm with 78 % accuracy, exhibited higher RTs and IES scores in unexpected statements than those classified as satisfied. These results suggest that rehabilitation professionals with latent work demotivation take longer to respond to unexpected questions about their work attitude, especially in providing a coherent response to statements where a negative response is expected.

Consequently, the four variables of RT_No-No_Unexp (Reaction Time: expected response No – given response No), RT_Unexp_right (Reaction Time for correct responses), RT_Unexp (total Reaction Time) and IES_Unexp (ratio between Reaction Time and accuracy) may be considered as predictive indicators of job satisfaction and dissatisfaction, as suggested by the ML algorithm. These preliminary findings are consistent with previous research (Melis et al., 2024; Monaro et al., 2021; 2017; Sartori et al., 2018; Vrij et al., 2008), which suggests that those who manipulate information to deceive take longer to respond to unexpected statements.

Regarding paper-and-pencil tests, self-report questionnaires on work motivation (MAWS) and social desirability (BIDR) did not appear to capture key elements needed to identify dissatisfied individuals, suggesting that implicit measures could be more reliable in detecting true work motivation than explicit self-report tests, likely because explicit measures are more prone to biases and allow participants greater control over their responses. The limited effectiveness of these questionnaires may also be explained by social desirability bias, namely, the tendency to underreport negative attributes or emotions while overreporting those considered positive or more acceptable (Lanz et al., 2022). In professional contexts such as healthcare and rehabilitation, individuals may consciously or unconsciously mask demotivation or negative feelings to protect a competent and caring image or to preserve their job. Consequently, explicit self-report instruments may fail to capture the actual variability of work motivation, reinforcing the need for implicit, latency-based measures, which are less susceptible to conscious control and better suited to detecting hidden motivational states.

This interpretation can also be understood within the framework of SDT (Deci & Ryan, 2013; Ryan & Deci, 2000), which conceptualizes motivation along a continuum ranging from autonomous to controlled regulation.

According to SDT, autonomous motivation - driven by personal interest and internal endorsement - promotes engagement and well-being, whereas controlled motivation and amotivation, often shaped by external pressures or social expectations, are associated with disengagement, burnout, and negative work attitudes (Moran et al., 2012; Nunes et al., 2024).

The present study extends this theoretical framework, suggesting that latency-based implicit measures can operationalize motivational regulation within the SDT continuum. Specifically, longer reaction times and higher inconsistency indices may reflect controlled or conflicted regulation, in which professionals experience tension between internal values and external demands. Conversely, faster and more consistent responses may correspond to autonomous regulation, characterized by coherence between implicit and explicit motivational processes (Radel et al., 2017). These findings suggest that implicit behavioral indices can serve as objective markers of motivational quality, providing a behavioral operationalization of implicit motivation within SDT.

This integration refines SDT by introducing a measurable dimension, based on latency, that links motivational regulation to actual behavioral performance, in line with the suggestions of Radel et al. (2017). This approach would improve our understanding of professional commitment beyond traditional self-assessment methods.

Importantly, while this study draws methodological inspiration from deception detection paradigms, it does not conceptualize professional demotivation as an act of intentional deception. The use of latency-based measures and cognitive-load indicators in this context serves a purely methodological purpose: to capture subtle discrepancies between implicit and explicit motivational processes. These discrepancies are interpreted as expressions of controlled or externally regulated motivation, rather than deliberate falsification.

Beyond its theoretical implications, the current findings also have significant practical relevance for professional settings. Implicit, latency-based assessments—particularly when combined with ML—can serve as innovative tools for monitoring and promoting occupational well-being in healthcare and rehabilitation services. Since episodes of neglect and abuse toward vulnerable individuals have been documented internationally (Duffy et al., 2024; Reader & Gillespie, 2013; The Lancet, 2013; Yon et al., 2019), this approach can be employed for both prevention and monitoring. In recruitment and staff selection, these measures could complement traditional interviews and self-report questionnaires by identifying candidates who display subtle signs of demotivation or inconsistency between implicit and explicit responses, which may not emerge through conventional evaluation. In professional supervision and ongoing training, implicit tasks could be periodically administered to detect early indicators of stress, emotional disengagement, or declining motivation, enabling timely supportive interventions before these factors evolve into burnout or turnover. In the context of organizational well-being programs, implicit measures could also be used longitudinally to monitor motivational dynamics within teams, evaluate the effectiveness of interventions designed to enhance job satisfaction, and support data-driven policy decisions aimed at improving staff retention and care quality. Overall, incorporating implicit assessments into professional settings could foster a more objective, preventive, and personalized approach to human resource management in the healthcare and rehabilitation settings.

Although the findings are significant, the study has some limitations, including the small sample size and predominantly female gender. Moreover, although the Random Forest model reached an accuracy of 78 % in classifying satisfied and dissatisfied professionals, this result should be regarded as preliminary and exploratory, given the small sample size and the risk of model overfitting. Consequently, the generalizability of these findings is limited, and future studies should validate the predictive model on larger samples, as well as explore additional ML algorithms to enhance decision-making accuracy. Therefore, given the exploratory nature of the study, our results do not claim causal inferences or definitive classificatory conclusions; consequently, the model's predictive capacity must be further tested before real-world application.

Furthermore, although a sample of rehabilitation professionals was included, an important procedural limitation of the present study concerns the use of university students, who were asked to assume the roles of "satisfied" and "dissatisfied" operators. This role-playing procedure was adopted as an exploratory phase, with the aim of eliciting controlled motivational conditions and reducing confounding variables in a preliminary experimental context. However, we acknowledge that such artificial roles cannot fully reflect the psychological experiences of real professionals, and the absence of a manipulation check prevents verifying the extent to which students understood and represented the assigned states. At the same time, we consider it plausible that simulating a motivational state engages processes that partially overlap with the cognitive load involved when motivation is concealed; this overlap motivates the exploratory use of simulation and requires cautious interpretation as it clearly limits direct student-professional conceptual transfer. Therefore, future studies should include manipulation checks and validate the findings in larger professional contexts of healthcare professionals. Future research should also include long-term performance observations, such as employee interviews and evaluations by supervisors or even service users, in order to monitor and ensure the accuracy of the model.

5. Conclusion

In conclusion, work motivation and attitude are crucial factors in the workplace, as they contribute to improved job performance (Li et al., 2019). This is especially critical for professionals working with disabilities, particularly with autism, who require consistency, structured routines, and emotional stability over time.

The computerized task, which measures implicit variables, demonstrated its potential for classifying satisfied and dissatisfied professionals.

This method could be implemented for worker monitoring and might be utilized in personnel selection, helping to identify specific profiles that may not be well-suited for the job in some cases.

CRediT authorship contribution statement

Monica Mazza: Writing – review & editing, Writing – original draft, Project administration, Methodology, Formal analysis, Data curation, Conceptualization. **Margherita Attanasio:** Writing – review & editing, Writing – original draft, Project administration, Methodology, Formal analysis, Data curation, Conceptualization. **Erika Di Giminiani:** Writing – original draft, Methodology, Investigation, Formal analysis, Data curation. **Ilenia Le Donne:** Writing – original draft, Methodology, Investigation, Formal analysis, Data curation. **Francesco Masedu:** Writing – original draft, Methodology, Formal analysis. **Marco Valenti:** Writing – original draft, Supervision, Project administration, Conceptualization.

Ethics approval and consent to participate

The study was conducted under the Declaration of Helsinki and the rules of good clinical practice. The ethics committee of the Internal Review Board of the University of L'Aquila approved the experimental protocol (n. 41769, ID number 09/2022).

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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