

Emotional Artificial Intelligence for Sustainable Talent Management - An Empirical Study on IT sector

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ABSTRACT

Purpose – This study is to investigate how 'Emotional Artificial Intelligence' ('EAI'), defined as the integration of 'Emotional Intelligence' ('EI') into 'Artificial Intelligence' ('AI'), drives sustainable talent management (STM) outcomes for 'the Information Technology (IT) sector.'

Methodology – The study explores the potential of EAI to ensure STM outcomes in the IT sector. Latent constructs were derived through literature review and hypotheses, and initial conceptual model was developed. Sets of questionnaires were designed, and data were collected from 226 IT professionals between September and October 2025 for this quantitative study. The measurement model was statistically validated using exploration by EFA and provisional testing of model fit through CFA, followed by 'covariance-based structural equation modelling (CB-SEM)' to evaluate the proposed relationship with constructs.

Findings – The study indicates that EAI comprises two correlated factors, namely Adaptive Intelligence and Affective Intelligence. It was found that the two-dimensional EAI do not have a statistically correct direct impact on STM, however Adaptive Intelligence is the main driver for achieving STM outcomes only when the organization is infrastructurally ready. On the other hand, despite increasing employee satisfaction, Affective Intelligence has a very low impact on STM outcomes.

Research Limitations – This study broadly examines the effect of EAI on generic TM practices within the IT sector. Future research could examine the specific areas of the IT industry such as technical skill acquisition, agile team collaboration, leadership development, etc. Two separate sample size could be more appropriate to conduct EFA and CFA separately.

Practical application – This study introduces Emotional Artificial Intelligence (EAI) into the TM discourse specifically within the IT sector. The true effect of EAI depends on its systematic implementation within the organizational structure. These results will help IT industries leverage EAI in the context of STM to fulfill their expected outcomes.

Originality/Novelty – This study unfolds a novel path towards the adoption of EAI in TM practices for the IT sector by revealing the different dimensions of EAI-aided technologies and their influence on organizational effectiveness.

Keywords: Talent Management, Artificial Intelligence, Emotional Intelligence, Emotional Artificial Intelligence, Information Technology.

1. Introduction

TM is considered as a significant area of study for management as it is of the utmost necessity for organizational practice [1]. It has been realized by organizations that optimizing employee engagement is essential to achieve strategic objectives. McKinsey & Company invented the terminology "talent management" for the 1st time in the late 1990s [2]. "The war for talent," conceptualized by 'McKinsey', defines the field of TM as a strategically unique approach to identify, develop, and retain high-potential individuals [3]. Research [4] shows that TM can be considered as a strategic approach for the IT sector through identifying, developing, and providing the right talent with a platform to perform, which leads to improved talent outcomes.

As per previous research [5], modern IT companies need to implement effective TM practices to boost their organizational performance. 'Research suggests that AI-aided HR solutions ensure greater speed in hiring, more accurate candidate-job matching and better data-driven talent decisions [6]. The authors of another study [7] suggested that IT companies or MNEs operating in an emerging market need innovative knowledge sharing, leading them to focus on Global Talent Management practices with AI-aided technology to elevate employee attitudes and behavioral outcomes. The findings of the research [8] show that the implementation of TM practices is not sufficient' to generate effective leadership capacity unless supported by EI as per 'talent-based theory' and 'social cognitive theory'.

Traditional AI was based on algorithmic systems and lacked human touch, which gave rise to the concept of Emotional AI. As per "socio-technical systems theory (STS)", the success of digital transformation is largely dependent on the joint application of technological systems (AI) and social capabilities (EI) [9]. This study examines the combined 'effect of Emotional Intelligence and Artificial Intelligence' in TM practices for the IT sector. Consequently, the current study opens a novel path toward the adoption of EAI in TM

practices for the IT sector by revealing the different dimensions of EAI-aided technologies and their influence on organizational effectiveness to achieve STM outcomes. Accordingly, the two main research questions have arrived as follows:

Q1. What dimensions of EAI emerge in TM practices within the IT sector?

Q2. How do Affective and Adaptive Intelligence influence perceived STM outcomes directly and indirectly through Employee Satisfaction and Organizational Readiness?

The paper is designed as follows: Section 2 presents the theoretical framework, reviews the literature, and develops the hypotheses. 'Section 3' explains the methodology, 'section 4' reports the analysis, 'section 5' discusses the findings, and 'section 6' presents the implications, limitations and conclusion.

2. Literature Findings & Hypothesis Development

2.1. Theoretical Framework: In the context of TM practices, EAI drives a transformative 'process through which an organization' attracts, engages, develops, and retains employees. The study's theoretical framework adopts a multidisciplinary perspective, drawing from behavioral science, management theory, and AI technology integration.

2.1.1. Foundations of AI and Behavioral Integration

The foundational concept of conventional and general AI originates from the Alan Turing Test (1950). This benchmark proposes that 'a machine can be considered intelligent if it can mimic human responses closely enough to' be indistinguishable from human responses [10]. According to Bayesian Inference Theory, an AI system can update its beliefs based on new evidence [11]. Regarding optimization and creative tasks, it is important to know that AI systems evolve through a process of natural selection as mentioned in Evolutionary Computation Theory [12]. According to the capability approach, AI should enhance human capabilities and freedoms [13,14]. This includes the technological ability of AI systems to process HR data and make predictions. AI's task-automation feature enables the replacement of repetitive HR tasks like resume screening, scheduling, etc. [15]. Additionally, predictive analytics in AI help forecast employee turnover, performance, engagement, retention, and development [15, 16]. 'As per the "Ability-Motivation-Opportunity (AMO)" framework, the performance of employees depends on their ability to do the work, motivation to perform, and opportunity to participate [17,18].' Integrating AI applications into TM practices can enhance employee performance because AI tools automate and optimize the process, which 'has a direct positive impact on' employee experience, engagement, and satisfaction' [19,20]. When AI is combined with EI, organizations can develop personalized engagement, learning, and motivation strategies. Consequently, these EAI-TM practices will enhance employee satisfaction and their overall performance level [21,22].

The concept of EI in the workplace came from 'Daniel Goleman's Emotional Intelligence Framework [23], which establishes five core components: self-awareness, self-regulation, motivation, empathy, and social skills as pivotal to understanding human behaviour on both personal and professional grounds.' In an organizational context, interpersonal relationships, employee engagement, satisfaction levels, and work commitment are heavily influenced by an employee's EI. The infusion of EI into AI-driven practices aims to replicate or approximate these human traits in TM systems [24]. Therefore, EI can be considered a lens through which the ability of an AI application is evaluated for handling complex, emotional, and interpersonal aspects of employees [25].

2.1.2. System Acceptance and Strategic Capability

'The Technology Acceptance Model (TAM) is highly relevant to this research context for understanding user acceptance of new technologies based on perceived usefulness and ease of use [26].' As IT employees need to interact with AI-driven TM tools on a regular basis, their future expectations and satisfaction levels can be assessed through this model. Consequently, it is essential for this research to explore the acceptance of and expectations for AI among IT employees and diagnose the areas where EI infusion is feasible.

As per the 'Resource-Based View (RBV) [27], human capital is a strategic asset that offers a sustained competitive advantage.' When AI is combined with EI, it can help to identify, nurture and retain such valuable talent through personalized and empathetic employee experiences. Therefore, EAI serves as a strategic capability to support sustainable TM practices and long-term organizational performance.

2.1.3. Holistic Integration: STS Theory and AMO Framework

"STS theory" proposes that organizational performance is the outcome of optimally integrating social and technical systems. Infusing the social dimension of EI into the technical dimension of AI is essential for the effectiveness of the TM system. The framework provides a holistic view of the coexistence of EI and AI within the organizational landscape to ensure sustainable outcomes through employee satisfaction and organizational readiness [28].

2.2. Hypotheses Development

The synthesis of the above-mentioned theories proposes the following hypotheses to examine the effectiveness of EI-infused, AI-aided technology in TM practices to achieve sustainable TM outcomes through employee satisfaction and organizational readiness.

2.2.1. Conceptualized EAI and its connection with Sustainable Outcomes

Traditional AI-TM practices are helpful for operational efficiency and task automation [29], yet they lack the contextual depth required to ensure algorithmic alignment among the workforce to ensure sustainable human assets over a longer period [30]. Drawing from STS theory, the integration of social intelligence with technical automation should theoretically enhance the longevity and effectiveness of talent practices to meet organizational equilibrium [31]. EAI bridges this gap by infusing an emotional framework into automated systems to translate the HR tools from mere monitoring mechanisms into supportive enablers of employee well-being [32]. Consequently, an EI-infused TM system will protect the social infrastructure of the organization by driving the experience, commitment and performance of its human assets.

2.2.2. The Role of Employee Satisfaction

The TAM dictates that the acceptance of technology and its positive evaluation depend on its 'perceived ease of use and perceived usefulness [33]'. Traditional AI systems often create cognitive barriers due to their "black box" approach or lack of empathy [34], whereas EAI in TM helps introduce a higher level of personalization and active support to TM practices, such as effective onboarding, continuous performance feedback and customized learning paths [35]. This automatically elevates employee satisfaction and their performance levels. The AMO framework confirms that HR systems enhance organizational performance through the development of employee ability, proper motivation, and the provision of the right opportunities [34]. EI-infused AI-TM practices have a multiplicative effect on these three dimensions to drive employee satisfaction.

2.2.3. The Role of Organizational Readiness

'According to the RBV perspective, competitive advantage can be sustained through valuable, inimitable, rare, and non-substitutable resources [36].' Traditional AI works on pure data infrastructure and speeds up operational processes. However, EI-infused AI-TM practices build affective capability through emotion recognition, empathetic feedback resolution, and contextual learning mechanisms [37]. As per the STS perspective, conventional AI-TM can create human resistance, change anxiety, and cultural barriers due to preconceived mechanical rigidity. EI-infused AI-TM can reduce these resistive forces through adaptive interventions that identify the emotional states of employees [38]. Technical preparedness and infrastructural readiness ensure long-term strategic alignment and prevent the failure of advanced technological implementation [39]. When organizational readiness encompasses robust cultural and leadership support, it becomes easy to drive high-end technologies and thus it can achieve sustainable growth [40].

2.3. Proposed 'Conceptual Model'

Figure 1 presents the proposed model and depicts the paths from EAI practices toward sustainable TM outcomes,' mediated by employee satisfaction and organizational readiness.

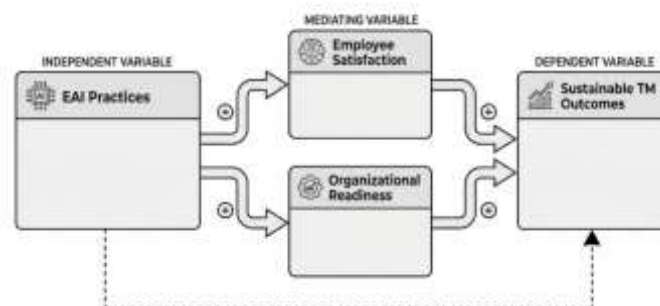


Fig 1: Proposed Model for EAI practices and Sustainable Talent Outcomes

2.4. The Deconstruction of EAI: Affective vs. Adaptive Dimensions

The original model as proposed was refined after EFA and two dimensions appeared with the name of Affective Intelligence and Adaptive Intelligence. Hypotheses are reconstructed and the final structural model tests the two theoretically interpretable post-EFA dimensions.

2.4.1. Structural Transformation and Reconstruction of Hypotheses

2.4.1a. Affective Intelligence, Employee Satisfaction, and Sustainable Talent Management Outcomes

'Affective Events Theory [41] posits that workplace events shapes employees' emotional states, which subsequently influence their behaviour. In the era of digital transformation,' when an affective AI system successfully recognizes the emotional cues and aligns with an employee's psychological state, this interactive functionality constitutes a "positive affective event" [42]. This technological capability of supporting worker psychology directly enhances employee satisfaction and thereby advancing STM outcomes [43]. Below is the proposed hypothesis:

H1: Affective Intelligence 'has a positive association' with sustainable TM outcomes.

H2: Affective Intelligence has a 'positive relationship with Employee Satisfaction.'

H3: Employee satisfaction positively mediates the effect of Affective Intelligence on sustainable TM outcomes.

2.4.1b. Adaptive Intelligence, Organizational Readiness, and STM Outcomes

As per the Dynamic Capabilities Theory [44], an organization can survive in the long run if it can continuously reconfigure its resources to adapt to a rapidly changing environment. Correspondingly, Adaptive Intelligence indicates the functional dimension of EAI. Adaptive intelligence in TM makes the practices more agile so that they can be reconfigured as per the market demands [45]. Instead of relying on a static framework, this adaptive AI-driven technology can continuously optimize the workforce allocation and thereby build proactive organizational readiness [46]. This adaptive nature of TM practices ensures organizational resilience and STM outcomes [47]. Based on this rationale, the remaining structural hypotheses are formulated as follows:

H4: Adaptive Intelligence is positively associated with sustainable TM outcomes.

H5: Adaptive Intelligence has a positive relationship with Organizational Readiness.

H6: Organizational readiness positively mediates the effect of Adaptive Intelligence on sustainable TM outcomes.

2.5 Model Reconstruction

The final conceptual framework in Figure 2 depicts the structural paths from Affective Intelligence and Adaptive Intelligence toward sustainable TM outcomes, mediated by employee satisfaction and organizational readiness, respectively.

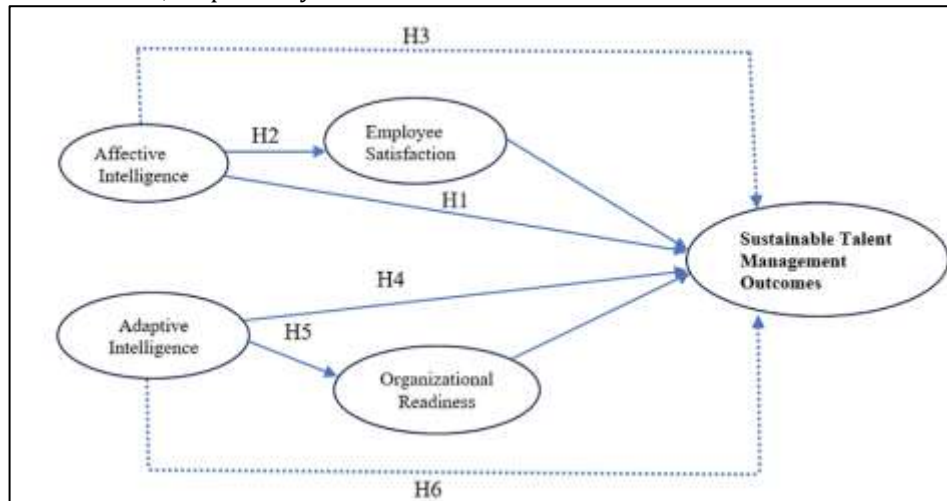


Fig 2: Refined Structural Model

3. Methodology

3.1. Research Approach: The study uses an exploratory design with provisional testing following EFA-CFA-SEM path to examine the integrative effect of EI-infused AI in TM practices to enhance effectiveness within the IT sector.

The investigation was conducted through a structured questionnaire derived from prior studies to collect responses from employees of IT companies. The data collection was conducted through convenience sampling, yielding 226 responses from participants worldwide. 'Responses were recorded on a 5-point Likert scale from strongly disagree (1) to strongly agree (5).' Due to scale, the data are inherently discrete and ordinal, meaning they are not truly continuous. Literature indicates that Likert-type responses cannot be considered strictly equidistant [48], simulation studies suggest that 5-point scale items can be safely approximated as continuous variables when utilizing robust estimators. Robust Maximum Likelihood (MLR) estimation was applied within the CB-SEM framework to prevent inflated Chi-square values and underestimated standard errors [49].

3.2. Sample Size Conformity: As per prior literature [50], 5 to 10 observations are required per measured variable (indicator) for SEM. In this study, there are 5 constructs and a total of 35 initial indicators. A sample size of 226 is sufficient to meet this requirement, giving a ratio of approximately 6.5 observations per indicator. Prior research [51,52] classifies a sample size of 200 as fair and 300 as good for factor analysis (EFA and CFA). The present analysis ensures that the factor loadings and model fit indices are reliable considering these recommended sample sizes. Previous research shows that SEM is a large-sample technique and a sample size of 226 is well within the recommended range for a model comprising 5 constructs with 35 indicators [53].

3.3. Analysis Approach: The structural model and the relationships among the constructs were rigorously

examined through a multi-stage quantitative analysis performed in RStudio using the 'lavaan' package [49]. Given the ordinal nature and multivariate non-normality of the survey data, the analysis systematically progressed from data preparation and exploratory screening to advanced SEM via provisional testing through CFA.

Data suitability was evaluated using the 'Kaiser-Meyer-Olkin (KMO)' measure for sampling adequacy, while 'Bartlett's Test of Sphericity' examined whether the variables were sufficiently correlated [54]. For factor extraction, Principal Axis Factoring (PAF) extracted shared variance to identify the underlying latent constructs. Because human traits and organizational behaviours are naturally intertwined in social science research, an oblique rotation (Direct Oblimin) was applied [55] to obtain a realistic view of factor correlations. Item retention was guided by communality thresholds appropriate for the sample size (N=226) [53], requiring a minimum factor loading of 0.4 and ratio of square loading greater than 2 (checking from pattern matrix).

When EFA was applied globally to the entire dataset, a four-factor solution was statistically justified by isolating the factors such as EAI, SAT, OR, STM. The scenario changed when EFA was applied to individual constructs. It revealed that SAT, OR, and STM were validated as unidimensional constructs, whereas EAI was bifurcated into two theoretically rich subdimensions as Affective Intelligence and Adaptive Intelligence.

In CFA, the "Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), Root Mean Square Error of Approximation (RMSEA), and Standardized Root Mean Residual (SRMR)" are used both for individual constructs and the overall measurement model [56]. Reliability and validity were confirmed using 'Composite Reliability (CR)' and 'Average Variance Extracted (AVE)' to ensure 'convergent validity' [57] and the 'Heterotrait-Monotrait Ratio of Correlations (HTMT)' was utilized to ensure 'discriminant validity' [58].

To address CMB, procedural controls were applied before the circulation of the questionnaire [59]. CMB was then statistically verified prior to EFA through "Harman's single-factor test" and prior to SEM through a CFA-based single-factor model comparison.

Finally, the structural path analysis was conducted via CB-SEM using the MLR estimator. Hypotheses were assessed using confidence intervals (CIs) and p-values to establish path significance, while standardized beta (β) coefficients indicated the effect's strength and direction. Additionally, the variance inflation factor (VIF) was computed to assess multicollinearity, R^2 quantified explained variance in the endogenous constructs, and Cohen's f^2 measured each predictive path's effect size [60].

4. Findings

4.1. Data Adequacy and Diagnostic Checks

The data matrix containing all survey items was evaluated, and the 'overall KMO measure was 0.94, which exceeds the conventional threshold of 0.7 [61]. The individual MSA values ranged from 0.88 to 0.97, which is in the safe range. 'Bartlett's Test of Sphericity' showed a highly significant Chi-square value ($p < 0.001$), rejecting the null hypothesis and indicating that multi-item correlations existed, which ensured the possibility of factorization [62].

4.2. Scale Refinement and Construct Dimensionality after EFA

'EFA was conducted using PAF with oblimin rotation. Item retention and removal were performed as per the approved statistical criteria mentioned earlier [53].' Initially, EFA was applied to the entire dataset, including all items, and the analysis suggested four factors: EAI, SAT, OR, and STM. Further scale refinement was conducted through isolated construct evaluation. This validated that SAT, OR, and STM are unidimensional constructs, but EAI is bifurcated into two correlated factors, namely affective intelligence and adaptive intelligence with explained variance of EAI 50.19% (Affective Intelligence = 29.72%, Adaptive Intelligence = 20.47%), SAT = 50.1%, OR = 54.7%, and STM = 57.4%, respectively. The final indicators after item reduction is 26 with a variance explained as follows : EAI = 56.14% (Affective Intelligence = 29.13%, Adaptive Intelligence = 27.01%), SAT = 50.95%, OR = 60.13%, and STM = 61.72% , respectively.

4.3. Evaluation of Model Fit Indices by CFA

Before structural path analysis, model fit indices were checked using CFA. As the value of chi-square is highly sensitive to the sample size [64], in this case, alternative indices were taken into account.

Table 1 Summary of Individual Construct Model Fit

Construct	'Robust CFI'	'Robust TLI'	'Robust RMSEA'	'SRMR'
'EAI (2-Factor)'	0.973	0.960	0.069	0.043
Org. Readiness	0.985	0.978	0.066	0.034
Sustainable TM	0.994	0.990	0.048	0.029

Emp. Satisfaction	0.987	0.973	0.068	0.035
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Table 2 Summary of Measurement Model Fit

Fit Index	Value	Threshold
'Robust CFI'	0.976	>0.95
'Robust TLI'	0.973	>0.95
'Robust RMSEA'	0.036	<0.06
'SRMR'	0.052	<0.08

The results show that all individual models and the measurement model met the model-fit criteria. The values of incremental fit indices are well above the threshold (Robust CFI & Robust TLI > 0.95) which means the individual models (Table 1) & measurement model (Table 2) are significantly better than the baseline model [56]. The absolute fit indices (Robust RMSEA & SRMR) were lower than or only slightly above the threshold values (Robust RMSEA <0.06, SRMR <0.08), indicating a near-perfect fit of specific measurement scales [65].

4.4. Convergent Validity and Reliability

Table 3 Standardized loading for Individual Model:

Construct	Item	Std. Loading
Affective Intelligence	EAI4	0.805
	EAI5	0.756
	EAI7	0.743
	EAI2	0.697
Adaptive Intelligence	EAI14	0.822
	EAI15	0.714
	EAI10	0.681
	EAI13	0.695
OR	OR6	0.827
	OR2	0.794
	OR4	0.791
	OR3	0.763
	OR7	0.758
	OR1	0.762
STM	OR5	0.729
	SO10	0.83
	SO12	0.807
	SO11	0.787
	SO6	0.780
	SO9	0.772
SAT	SO4	0.734
	SAT5	0.792
	SAT6	0.640
	SAT11	0.690
	SAT3	0.719
	SAT4	0.719

Table 4

Standardized loading for Measurement Model.

Construct	Item	Std. Loading
Affective Intelligence	EAI4	0.803
	EAI5	0.761
	EAI7	0.727

	EAI2	0.709
Adaptive Intelligence	EAI14	0.797
	EAI15	0.715
	EAI13	0.692
	EAI10	0.708
OR	OR6	0.822
	OR2	0.798
	OR4	0.781
	OR3	0.766
	OR1	0.761
	OR7	0.766
	OR5	0.734
STM	SO10	0.820
	SO12	0.803
	SO11	0.800
	SO6	0.782
	SO9	0.771
	SO4	0.735
SAT	SAT5	0.752
	SAT3	0.666
	SAT4	0.659
	SAT11	0.733
	SAT6	0.734

The standardized factor loadings of each individual model (Table 3) and the final measurement model (Table 4) suggest that indicator reliability is satisfactory as all retained items exceeds the recommended minimum loading of 0.60. Within the measurement model, loadings for Affective Intelligence were between 0.709 and 0.803 and for Adaptive Intelligence 0.692–0.797. The constructs of OR, STM and SAT also had acceptable loadings to sufficiently represent the latent constructs. Moreover, the Composite Reliability (CR) and the Average Variance Extracted (AVE) were applied to assess the construct reliability and the convergent validity [57, 63].

CR & AVE for Individual Model

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> compRelSEM(fit_EAI)
AffectiveInt  AdaptiveInt
0.842         0.822
> AVE(fit_EAI)
AffectiveInt  AdaptiveInt
0.570         0.529

> compRelSEM(fit_OR)
OrgReadiness
0.913
> AVE(fit_OR)
OrgReadiness
0.601

> compRelSEM(fit_STM)
STM
0.907
> AVE(fit_STM)
STM
0.618

> compRelSEM(fit_SAT)
EmpSatisfact
0.838
> AVE(fit_SAT)
EmpSatisfact
0.511

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Image 1: Source@Rstudio

CR & AVE for Measurement Model

```
> compRelSEM(fit_measurement)
AffectiveInt AdaptiveInt OrgReadiness STM EmpSatisfact
0.840 0.823 0.914 0.907 0.826
> AVE(fit_measurement)
AffectiveInt AdaptiveInt OrgReadiness STM EmpSatisfact
0.567 0.530 0.602 0.619 0.501
```

Image 2 : Source@Rstudio

The CR values of all constructs are greater than the threshold value of 0.7 both for individual model (Image 1) and measurement model (Image 2). This shows that the constructs are made up of internally consistent items. The values of AVE range from 0.501 to 0.619, which indicates that each construct not only crosses the acceptable level of 0.50 but also explains more than half of the variance of its indicators. Thus, the result confirms convergent validity. These results are strong enough to prove the statistical adequacy and theoretical consistency of the measurement model. It further confirms the empirical distinction between Affective Intelligence and Adaptive Intelligence as two different aspects of Emotional AI [66] though they are interrelated. This paved the way for further assessment of discriminant validity.

4.5. Discriminant Validity with HTMT matrix

	AffctI	AdptvI	OrgRdn	STM	EmpSts
AffectiveInt	1.000				
AdaptiveInt	0.778	1.000			
OrgReadiness	0.594	0.790	1.000		
STM	0.698	0.798	0.769	1.000	
EmpSatisfact	0.707	0.801	0.719	0.740	1.000

Image 3 : Source@Rstudio

The above shows (Image 3) that the values are below the threshold of 0.85 [58], with the highest correlation observed between Employee Satisfaction and Adaptive Intelligence (0.801). Therefore, the result satisfies the modern gold standard of discriminant validity. With the convergent validity, reliability, and discriminant validity confirmed, the measurement model is now validated for the structural path model [67].

4.6. CMB analysis with “Common Method” factor

Procedural controls were imposed by choosing the items in a neutral manner, respondents were anonymous, no guiding definitions were provided in sections of the questionnaire, and the item order was varied to reduce response bias. Design controls were used to capture the true perceptions of the respondents about EAI-enabled TM practices. “Harman’s single-factor test” was originally designed as a statistical screening device [68]. The result showed that the single factor accounted for 44.3% of total variance, below the commonly accepted level of 50% [69]. This means that there was no latent factor that was common to the covariance structure of the data set. Thus, at the exploratory level CMB was not considered a real threat.

	Index	One_Factor	Five_Factor	Delta
cfi.robust	Robust CFI	0.837	0.976	0.138
tli.robust	Robust TLI	0.823	0.973	0.150
rmsea.robust	Robust RMSEA	0.090	0.036	-0.055
srmr	SRMR	0.071	0.052	-0.019
aic	AIC	12845.969	12373.461	-472.508

Image 4 : Source@Rstudio

Then, CFA then compared the single-common-method-factor specification with the theoretical model. The one-factor model (Image 4), in which all indicators loaded on one common factor, showed marginal fit (Robust CFI and TLI < 0.90, Robust RMSEA = 0.09, SRMR = 0.071). In contrast, the theoretical five-factor model fitted substantially better, Robust CFI and TLI > 0.9, Robust RMSEA = 0.036, SRMR = 0.052 [56]. Model fit and AIC improved [77], indicating that five theoretical constructs are better than one common method factor to account for the data. Together, the procedural safeguards, the Harman test, and the CFA comparison suggest that common method variance did not materially affect the findings. Accordingly, the measurement model was considered sufficiently robust for structural estimation and hypothesis testing.

4.7. Structural Model Fit

After the CMB assessment, the structural model was estimated using CB-SEM. The structural model demonstrated good fit to the observed data. Robust CFI (= 0.922) and Robust TLI (= 0.913) exceeded the recommended 0.90 threshold, indicating that the hypothesized model fitted significantly better than the null model. Robust RMSEA (= 0.065) remained below 0.08, with a narrow CI (0.057 to 0.073), indicating reasonable approximation in the population [70]. Standardized SRMR (= 0.071) was also below 0.08, indicating acceptable residual differences between the observed and model-implied covariance matrices. Overall, the model fit was acceptable. Affective Intelligence accounted for 61.7% of the variance of Employee Satisfaction. The R^2 for Employee Satisfaction was 0.617. The R^2 for Organizational Readiness was 0.608, meaning that Adaptive Intelligence explained 60.8% of the variance in Organizational Readiness. More importantly, the results of the Sustainable TM Outcomes showed an R^2 of 0.714, which means that the whole set of predictors accounted for 71.4% of the variance in the dependent construct. The findings support the structural model's statistical adequacy and substantive significance [50]. The results support the use of the refined dual-path model to investigate the role of different dimensions of EAI in influencing STM outcomes through different mediating mechanisms.

4.8. Path Dynamics and Parallel Mediation

Structural equation modeling (Fig 3) provides strong support for the distinct effects of Affective Intelligence and Adaptive Intelligence on STM outcomes. The direct effect of Affective Intelligence on STM was positive but not significant ($\beta = 0.167$, $p = 0.443$, 95% BCa CI: -0.259 to 0.592). Therefore, H1 is not supported. Affective Intelligence is found to have a significant positive association with SAT ($\beta = 0.786$, $p < 0.001$; 95% BCa CI: 0.647 to 0.924). Therefore, H2 is supported. There was no significant relationship between SAT and STM ($\beta = 0.190$, $p = 0.287$; 95% BCa CI: -0.160 to 0.541). The relationship from Adaptive Intelligence to STM was not statistically significant ($\beta = 0.254$, $p = 0.268$; 95% BCa CI: -0.196 to 0.703). Thus, H4 was not supported. However, Adaptive Intelligence was a significant predictor of OR ($\beta = 0.780$, $p < 0.001$; 95% BCa CI: 0.681 to 0.879), which supports H5. OR is significantly related to STM ($\beta = 0.347$, $p = 0.003$; 95% BCa CI: 0.115 to 0.580). Here, CI values determine the significance (if the interval does not include zero, it is significant). The mediation results [71, 72] further revealed these dynamics. The indirect effect of Affective Intelligence on STM through Employee Satisfaction was not significant ($\beta = 0.149$, $p = 0.298$; 95% CI: -0.132 to 0.431). Therefore, H3 is not supported. Adaptive Intelligence had a significant indirect effect on STM through Organizational Readiness ($\beta = 0.271$, $p = 0.004$; 95% CI: 0.088 to 0.454). Therefore, H6 is supported.

Table 5: R^2 (Coefficient of Determination)

Construct	R-Square	Interpretation
Employee Satisfaction (SAT)	0.617	Variance of satisfaction can be explained by affective EAI: 61.7%
Organizational Readiness (OR)	0.608	Variance of OR can be explained by adaptive EAI: 60.8%
Sustainable TM (STM)	0.714	Variance of STM can be explained by all predictors: 71.4%

As per the values (R^2) shown in Table: 5 , Affective EAI towards Employee Satisfaction and Adaptive EAI towards Organizational readiness indicate moderate to strong predictive capability whereas all predictors together demonstrate substantial explanatory power for the primary target construct Sustainable Talent Management outcomes [53].

Table 6: Variance Inflation Factor (VIF)'

Variable Set	VIF	Result
AffectiveInt & EmpSatisfact	3.986	Acceptable (Moderate)
AdaptiveInt & OrgReadiness	3.98	Acceptable (Moderate)

All VIF values (Table 6) were below the conservative threshold of 5.0 (ranging from 3.980 to 3.986), indicating that while the constructs are moderately correlated, multicollinearity does not pose a threat to the stability of the structural path estimates [63]

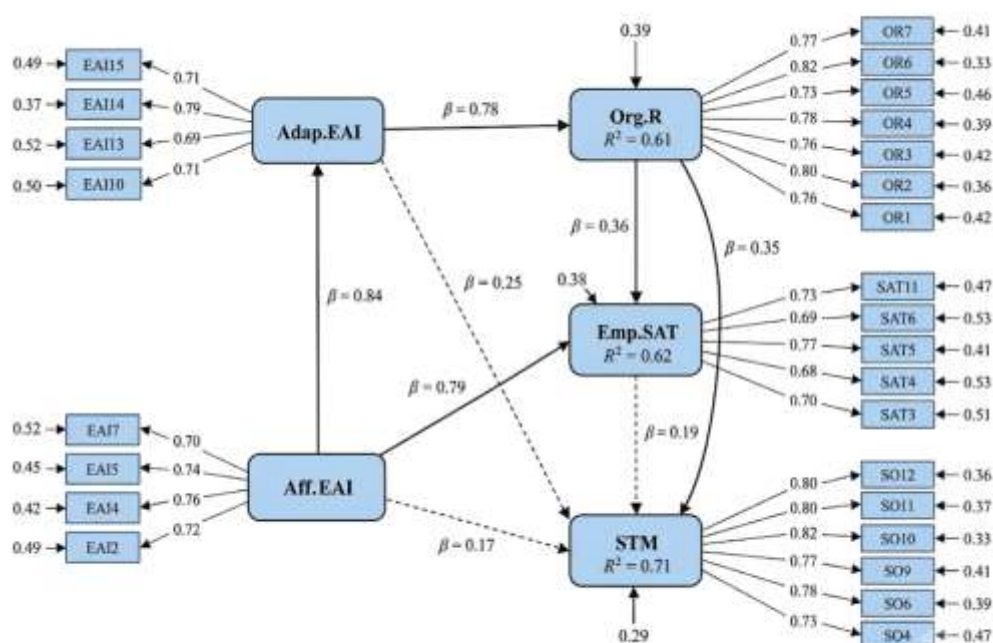
'Cohen f-square' value for effect size:

Among the predictors, Organizational Readiness emerged as the most impactful construct, demonstrating

a medium effect size ($f^2 = 0.141$) and contributing the highest unique variance to the dependent construct. Both Adaptive Intelligence and Employee Satisfaction yielded small but relevant unique contributions to the model, with effect sizes of $f^2 = 0.047$ and $f^2 = 0.039$, respectively. Conversely, Affective Intelligence exhibited a negligible effect ($f^2 < 0.02$), falling below the traditional 0.02 threshold (Image 5). This indicates that Affective Intelligence adds almost no unique explanatory power to the model once Employee Satisfaction is controlled [60]. Collectively, these effect size metrics offer a granular understanding of how individual dimensions of EAI, and organizational mechanics drive STM outcomes.

```
> f2_aff      > f2_or      > f2_sat      > f2_adp
[1] 0.01264198 [1] 0.1410641 [1] 0.0393 [1] 0.04720071
```

Image 5: Source@Rstudio



Notes: Standardized path coefficients (β) and factor loadings are shown, R^2 values are inside the endogenous constructs. Solid lines indicate significant paths ($p < .05$); dashed lines indicate non-significant paths.

Fig 3: Structural Equation Model (SEM)

5. Discussion and Implications

5.1. Discussion

The findings offer a nuanced account of how Emotional Artificial Intelligence contributes to sustainable TM outcomes in the Information Technology sector [2]. The study distinguishes between two dimensions of EAI, namely Affective Intelligence and Adaptive Intelligence. The study investigates the impact of both types of EAI on TM outcomes and identifies clear differences in the effects of Affective and Adaptive Intelligence. Affective Intelligence was found to positively and significantly influence Employee Satisfaction with current TM practices. However, Employee Satisfaction with current TM practices supported by EAI has no significant influence on Sustainable TM outcomes. On the other hand, Adaptive Intelligence of EAI has a highly significant positive influence on organizational factors that determine the potential for the implementation of Sustainable TM in the IT sector, i.e., Organizational Readiness for Sustainable TM. Thus, the primary route to sustainable TM outcomes in the IT sector is the indirect adaptive-readiness route: the embedding of EAI in adaptive, culturally prepared, and structurally aligned organizational systems [73].

5.2. Theoretical Implications

The current research has several theoretical innovations. Firstly, it is one of the first studies that looks at the role of Emotional AI from a TM perspective. It investigates the applicability of newly developed solutions within the field of TM and examines how the human-centered nature of AI can be designed to develop employees and fully utilize their potential in order to develop the potential of an organization as a whole [74]. In other words, the current research investigates new technological solutions for sustainable

TM from a human-centered view. Hence, within the framework of the current research, the human dimension of technology is studied from a sustainable TM perspective and, therefore, the term Emotional Artificial Intelligence (EAI) is introduced in the field of Talent and HRM. This research tested Employee Satisfaction as a necessary condition for achieving sustainable TM results. However, the study revealed that Employee Satisfaction was not sufficient for achieving sustainable TM results. This research described sustainable TM results in terms of technological intelligence being aligned with organizational preparedness and the cultural and human-centered readiness of employees and their managers. The study of EAI results in the development of human-intelligence-embedded organizational capability [44].

5.3. Implications To Managers

The findings have practical relevance for HR managers, technology leaders, and IT decision-makers. Managers cannot use EAI-aided TM systems as a self-sufficient means of achieving sustainable TM practices. Managers have to clarify three issues because EI-infused AI does not automatically lead to sustainable TM: 1) the preparedness of their organization for the implementation of EAI-aided TM systems, 2) how EAI will be integrated with existing practices and systems, and 3) how EAI will be governed within the organization. Thus, EAI is not only another HR technology; it is a strategic transformation project within an organization.

'It is important for managers to realize the difference between the TM system's affective and adaptive capabilities.' As mentioned above, affective features of a TM system can satisfy employees for a long time and positively influence employees' perception of the organization's HR systems. However, as mentioned before, satisfying employees for a long time is difficult; therefore, affective features alone are not enough to achieve sustainable TM outcomes. A manager leading an EAI implementation for TM must therefore focus on the adaptive capability path.

Thus, the IT organization will need to invest in building the necessary technical and data-governance infrastructure, developing leadership capability, organizational culture, ethical practices, and process-redesign capability that will enable the organization to practice sustainable TM practices supported by EAI [75]. Hence, across all practices, 'including recruitment, talent development, performance management, employee engagement, and employee retention, AI systems should support the decisions of managers. The key architecture for responsible and sustainable TM is therefore composed of algorithmic intelligence, emotional intelligence, human intelligence, and organizational readiness.

6. Conclusion

In order to develop more effective TM practices in the IT sector, EAI has potential but is a significant yet conditional advancement. The objective of this research study is to explore and understand the impact that EAI can have on TM practices and how this impact is created. The main contribution of this study is that unlike other technologies, EAI should not be viewed as a means to automate TM practices and that it must be incorporated into TM systems and supported by the organization's infrastructure, culture and strategic readiness.

EAI as studied in the present research is a two-dimensional construct consisting of Affective Intelligence and Adaptive Intelligence. As discussed above, while Affective Intelligence can make the best use of available technology in TM to enhance Employee Satisfaction, the impact of this factor would be short-lived and thus would not be sufficient for sustaining processes of TM. On the other hand, Adaptive Intelligence would help an organization make the best use of available technology in TM by making the organization ready for future demands, thus, in turn, enhancing the sustainability of processes of TM by enabling conversion of Adaptive AI into human practices that can function optimally in the organization's structure and culture.

This study extends TM research by conceptualizing EAI as a human-centered technology, or a technological capability that enhances human capability. In doing so, it integrates the potential of EI and the latest AI technologies with the established body of knowledge from the field of Information Technology, including TAM [26], AMO [17], RBV [27], and Dynamic Capabilities, as well as from the field of Organization and Management, including the "Socio-Technical Systems"[28] perspective. An empirical framework is developed to study the relationship between EAI and sustainable TM practices. IT organizations need to recognize that the latest AI technologies could significantly enhance TM practices but do not guarantee STM outcomes. Thus, managing human-AI interaction, ensuring ethical use of technology, gaining employees' trust, being adaptable to organizational contexts, and, above all, building organizational readiness to leverage EAI are critical for creating value from it.

A principal limitation is the modest sample size and the use of the same sample for both EFA and CFA. The findings' generalizability is constrained by the selected sector, geographic setting, and study period. Future research should adopt longitudinal designs to examine how EAI's effects on different TM dimensions evolve over time [76]. These future studies could be conducted in different sectors of the economy across various geographies. Future research should attempt to correlate EAI with various TM measures such as skills development, leadership development, forming and making agile teams, retention analytics and employee

well-being. The study is not intended to forecast the future of TM through EAI but EAI is a powerful approach to achieve sustainable talent outcomes with strategic organizational readiness.

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