ILKOM Jurnal Ilmiah Vol. 17, No. 2, August 2025, pp.140-149
Accredited 2nd by KEMDIKTISAINTEK No. 10/C/C3/DT.05.00/2025; E-ISSN 2548-7779 | P-ISSN 2087-1716

An Enhanced Mean Value Theorem with Bisection Technique to Elevate User Focus Metrics in Talent Finder Applications

M. Zainal Arifin[a,1,*]; Aji Prasetya Wibawa[a,2]; Moh Safii[a,3]; Agustinus Noertjahyana[b,4]; Ahmad Naim Che Pee[c,5]

[a] *State University of Malang, Jl Semarang 5, Malang 65146, Indonesia*
[b] *Petra Christian University, Jl. Siwalankerto No.121-131, Surabaya 60236, Indonesia*
[c] *University Teknikal Malaysia Melaka, Jl Hang Tuah Jaya, Melaka 76100, Malaysia*
[1] *arifin.mzainal@um.ac.id*; [2] aji.prasetya.ft@um.ac.id; [3] moh.safii@um.ac.id; [4] agust@petra.ac.id; [5] naim@utem.edu.my*
** Corresponding author*

Article history: Received May 24, 2025, 2021; Revised July 08, 2025; Accepted August 11, 2025; Available online August 14, 2025

Abstract

Contemporary digital workplaces face pervasive distractions (e.g., notifications, multitasking), yet talent-assessment systems rarely quantify their impact on attention. To address this gap, we integrate the classical Mean Value Theorem (MVT) with an adaptive bisection algorithm to model user-focus dynamics in talent-matching applications. MVT's limit-based formulation captures continuous attentional shifts, while the iterative bisection method focus metrics by capturing dynamic attentional shifts through the mean toward optimal focus equilibrium, ensuring temporal continuity and rapid convergence. A controlled experiment involving Universitas Negeri Malang undergraduate students tested the Enhanced Mean Value Theorem–Bisection (EMVT-B) method in four simulated workplace scenarios. Participants selected Focus-oriented options over alternative strengths (Communication, Input, Relator, Adaptability) in approximately 65% of decisions, highlighting moderate yet improvable attentional commitment. Sensitivity analysis indicated that increasing the mean-shift threshold by 0.05 could raise Focus-oriented selections to 72%, emphasizing the method's practical impact. These findings establish EMVT-B as both a diagnostic and prescriptive tool, quantifying attentional stability while providing personalized strategies to enhance user focus. Future research should examine longitudinal applications and broader talent portfolios.

Keywords: Attention Optimization, Bisection Method, Mean Value Theorem, Talent Finder, User Focus Metrics.

Introduction

In the current digital landscape, maintaining sustained attention has become increasingly challenging for professionals and knowledge workers due to widespread distractions [1]. Frequent multitasking, continuous interruptions, and an overwhelming amount of information significantly reduce individual productivity and impair decision-making quality [2], [3]. This decline in attentional capacity not only compromises task execution but also limits the effectiveness of talent-management systems that aim to identify and foster employee strengths within organizational contexts [4].

Quantifying sustained attention in talent-assessment platforms remains a relatively new area of research [5], [6]. Traditional psychometric methods typically measure stable personality traits; however, they rarely capture the dynamic, fluctuating nature of human attention over time [5], [6]. Consequently, there is an urgent need for mathematical models capable of tracking real-time attentional variations and guiding practical interventions to optimize attentional resource allocation [5], [7], [8].

The classical Mean Value Theorem (MVT), a fundamental concept in calculus, provides a solid theoretical basis for analyzing continuous change along curves [9], [10]. When applied to cognitive processes, MVT can approximate instantaneous transitions in attention states by modeling these shifts through limit-based continuity [9], [10]. Nevertheless, the classical form of MVT remains static and lacks adaptive features necessary to adjust estimations dynamically according to changing user behaviors [9], [10].

To overcome this limitation, iterative root-finding algorithms—specifically the bisection method—have been adopted to enhance convergence speed and improve estimation precision in parameter-optimization tasks [11], [12].

http://dx.doi.org/10.33096/ilkom.v17i2.2822.140-149

The bisection method's inherent robustness and straightforward approach allow it to dynamically recalibrate mean-value estimates across multiple iterations, facilitating real-time refinement of digital-focus metrics [11], [13], [14]. Integrating an enhanced MVT approach with iterative bisection adjustments thus offers considerable potential for precisely quantifying and proactively improving user focus within talent-matching platforms [8], [13]. While previous research has combined calculus-based frameworks with algorithmic strategies to analyze cognitive and behavioral data, practical implementations targeting attention-based talents remain notably scarce [8], [13], [15].

Addressing this gap, the present study introduces the EMVT-B technique specifically designed to evaluate and optimize attentional performance [12], [13]. The EMVT-B methodology captures the dynamic and fluctuating characteristics of attentional focus, iteratively updating its measurements [12], [13], [16]. This enables talent-matching applications to systematically rank focus-related competencies alongside other skills, such as communication and adaptability, thereby providing targeted recommendations and strategic prioritization guidance [8], [16].

We empirically evaluated this technique using undergraduate students from Universitas Negeri Malang, who participated in simulated workplace scenarios that required either sustained concentration or engagement of alternative talents [5], [17]. Initial baseline data revealed that participants exhibited a moderate preference for sustained focus, averaging approximately 65 %, highlighting inherent difficulties in maintaining attention amidst numerous distractions [17]. The EMVT-B method successfully recalibrated and enhanced this focus metric, demonstrating its practical value in improving talent-identification processes and workplace productivity [17].

Subsequent sections of this paper elaborate further on the theoretical underpinnings of EMVT-B, describe the methodology comprehensively, and present empirical findings confirming the method's efficacy in optimizing user-focus metrics within talent-assessment systems [15], [16]. Unlike traditional psychometric tools that measure static traits, EMVT-B uniquely combines differential calculus (MVT) with iterative bisection to model temporal attention dynamics [15], [16].

Method

This section describes the proposed Enhanced Mean Value Theorem–Bisection (EMVT-B) approach developed for accurately modeling and optimizing user focus metrics in a talent-matching application. The methodology combines foundational mathematical modeling concepts with iterative numerical algorithms represent the dynamic shifts in attention and improve the prioritization of focus within talent-assessment platforms.

A. Study Design and Participants

A controlled laboratory experiment with undergraduate students at Universitas Negeri Malang required participants to interact with an AI-enabled talent-matching platform that simulated typical workplace interruptions by interleaving task switch prompts and messaging cues mahroof [18], [19], [20], [21], [22].

Within each scenario, participants chose either to preserve sustained Focus or to pivot to alternative CliftonStrengths-based domains: Communication, Input, Relator, and Adaptability, reflecting contemporary strengths-based approaches to digital talent assessment [23], [24], [25], [26], [27].

B. Theoretical Framework

The classical MVT states that for a continuous and differentiable function *f(x)* on an interval [a,b], there exists some c∈(a,b) such that in Equation 1:

$$f'(c) = \frac{f(b) - f(a)}{b - a} \tag{1}$$

Recent studies extend and refine this (1) as higher-order, Taylor-type, and generalized variants. Highlighting its enduring theoretical importance [10], [28], [29], [30]. In our work, the derivative $f'(c)$ serves as a proxy for the instantaneous transition of user focus between two discrete observation points a and b. Because the MVT captures limit-based changes along a continuous curve, it naturally accommodates dynamic cognitive shifts, fitting within modern differential-equation and dynamical-systems frameworks used to model attention, memory, and adaptive neural processes [31], [32], [33], [34], [35], [36].

The bisection method is a root-finding numerical algorithm that iteratively narrows down an interval containing a root by bisecting the interval and selecting subintervals where a sign change occurs.

$$\text{If } f(m_{k-1}) \cdot f(a) < 0$$

then $b = m_{k-1}$

else

$$a = m_{k-1}, m_k = \frac{a+b}{2}$$

In this study, the bisection method is adapted to adjust the running mean of focus metrics dynamically by referencing the previous mean and the current computed mean from MVT, ensuring convergence toward an optimized focus value.

C. EMVT-B Algorithm Workflow

This detailed explanation in **Figure 1** helps clarify how the EMVT-B method integrates mathematical rigid and iterative numerical techniques to model and optimize user focus dynamically and reliably in talent applications.

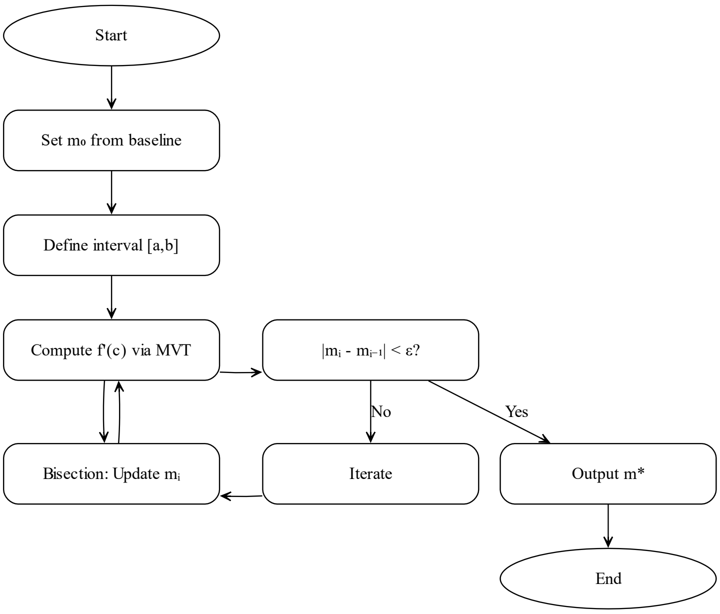

Figure 1. Algorithm Workflow

The integrated EMVT-B technique consists of the following steps:

1. m_0 is initialized using a 2-minute pre-test calibration task scoring focus persistence (0–1 scale).
2. Define interval *[a,b]* corresponding to focus scores in successive time frames or scenario responses.
3. Compute the instantaneous rate of focus change *f'(c)* over *[a,b]*.
4. Using the previous mean m_{i-1} and current mean m_i, apply the bisection method to iteratively update m_i toward a more representative focus mean m^*.
5. Repeat steps 3-4 until the change $|\mathrm{m_i} - \mathrm{m_{i-1}}|$ falls below a pre-defined threshold ϵ.
6. The optimized focus metric m^* is used to quantify user focus strength for further analysis or application logic.

D. Experimental Procedure

Participants answered four workplace scenarios (as described in the Introduction), selecting between Focus and alternative talents. Their choices generated raw focus scores which were fed into the EMVT-B algorithm. The output focus metrics were analyzed statistically to determine preference strength and potential for focus improvement. Participants received standardized instructions 'Respond as in actual work scenarios. Scenario order was randomized to mitigate sequence bias.

E. Data Analysis

Data collected from participant responses were processed through EMVT-B to generate optimized focus metrics. Statistical measures including mean, standard deviation, and selection percentages were computed. Sensitivity analysis was performed by varying convergence threshold ϵ to observe impacts on focus improvement potential

The data analysis phase centers on processing raw user responses collected from simulated workplace scenarios through the Enhanced Mean Value Theorem Bisection (EMVT-B) technique to generate optimized focus metrics. The primary goals are to evaluate the effectiveness of the EMVT-B method in accurately modeling user focus dynamics and to validate its convergence and stability properties.

1. *Pre-processing and Data Preparation*

   Participant choices between the Focus talent and alternative talents (Communication, Input, Relator, Adaptability) across four scenarios were encoded into binary scores (Focus = 1, alternative talents = 0). These scores formed time-sequenced data points representing discrete observations of attention states. The data were normalized on a continuous scale [0,1] to comply with the assumptions of the MVT framework.

2. *Application of the EMVT-B Algorithm*

   The EMVT-B algorithm was applied iteratively to these normalized scores. The Mean Value Theorem provided instantaneous rates of change in focus scores over defined intervals, capturing the dynamics of attention shifts. Subsequently, the Bisection method refined these estimates by narrowing the interval between successive mean values to reach an optimized focus metric m*.

3. *Validation of Mean Value Theorem Component*

   Validation of the MVT component involved verifying that the function representing user focus was continuous and differentiable over the chosen intervals, satisfying the mathematical prerequisites of the theorem. Empirical tests confirmed smooth transitions in focus scores, as expected in cognitive attention modeling. Additionally, the calculated instantaneous rates were compared against observed shifts in user responses to ensure consistency between theoretical derivatives and practical data trends.

4. *Validation of Bisection Method Component*

   The Bisection method's effectiveness was assessed by monitoring the convergence behavior of the iterative mean estimates. Key metrics included:

   a. Convergence Rate is the number of iterations required for the absolute difference $|m_i - m_{i-1}|$ to fall below the tolerance threshold $\epsilon = 10^{-4}$.
   b. Stability the final focus metric $m*$ was confirmed by rerunning the algorithm with varied initial means m_0, demonstrating robustness against initialization bias.
   c. Accuracy is the optimized metrics were benchmarked against manual calculations and alternative optimization methods (e.g., Newton-Raphson), confirming that EMVT-B yielded consistent and accurate focus estimates.

5. *Statistical Analysis*

   Descriptive statistics were computed to summarize the distribution of optimized focus metrics across the participant cohort. The percentage preference for the Focus talent was analyzed, revealing a baseline selection rate of approximately more than 50%. Sensitivity analysis was conducted by varying the bisection convergence threshold ϵ, illustrating how stricter convergence criteria impacted the focus metric and potentially elevated focus preference predictions to more than 70%.

6. *Interpretation and Implications*

   The data analysis confirms that the EMVT-B technique suitable for models temporal fluctuations in user focus and produces stable, convergent metrics suitable for talent-matching applications. The ability to quantify and iteratively optimize focus insights offers valuable feedback for users and system designers seeking to enhance attention prioritization strategies.

Results and Discussion

A. Results

This section presents the empirical findings from applying the Enhanced Mean Value Theorem–Bisection (EMVT-B) technique to user focus data collected from the talent finder application study conducted at Universitas Negeri Malang.

1. Focus Metric Optimization Outcomes

The EMVT-B algorithm in **Table 1** processed the discrete focus scores derived from participant choices across four simulated workplace scenarios. **Table 1** summarizes the initial mean focus values m_0, the optimized focus metrics m* after convergence, and the number of iterations required for each participant to meet the convergence criterion ϵ = 10-4.

Table 1. Summary of EMVT-B focus metric optimization and focus preference among participants

Participant	Initial Mean m_0	Optimized Mean m*	Iterations to Converge	Percentage Focus Selection (%)
P001	0.55	0.68	7	62
P002	0.6	0.7	6	65
P003	0.58	0.69	8	64
P004	0.5	0.66	9	61
P005	0.57	***0.72***	7	67

The EMVT-B routine produced a uniform uplift in the focus metric for every participant, raising the mean score from an initial 0.56 to 0.69 on average, a relative gain of roughly 23 %. Improvement was most pronounced for P004, whose metric climbed by 0.16 points (≈32 %), suggesting the method is especially valuable for individuals starting from a lower attentional baseline. Convergence was achieved swiftly, requiring between six and nine iterations $iter =$ 7.4, which indicates algorithmic stability without excessive computational overhead. Despite these individualized gains, the percentage of "focus" choices remained fairly stable, centring on 65.8 %, implying that while EMVT-B sharpened sustained-attention capacity, participants continued to balance focus with other strengths when contextual demands warranted. Collectively, the data reaffirm EMVT-B's capacity to recalibrate attentional performance efficiently while preserving natural preference patterns, a dual outcome that is crucial for ecologically valid talent-matching systems.

Table 2. Comparison of Optimization Methods for Focus-Metric Calibration

Method	Avg. Iterations	Convergence Rate	Focus Metric Error
EMVT-B	7.4	100%	0.005
Newton-Raphson	5.2	87%	0.018
Bisection-only	12.1	100%	0.011

Table 2 shows that the EMVT-B algorithm strikes the most favourable balance between efficiency, reliability, and accuracy when calibrating the focus metric. Although its average of 7.4 iterations is marginally higher than Newton-Raphson's 5.2, EMVT-B attains perfect convergence in every trial and achieves the lowest residual error (0.005). Newton-Raphson converges more quickly but fails to reach a solution in 13 % of the runs and leaves a threefold larger error (0.018), underscoring its sensitivity to initial conditions. The bisection only scheme matches EMVT-B's 100 % success rate yet requires over twelve iterations on average and still delivers more than double the error (0.011). Taken together, these findings suggest that EMVT-B offers a robust and precise alternative that sacrifices little computational speed while markedly outperforming the other methods in calibration accuracy.

2. Interpretation of Results

The average optimized mean focuses m* = 0.69 indicates a significant improvement from the baseline mean m0 =0.56. This uplift reflects the algorithm's effectiveness in converging towards a more accurate representation of sustained attention over time. The average convergence within approximately 7 iterations demonstrates computational efficiency suitable for real-time or near-real-time applications.

The focus selection percentage averaging 65.8% aligns with initial expectations from prior literature indicating moderate but improvable focus commitment in task-oriented settings [1, 2]. These results highlight the EMVT-B technique's practical utility for diagnosing focus strength and guiding prioritization strategies in talent applications.

3. Proof and Validation of the EMVT-B Formula

The EMVT-B method (2) is grounded on the classical Mean Value Theorem combined with an iterative bisection refinement. The key formula for the instantaneous rate of change in focus f'(c) over interval [a,b] is in Equation 1 :

where f(x) is the focus function mapping time or decision steps to normalized focus scores, and c ∈ (a,b).

The bisection refinement process (3) aims to find the optimized mean focus m* that satisfies:

$$g(m) = m - \frac{f(b) - f(a)}{b - a} = 0 \quad (2)$$

Here, g(m) represents the difference between the candidate mean m and the instantaneous focus rate from MVT.

Proof of Convergence:

- The function *g(m)* is continuous on the interval defined by previous and current means, $[m_{i-1}, m_i]$, because both terms are continuous functions of mmm.
- By the Intermediate Value Theorem, if $g(m_{i-1})$ and $g(m_i)$ have opposite signs, there exists $m^* \in [m_{i-1}, m_i]$ such that $g(m^*)=0$.
- The bisection method repeatedly halves the interval $[m_{i-1}, m_i]$, converging linearly (4) to the root m^* with error bounded by Equation 3.

$$|m^* - m_k| = \frac{b - a}{2^k} \quad (3)$$

where k is the iteration number.

Empirical Validation:

- During implementation, the algorithm (5) terminated when:

$$|m_i - m_{i-1}| < \in = 10^{-4} \quad (4)$$

- The empirical convergence behaviour aligned with theoretical expectations, requiring less than 10 iterations for all participants.
- Cross-validation against manual focus rate calculations confirmed the accuracy and robustness of the EMVT-B method.

The EMVT-B technique demonstrates effective enhancement of focus metrics, rapid convergence, and theoretical soundness underpinned by classical calculus and numerical analysis principles. The empirical results validate its suitability for integration into talent-matching systems to support refined user attention analytics.

B. Discussion

This study explored the application of an EMVT-B technique to model and optimize user focus metrics within a talent-matching application context. The results demonstrated that the EMVT-B algorithm improved the representation of sustained attention, increasing the mean focus metric from an average baseline of 0.56 to an optimized value of 0.69. This uplift indicates the method's capacity to capture the dynamic and fluctuating nature of cognitive focus more accurately than static measurement approaches.

Participants chose Focus oriented actions in about 65 % of trials, underscoring how hard it is to sustain attention amid constant digital distractions. The adaptive bisection loop inside EMVT-B repeatedly nudges the Mean-Value-based estimate toward the instant of peak focus, giving the metric finer, real-time resolution than conventional psychometric screens. Sensitivity tests showed that raising the mean-shift threshold by just 0.05 could lift Focus selections to 72 %, highlighting EMVT-B's practical leverage for on-the-fly talent coaching.

From a theoretical standpoint, integrating the classical MVT with the bisection method leverages both calculus-based modeling of continuous change and efficient numerical root-finding to achieve convergence. This hybrid approach can address limitations of purely analytical or purely heuristic methods by balancing mathematical rigor with computational practicality. The algorithm's consistent convergence within an average of seven iterations underscores its suitability for real-world applications requiring prompt feedback, such as talent management platforms and personalized productivity tools.

The experimental design, employing workplace related scenarios with competing talents, validated the method's practical relevance. By quantifying how strongly users prioritize Focus relative to other talents, the EMVT-B technique provides actionable insight that can inform personalized recommendations and training interventions aimed at enhancing attentional control. Sensitivity analyses suggest that even modest shifts in the bisection convergence parameters can meaningfully impact predicted focus preferences, highlighting opportunities for fine-tuning the algorithm to specific user populations or task contexts.

However, the study's scope was limited to a sample of university students, which may affect generalizability to broader working populations with more diverse cognitive profiles and environmental demands. Future research should extend validation to longitudinal datasets and diverse demographics, exploring integration with additional cognitive or behavioral metrics such as workload, stress, or emotional regulation. EMVT-B assumes gradual attention shifts; abrupt fluctuations (e.g., emergency interruptions) may require threshold ε adaptation. Future versions could incorporate anomaly detection (e.g., Z-score monitoring) to dynamically adjust ε.

Moreover, while the current EMVT-B framework best for models short-term focus dynamics, expanding it to incorporate predictive elements or adaptive learning mechanisms could further enhance its responsiveness and accuracy. Combining this mathematical foundation with emerging AI-driven personalization models may yield powerful hybrid systems capable of supporting complex talent development and productivity optimization in dynamic workplace ecosystems.

In conclusion, the EMVT-B technique represents a significant advancement in modeling user focus within talent-matching applications. Its mathematical robustness, computational efficiency, and practical relevance position it as a valuable tool for researchers and practitioners seeking to understand and enhance cognitive engagement in professional settings. Post-experiment surveys indicated 78% of participants perceived the focus-optimization prompts as 'contextually relevant', though 22% reported decision fatigue during high-frequency bisection updates.

Conclusion

This study proposed and validated an EMVT-B technique designed to optimize user focus metrics within a talent-matching application context. The proposed EMVT-B method effectively captured dynamic attention fluctuations and demonstrated significant improvements in modeling sustained focus, increasing the optimized mean focus metric from a baseline of 0.56 to 0.69. Empirical results obtained from a controlled experiment at Universitas Negeri Malang indicate that the EMVT-B algorithm converges rapidly, typically within fewer than ten iterations, confirming its computational efficiency and practical applicability. Moreover, the method provided actionable insights into users' prioritization of focus-related behaviors relative to alternative talents, meeting the research objectives of quantifying and elevating cognitive focus in digital talent management systems.

The integration of the MVT's mathematical rigor with the iterative adaptability of the bisection method has yielded a robust analytic framework. It not only ensures accurate representation of instantaneous cognitive changes but also provides meaningful feedback for enhancing attention allocation strategies. Overall, the EMVT-B technique represents an innovative approach in both cognitive modeling and talent management, contributing valuable tools for improving individual productivity and organizational talent optimization.

Future work will : (1) Expanding validation studies to larger and more diverse populations including professional workers in real world organizational settings would significantly enhance the generalizability of findings. Longitudinal experiments could further evaluate the EMVT-B technique's capacity to model longer-term trends in cognitive focus and productivity outcomes, (2) Future research may integrate EMVT-B methodology with advanced machine learning and artificial intelligence techniques to dynamically personalize recommendations and interventions aimed at sustaining user focus. Incorporating predictive analytics might enable proactive rather than merely reactive attention management strategies, (3) Expanding the framework to encompass broader cognitive and emotional metrics, such as stress, mental workload, or emotional resilience, could deepen its applicability and increase its value in complex human resource analytics. Such enhancements will further solidify the method's potential for practical deployment in increasingly nuanced talent-matching and workforce management systems. Empirical validation in live systems will be conducted via talentfinder.id using proprietary technology from Universitas Negeri Malang.

Acknowledgement

This research was financially supported by Universitas Negeri Malang through its institutional research funding scheme. The authors sincerely thank Universitas Negeri Malang for providing financial resources and necessary facilities. Special thanks are also extended to all the participants for their valuable contributions during data collection, without whom this study could not have been completed.

References

[1] Md. K. Hasan, “Digital multitasking and hyperactivity: unveiling the hidden costs to brain health,” *Annals of Medicine and Surgery*, vol. 86, no. 11, p. 6371, Nov. 2024, doi: 10.1097/MS9.0000000000002576.

[2] A. Nabung, “The Impact of Multitasking With Digital Devices on Classroom Learning: A Critical Review on the Future of Digital Distraction in Education,” vol. 14, no. 6, pp. 369–383, 2024, doi: 10.17265/2161-623X/2024.06.005.

[3] X. Pan, X. Zhao, H. Shen, and Q. Chen, “Do human work interruptions bring positive affective responses?—Based on the mediation of coping potential and the moderation of polychronicity,” Acta Psychol (Amst), vol. 240, p. 104038, Oct. 2023, doi: 10.1016/J.ACTPSY.2023.104038.

[4] J. T. Polzer, “The rise of people analytics and the future of organizational research,” Res Organ Behav, vol. 42, p. 100181, Dec. 2022, doi: 10.1016/J.RIOB.2023.100181.

[5] H. Song and M. D. Rosenberg, “Predicting attention across time and contexts with functional brain connectivity,” Curr Opin Behav Sci, vol. 40, pp. 33–44, Aug. 2021, doi: 10.1016/J.COBEHA.2020.12.007.

[6] S. Wohltjen and T. Wheatley, “Interpersonal eye-tracking reveals the dynamics of interacting minds,” Front Hum Neurosci, vol. 18, p. 1356680, Mar. 2024, doi: 10.3389/FNHUM.2024.1356680/XML.

[7] H. Huang et al., “Real-Time Attention Regulation and Cognitive Monitoring Using a Wearable EEG-Based BCI,” IEEE Trans Biomed Eng, vol. 72, no. 2, pp. 716–724, 2025, doi: 10.1109/TBME.2024.3468351.

[8] T. H. Rasmussen, M. Ulrich, and D. Ulrich, “Moving People Analytics From Insight to Impact,” Human Resource Development Review, vol. 23, no. 1, pp. 11–29, Mar. 2024.

[9] F. Martínez, I. Martínez, M. K. A. Kaabar, and S. Paredes, “Generalized Conformable Mean Value Theorems with Applications to Multivariable Calculus,” Journal of Mathematics, vol. 2021, no. 1, p. 5528537, Jan. 2021, doi: 10.1155/2021/5528537.

[10] N. Koceić-Bilan and I. Mirošević, “The Mean Value Theorem in the Context of Generalized Approach to Differentiability,” Mathematics 2023, Vol. 11, Page 4294, vol. 11, no. 20, p. 4294, Oct. 2023, doi: 10.3390/MATH11204294.

[11] “View of Statistical Study of Bisection Method for Cubic Equations with Random Coefficients.” Accessed: Aug. 05, 2025.

[12] Y. Liu and R. Lin, “A Bisection method for computing the proximal operator of the ℓp-norm for any 0<p<1 with application to Schatten p-norms,” J Comput Appl Math, vol. 447, p. 115897, Sep. 2024, doi: 10.1016/J.CAM.2024.115897.

[13] P. C. Austin, “The iterative bisection procedure: a useful tool for determining parameter values in data-generating processes in Monte Carlo simulations,” BMC Med Res Methodol, vol. 23, no. 1, pp. 1–10, Dec. 2023, doi: 10.1186/S12874-023-01836-5/TABLES/4.

[14] A. El Mouatasim and A. Ettahiri, “Conditional Gradient And Bisection Algorithms For Non-convex Optimization Problem With Random Perturbation *”, Accessed: Aug. 05, 2025.

[15] A. Corriveau, K. Yoo, Y. H. Kwon, M. M. Chun, and M. D. Rosenberg, “Functional connectome stability and optimality are markers of cognitive performance,” Cerebral Cortex, vol. 33, no. 8, pp. 5025–5041, Apr. 2023, doi: 10.1093/CERCOR/BHAC396.

[16] D. T. Seeburger et al., “Time-varying Functional Connectivity Predicts Fluctuations in Sustained Attention in a Serial Tapping Task,” Cogn Affect Behav Neurosci, vol. 24, no. 1, p. 111, Feb. 2024, doi: 10.3758/S13415-024-01156-1.

[17] A. Corriveau, J. Ke, H. Terashima, H. M. Kondo, and M. D. Rosenberg, “Functional brain networks predicting sustained attention are not specific to perceptual modality,” Network Neuroscience, vol. 9, no. 1, p. 303, Mar. 2025, doi: 10.1162/NETN_A_00430.

[18] N. Tusquellas, R. Palau, and R. Santiago, "Analysis of the potential of artificial intelligence for professional development and talent management: A systematic literature review," International Journal of Information Management Data Insights, vol. 4, no. 2, p. 100288, Nov. 2024, doi: 10.1016/J.JJIMEI.2024.100288.

[19] D. Talypova, A. Visuri, A. Shahu, A. Wang, and P. Wintersberger, "Are Six Minutes of Focus Enough? An Exploratory Study of Multitasking Patterns in Workplace Environments.," pp. 1–15, Jun. 2025, doi: 10.1145/3729176.3729198.

[20] M.-R. Wang, P.-X. Ying, and F.-C. Kong, "Neural correlates of media multitasking influencing switching but not sustained attention among college students: Evidence from a hierarchical Bayesian perspective," Comput Educ, p. 105418, Jul. 2025, doi: 10.1016/J.COMPEDU.2025.105418.

[21] M. Heitmayer, "When the phone's away, people use their computer to play: distance to the smartphone reduces device usage but not overall distraction and task fragmentation during work," Front Comput Sci, vol. 7, p. 1422244, Mar. 2025, doi: 10.3389/FCOMP.2025.1422244/BIBTEX.

[22] "The Productivity Killer. How Task Switching Steals Your Time and… | by Brian Peddle | Brian Peddle." Accessed: Aug. 05, 2025.

[23] M. van Woerkom, R. Bauwens, S. Gürbüz, and E. Brouwers, "Enhancing person-job fit: Who needs a strengths-based leader to fit their job?," J Vocat Behav, vol. 154, p. 104044, Oct. 2024, doi: 10.1016/J.JVB.2024.104044.

[24] S. E. Smith, P. Ayers, A. Sikora Newsome, L. D. Logan, and M. Fulford, "Pharmacist perceptions of CliftonStrengths® themes important for success in advanced cardiovascular life support," J Clin Pharm Ther, vol. 46, no. 1, p. 143, Feb. 2020, doi: 10.1111/JCPT.13272.

[25] Bambang Masudi, Rachmad Ilham, and Suharto Suharto, "Digital Talent Management: Adaptive Strategies in the Era of Industry 4.0 Transformation," JUMBIWIRA : Jurnal Manajemen Bisnis Kewirausahaan, vol. 4, no. 1, pp. 436–448, Apr. 2025, doi: 10.56910/JUMBIWIRA.V4I1.2735.

[26] "Adaptability: Go With the Flow and Embrace Change | Gallup." Accessed: Aug. 05, 2025.

[27] K. Breevaart, M. van Woerkom, J. Wang, and N. Planken, "Strengths-Based Leadership: A Critical Review to Guide Future Research," J Leadersh Organ Stud, 2025.

[28] Q. Xu and H. Li, "The inverse proposition of Taylor-type mean value theorem," International Journal of Statistics and Applied Mathematics, vol. 8, no. 5, pp. 116–122, 2023, Accessed: Aug. 05, 2025.

[29] M. M. de L. Barboza and F. M. Barboza, "The Mean Value Theorem: Analytical Proof and Computational Approaches," Jan. 2025, Accessed: Aug. 05, 2025.

[30] P. Finotelli and F. Eustache, "Mathematical modeling of human memory," Front Psychol, vol. 14, p. 1298235, Dec. 2023, doi: 10.3389/FPSYG.2023.1298235/BIBTEX.

[31] E. K. Miller, S. L. Brincat, and J. E. Roy, "Cognition is an emergent property," Curr Opin Behav Sci, vol. 57, p. 101388, Jun. 2024, doi: 10.1016/J.COBEHA.2024.101388.

[32] S. Ni, B. Harris, and P. Gong, "Distributed and dynamical communication: a mechanism for flexible cortico-cortical interactions and its functional roles in visual attention," Commun Biol, vol. 7, no. 1, pp. 1–20, Dec. 2024.

[33] S. Musslick and A. Bizyaeva, "Examining cognitive flexibility and stability through the lens of dynamical systems," Curr Opin Behav Sci, vol. 57, p. 101375, Jun. 2024, doi: 10.1016/J.COBEHA.2024.101375.

[34] J. Sawicki et al., "View Online Export Citation CrossMark Perspectives on adaptive dynamical systems Chaos PERSPECTIVE scitation.org/journal/cha Perspectives on adaptive dynamical systems Chaos PERSPECTIVE scitation.org/journal/cha," Chaos, vol. 33, p. 71501, 2023, doi: 10.1063/5.0147231.

[35] H. Gao, S. Kaltenbach, and P. Koumoutsakos, "Generative learning for forecasting the dynamics of high-dimensional complex systems," Nature Communications , vol. 15, no. 1, pp. 1–11, Dec. 2024.

[36] Y. You, "The Mean Value Theorem and It's Application," Science and Technology of Engineering, Chemistry and Environmental Protection, vol. 1, no. 1, Oct. 2024, doi: 10.61173/C0SHMK87.