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RESEARCH ARTICLE

Construct Validity of the TalentDNA Inventory

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Abstract

The emergence of 'talentism' aligns with positive psychology's central concern that is what enables individuals and communities to thrive. This study aimed to examine psychometrics properties of the TalentDNA Inventory, particularly its content validity, factorial validity and reliability. This scale consists of three major domains; drive, network and action. A survey was conducted and 1217 responses (n=1217) obtained from Indonesian adults. The obtained findings indicate that this scale exhibits sound psychometrics properties particularly on its content validity, factorial validity and reliability. Results on item level Content Validity Index indicates that the items content are acceptable (I-CVI>0.78) based on the rating given by 10 subject matter experts. Confirmatory Factor Analysis (CFA) result also indicated that this scale possesses a stable three-factor structure with two underlying sub-factors for each factor. In terms of reliability, findings indicated that reliability for each domain, sub-domain and the overall scale are acceptable and good with Cronbach's alpha values above 0.80. Therefore, this TalentDNA Inventory is valid, reliable and suitable to be used by adult group.

Keywords

Talent Assessment, Construct Validity, Psychometric Evaluation, Confirmatory factor analysis

Introduction

According to the World Economic Forum's Future of Jobs Report (2025), talent management is projected to become a significantly more important skill in the workplace by 2030. This reflects a broader shift in how organizations view their workforce: not merely as a source of labor, but as a strategic asset whose development, engagement, and retention are central to long-term competitiveness. The concept of talentism is rooted in an economic paradigm in which human talent becomes the primary source of value creation, and it can be productively interpreted through the theoretical lens of positive psychology. Positive psychology, grounded in the scientific study of human strengths, well-being, and optimal functioning, provides a framework for understanding why talent, rather than financial capital or industrial assets constitutes the most significant economic resource in the modern era.

From a positive psychology standpoint, talentism is fundamentally aligned with the idea that individuals possess unique strengths that, when cultivated, lead not only to personal fulfillment but also to collective flourishing. Core constructs such as strengths identification, intrinsic motivation, engagement, and self-efficacy suggest that human potential is maximized when individuals operate from their signature strengths rather than external pressures or purely economic incentives [1]. Within this framework, talentism reframes economic productivity not as the outcome of labor commodification, but as the result of strengths-based contribution. Organizations and societies that invest in developing individuals' psychological resources such as resilience, creativity, meaning-making, and optimism more likely to enhance both well-being and performance [2]. This aligns with research showing that individuals who leverage their strengths exhibit higher motivation, greater innovation, and deeper

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engagement, all of which are essential drivers in talent-centered economies.

Moreover, positive psychology emphasizes critical role of supportive environments in fostering individual flourishing, highlighting how interpersonal support, meaningful engagement, and conducive social contexts enable individuals to thrive [3]. This perspective reinforces the notion that talentism requires structural conditions within education systems, workplaces, and social institutions that cultivate human potential rather than merely extract labor [4]. A talent driven economy thrives when individuals experience autonomy, purpose, mastery, and psychological safety, as these conditions foster both psychological wellbeing and high-level performance. In essence, positive psychology provides the conceptual and emiprical foundation for understanding talentism as more than an economic model, it represents a human development paradigm in which flourishing individuals contribute to the flourishing of society as a whole.

Psychologists Christopher Peterson and Martin Seligman (2006), proposed the VIA (Values in Action) framework in explaining character strength. Within the VIA framework, human character is defined as the moral dimension of individual functioning, distinguishing it from temperament or cognitive ability. The VIA framework is grounded in several theoretical assumptions. First, human character strengths are value-laden, meaning they are morally desirable and socially beneficial. Second, they are trait-like, exhibiting stability over time while remaining open to development. Third, character strengths are distinct from talents and abilities, focusing on how individuals act rather than how well they perform. These assumptions position character strengths as foundational psychological resources that shape ethical behaviour, resilience, and well-being. According to Peterson and Seligman (2006) [5], it focuses on what is best in people rather than their deficits, providing a common language for understanding and building human goodness.

Materials and Methods

Respondents consisted of 1217 adults (n=1217) from Indonesia, whose age ranging from 45 to 60 years old, with M=49.9 and SD=3.7. With regards to educational background, majority were bachelor degree holders (36.5%), followed by masters' degree holder (21.2%), senior high schools (12.3%) and others (30%).

Measure

TalentDNA Inventory is an inventory developed to reveal an individual's talents particularly the natural talents and behavioural tendencies. While other conventional inventories mostly focus on acquired traits, competencies, or learned skills, TalentDNA emphasizes the identification of innate strengths that constitute the core "DNA" of human behaviour, which consistently shapes how individuals think, feel, and act across contexts. This instrument organizes human talents into three primary domains (D-N-A): Drive, Network and Action.

Drive domain reflects individuals' intrinsic motivations and inner forces that propel individuals toward goals and aspirations. It consists of two sub-domains; achieving and understanding. Achieving-drive consists of seven facets which are competitive, directive, goal-getting, optimiser, perfectionist, confidence and significance. Understanding-drive consists of eight facets which are aversive, collector, contemplative, equitable, explorer, noble, vigorious and visionary. Each of them consists of four items.

Network domain describes individuals' interpersonal capacities that influence how people build, maintain, and nurture social relationships. It consists of two sub-domains; influencing and relating. Influencing encompasses seven facets which are advisor, articulative, collaborator, courageous, convincing, developer and energiser. Meanwhile, relating consists of eight facets which are affectionate, caring, forgiving, generous, genuine, harmony, personaliser and sociable.

Action domain defines individuals' cognitive and problem-solving orientation tendencies that guide how individuals process information and transform it into decisions or strategies. This domain encompasses two sub-domains; thinking and doing. Thinking-action consists of seven facets; contextual, focused, intuitive, innovative, logical, strategiser and troubleshooter. Doing-action consists of eight facets which are accountable, authoritative, decisive, fixer, flexible, initiator, resourceful and structured. Each of these facets consist of four items.

Across these three domains, the scale measures 45 talent themes, offering a comprehensive portrait of an individual's unique profile. Test results typically highlight the top 10 most dominant talents, which serve as the person's signature strengths, as well as the bottom 5 talents, which represent areas that may require management rather than improvement.

Procedure

Convenience sampling technique was employed. During a public event, participants were invited to take the TalentDNA Inventory Test. The benefits and procedures of taking TalentDNA were explained. Participants submitted their email addresses. The link to the TalentDNA Inventory Test was emailed to participants. Participants took 25-35 minutes to fill in the TalentDNA Inventory Test at their convenience online. Respondents receive instant feedback, including a personalized report that outlines their key talents, practical applications of their strengths, and strategies for optimizing personal and professional growth.

Results

Content validity: Hypothesis 1 aimed to examine content validity of the TalentDNA inventory. Ten (n=10) subject matter experts (SME) were appointed based on their agreement. All of them were psychologists and work either as a practitioner or academicians. In the content validation form, the definition of domain and the items represent the domain are clearly provided. The SMEs were requested to critically review the domain and its items before providing score on each item. They were required to indicate the degree of relevance for each item. The degree was ranged from (1) the item is not relevant to the measured domain; (2) the item is somewhat relevant to the measured domain; (3) the item is quite relevant to the measured domain and (4) the item is highly relevant to the measured domain.

Results on item level Content Validity Index (CVI) indicates that the items content are acceptable (I-CVI>0.78) based on the rating given by the experts. With all CVI values above 0.78, this finding indicates that the items content are valid [6,7].

Factorial validity

Hypothesis 2 proposed to gather evidence on the internal factor structure of TalentDNA Inventory construct. As de- scribed earlier in the introduction section, confirming factorial validity of a particular construct is important in testing construct validity as factorial validity aims to confirm the conceptual framework of a construct. Factorial validity assesses how well the internal factor structures represent the TalentDNA Inventory construct, specifically, it examines whether the measured items map onto to their respective domains [8,9]. The measurement model of TalentDNA Inventory construct was evaluated using Structural Equation Modelling (SEM) with AMOS software through confirmatory factor analysis (CFA). CFA is a statistical tool in SEM used to confirm factor structures that underlie a particular construct [10-12]. Maximum Likelihood Estimation (MLE) was employed to assess the adequacy of the model as the parcels are generally treated as continuous data [11]. Factorial validity for all sub-domains were examined. Each domain (D-N-A) consists of two sub-domains. CFA were conducted on achieving, understanding (Drive), influencing, relating (Network), thinking and doing (Action) sub-domains.

A. Factorial validity of the 'achieving' sub-domain

CFA result on the hypothesized model for achieving domain

The CFA results showed adequate support for the hypothesized model, χ^2 (329) = 2042, p = 0.000, χ^2/df = 6.209, CFI = 0.903 and RMSEA = 0.065. The goodness-of-fit indices of the hypothesized model indicate an acceptable model fit based on certain index; the CFI was higher than 0.9 [8,13] and the RMSEA was below than 0.08 [12]. Furthermore, an examination of the Standardized Regression Weights or loading estimates showed that all of the items had a Critical Ratio bigger than 1.96 (CR < +1.96) (ranging from 8.9 to 29.5) indicating that they were significant indicators of the achieving-drive sub-domain [10]. The loading estimates for majority of the items were also larger than 0.5 signifying that they were satisfactorily related to the measured domain [8].

See Table 1 below for the fit statistics, loading estimates and reliability.

Factorial validity of the 'understanding' sub-domain

CFA result on the hypothesized model for understanding sub-domain

The CFA results showed adequate support for the hypothesized model, χ^2 (436) = 2269.7, p = 0.000, χ^2/df = 5.206, CFI = 0.90 and RMSEA = 0.094. The goodness-of-fit indices of the hypothesized model indicate that this model is statistically fit and acceptable based on certain index; the CFI was equal to or higher than 0.9 [8,13] and the RMSEA was below than 0.08. The RMSEA value was below than .06 indicating that the model fit is good. Furthermore, an examination of the Standardized Regression Weights or loading estimates showed that all of the items had a Critical Ratio bigger than 1.96 (CR < +1.96) (ranging from 7.5 to 32.7) indicating that they were significant indicators of the understanding-drive domain [10]. Majority of the items show loading estimates higher than 0.50 which indicates a stronger relationship between an observed variable (item) and an underlying latent domain. See Table 2 below for the fit statistics, loading estimates and reliability.

C. Factorial validity of the 'influencing' sub-domain

sub- CFA result on the hypothesized model for influencing

The CFA results showed adequate support for the hypothesized model, χ^2 (329) = 2076.2, p = 0.000, χ^2/df = 6.30, CFI = 0.926 and RMSEA = 0.066. The goodness-of-fit indices of the hypothesized model indicate that this model is acceptable and fit based on certain index; the CFI was higher than 0.9 [8,13] and the RMSEA was below than 0.08. Furthermore, an examination of the Standardized Regression Weights or loading estimates showed that all of the items had a Critical Ratio bigger than 1.96 (CR < +1.96) (ranging from 11.07 to 37.2) indicating that they were significant indicators of the influencing-network subdomain [10]. Majority of the items show loading estimates higher than 0.50 which indicates a stronger relationship between an observed variable (item) and an underlying latent domain. See Table 3 below for the fit statistics, loading estimates and reliability.

Table 1: The measurement model of 'Achieving' sub-domain: Fit statistics.

Item	Domain	Std *L*	P	Cronbach's α for each domain	Over-all Cronbach's α
Comp1	Competitive	0.783		0.664	0.939
Comp2	Competitive	0.649	***		
Comp3	Competitive	0.662	***		
Comp4	Competitive	0.3	***		
Dir1	Directive	0.357		0.639	
Dir2	Directive	0.605	***		
Dir3	Directive	0.616	***		
Dir4	Directive	0.689	***		
Got1	Goal	0.769		0.77	
Got2	Goal	0.502	***		
Got3	Goal	0.77	***		
Got4	Goal	0.706	***		
Got3	Goal	0.77	***		
Got4	Goal	0.706	***		
Opt1	Optimiser	0.71		0.808	
Opt2	Optimiser	0.76	***		
Opt3	Optimiser	0.644	***		
Opt4	Optimiser	0.773	***		
Per1	Perfectionist	0.584		0.692	
Per2	Perfectionist	0.767	***		
Per3	Perfectionist	0.833	***		
Per4	Perfectionist	0.354	***		
Sel1	Confidence	0.716		0.764	
Sel2	Confidence	0.524	***		
Sel3	Confidence	0.803	***		
Sel4	Confidence	0.681	***		
Sig1	Significance	0.346		0.665	
Sig2	Significance	0.61	***		
Sig3	Significance	0.759	***		
Sig4	Significance	0.641	***		

* The first item for each subscale was set to 1.00. All factor loadings were significant at p< 0.001.

D. Factorial validity of the 'relating' sub-domain

Description of the hypothesized model for 'relating' sub-domain

Prior to Confirmatory Factor Analysis (CFA), all of the items were exposed to Exploratory Factor Analysis (EFA) to examine items which are highly overlapped or non-significant. The EFA result indicated that item personaliser 4, genuine 2 and affectionate 4 were non-significant due to low loading estimates. Therefore, these three items were excluded for the CFA analysis.

CFA result on the hypothesized model for relating sub-domain

The CFA results showed adequate support for the hypothesized model, χ^2 (349) = 1943.9, p = 0.000, χ^2/df = 5.5, CFI = 0.92 and RMSEA = 0.061. The goodness-of-fit indices of the hypothesized model indicate that this model is statistically fit and acceptable based on certain index; the CFI was equal to or higher than 0.9 and the RMSEA was below than 0.08 [8,13]. An examination of the Standardized Regression Weights or loading estimates showed that all of the items had a Critical Ratio bigger than 1.96 (CR < +1.96) indicating that they were significant indicators of the relating sub-domain [10]. The CR values were ranging from 5.0 to 38.2.

Majority of the items show loading estimates higher than 0.50 which indicates a stronger relationship between an observed variable (item) and an underlying latent domain. See Table 4 below for the fit statistics, loading estimates and reliability.

E. Factorial validity of the 'thinking' sub-domain

CFA result on the hypothesized model for thinking sub-domain

The CFA results showed adequate support for the hypothesized model, χ^2 (329) = 1690.4, p = 0.000, χ^2/df = 5.13, CFI = 0.950 and RMSEA = 0.058. The goodness-of-fit indices of the hypothesized model indicate that this model is good and fit based on certain index; the CFI was equal to or higher than 0.95 and the RMSEA was below than 0.06 [8,13]. Furthermore, an examination of the Standardized Regression Weights or loading estimates showed that all of the items had a Critical Ratio bigger than 1.96 (CR < +1.96) (ranging from 7.9 to 40.3) indicating that they were significant indicators of the thinking sub-domain [10]. Majority of the items

Table 2: The measurement model of 'understanding' sub-domain: Fit statistics.

Item	Domain	Std *L*	P	Cronbach's α for each domain	Overall Cronbach's α
Avr1	Aversive	0.513		703	0.927
Avr2	Aversive	0.542	***	.	
Avr3	Aversive	0.67	***		
Avr4	Aversive	0.745	***		
Col1	Collector	0.785		0.773	
Col2	Collector	0.517	***		
Col3	Collector	0.838	***		
Col4	Collector	0.582	***		
Con1	Contemplative	0.755		0.759	
Con2	Contemplative	0.496	***		
Con3	Contemplative	0.759	***		
Con4	Contemplative	0.691	***		
Equi1	Equitable	0.381		0.547	
Equi2	Equitable	0.323	***		
Equi3	Equitable	0.842	***		
Equi4	Equitable	0.36	***		
Exp1	Explorer	0.31		0.613	
Exp2	Explorer	0.825	***		
Exp3	Explorer	0.433	***		
Exp4	Explorer	0.835	***		
Nob1	Noble	0.82		0.729	
Nob2	Noble	0.68	***		
Nob3	Noble	0.397	***		
Nob4	Noble	0.781	***		
Vig1	Vigorious	0.663		0.668	
Vig2	Vigorious	0.583	***		
Vig3	Vigorious	0.575	***		
Vig4	Vigorious	0.514	***		
Vis1	Visionary	0.718		0.715	
Vis2	Visionary	0.774	***		
Vis3	Visionary	0.592	***		
Vis4	Visionary	0.374	***		

* The first item for each subscale was set to 1.00. All factor loadings were significant at p< 0.001.

Table 3: The measurement model of 'influencing' sub-domain: Fit statistics.

Item	Domain	Std L	P	Cronbach's α
Adv1	Advisor	0.788		0.959
Adv2	Advisor	0.784	***	
Adv3	Advisor	0.321	***	
Adv4	Advisor	0.777	***	
Art1	Articulative	0.69		
Art2	Articulative	0.734	***	
Art3	Articulative	0.633	***	
Art4	Articulative	0.768	***	
Coll1	Collaborator	0.717		
Coll2	Collaborator	0.693	***	
Coll3	Collaborator	0.85	***	
Coll4	Collaborator	0.809	***	
Cor1	Courageous	0.768		
Cor2	Courageous	0.549	***	
Cor3	Courageous	0.724	***	
Cor4	Courageous	0.744	***	
Conv1	Convincing	0.607		
Conv2	Convincing	0.793	***	
Conv3	Convincing	0.534	***	
Conv4	Convincing	0.607	***	
Dev1	Developer	0.821		
Dev2	Developer	0.789	***	
Dev3	Developer	0.857	***	
Dev4	Developer	0.771	***	
Enz1	Energiser	0.744		
Enz2	Energiser	0.825	***	
Enz3	Energiser	0.684	***	
Enz4	Energiser	0.853	***	

* The first item for each subscale was set to 1.00. All factor loadings were significant at p< 0.001.

Table 4: The measurement model of 'relating' sub-domain: Fit statistics.

Item	Domain	Std *L*	P	Cronbach's α
n.Aff1	Affectionate	0.733		0.942
n.Aff2	Affectionate	0.695	***	
n.Aff3	Affectionate	0.798	***	
n.Car1	Caring	0.692		
n.Car2	Caring	0.708	***	
n.Car3	Caring	0.613	***	
n.Car4	Caring	0.338	***	
n.Forg1	Forgiving	0.437		
n.Forg2	Forgiving	0.547	***	
n.Forg3	Forgiving	0.756	***	
n.Forg4	Forgiving	0.722	***	
n.Gen1	Generous	0.717		
n.Gen2	Generous	0.472	***	
n.Gen3	Generous	0.614	***	
n.Gen4	Generous	0.831	***	
n.Genu1	Genuine	0.782		
n.Genu3	Genuine	0.721	***	
n.Genu4	Genuine	0.314	***	
n.Har1	Harmony	0.852		
n.Har2	Harmony	0.831	***	
n.Har3	Harmony	0.737	***	
n.Har4	Harmony	0.849	***	
n.Pers1	Personaliser	0.318		
n.Pers2	Personaliser	0.845	***	
n.Pers3	Personaliser	0.779	***	
n.Soc1	Sociable	0.721		
n.Soc2	Sociable	0.326	***	
n.Soc3	Sociable	0.751	***	
n.Soc4	Sociable	0.826	***	
* The first item for each subscale was set to 1.00. All factor loadings were significant at p< 0.001.				

Table 5: The measurement model of 'thinking' sub-domain: Fit statistics.

Item	Domain	Std L	P	Cronbach's α
Count1	Contextual	0.467		0.962
Cont2	Contextual	0.883	***	
Cont3	Contextual	0.85	***	
Cont4	Contextual	0.309	***	
Foc1	Focused	0.82		
Foc2	Focused	0.839	***	
Foc3	Focused	0.842	***	
Foc4	Focused	0.694	***	
Int1	Intuitive	0.612		
Int2	Intuitive	0.754	***	
Int3	Intuitive	0.854	***	
Int4	Intuitive	0.851	***	
Ino1	Innovative	0.817		
Ino2	Innovative	0.697	***	
Ino3	Innovative	0.878	***	
Ino4	Innovative	0.658	***	
Log1	Logical	0.865		
Log2	Logical	0.778	***	
Log3	Logical	0.812	***	
Log4	Logical	0.84	***	
Stra1	Strategiser	0.866		
Stra2	Strategiser	0.701	***	
Stra3	Strategiser	0.845	***	
Stra4	Strategiser	0.475	***	
Tro1	Troubleshooter	0.753		
Tro2	Troubleshooter	0.731	***	
Tro3	Troubleshooter	0.806	***	
Tro4	Troubleshooter	0.801	***	
* The first item for each subscale was set to 1.00. All factor loadings were significant at p< 0.001.				

Table 6: The measurement model of 'doing' sub-domain: Fit statistics.

Item	Domain	Std *L*	P	Cronbach's α
A.Acc1	Accountable	0.552		0.949
A.Acc2	Accountable	0.826	***	
A.Acc3	Accountable	0.363	***	
A.Acc4	Accountable	0.671	***	
Aut1	Authoritative	0.625		
Aut2	Authoritative	0.608	***	
Aut3	Authoritative	0.72	***	
Aut4	Authoritative	0.772	***	
Decs1	Decisive	0.624		
Decs2	Decisive	0.703	***	
Decs3	Decisive	0.709	***	
Decs4	Decisive	0.741	***	
Fix1	Fixer	0.555		
Fix2	Fixer	0.534	***	
Fix3	Fixer	0.525	***	
Fix4	Fixer	0.783	***	
Flex1	Flexible	0.858		
Flex2	Flexible	0.794	***	
Flex3	Flexible	0.511	***	
Init1	Initiator	0.743	***	
Init2	Initiator	0.668		
Init3	Initiator	0.639	***	
Init4	Initiator	0.204	***	
Res1	Resourceful	0.83	***	
Res2	Resourceful	0.774		
Res3	Resourceful	0.832	***	
Res4	Resourceful	0.775	***	
Str1	Structured	0.708	***	
Str2	Structured	0.317		
Str3	Structured	0.731	***	
Str4	Structured	0.152	***	

* The first item for each subscale was set to 1.00. All factor loadings were significant at p< 0.001.

show loading estimates higher than .50 which indicates a stronger relationship between an observed variable (item) and an underlying latent domain. See Table 5 below for the fit statistics, loading estimates and reliability.

F. Factorial validity of the 'doing' sub-domain

Description of the hypothesized model for 'doing' sub-domain Prior to CFA, the EFA result indicated that one item from this sub-domain (item flexible 4) was non-significant due to low loading estimate. Hence, this item was excluded for the CFA. Action-doing sub-domain consists of eight facets which are accountable, authoritative, decisive, fixer, flexible, initiator, resourceful and structured. Each of them consists of four items and only flexible sub-domain consists of three items.

CFA result on the hypothesized model for 'doing' sub-domain.

The CFA results showed adequate support for the hypothesized model, χ^2 (406) = 2267.7, p = 0.000, χ^2/df = 5.5, CFI = 0.912 and RMSEA = .061. The goodness-of-fit indices of the hypothesized model indicate that this model is statistically fit and acceptable based on certain index; the CFI was equal to or higher than 0.9 and the RMSEA was below than 0.08 [8,13]. Meanwhile, an examination of the Standardized Regression Weights or loading estimates showed that all of the items had a Critical Ratio bigger than 1.96 (CR < +1.96) (ranging from 5.1 to 36.1) indicating that they were significant indicators of the 'doing' sub-domain [10]. Majority of the items show loading estimates higher than 0.50 which indicates a stronger relationship between an observed variable (item) and an underlying latent domain. See Table 6 below for the fit statistics, loading estimates and reliability.

Discussion

The TalentDNA inventory is self-scoring and describes tendencies as indicated by the self-reported responses. The findings of this study confirm that the item content within the TalentDNA inventory is both valid and highly relevant to the constructs being measured. Thus, this result reflect that each item does measure what it intends to measure based on its underlying domain. H1 can therefore be said to be supported. The CFA results revealed that for each domain of this measure, it shows a stable and valid factor structure. These findings signify that the items do map onto their respective domain. Out

of 176 items, all items were significant in measuring its respective domain. Hence H2 was supported. It must be noted that there were 4 items which were non-significant at the preliminary analysis and were excluded from CFA. These items shall be revised for the future application and research. The reliability analysis results indicated that this scale shows good reliability; indicating that all of the items in its respective domain are internally consistent. Therefore, H3 was also supported. Hence, the present findings provide empirical support for the viability of these three dimensional-structures (drive, network and action) as well as the content validity and reliability of the TalentDNA Inventory. The study suggests that the TalentDNA Inventory is useful for measuring specific individual talents and behavioural tendencies. It facilitates individuals' understanding of their own and others' characteristic styles, thereby supporting better adaptation to individual differences. As the result, we are more accountable to flex our behaviours when we understand and tolerate the behaviours and actions of others. This understanding is also helpful in planning, making decision and behavioural management.

Implications and recommendations for future research

Psychometric assessments play a vital role in modern hiring by providing insights into individuals' behavioural tendencies, enabling better adaptation to workplace challenges and enhancing team dynamics. The TalentDNA Inventory is helpful for use in a workplace setting. Much like genetic DNA encodes the blueprint of a person's biological makeup, TalentDNA seeks to uncover the intrinsic patterns that shape how a person thinks, feels, and acts in various contexts. Its primary purpose is to help individuals gain deeper self-awareness while providing organizations with valuable insights into employee potential, team dynamics, and leadership development.

In practical use, the TalentDNA test serves several functions. At the individual level, it helps participants recognize their natural strengths, blind spots, and motivational drivers. This self-knowledge can guide career choices, personal growth, and strategies for building more effective interpersonal relationships. For organizations, TalentDNA acts as a tool for recruitment, succession planning, and talent management. By aligning individual behavioural profiles with job requirements and organizational culture, organizations are better positioned to enhance productivity, reduce employee turnover, and foster stronger team cohesion. Moreover, TalentDNA extends its utility to learning and development initiatives. By pinpointing individual learning styles and leadership potential, it supports tailored training programs that accelerate growth. In a broader sense, the test contributes to creating a culture of self-reflection and continuous improvement either at the personal or organizational levels. Ultimately, the TalentDNA Inventory is not merely about labeling individuals but about unlocking human potential. Its use lies in bridging the gap between self-understanding and practical application, empowering people to thrive in their chosen paths while enabling organizations to harness the diverse talents of their workforce. Further research should focus on other types of validity evidence, such as convergent validity, discriminant validity, and predictive validity, to gain more evidence on the usefulness and meaningfulness of this measure.

Conclusion

Within the evolving landscape of future work, organizations that prioritize strategic talent management over an exclusive reliance on technology or capital are anticipated to achieve a competitive advantage over their competitor. A pivotal study by the Budhwar, et al., (2023) [14], sustainable competitive advantage is not achieved through AI adoption alone, but by "redesigning, restructuring, retooling, and reskilling" the workforce to focus on creative and innovative endeavours that machines cannot replicate. This implies that human skills will continue to complement technical capabilities, making strategic talent management essential for cultivating a hybrid workforce that maximizes the potential of both people and technology. By investing in people, companies gain a sustainable competitive edge: engaged and skilled employees are not only more productive but also more innovative [15]. As projected by World Economic Forum (2025), human ingenuity will increasingly serve as a vital complement to technical proficiencies. This shift renders strategic talent management an essential pillar for cultivating a high-performing hybrid workforce in the future.

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