Checklist for dissertation submission

Introduction	Have you presented/stated the problem or issue which is to be addressed?	✓
	Have you stated why your research is worthy of study?	✓
	Have you given your research problem context? i.e. have you said what has been done previously or why this is an important area of study?	✓
	Have you given some indication of the key literature identifying any gaps that your research hopes to address?	✓
	Have you provided an overview of the structure of the research project?	✓
	Are there references in your introduction? There should be!	✓
Literature Review	Is there evidence of up-to-date material pertaining to your area of study?	✓
	Is the material mostly journal-based rather than textbook-based?	✓
	Have you provided a synthesis, not a summary, of previous studies/research?	✓
	Are you guilty of summarising/describing what others have said? If so you need to address this!	✓
	Does each paragraph describe simply what someone else has said? i.e. does it only contain one reference albeit multiple times to the same piece of work? If so you need to address this!	✓
	Does your literature have a logical flow? Does it jump from one section to another without any link?	✓
	Does your literature review have a conclusion?	✓
Research Question	Do you have a clearly stated research question or hypothesis?	✓
	Have you identified and explained the aims and objectives of your study?	✓
Methodology	Have you provided summaries of each possible research method without ever linking it to your own work? If so please revisit.	✓
	This section should describe how the problem was investigated and why particular methods and techniques were employed. Have you done this?	✓
	Have you been able to link your methodological approach to other previous research in terms of adopting a similar approach?	✓
	Have you stated what you did? Often referred to as the procedure adopted.	✓
	Have you provided details of your sample? Who did you ask and why these and not others?	✓
	What did you ask them? Details about your research instrument	✓
	How did you ask them? Details about your data collection	✓
	What you did do with what you collected? Data analysis – i.e. how you treated the data. This is NOT what they actually said – that comes in the next section! Here you want to be clear about how you treated the data not what you found.	✓
	Did you pilot your data collection tool?	✓
	Does your methodology section refer to ethical considerations?	✓
	Have you included a limitations section?	✓

Findings / Results	Does your findings section simply list the answer to each question in your questionnaire/interview etc, one after the other? If so revisit!	✓
	Is there a logical flow to your findings?	✓
	Have you highlighted the key findings for the reader?	✓
Discussion	Have you linked your findings back to your literature?	✓
	Have you highlighted for the reader what was important in your findings and how this relates back to previous studies/knowledge on your research topic?	✓
	Have you included practical implications (if appropriate)?	✓
	Have you considered the limitations of your study including your methodological approach?	✓
Conclusions	Have you provided a strong conclusion to your work?	✓
	Have you provided a summary of what you have found out in relation to each research question posed?	✓
	Is your conclusion section less than 1 page in length? If so please revisit.	✓
	What are the next steps? Future research possibilities?	✓
Reference List	Have you included ALL references cited in your work?	✓
	Have you adhered to the Harvard referencing system?	✓
	Have you included all references in alphabetical order by surname?	✓
	Have you separated books from journals etc? If so please revisit. All reference material should appear in alphabetical order irrespective of whether it is a book or journal or working paper etc.	✓
	Have you included material that is not directly referenced in your research report? If so please revisit. Only material directly cited/referenced in your report should be included in your reference list. All other material consulted but not directly cited should appear in your bibliography should you choose to include one.	✓
In-text referencing	Have you ensured that all in-text references appear in your reference list?	✓
	Have you used the Harvard method? Surname/Date approach?	✓
	Have you put the full stop after the close bracket for in-text references – example below; Students should pay attention to the advice they have been given by their lecturer (Darcy 2013).	✓
	Have you included an author's initial in your in-text referencing? If so please revisit. Only the surname and year should appear.	✓
House-keeping	Have you checked your spelling and grammar?	✓
	Are there unexplained gaps between sections of work/ blank pages or pages where the work begins halfway down the sheet? If so please revisit	✓
	Is your work neat and tidy with a professional presentation?	✓

National College of Ireland

Project Submission Sheet

Student Name:	Juanita O'Mahony
Student ID:	22129685
Programme:	MSc International Business **Year:** 2023/2024
Module:	Dissertation
Supervisor:	Gerard Loughnane
Submission Due Date:	10 August 2024
Project Title:	To what extent does strategic talent measurement impact talent management strategies in STEM industries.
Word Count:	11,076

I hereby certify that the information contained in this (my submission) is information pertaining to research I conducted for this project. All information other than my own contribution is fully referenced and listed in the relevant References section at the rear of the project.

<u>ALL</u> Internet material must be referenced in the References section. Students are encouraged to use the Harvard Referencing Standard supplied by the Library. To use another author's written or electronic work is illegal (plagiarism) and may result in disciplinary action. Students may be required to undergo a viva (oral examination) if there is suspicion about the validity of their submitted work.

Signature: **Date: 10 August 2024**

PLEASE READ THE FOLLOWING INSTRUCTIONS:

1. Please attach a completed copy of this sheet to each project (including multiple copies).
2. Projects should be submitted to your Programme Coordinator.
3. **You must ensure that you retain a HARD COPY of ALL projects**, both for your own reference and in case a project is lost or mislaid. It is not sufficient to keep a copy on a computer. Please do not bind projects or place them in covers unless specifically requested.
4. You must ensure that all projects are submitted to your Programme Coordinator on or before the required submission date. **Late submissions will incur penalties.**
5. All projects must be submitted and passed in order to successfully complete the year. **Any project/assignment not submitted will be marked as a fail.**

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AI Acknowledgement Supplement

Dissertation

Title: To what extent does strategic talent measurement impact talent management strategies in STEM industries.

Your Name/Student Number	Course	Date
Juanita O'Mahony / 22129685	MSc International Business	10 August 2024

This section is a supplement to the main assignment, to be used if AI was used in any capacity in the creation of your assignment; if you have queries about how to do this, please contact your lecturer. For an example of how to fill these sections out, please click here.

AI Acknowledgment

This section acknowledges the AI tools that were utilized in the process of completing this assignment.

Tool Name	Brief Description	Link to tool
Grammarly	A software program designed to support student proofreading and grammar learning in the context of their own writing.	Link
QuillBot	A software program that uses AI to rewrite and paraphrase text.	Link

Description of AI Usage

This section provides a more detailed description of how the AI tools were used in the assignment. It includes information about the prompts given to the AI tool, the responses received, and how these responses were utilized or modified in the assignment. **One table should be used for each tool used**.

Grammarly	
Grammarly was used to ensure accurate spelling, punctuation and grammar.	
Grammarly will identify the spelling of 'Organi**z**ation' and suggest changing it to 'Organi**s**ation'.	Right-click and select the word 'Organisation' when prompted to change the spelling or grammar.

QuillBot	
QuillBot was used to suggest alternative words or phrases.	
Requesting a different word for 'management decided'.	QuillBot suggests 'Management made a decision'.

Evidence of AI Usage

This section includes evidence of significant prompts and responses used or generated through the AI tool. It should provide a clear understanding of the extent to which the AI tool was used in the assignment. Evidence may be attached via screenshots or text.

Additional Evidence:

Not applicable.

Additional Evidence:

Not applicable.

Title

To what extent does strategic talent measurement impact talent management strategies in STEM industries.

A Written Assessment

By Juanita O’Mahony

In fulfillment of the requirements

for a Master’s Degree in International Business

Submitted to the National College of Ireland

August 2024

Abstract

Technology is driving change in the global talent management industry which is projected to grow from its estimated value of USD 8.6 billion to USD 15.29 billion by 2028 (PR Newswire 2023). Talent Measurement is a crucial component of talent management given that it enables companies to determine both the short and long-term human capital requirements for their business, in order to remain innovative and competitive.

This study has been conducted to determine to what extent strategic Talent Measurement impacts talent management strategies in STEM industries. Specifically, who measures what, and how. The currently available literature on Talent Measurement is limited and one-dimensional and does not provide sufficient evidence of what, or how, talent is measured in practice (Yogalakshmi and Supriya 2020; Thunnissen, Boselie and Fruytier 2013; Guthridge, Komm and Lawson 2008).

Primary data was collected from a sampling selection of HR professionals and Hiring Managers working within enterprises in STEM Industries. Quantitative data was obtained through cross-sectional research, a questionnaire was constructed and self-administered online, and the data analysis was completed using SPSS software, applying regression and correlation techniques (Field 2018). The reliability of the constructs was assessed by Cronbach's alpha.

The evidence revealed a significant finding that users' interest in strategic outcomes appears to be influenced by their use of predictive techniques, such as AI and machine learning. The results revealed that the more technology-savvy HR professionals are, the increased likelihood they will use predictive techniques when measuring talent. The findings confirm that not a single participant “Always” employed predictive analysis in skill assessments, implying that current measuring methodologies are not rooted in facts, but instead based on “gut” and influenced by bias.

This study highlights the acute necessity for disruption in the Talent Management industry. Most HR users are not using predictive techniques, and companies may have unknowingly contributed to perceived skill shortages by declining suitably qualified candidates, due to inexperienced HR professionals and Hiring Manager's bias. This study adds to the field of Strategic Measurement by identifying a link between manual selection and strategic measurement, which offers support to HR policies and encourages investments in HR users' analytical skills, as a means to expedite knowledge and growth.

The researcher would hope that the core finding regarding users' interest in strategic outcomes, which appears to be influenced by their use of predictive techniques and AI, will provide the basis for future research into skill combination and strategic performance.

Declaration

Submission of Thesis and Dissertation

National College of Ireland
Research Students Declaration Form
(Thesis/Author Declaration Form)

Name: Juanita O'Mahony
Student Number: 22129685
Degree for which thesis is submitted: MSc International Business
Title of Thesis: To what extent does strategic talent measurement impact talent management strategies in STEM industries.
Thesis supervisor: Dr. Gerard Loughnane
Date: 10 August 2024

Material submitted for award:

A. I declare that this work submitted has been composed by myself. ☑

B. I declare that all verbatim extracts contained in the thesis have been distinguished by quotation marks and the sources of information specifically acknowledged. ☑

C. I agree to my thesis being deposited in the NCI Library online open-access repository NORMA. ☑

D. I declare that no material contained in the thesis has been used in any other submission for an academic award. ☑

Dedication

I would like to dedicate this research to the Mother who raised me, who loved me, and who taught me the value of self-confidence. The woman who taught me to do everything to the best of my ability, not because someone else is watching me, but because of who I am and of what I am capable. After 24 years since you have gone, your voice still echoes in my head and heart, but the desire and longing to hear it, has never faded. Thank you for teaching me how to be a good, decent human being and knowing the difference between right and wrong. I will be forever grateful and proud to have called you *my* Mother.

“You can always give something, even if it is only kindness“.

Anne Frank

Acknowledgments

I would like to thank my best friend, mentor and husband, John O’Mahony, who persuaded me to pursue my tertiary education with my Bachelor of Business degree in International Business, and again to enroll for this Master’s degree. Without your nudging, support, guidance, love, food, patience, and editing (*more than you ever wanted to read or know about talent measurement*) and generally planning life around my studies, this would not have been as manageable and enjoyable. Thank you darling Husband for encouraging me and making me believe that I am capable of achieving this.

I would also like to express my gratitude to Dr. Gerard Loughnane, my Supervisor, who inadvertently convinced me to change my approach to quantitative studies. The ease with which you explained the nuts and bolts of statistics and explaining the technicalities made for enjoyable learning, thank you. This thesis in the time frame would have been more difficult without your continuous advice and assistance, thank you very much.

To every one of my friends, connections, colleagues, and acquaintances who took part in the study, I would like to express my gratitude.

Lastly, to the youngest-ever graduate in the history of Pretoria, thank you for not giving up.

Table of Contents

List of Tables and Figures

List of Abbreviations

AI	Artificial Intelligence
CV	Curriculum Vitae
DV	Dependent Variable
GDPR	General Data Protection Regulation
HR	Human Resources
I.E.	Id Est
IV	Independent Variable
ML	Machine Learning
SHRM	Society for Human Resource Management
SPSS	Statistical Package for Social Sciences
SRA	Social Research Association
STEM	Science, Technology, Engineering and Mathematics
USD	United States Dollar

1. Introduction

Given practical and ethical considerations, the research area of “Talent Measurement” has been chosen for business reasons. Talent Measurement is a critical input to Talent Management, as it determines the current and long-term human capital a business requires, to remain innovative and competitive. Driven by technological advances, the global Talent Management market, estimated at USD 8.6 billion and expected to reach USD 15.29 billion by 2028, is poised for disruption (PR Newswire 2023). However, the lack of skilled staff is increasingly becoming a major issue for employers.

A recent study among 21 European countries found that three in four employers could not find the skills they required (Yanatma 2024). Previous research has taken the approach that Talent Management remains underdeveloped, and this gives rise to the question of what should be measured, and how (Zhang *et al.* 2023; Anlesinya, Dartey-Baah and Amponsah-Tawiah 2019). Studies highlight no systematic review of “drivers, outcomes, and challenges" on this topic (Anlesinya *et al.* 2019). While many studies have been conducted, how talent is measured in practice, and how well, are under-explored areas, creating a gap in the literature and promoting this research.

Research is required to fully understand how Talent Measurement is developed, implemented and used within an organisation. In particular, its lack of effectiveness and functionality leaves a significant void in the current literature. Since most frameworks and systems are built for an organisation to measure skills, typically without sharing this information with its employees, the provision of employee agency or ownership of skills measurement, may be the market disruptor that is currently missing.

The primary aim of this study is to critically evaluate how strategic Talent Measurement impacts talent management strategies in STEM industries. Specifically, who measures what, and how. As knowledge can be verified by science, a positivist philosophy is used as the research paradigm, as this allows the researcher to remain objective, focusing on facts (Saunders *et al.* 2019). The following research objectives are directed towards achieving the research aim; i) Identify key predictors outlining critical competencies for talent measurement and ii) Determine the current measuring methodologies used and the efficiencies of the users and iii) Assess the impact of measurement on the effectiveness of Talent Management strategies.

‘HR users' interest in strategic outcomes appears to be influenced by their use of predictive techniques and AI’.

This paper will argue that human capital has value if it can be precisely quantified and assessed through the use of strategic talent measurement, which can greatly benefit talent management strategies. Consequently, inaccurate measurement can lead to an increase in cost and a perception of talent shortages. Quantitative data was collected through a constructed survey and self-administered online using Survey Monkey. The target respondents were adult males and females, with experience in screening and selecting CVs during a candidate application process. The statistical analysis was performed with the use of SPSS 28, applying regression and correlation methods. The reliability of the constructs was assessed by Cronbach's alpha.

This research adds to the body of knowledge in the following manner; i) The contribution to the Talent Measurement knowledge base with an understanding of who measures what and how. ii) The practical implications to assist businesses in exploiting talent measurement, through informed decision-making and reduced bias.

2. Background Literature

Significant contributions made by other authors to the field of study are critically analyzed in this section, serving as the literature review. Definitions of terminology, closely related to the research field, are included. The review also addresses classifications of major approaches to the issue of Talent Measurement. Additionally, major models and theoretical frameworks in the field of Talent Management, such as Human Capital theory (Marginson 2019), Bounded Rationality theory (Jordão *et al.* 2020), and Agency theory (Pološki Vokić 2016) have been analyzed. This literature review is completed by identifying and explaining a gap in the current pool of literature, that this paper attempts to bridge.

2.1. Talent Management

Talent Management is an acute strategic issue, as it contributes to strategic pliability and consequently, can influence business performance (Kafetzopoulos, Psomas and Bouranta 2022). This description is close to Collings and Mellahi (2009), who define Talent Management as, "activities and processes that involve the systematic identification of key positions, which differentially contribute to the organization's sustainable competitive advantage". The ability to attract, select, and retain talent, remains an issue for business. Conversely, strategies that recognize a limited definition of "talent" can adversely affect a company's ability to utilize its entire workforce (Gallardo-Gallardo, Thunnissen and Scullion 2020; Marginson 2019; Tansley 2011).

Current definitions of talent are broadly specific to the company, and heavily impacted by the type of work performed (Gallardo-Gallardo *et al*. 2020; Tansley 2011). Collings and Mellahi (2009) argue for the focus of Talent Management strategies to be on high-potential and high-performing employees. Considering the theory of Human Capital, unless human capital is used to carry out the company's strategic intent, it has little economic value (Becker 2009). However, according to Marginson (2019), the Human Capital theory has no value as it “fails the test of realism", suggesting that it incorrectly uses mathematical instruments that lack diverse, and cultural, norms, and perspectives.

Corporate talent should be viewed as a long-term asset, and therefore it is important to understand the environment in which an organisation operates, to determine the most effective strategy (Gallardo-Gallardo *et al.* 2020). Beyond the typical focus on strategic or cultural fit, Thunnissen *et al.* (2013) advocate for a greater awareness of contextual fit. Organisational context influences the use, significance, and execution of Talent Management, however, less research has been conducted on particular context issues (variables) at the individual level, i.e. skills measurement, which has been overlooked, leaving a void in the knowledge for efficient Talent Measurement, that this paper attempts to bridge (Stephany and Teutloff 2024; Gallardo-Gallardo *et al.* 2020).

2.2. Talent Measurement

Lee (2018) defines Talent Measurement as, "the practice of applying specific measurement methodologies to employees, to determine their potential current and longer-term competencies and contribution to the organization". The literature currently relating to Talent Measurement is limited and one-dimensional and in practice does not provide sufficient evidence of what, or how, talent is measured (Yogalakshmi and Supriya 2020; Thunnissen *et al.* 2013; Guthridge *et al.* 2008). Despite extensive research on Talent Management, less research has been conducted on specific measurement methods, and theoretical foundations have equally not received sufficient attention, creating a gap in the literature (Thakral *et al.* 2023; Zhang *et al.* 2023; Fernandez and Gallardo-Gallardo 2021).

This paper attempts to bridge this gap in the literature by contributing knowledge on specifically who measures what, and, how. Anlesinya *et al.* (2019) report a downward trend in empirical Talent Management research, suggesting satisfaction with the status quo. They also report inaccurate selection increases an organisation's exposure to risk. The ambiguity and controversy surrounding Talent Measurement are exacerbated in the following statement; "Talent Measurement for inclusive Talent Management must by necessity provide some more complex information than in/out attributions, which by definition, do not apply to it" (Lee 2018).

Recent studies reveal the primary cause of skill shortages, as reported by employers, is applicants' lack of experience, education, or training (Yanatma 2024). Talent Measurement requires practitioners to take comprehensive steps to strategically and accurately measure talent, however, recent studies revealed that only 21% of HR professionals are confident with the use of measurement techniques such as predictive analytics (Gamba Quilliam 2023). The position in this research draws on the suggestion that skills are not measured accurately, adding to the perception of skill shortages.

Considering that "cognitive ability is the single most valuable assessment", who measures what, and how, should be of significant importance to organisations, as well as their employees (Walford-Wright and Scott-Jackson 2018). This paper attempts to determine who measures what, and how, based on a theory that explains known facts. The theory of Bounded Rationality describes a rational decision-making process, that considers the decision-makers cognitive constraints, such as knowledge and computational limitations (Jordão *et al.* 2020; Tafti, Mahmoudsalehi and Amiri 2017). According to this theory, decision-makers go through an extremely difficult and convoluted process to fully understand the talent setting within the organisation (Jordão *et al.* 2020; Tafti *et al.* 2017). This process is beyond most HR professionals' capabilities, consequently, their decisions are based on incomplete information, increasing the risk of poor candidate selection.

Since talent is scarce, talent assessment has become essential to ensure employee performance consistently reflects the goals of the organisation. The complexity of human capital in knowledge-intensive industries, such as Science, Technology, Engineering, and Maths (STEM), has made worker skill assessment more challenging, contributing to talent shortages (Anderson 2017). Previous studies by McGunagle and Zizka (2020) have not dealt with identifying employability skills and offer no clear solution to bridging the gap between what skills are innate and what skills are taught, or their value and the subsequent cost to the organisation. For Talent Measurement to be effective, these elements must be understood with an obvious measure, that is apparent.

Talent Management strategies should take into consideration business practices and procedures, as well as the levels of operational and strategic responsibility and ability, within the organisation (Filippus and Schultz 2019). Talent is predominately defined by Hiring Managers and HR specialists within an organisation, and as with all individuals, are prone to biases. Mental and cognitive prejudices are barriers to Talent Measurement, consequently, these barriers, as well as any enablers, should be acknowledged as part of the process for the measurement to be effective (Tafti *et al.* 2017). Once barriers are identified, solutions can be considered and likewise, enablers can improve efficiencies.

Current Talent Management approaches primarily reflect a traditional, top-down managerial approach, and leave little room for employee involvement. Agency theory provides a framework to address these complexities, as fundamentally, the theory is based on “self-interest” and could be the solution if talent controls the measurement of its skills (Yogalakshmi and Supriya 2020; Pološki Vokić 2016). Employees who are engaged, with a sense of commitment toward their work, are investing in continuous learning and development, enhancing their value (Stephany and Teutloff 2024). If the theory holds, self-interest can positively contribute to the accurate measuring of skills, particularly when talent is involved in the measuring methodology.

2.3. Measurement Methodologies

The term "Measurement", is broadly defined as the "estimation of the ratio of some magnitude of a quantitative attribute, to a unit of the same attribute" (Michell 1997). Essentially, it is the process of comparing a known measure with an unknown one. Measurement and quantity are synonymous: in theory, attributes that can be measured are considered quantitative (Michell 1997). Traditional measurement methods typically divide employees into, a) broad categories (i.e. employees and management), b) years of industry experience, and c) education. However, in doing so it overlooks the importance of human capital and fails to take an all-encompassing view of talent, for sustained advantage.

Studies by Siepel, Camerani and Masucci (2021) strongly point out that skill combinations positively contribute to innovation and growth in companies and encourage businesses to invest in skill combinations for superior performance. Talent offers more than just educational attainment. It contributes a combination of industry knowledge, occupation knowledge, and soft, hard, and transferrable skills. Table 1 describes these skills. The value of a particular skill however is relative, as it is dependent on the measurements with which it is combined (Stephany and Teutlof 2024; Michell 1997).

Table 1: Description of Skills.

Hard Skills	Measurable skills acquired through training, education, and practice required for a particular job.
Knowledge-based	Knowledge of a particular subject matter, process, or software application.
Industry Knowledge	The accumulation of knowledge and awareness of the intricacies of what is happening to specific industries of interest, i.e. Pharmaceuticals.
Soft Skills	Character traits and interpersonal skills.
Transferrable Skills	Soft skills that can be applied across various industries and roles, i.e. Time management, empathy, adaptability, problem-solving, and leadership.

(Adapted from Source: Anderson 2017)

These results are similar to those reported by Anderson (2017) who proposes a network-based method for measuring skills. This approach determines not only individual skills but also skill combinations, suggesting that a combination is more valuable than the sum of individual skills. For example, electrical engineering and Chinese translation skills are more valuable together than individually and can command a premium. Similarly, Siepel *et* *al.* (2019) assert that companies can benefit from increased employee performance when skills are combined, rather than when deployed individually.

Furthermore, Dries (2013) observed when you approach Talent Measurement with a social exchange framework, you can examine and match the potential relationship between employers and employees. This significantly shifts the focus from individual perceptions, reducing bias in the selection process, and therefore improving Talent Measurement (Giermindl *et al.* 2022; Dries 2013). Using network analysis tools provides clarity, as skills can be divided into categories based on their relationship with other skills, i.e. a chemical process engineer working in the Oil and Gas Industry, has transferrable skills that can be used in the Pharmaceutical Industry.

Simplicity is key for inexperienced system users as the qualities and skills of individuals differ, however, design elements in standard system measurement are not sufficiently agile to create this simplicity (Lee 2018; Walford-Wright and Scott-Jackson 2018). The impact of variation in cognitive styles on performance in task execution can affect strategic focus, which leads to inaccuracies and errors (Aggarwal and Woolley 2013). These failings can be costly, consequently, to fully capture the benefits of Talent Measurement and skill combinations, the importance of the breadth of knowledge and use of technology, cannot be overlooked.

2.4. Intelligence and Technology

Specific measurement options are not widely examined, however the impact of artificial intelligence (AI) is ubiquitous. AI generates pertinent analytics for improved data-driven decision-making, by automatically identifying patterns in both structured and unstructured data (Giermindl *et al.* 2022). People analytics will revolutionize human decision-making and the nature of work in the future. Rather than relying on intuition, HR professionals are increasingly using predictive techniques such as artificial intelligence (AI) and machine learning (ML) to measure strengths and weaknesses (Thakral *et al.* 2013).

Technology-derived people analytics is unbiased, democratic, and meritocratic, facilitating quicker decision-making (Walford-Wright and Scott-Jackson, 2018). People analytics as a predictive tool is of great value to HR professionals and businesses, as it enables an unbiased template for future hiring. However, there is much room for theoretical development in the field of HR analytics, its application, and the techniques used in analytics (Thakral *et al.* 2023). Similar studies by Giermindl *et al.* (2022) report a lack of empirical research on the outcome of people analytics and suggest limited forms of analytics.

To stay competitive, businesses should understand their current talent and future requirements. These requirements have to be precise, unambiguous, and tallied to add value. Companies can obtain salient information regarding the abilities, knowledge, and characteristics of their employees, by utilizing talent intelligence, including Talent Measurement (Lee 2018). Conversely, Bell (2013) argues that talent intelligence "is not that intelligent" considering that most businesses lack a thorough understanding of their employees' capabilities, and consequently how this lack of knowledge affects the broader talent strategy.

Automation with AI does, however, come with several risks and moral dilemmas. Studies by Pillay and Sivathanu (2020) highlight that security and privacy issues negatively influence the adoption of AI technology. Research has demonstrated that automation lacks critical components, such as a sense of belonging, that negatively impact managerial jobs and morale (Malukani and Paranjape 2023). Automated systems therefore require collaboration between people and the systems, and as human interaction is essential, new technologies should be led by people-centered design principles (Langer König and Busch 2020).

Finally, the human factor is the significant driving force of long-term success, and people, not technology, are responsible for securing organisational excellence and goal accomplishment (Giermindl *et al.* 2022; Walford-Wright and Scott-Jackson 2018). Talent, when observed as a competitive advantage, will require businesses to innovate and improve on selection methods to accurately identify talent. Data analysis choices have a significant impact on the quality and accuracy of outcomes that can be achieved, consequently to avoid misperception in selection, the "measure" must be clear (Lee 2018).

Accordingly, additional research is required to determine who measures, what, and how, to provide clarity.

3. Objective of the Study

The objective of this study is to determine to what extent strategic Talent Measurement impacts talent management strategies in STEM industries.

The following research objectives enable the achievement of the research aim:

1. To identify key predictors outlining critical competencies for Talent Measurement.
2. To determine current measuring methodologies used and the efficiencies of users.
3. To assess the impact of measurement on the effectiveness of Talent Management strategies.

The supposition is that strategic Talent Measurement permits human capital to be accurately measured and evaluated, which can be of significant value to talent management strategies. Consequently, the converse is true, all things being equal.

The study is divided as follows; A hypotheses section below, followed by an Exploratory analysis in Chapter 5.

3.1. Hypothesis One

Marginson (2019) suggests that the Human Capital theory has no value as it failed the test of realism, is biased, and lacks diversity. Tafti *et al.* (2017) disclosed mental and cognitive prejudices as barriers to talent measurement, consequently, a lack of automated performance measures to reduce prejudices can increase biases, thus negatively affecting the value of talent. Research objective 1 above will apply and test the value of Human Capital theory in this context and a different sector, such as STEM industries.

Null Hypothesis: $\mathbf{H_{0:}}$ There is no relationship between automated CV selection and the adoption of performance metrics.

Alternative Hypothesis: $\mathbf{H_a}$**:** There is a positive relationship between automated CV selection and the adoption of performance metrics.

3.2. Hypothesis Two

Considering the theory of Bounded Rationality, HR professionals and Hiring Managers are constrained by knowledge and computational limitations during the process of talent selection (Jordão *et al.* 2020; Tafti *et al.* 2017). The extent to which users have technological knowledge and abilities can dramatically influence the adoption and use of measurement techniques, yet many may not be confident with these advanced techniques. Research objective 2, will attempt to establish the current methods of measurement used, in addition to users' abilities using measurement techniques.

Null Hypothesis: $\mathbf{H_{0:}}$ The less technology-savvy users are, the less likely they are to use advanced techniques when measuring talent.

Alternative Hypothesis: $\mathbf{H_a}$**:** The more technology-savvy users are, the more likely they are to use advanced techniques when measuring talent.

3.3. Hypothesis Three

Testing the theory of Bounded Rationality that HR professionals and Hiring Managers base their decisions on incomplete information as they rely on intuition, and not performance measures, when measuring talent. The use of advanced predictive techniques can reduce reliance on intuition and biases, however, recent studies (Gamba Quilliam 2023) have shown that only 21% of HR professionals are confident with techniques such as predictive analytics. Thakral *et al.* (2013) however suggested HR departments are increasingly using predictive techniques, rather than relying on intuition. Research objective 2 will apply and test these contrasting variables (intuition and predictive analytics) amongst HR professionals and Hiring Managers.

Null Hypothesis: $\mathbf{H_0}$: If you conduct more manual CV screening you are less likely to use predictive techniques.

Alternative Hypothesis: $\mathbf{H_a}$: The less manual CV screening performed, the more likely the use of predictive techniques.

3.4. Hypothesis Four

Siepel *et al.* (2021) highlighted the importance of organisations having diverse knowledge and skills among employees, to enable the creation of "novel combinations" for sustained economic activity. Talent strategies that take into account limited conceptions of talent, negatively impact an organisation's capacity to leverage its entire workforce for a competitive advantage (Gallardo-Gallardo *et al.* 2020; Marginson 2019; Tansley 2011). HR professionals and Hiring Managers manually create skill combinations, AI or predictive analysis is not used in the process, and can therefore affect the full benefit of skill combinations. Research objective 3 will assess the effectiveness of skill combinations and predictive analysis on talent strategies.

Null Hypothesis: $\mathbf{H_0}$: There is no relationship between skill combinations and predictive analysis.

Alternative Hypothesis: $\mathbf{H_a}$: There is a positive relationship between skill combinations and predictive analysis.

4. Methodology

The collection of reliable and legitimate data to support decisions, and answer the research question, served as the primary justification for the methodology.

4.1. Data and Method

Gallardo-Gallardo *et al.* (2020) identified that methodology sections frequently omit information concerning the organisational context, even regarding some basic descriptive information. Context and information are important to accurately measure variable skills. Relevant talent management studies (Malukani and Paranjape 2023; Anlesinya *et al.* 2019; Tafti *et al.* 2017) predominately used qualitative methods and interview techniques to collect data, however, for improved selection, Sackett and Lievens (2008) suggest measuring the same construct using an alternative method.

Given the uncertainty and ambiguity of what is measured, how, and by whom, quantitative research, in contrast, was chosen. Quantitative research "describes, infers, and resolves problems" by using numerical data, and is selected to test or confirm hypotheses, assumptions, and theories, to establish facts (Saunders *et al.* 2019). This method allowed for a larger sample to be surveyed, generating factual and reliable data for observing trends, making predictions, running experiments, and testing hypotheses concerning Talent Measurement (Saunders *et al.* 2019). Conversely, non-numerical and unquantifiable elements such as language, feelings, emotions, and sounds associated with qualitative research, are not appropriate and were not selected.

Adhering to ethical guidelines (SRA 2024), the gathering of numerical data, their summary and the deductions made were prioritized, providing a conclusive, causal research design and thus satisfying the research objectives (Bell, Bryman and Harley 2019; Saunders *et al.* 2019). The reliability of the constructs was assessed by Cronbach's alpha. This study has some limitations, including the small number of participants as the study was limited to HR professionals and Hiring Managers with experience in screening and selecting CVs. However, according to Bell *et al.* (2019), it is unrealistic to base a sample size determination on the intended level of precision.

4.2. Research Philosophy and Instrument

The epistemology research philosophy that was used is a highly structured methodology, to ensure objectivity and reliability (Saunders *et al.* 2019). A positivist philosophical research paradigm was chosen as knowledge can be scientifically verified, consequently, the researcher maintained an impartial position, concentrating on facts (Michell 1997). The deductive approach explains casual relationships between concepts and variables and is useful when observing trends, and fulfilling the goals of the research aim (Saunders *et al.* 2019). A disadvantage however of positivist studies is that due to their descriptive nature, they can lack an understanding of complex issues.

All instruments used in this study are based on established and validated measures previously tested and verified in the relevant literature (Malukani and Paranjape 2023; Kafetzopoulos *et al.* 2022; Pillai and Sivathanu 2020). Quantitative data was obtained through cross-sectional research, as variables can be measured and controlled statistically (Saunders *et al.* 2019). A questionnaire, selected as the most appropriate instrument as per previous studies, was constructed and self-administered online, using Survey Monkey (Kafetzopoulos *et al.* 2022; Pillai and Sivathanu 2020). The survey strategy allowed for the collection of data that can be analyzed quantitatively, using descriptive and inferential statistics.

A pilot study was conducted, online using Survey Monkey, to improve the reliability and validity of the questionnaire. To avoid bias, the pilot study was conducted independently of the main study and no results from the pilot study were included in the final sample or used to test hypotheses (Saunders *et al.* 2019; Dudovskiy 2018). The pilot study identified no potential ethical issues however did improve on instructions, resulting in the content validity of the instrument.

The clarity of the questionnaire presentation can improve the ease with which respondents can complete a questionnaire (Saunders *et al.* 2019). This involved grouping and sequencing questions into an appropriate order, numbering questions, and inserting respondent instructions, for ease of completion. The questionnaire consisted of four sections focusing on Technology, Strategy, Skill Combinations, and Demographics (Appendix 1). The ideal survey length was 5-10 minutes, balancing the audience profile and survey goals with the total number of questions. Survey Monkey (2024) reported that respondents took an average of 6 minutes and 22 seconds to complete the full survey, which satisfies the time to complete objective.

The questionnaire consisted of 22 closed-ended survey items, predetermined approaches, and numeric data observations, enabling respondents to answer conveniently on a five-point Likert scale, recording responses ranging from (1) Always to (5) Never (Saunders *et al.* 2019). Similar studies by Malukani and Paranjape (2023) used the same scale and were relevant to this study. The data was collected over a period of four weeks in June 2024, with a hundred percent completion rate. Finally, 72 fully completed questionnaires were available for the analysis.

4.3. Sampling

Primary data was collected from a sampling selection of HR professionals and Hiring Managers working in enterprises in STEM Industries. The target respondents were adult males and females, with experience in screening and selecting CVs during a candidate application process. The representative sample was collected through social websites, such as LinkedIn, based on informed consent, adhering to ethical guidelines and GDPR legislation. Non-probability sampling allowed for convenience sampling of individuals, who met the above criteria, and voluntarily took part in the study, reducing the risk of sampling errors and bias (Saunders *et al.* 2019).

4.4. Data Analysis

Questionnaire data was statistically analyzed using Statistical Package for the Social Sciences (SPSS) software, applying regression and correlation methods (Field 2018). Similar to previous studies, this statistical tool was selected as the most appropriate to test the hypotheses and related relationships (Kafetzopoulos *et al.* 2022; Saunders *et al.* 2019). A preliminary structure of variables was derived by screening, cleaning, and coding the data matrix, ready for analysis. Variables were reduced into a manageable set of scales, using numerical codes to facilitate analyses, with each variable number corresponding to the question number in the questionnaire (Kafetzopoulos *et al.* 2022).

The data matrix and frequencies for each variable were inspected to check for errors in the data file (Pallant 2016). Internal consistency and reliability were tested by calculating Cronbach's Alpha and critical analysis involved identifying common patterns in the responses, through inferential statistics for statistical validity (Saunders *et al.* 2019). The same approach has been long established in the literature for testing similar constructs (Kafetzopoulos *et al.* 2022). Table 2 provides details of the type of data analysis that was performed, in accordance with the research objectives and associated hypotheses.

Table 2: Specific Data Analysis.

Type of Analysis	Research Objective	Hypothesis
Bivariate Analysis (Correlation)	Research objective 1 applied and tested the value of Human Capital theory in a different sector, such as STEM industries.	Hypothesis 1: There is no relationship between automated CV selection and the adoption of performance metrics.
Bivariate Analysis (Correlation)	Research objective 2 established the current methods of measurement used, in addition to users' abilities using measurement techniques.	Hypothesis 2: The less technology-savvy users are, the less likely they are to use advanced techniques when measuring talent.
Linear Regression Analysis (Multiple)	Research objective 2 applied and tested contrasting variables (intuition and predictive analytics) amongst HR professionals.	Hypothesis 3: If you conduct more manual CV screening you are less likely to use predictive techniques.

Bivariate Analysis (Correlation)	Research objective 3 assessed the effectiveness of skill combinations and predictive analysis on talent strategies.	Hypothesis 4: There is no relationship between skill combinations and predictive analysis.

(Source: Researcher self-compilation from primary data analysis)

Descriptive statistics were analyzed to describe the characteristics of the data set and finally, an exploratory analysis was conducted to benefit future research. The results are presented in Chapter 5.

4.5. Ethical Risk

Ethical risks were taken into consideration and followed throughout the analysis process. Ethical considerations in research are a set of principles that guide the research designs and practices (Saunders *et al.* 2019). These principles ensure that participation in studies is voluntary, informed, and safe for research subjects. The following ethical risks were considered and proposed preventions are listed.

a. Voluntary participation - Participants were free to opt in or out of the study at any point in time.
b. Informed consent - Participants knew the purpose, benefits, risks, and funding behind the study before they agreed or declined to join.
c. Anonymity - Personally identifiable data were not collected.
d. Confidentiality - Anonymized personally identifiable data so that it cannot be linked to other data by someone else.
e. Potential for harm - Physical, social, psychological, and all other types of harm were kept to an absolute minimum.
f. Results communication - Ensured work is free of plagiarism or research misconduct, and accurately represented results.

5. Results

Consistent with the positivist philosophical research paradigm, this section presents and discusses the Hypotheses analysis and Salient findings, derived from objective observations and measurements. Following this, the inclusion of an Exploratory Analysis provides crucial information for future research, mainly to examine the information and potentially develop novel hypotheses that might motivate additional research in Talent Measurement.

5.1. Descriptive Statistics

Descriptive statistics for the demographic variables of the sample are included in Table 3. This shows that 57% of the respondents were male and 39% were female with the remainder declining to identify. The largest categories represented were 25% Recruiters, 21% Talent Acquisition Managers, and 18% Talent Acquisition Specialists. 29% of the respondents have 5-10 years' experience reviewing CVs, 28% have 10-15 years' experience, with 21% of the respondents having in excess of 20 years' experience.

Table 3: Demographic characteristics (N=72).

Demographic	Characteristics	No. of Respondents	Percentage
Respondent Gender	Female	28	39
	Male	41	57
	Other	3	4
Experience reviewing CVs	0-5 Years	7	10
	5-10 Years	21	29
	10-15 Years	20	28
	15-20 Years	9	12
	20+ Years	15	21
Respondent Job Title	Director	15	21
	Hiring (Line) Manager	4	5
	HR Business Partner	5	7
	Recruiter	18	25
	Talent Sourcer	2	3
	Talent Acquisition Manager	15	21
	Talent Acquisition Specialist	13	18

(Source: Researcher self-compilation from primary data analysis)

Location and industry information are presented in Table 4. Based on the data, 65% of the participants are based in Ireland, followed by 10% in the United Kingdom, and 8% in the United States. Germany accounted for 4% of responses, followed by Canada and Poland at 3% each, with 1% of the sample each from Belgium, France, Hungary, India, and Singapore. 50% of the respondents worked in the Pharmaceutical, Biotechnology, and Life Sciences Industries, with 22% of the respondents categorizing their sector as Other, which included the Recruitment and Construction sectors.

Table 4: Location and industry demographics (*N*=72).

Demographic	Characteristics	No. of Respondents	Percentage
Country of Residence	Belgium	1	1
	Canada	2	3
	France	1	1
	Germany	3	4
	Hungary	1	1
	India	1	1
	Ireland	47	65
	Poland	2	3
	Singapore	1	1

	United Kingdom	7	10
	United States	6	8
Work Sector	Automobiles and Components	1	1.4
	Commercial and Professional Services	5	7
	Energy	1	1.4
	Food and Staples Retailing	1	1.4
	Insurance	1	1.4
	Other	16	22
	Pharmaceutical, Biotechnology and Life Sciences	36	50
	Retailing	1	1.4
	Semiconductors and Semiconductor Equipment	2	3
	Software and Services	5	7
	Technology Hardware and Equipment	1	1
	Utilities	2	3

(Source: Researcher self-compilation from primary data analysis)

5.2. Inferential Statistics

5.2.1. Hypothesis 1: To evaluate the strength of the relationship between automated CV selection and the adoption of performance metrics.

A correlation coefficient calculates, tests, and interprets the relationship between two variables, measured using an ordinal scale (Lind, Marchal and Wathen 2011). Hypothesis 1 was analyzed using Spearman's nonparametric correlation test, to evaluate the strength of the relationship between, automated CV selection (represented by Q3) and the adoption of performance metrics (represented by Q8) amongst users. Table 5 summarizes the output of the correlation test.

Table 5: Correlation between automated CV selection and adoption of metrics.

Correlations

			Q3TechnologyNum
Spearman's rho	Q8StrategyNum	Correlation Coefficient	0.187
		Sig. (2-tailed)	0.116
		N	72

(Source: IBM SPSS 2021)

There was a weak, positive correlation between automatic CV selection and the adoption of performance metrics, which was not statistically significant (rs(72) = 0.187, p = 0.116). Consequently, as the p-value is not significant, the results are interpreted as not significant thus, failing to reject the null hypothesis that there is no relationship between automatic CV selection and the adoption of performance metrics. The results indicate that there is no correlation between users who participate in automated CV selection and their adoption of performance metrics when measuring talent.

5.2.2. Hypothesis 2: To determine the strength of the relationship between users' abilities using technology for measurement techniques and its influence on strategic measurement.

Hypothesis 2 was examined using Spearman's nonparametric correlation test to determine the strength of the relationship between, users' abilities using technology for measurement techniques (represented by the average of Q4, Q5, and Q6), and its influence on strategic measurement (represented by Q8). Table 6 provides a summary of the test results.

Table 6: Correlation between users' abilities and influence on measurement.

Correlations

			Q8StrategyNum
Spearman's rho	AverageQ4Q5Q6	Correlation Coefficient	0.317*
		Sig. (2-tailed)	0.007
		N	72
** Correlation is significant at the 0.01 level (2-tailed).			

(Source: IBM SPSS 2021)

There was a medium, positive correlation between users' abilities to use technology for measurement techniques and strategic measurement, which was statistically significant ($r_s(72) = 0.317$, $p = 0.007$). Given that the p-value is significant, the results are interpreted as refuting the null hypothesis. Therefore the results confirm a correlation that the more technology-savvy HR professionals and Hiring Managers are, the increased likelihood that they will make use of advanced techniques when measuring talent.

5.2.3. Hypothesis 3: To predict the relationship between users who rely on intuition and manual CV screening and those using AI and predictive techniques, on the strategic outcome.

Hypothesis 3 was thoroughly examined using multiple regression analysis, as it allowed for the analysis of a relationship between several independent variables (IV), and, a dependent variable (DV) and, it also determines how changes in the IV are associated with changes in the DV (Lind *et al.* 2011). The test was performed to predict the relationship between users who rely on intuition and manual CV screening (IV represented by Q2), and those using AI and predictive techniques (IV represented by Q5 & Q4), on the strategic outcome (DV represented by Q7 & Q8). Table 7 provides the data required to perform this multiple-regression analysis.

Table 7: Analysis data required for multiple-regression test.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	0.208[a]	0.043	0.016	0.933

a. Predictors: (Constant), AverageQ5Q4, Q2TechnologyNum

(Source: IBM SPSS 2021)

Confidence levels were set at 95 percent. The coefficient of determination R square, indicates the percentage of the total variance, explained by the independent variable. In Table 6, it shows it to be 43%, implying that there is no significant influence on the strategic outcome. The ANOVA test results are summarized in Table 8.

Table 8: ANOVA - Multiple regression analysis on strategic outcome.

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	2.729	2	1.364	1.567	0.216[b]
	Residual	60.091	69	0.871		
	Total	62.819	71			

a. Dependent Variable: AverageQ7Q8

b. Predictors: (Constant), AverageQ5Q4, Q2TechnologyNum

(Source: IBM SPSS 2021)

There was a weak, positive correlation in the strategic outcome between users who rely on intuition and manual CV screening, and those using AI and predictive techniques, which was not statistically significant, $F(2,95) = 1.567$, p.216. Consequently, as the p-value is not significant, the results are interpreted as not significant thus, failing to reject the null hypothesis. Therefore the results indicate that the more manual CV screening is performed, the less likely HR professionals and Hiring Managers will utilize predictive techniques.

Multiple linear regression was used to predict an outcome variable (y) based on multiple distinct predictor variables (x), specifically to test if users who rely on intuition and manual CV screening (IV represented by Q2) and using AI and predictive techniques (IV represented by Q5 & Q4) significantly predicted strategic outcomes. The fitted regression model was: $Y= b_0+b_1x_1+b_2x_2$ where: b_0 is a constant, b_1, b_2 represents the regression coefficient, x is the value of the independent variable, and $\hat{y}$ is the predicted value of the dependent variable. Therefore, Y= 1.801 + -0.008 (Q2TechnologyNum) + 0.217 (Q5 & Q4 Technology). Table 9 below presents a summary of the coefficient results.

Table 9: Coefficients of Multiple Regression.

Coefficients[a]

Model		Unstandardized B	Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	95% Confidence Interval for B Lower Bound	Upper Bound
1	(Constant)	1.801	0.588		3.066	0.003	0.629	2.974
	Q2TechnologyNum	-0.008	0.103	-0.010	-0.080	0.936	-0.213	0.196
	AverageQ5Q4	0.217	0.128	0.206	1.702	0.093	-0.037	0.472

a. Dependent Variable: AverageQ7Q8

(Source: IBM SPSS 2021)

The results indicate that Coefficient B_1 is -0.008, which is not significant and likewise, the P-value is 0.936. Consequently, as the p-value is not significant, the results are interpreted as not significant thus failing to reject the null hypothesis. Therefore the results indicate no relationship between manual CV screening on strategic outcomes.

What is striking in Table 9, however, is the trending effect for Coefficient B_2 at 0.217, with a P-value of 0.093, which can be interpreted as predicting some effect. As the p-value is close to significant, the results can be interpreted as practically refuting the null hypothesis and accepting the alternative hypothesis. Consequently, the findings support the theory that users' interest in strategic outcomes seems to be influenced by their use of predictive techniques and AI. Further research can develop this noteworthy trending discovery.

5.2.4. Hypothesis 4: To assess the strength of the relationship between skill combinations and predictive analysis.

Finally, hypothesis 4 was completed using a nonparametric correlation test to assess the strength of the relationship between skill combinations (represented by Q11) and predictive analysis (represented by the average of Q4 & Q5). Table 10 presents the output of the correlation test.

Table 10: Correlation between skill combinations and predictive analysis.

Correlations

			Q11SkillCombNum
Spearman's rho	AverageQ5Q4	Correlation Coefficient	-0.169
		Sig. (2-tailed)	0.156
		N	72

(Source: IBM SPSS 2021)

There was a weak, negative correlation between skill combinations and predictive analysis, which was not statistically significant ($r_s(72) = -0.169$, $p = 0.156$). Consequently, as the p-value is not significant, the results are interpreted as not significant thus failing to reject the null hypothesis. Therefore the results confirm there is no relationship between skill combinations and predictive analysis which concludes the analysis.

5.3. Salient Findings

5.3.1. Current Measurement Methodologies used and the efficiencies of users

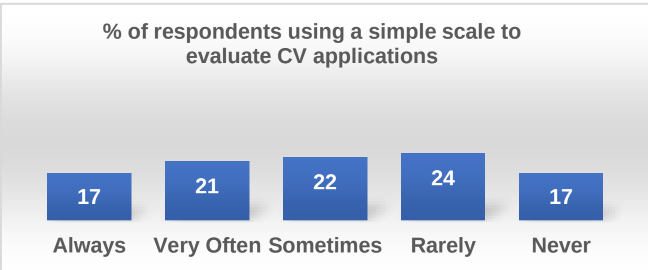
The purpose of research objective 2 was to determine the current measuring methodologies used and, the efficiencies of users using advanced techniques for talent measurement.

The objective was satisfied by the outcomes of the multiple regression analysis, which observed no significant influence on the strategic outcome between users who rely on intuition and manual CV screening, and those using AI and predictive techniques. What is intriguing from the study, is the salient finding that supports a theory that users' interest in strategic outcomes seems to be impacted by their use of predictive techniques and AI. From this, it is suggested to dispute Thakral *et al.'s* (2013) findings that contend that HR departments are increasingly using predictive techniques, rather than depending on intuition. The results suggest that the majority of users are not using predictive techniques.

The results confirm that the more manual CV screening is performed, the less likely HR professionals and Hiring Managers will utilize predictive techniques. The results from the analysis indicate no relationship between manual CV screening on strategic outcomes, which questions why 58% of respondents carry out manual CV screening. 4% reported that CVs are always automatically screened. The balance of probability for accurate measurement seems to be completely ignored, or, not considered to be in any way connected to the decline of strategic outcomes, i.e. skill shortages.

What stands out in Table 11 below is that 17% of the respondents who screened CVs manually, 'Always' used a simple scale to evaluate each applicant's capability, as opposed to relying on intuition and bias. 17% have never used such a scale and 24% rarely used it. The results substantiate the concept that bias in selection is a barrier to talent measurement. Are these rejections of techniques and basic actions for accurate measurement, perhaps contributing to the perceived skill shortages?

Table 11: Respondents who used a simple scale for evaluation.



(Source: Researcher self-compilation from primary data analysis)

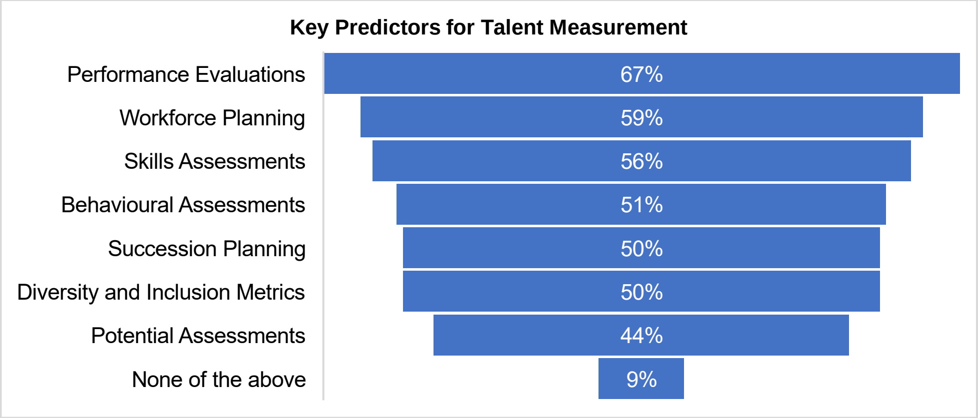
5.4. Exploratory Analysis

The inclusion of the following exploratory analysis is provided to encourage additional research, specifically to explore the data and potentially formulate new hypotheses that could lead to further data collection and experiments. Ideally, future research questions could include specific measurements, influenced by predictive techniques, such as ML and AI, on the effectiveness of skill combinations and strategic performance.

5.4.1. Key Predictors Outlining Critical Competencies

The purpose of research objective 1 was to identify key predictors outlining critical competencies for Talent Measurement. The results obtained from the study satisfy the objective and are incorporated in Table 12.

Table 12: Key Predictors for Talent Measurement.



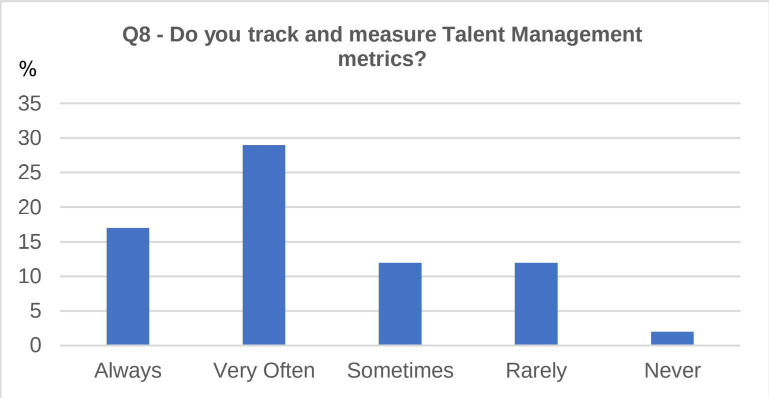
(Source: Researcher self-compilation from primary data analysis)

The results revealed that 67% of respondents carried out Performance Evaluations to measure talent, which is a regular review of an employee's job performance and overall contribution to a company. 59% make use of Workforce Planning to analyze the current workforce and determine future needs. Skills Assessments, that is tests designed to assess whether individuals have the necessary skills to perform various and essential aspects of a job, were employed by 56% of the respondents. 9% of respondents do not use any metrics to be accountable for measuring talent.

51% utilized Behavioural Assessments, which are the systematic study and evaluation of an individual's behavior, using a wide variety of techniques, including direct observation (body language), interviews, and self-monitoring. Succession Planning, which is the process of selecting and developing key talent to ensure the continuity of critical roles, was used by 50% of respondents. Diversity and Inclusion Metrics, which are quantifiable measures to track diversity, equity, and inclusion, were utilized by 50% of the respondents. 44% deployed Potential Assessments to identify persons with high potential, that can be developed and nurtured to reach their full potential.

The results obtained by performing a correlation coefficient test implied no correlation between automated CV selection, which can reduce bias, and users adopting performance metrics, that can address diversity and accountability. The results corroborate the findings of Marginson (2019) who found bias, and a lack of diversity, caused the demise of the Human Capital theory, and consequently the decline in its value. In this survey, the respondents were asked if they track and measure Talent Management metrics (Table 13). Less than a quarter of the respondents indicated that they 'Always' used key predictors when measuring talent.

Table 13: Q8 - Do you track and measure Talent Management metrics?



(Source: Researcher self-compilation from primary data analysis)

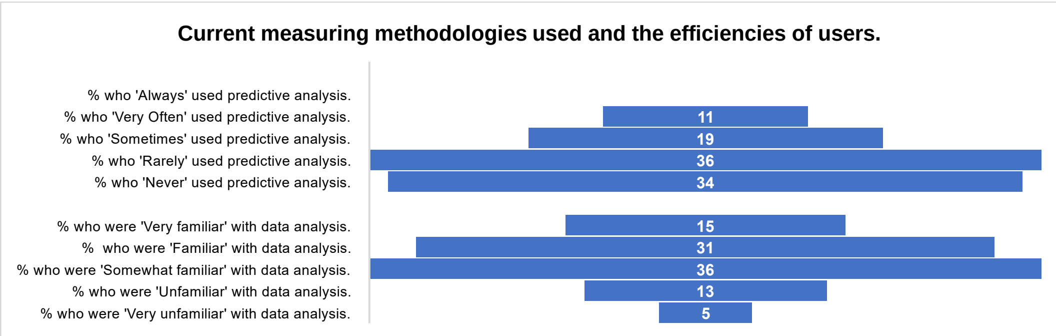
Contrastingly, 3% have never used a key predictor to measure critical skills that were essential for performing job-specific tasks. As a result, the lack of accountability for accurate measurement demonstrates the deterioration of the value of the Human Capital theory. This decline in capital value has an impact on the value of talent in current work environments, and the risk is that it may be worth less than it was before, particularly when measured by inexperienced users, who do not track and measure talent metrics for visibility and accountability. This is borne out with the example of a qualified candidate who applies for a role and receives a rejection letter stating that they are 'over qualified' for the role and are not being considered.

5.4.2. Current Measurement Methodologies used and the efficiencies of users

The aim of research objective 2 was to determine the current measuring methodologies used, and the efficiencies of users. The outcomes of a correlation test, which was essential to achieving the goal, confirmed a positive correlation between users' abilities to use technology for measurement techniques and strategic measurement. This implies that the more technology-savvy HR users are, the more likely they are to use advanced techniques when measuring talent. Advanced techniques and predictive analysis can significantly reduce intuition and biases in the talent selection process.

When surveyed, 1% of respondents confirmed they 'Always' made use of AI and ML when measuring skills, with 6% of the respondents using AI and ML 'Very Often'. 45% of respondents indicated that they have never made use of AI or ML when measuring skills. The use of AI and ML in talent measurement can reduce the risk of inaccurate selection as it is unbiased and objective. Current measuring methodologies used and the efficiencies of users which was the aim of the objective are presented in Table 14, and the results satisfied the second objective. The results attest to the fact that not a single participant 'Always' used predictive analysis when measuring skills.

Table 14: Current measuring methodologies used and the efficiencies of users.



(Source: Researcher self-compilation from primary data analysis)

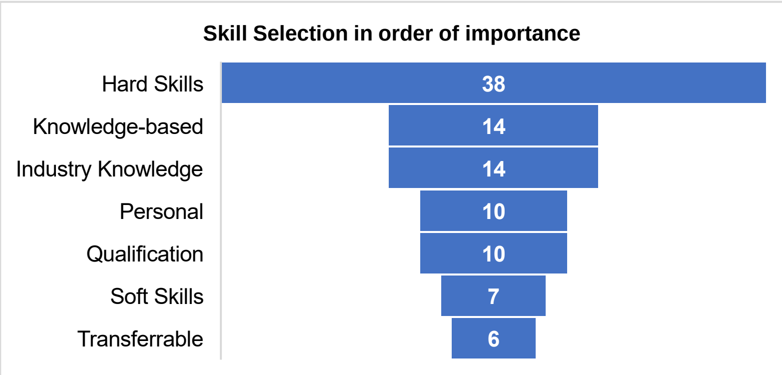
The results corroborate the theory of Bounded Rationality that users are constrained by knowledge and computational limitations (Jordão *et al.* 2020; Tafti *et al.* 2017). Given the technological advances and successes achieved through the use of predictive analysis in several other industries, i.e. Airbnb, Amazon, etc. this result highlights the acute necessity for disruption in the Talent Management industry. 11% stated they use predictive analysis 'Very Often' when measuring skills. 36% of respondents confirmed that they 'Rarely' used predictive analysis, consequently, these results substantiate recent studies which indicated only 21% of HR professionals are confident with the use of advanced techniques, such as predictive analysis (Gamba Quilliam 2023).

5.4.3. Effectiveness of Measurement on Talent Management Strategies

The purpose of research objective 3 was to assess the impact of measurement on the effectiveness of Talent Management strategies. The results obtained by performing a correlation test, central to the objective, confirmed that there is no correlation between skill combinations and predictive analysis. Research by Siepel *et al.* (2021) suggests that skill combinations benefit innovation and growth in companies. Nevertheless, talent and its value could be misunderstood and undervalued by inexperienced users, especially when predictive analysis is not considered in assessing skill combinations, which could be detrimental to talent management strategies.

Not central to the objective, but to understand the value of skills, respondents were asked to rank skills in order of importance. Skill Selection is shown in Table 15 ranked by significance.

Table 15: Skill Selection in order of importance.



(Source: Researcher self-compilation from primary data analysis)

The results indicate that 'Hard Skills' are considered the number one skill to deem a candidate qualified for a position and move the application forward. Hard skills are measurable skills acquired through training, education, or practice and required for a particular job.

When surveyed, 40% of respondents confirmed that they 'Always' consider skill combinations and 41% confirmed that they 'Very Often' consider skill combinations. 3% 'Rarely' consider it and 17% attest they 'Sometimes' consider skill combinations. The results indicate that 40% of respondents 'Always' combine 'Industry Knowledge' and 'Hard Skills', with 35% 'Always' combining 'Knowledge-based' and 'Industry Knowledge'. 35% indicated they 'Always' combine 'Soft' and 'Hard Skills' when assessing talent. These findings show that even with over a decade of CV selection experience, less than half of users make use of skill combinations when assessing talent.

The results also identify that 35% of respondents ‘Sometimes’ keep to the list of skills that are strictly necessary for the job, i.e. job description. 18% will ‘Always’ do so and 10% ‘Rarely’ stick to the job description. Considering that job descriptions explicitly identify the skills required to perform a role, and given that 18% of respondents ‘Always’ adhere to the job description in CV selection, the results indicate that most CV selection is based on inaccurate information, performed manually and prone to biases, which has an adverse effect on talent management strategies.

Finally, the following key findings require comprehensive discussions, to fully determine the extent to which strategic Talent Measurement impacts talent management strategies in STEM industries;

i. There is no equivalence between manual CV screening on strategic outcomes. This is a significant finding. Users' interest in strategic outcomes appears to be influenced by their use of predictive techniques and AI.
ii. The more technology-savvy HR professionals and Hiring Managers are, the increased likelihood that they will make use of advanced techniques when measuring talent.
iii. The more manual CV screening is performed, the less likely HR professionals and Hiring Managers will utilize predictive techniques, which questions why 58% of respondents carry out manual CV screening.
iv. There is no relationship between skill combinations and predictive analysis. CV selection and in particular skill combination continues to be predominately performed manually, leading to a susceptibility to intuition and bias, rather than objective and predictive analysis.
v. Metrics are essential for accurate measurement, yet there is no correlation between users who participate in automated CV selection and their adoption of performance metrics when measuring talent.
vi. The deterioration and decline of the Human Capital theory and its value in accurate measurement of talent in current work environments.

6. Discussion

The study was conducted to determine to what extent strategic talent measurement impacts talent management strategies in STEM industries. In particular to determine who measures what, and how for effective talent intelligence, based on strategic measurement, to enable businesses to utilize their entire workforce for competitive advantage.

6.1. Key predictors outlining critical competencies for Talent Measurement.

According to the study findings, the deterioration of the Human Capital theory and its subsequent decline in value for accurate measurement of capital (human talent), was significant in the effectiveness of talent management strategies. Zhang *et al.* (2023) have also questioned why there has been a lack of agreement regarding the characteristics and assessment of the Human Capital theory construct. This study's findings suggest education is not a priority when selecting skills, which is an important finding in contrast with the existing literature by Zhang *et al.* (2023) which suggests that the Human Capital theory defines human capital in terms of education and experience.

‘The present study highlights the acute necessity for disruption in the Talent Management industry’.

From the results of the research it is observed that Hard Skills and Knowledge are used to benchmark talent, however, the use of talent metrics was not apparent, despite being essential for accurate talent measurement. It is important to bear in mind the possible bias in these responses. This study revealed that even if CVs are screened automatically it does not follow that HR users will adopt performance metrics when measuring talent.

This is an important element to consider when planning talent management strategies and is particularly noteworthy for businesses to be informed, and to incorporate performance metrics in automated applicant tracking systems. Despite the war on talent, companies may have unknowingly declined suitably qualified candidates, due to inexperienced HR professionals and Hiring Manager's inability to overcome bias and utilize performance measures to accurately measure talent.

6.2. Current measuring methodologies used and the efficiencies of users.

The study discovered that performance evaluations are widely used as a key predictor for talent measurement, however not a single participant from the study always uses predictive analysis when measuring skills, suggesting current measuring methodologies are based on “gut”, influenced by bias and intuition and not facts. These results are similar to those reported by (Walford-Wright and Scott-Jackson 2018) who found that HR users often rely on instinct in the absence of technology, which can lead to costly errors in talent measurement.

Based on the results of this study, there was no relationship between manual CV screening on strategic outcomes, quite the contrary, the increased manual CV screening is performed the less likely HR users will utilize predictive techniques. The findings of the study are similar to those by (Jordão *et al.* 2020) who reported the effect of bounded rationality and bias on decision-making, suggesting that overconfidence in user ability is a prominent bias observed at the individual, group, and organisational levels.

When the action of inaccurate CV screening has no impact on the strategic outcome, the user may experience false confidence in the actions they have taken for talent measurement. This finding has a significant effect on companies that rely on HR users who manually review CV applications. As similarly reported by Tafti *et al.* (2017) bias in the selection process hinders talent measurement and should be accounted for in the talent strategy.

The evidence from this study suggests that users' interest in strategic outcomes appears to be influenced by their use of predictive techniques and AI, which was a significant finding.

'The more technology-savvy HR users are, the more likely they are to use advanced techniques when measuring talent'.

Moreover, users are more likely to employ sophisticated assessment methods if they are more technology-savvy. The use of technology is inevitable, and an important step forward is for HR users to become knowledgeable and capable users of AI and ML to collectively validate measures for talent assessment. In their timely study of HR analytics, Thakral *et al.* (2023) concluded that HR departments are increasingly using predictive techniques rather than relying on intuition, however, this study discovered that is not the case. The reliance on intuition and manual selection is a likely explanation for skill shortages and a direct result of inaccurate measurement.

According to the study findings, HR users make judgments about talent without the use of facts, for example, users do not refer to the job description when reviewing CV applications, despite recognition by previous authors (Lee 2018) that the role may have a "profound influence" on talent measurement. This study supports the findings by (Jordão *et al.* 2020; Lee 2018) that talent measurement has not been extensively discussed and has potential for improvement. This concern is particularly critical given the perceived skill shortages that employers report and the emphasis on proficient users in the measurement of talent for sustained advantage. The evidence suggests that whomever measures what and how, is likely to contribute to the effectiveness or ineffectiveness of talent management strategies.

6.3. The impact of measurement on the effectiveness of Talent Management strategies.

According to the study findings, there is no relationship between skill combinations and predictive analysis, with the impact on the effectiveness of measurement being significant. This finding has some implications. Firstly, when skill combinations are performed manually by inexperienced users, not only is there a need to account for bias, concurrently but distinctly, there is also a need to account for mismatches in skill combinations within the talent management strategy. Second, the ability of an organisation to use its entire workforce to gain a competitive advantage is severely impacted by talent strategies that take into consideration narrow definitions of talent (Gallardo-Gallardo *et al.* 2020; Marginson 2019; Tansley 2011).

These results are similar to those reported by (Stephany and Teutloff 2024; Siepel *et al.* 2021) who propose when a skill is frequently combined with a variety of other useful skills, it is more likely to be valuable. Poor strategy formulation can impact the outcomes of talent measurement, consequently to avail of the benefits of skill combinations, talent measurement should be included and aligned to the talent strategy, in line with the overall business strategy. Lessons can be learned from Kodak's demise and how it implemented one of the world's worst business strategies, focusing on short-term profit goals rather than long-term viability, which ultimately led to its demise.

It is challenging to quantify talent as it is essentially an abstract concept, therefore the use of technology has proved valuable to accommodate these challenges. Talent has value, but unless organisations apply a measure to its value it has no impact and is perhaps indicative of the current perceived "skill shortages".

7. Conclusion

This paper determined to what extent strategic Talent Measurement impacts talent management strategies in STEM industries. Who measures what, and how, has a significant influence on the strategic outcome of talent management, consequently at the point where people and systems intersect in task execution, the who, what, and how should be clearly defined and quantified. As with any successful strategy execution, it requires users to provide leadership, communication, alignment, implementation, measurement, agility, and accountability.

The theory of Bounded Rationality has presented the case that HR professionals go through an extremely convoluted process to fully understand the talent landscape, and as this process is beyond most users' capabilities decisions are based on incomplete information, and prejudiced by bias, which has significantly increased the risk of inaccurate selection. The results indicated that the majority of users are not using predictive techniques, which the Author believes partly explains the perceived skill shortages that employers are reporting. Who measures what, and how, should be at the forefront of every HR professional, particularly given the overwhelming evidence for bias in the manual selection process.

Intuition and bias in the talent selection process can be greatly minimized by using advanced techniques and predictive analysis. The study discovered that the more technology-savvy HR users are, the more likely they are to use advanced techniques when measuring talent. This capability is beyond most current HR users' knowledge, consequently, HR professionals and Hiring Managers must consider upskilling to make use of these methodologies to ensure sustainable measurement in the future. What is evident is that the talent management industry requires significant change, as observed by the industry's lack of fundamental AI and ML knowledge and expertise. The risk of failing to do so can be detrimental to HR professionals and organisations across all sectors.

The study's findings point to the demise of the Human Capital theory and its applicability in effectively assessing talent in current workplaces and highlights the necessity for disruption in the Talent Management industry. Bias in selection is a barrier to talent measurement, accordingly accurate measurement performed by proficient users, should be linked to strategic outcomes, in an attempt to account for biases and alleviate skill shortages. The study has revealed that most CV selection is biased and based on inaccurate information which impacts the value of talent management strategies. Experienced HR users and Hiring Managers are neglecting to recognize the value of talent, as evident from the results that fewer than half of users employed skill combinations to evaluate talent.

The ability to attract, select, and retain talent, remains an issue for business. The value of human capital will continue to be challenged due to technological advances, and the more organisations can precisely quantify and assess the value of human capital through the use of strategic talent measurement, acknowledging barriers and reducing them, the greater the benefit to the overall talent management strategy. Consequently, the opposite is true, all things being equal.

Context and information are important to accurately measure complementary skills. The significant disruption question of a billion-dollar market is, given the awareness of this research on the importance and risk of accurate selection and, information about who measures what and how, what will change for the candidate in the future? Perhaps now is the time for Agency theory to disrupt current Human Capital theoretical practices, for self-interest to prevail and to cede control to the candidate for the measurement of their skills.

Interests between employees and employers are dichotomous, consequently, who measures what and how is the pinnacle for effective strategic measurement.

7.1. Theoretical Implications

This study adds to the field of Strategic Measurement by showing a link between manual selection and strategic measurement. The more technology savvy HR professionals are the increased likelihood they will use predictive techniques when measuring talent. Consequently, this research can assist HR policies in encouraging investments in HR users' analytical skills as a means to expedite knowledge and growth. The researcher would anticipate that the significant finding of this research regarding users' interest in strategic outcomes that appears to be influenced by their use of predictive techniques and AI, will provide the basis for future research into skill combination and strategic performance.

7.2. Managerial Implications

There are several managerial implications. First, HR professionals can use talent metrics to assess the efficiency of HR users and talent strategies, in addition to observing how well they compare to competitors and identifying gaps and opportunities for improvement. This research also assists businesses to consider ways to improve the selection of candidates, reducing bias, and benefiting from novel skill combinations thus enhancing the value of the candidate talent pool.

The research highlights a cautionary message for the need in the Society of Human Resource Management (SHRM) training modules to provide members with opportunities to enhance technological skills, in particular AI and ML, to ensure HR professionals can continue to add value through automated tasks and technological advances.

7.3. Limitations and directions for future research

Despite contributing to the knowledge of strategic measurement in STEM industries, this study has several limitations, and additional research is warranted.

First, the present study findings are based on a small sample of HR professionals in STEM industries. A small sample influences statistical testing as it may not be able to identify significant relationships within the data set. The inclusion of HR professionals from other industries on a global scale is needed to test the theoretical framework formulated and to generalize the results.

Second, skill combinations were examined in this paper, but no cost or value to the skill has been considered, which may affect the adoption of skill combinations, and could be explored in further detail.

In conclusion, studies could be conducted to analyze how skill measurement and combinations work in practice, and how well, to supplement the empirical research for the development of policies and frameworks to educate both organisations and talent on the significance and value of strategic talent measurement.

Appendices

Appendix 1: Instrument: The Questionnaire was constructed and self-administered in June 2024 online on Survey Monkey.

INSTRUMENT: THE QUESTIONNAIRE CONSTRUCTED AND SELF-ADMINISTERED IN JUNE 2024 ON SURVEY MONKEY

Survey Title:

To what extent does strategic talent measurement impact talent management strategies in STEM industries.

Page Title:

This survey is part of my thesis for the completion of a Master's degree in International Business due in August 2024. I would be deeply grateful for your assistance.

This survey aims to understand to what extent strategic talent measurement impacts talent management strategies in STEM industries.

Talent measurement is the process of collecting and utilizing data regarding employees. This plays a role in talent management procedures by providing objective data regarding employees. Given the cost and scarcity of talent, accurate measurement of employee skills can provide significant insight for business.

This is an anonymous survey and is intended to collect information that cannot be traced back to the respondent's identity or IP address, and will only be used for this research towards completion of a Master's Degree.

This survey is suitable for all HR professionals and Hiring Managers who screen and select CVs/Resumes during the candidate application process.
Please read the question carefully and select the most suitable response. If you are unable to answer, please select "Other" and if you could leave a comment where applicable. This survey is short and can be completed in less than 10 minutes.

Thank you for your help and participation. If you would like to see the result of this survey, please email me at x22129685@student.ncirl.ie and I would be happy to forward the same after September 2024.

Q1: Data Consent

If you would be willing to help with this research, I would be grateful if you can indicate below:

Answer Choices:

1. I am happy to take part in this survey

2. I do not want to take part in this survey

Q2: Technology

To what extent do you carry out manual CV screening?

Answer Choices:

1. Always
2. Very Often
3. Sometimes
4. Rarely
5. Never

Q3: Technology

To what extent are CVs automatically screened for you?

1. Always
2. Very Often
3. Sometimes
4. Rarely
5. Never

Q4: Technology

Do you make use of artificial intelligence or machine learning tools when measuring skills? *(Tools that leverage advanced algorithms and data analytics to automate tasks such as candidate screening, using AI chatbots/ChatGPT, etc.).*

1. Always
2. Very Often
3. Sometimes
4. Rarely
5. Never

Q5: Technology

Do you make use of predictive analysis when measuring skills? *(Predictive Analysis is the process of using data to forecast future outcomes).*

1. Always
2. Very Often
3. Sometimes
4. Rarely
5. Never

Q6: Technology

How familiar are you with recruitment data analysis? *(The use of statistical and predictive analysis in the hiring, selection, and sourcing stages of the recruiting process is known as recruitment analytics. For example, "Cost per hire: The internal and external costs associated with hiring" can identify which recruitment methods are most effective and which ones are not).*

1. Very unfamiliar
2. Unfamiliar
3. Somewhat familiar
4. Familiar
5. Very familiar

Q7: Strategy

Do you screen CV applications against a pre-defined strategic measure? *(Strategic measures are used to track your progress in achieving your objectives and goals, i.e. Diversity and Inclusion Metrics).*

1. Always
2. Very Often
3. Sometimes
4. Rarely
5. Never

Q8: Strategy

Do you track and measure Talent Management metrics? *(Talent management is putting in place processes to attract, identify, develop, engage, keep, and deploy employees valuable to an organisation. I.e. Attrition rates).*

1. Always
2. Very Often
3. Sometimes
4. Rarely
5. Never

Q9: Strategy

Which of these metrics do you track to measure talent? In no particular order.

1. Behavioural Assessments *(Systematic study and evaluation of an individual's behavior using a wide variety of techniques, including direct observation (body language), interviews, and self-monitoring).*
2. Diversity and Inclusion Metrics *(A quantifiable measure to track diversity, equity, and inclusion at an organisation).*
3. Performance Evaluations *(Regular review of an employee's job performance and overall contribution to a company).*
4. Potential Assessments *(Persons with high potential who can be developed and nurtured to reach their full potential).*
5. Skills Assessments *(Tests that are designed to assess whether individuals have the skills necessary to perform various and essential aspects of a job).*
6. Succession Planning *(The process of selecting and developing key talent to ensure the continuity of critical roles).*
7. Workforce Planning *(Analysing the current workforce and determining future needs).*

10: Skill Combinations

When reviewing a CV, what skills do you consider to deem a candidate qualified for the position and move the application forward? **Rank in order of importance.**

1. Hard Skills *(measurable skills acquired through training, education, and practice required for a particular job).*
2. Knowledge-based *(knowledge of a particular subject matter, process, software application).*
3. Industry Knowledge *(the accumulation of knowledge and awareness of the intricacies of what is happening to specific industries of interest, i.e. Pharmaceuticals).*
4. Personal *(Personal website/page such as LinkedIn etc., Portfolio, Languages, Geographical information).*
5. Qualification *(measurable qualifications through education and training, i.e. Degree level, Certifications, Core competencies, Physical requirements, Achievements, and Accomplishments).*
6. Soft Skills *(Character traits and interpersonal skills).*
7. Transferrable *(soft skills that can be applied across various industries and roles, i.e. Time management, Empathy, Adaptability, Problem-Solving, and Leadership).*

Q11: Skill Combinations

When reviewing a CV, do you consider skill combinations? *For example, a candidate may not have the qualification, but has the industry knowledge and transferrable skills (soft skills that can be applied across various industries and roles, i.e. Time management, Empathy, Adaptability, Problem-Solving, and Leadership).*

1. Always
2. Very Often
3. Sometimes
4. Rarely
5. Never

Q12: Skill Combinations

When reviewing a CV, I keep to the list of skills that are strictly necessary for the job, i.e. the job description.

1. Always
2. Very Often
3. Sometimes
4. Rarely
5. Never

Q13: Skill Combinations

When reviewing a CV, I evaluate each applicant's capability using a simple scale such as,

0 = No capability, 1 = Basic Capability, 2 = Intermediate capability, 3 = Advanced capability.

1. Always
2. Very Often
3. Sometimes
4. Rarely
5. Never

Q14: Skill Combinations

When reviewing a CV, I combine soft and hard skills when screening a candidate.

1. Always
2. Very Often
3. Sometimes
4. Rarely
5. Never

Q15: Skill Combinations

When reviewing a CV, I combine industry knowledge and hard skills when screening a candidate.

1. Always
2. Very Often
3. Sometimes
4. Rarely
5. Never

Q16: Skill Combinations

When reviewing a CV, I combine knowledge-based and industry knowledge when screening a candidate.

1. Always
2. Very Often
3. Sometimes
4. Rarely
5. Never

Q17: Demographics

What best describes your current job title?

1. Sourcer
2. Recruiter
3. HR Business Partner
4. Talent Acquisition Specialist
5. Supervisor
6. Talent Acquisition Manager
7. Hiring Manager (Line or Department Manager)
8. Director

Q18: Demographics

How many years of experience do you have in reviewing CV applications?

1. 0-5 Years
2. 5-10 Years
3. 10-15 Years
4. 15-20 Years
5. 20+ Years

Q19: Demographics

In what age category do you fit? *(Determining the respondents' age ranges will allow for analysing similarities and differences between differing age groups. Please do not be shy!).*

1. Under 18
2. 18-24
3. 25-34
4. 35-44
5. 45-54
6. 55-64
7. 65+

Q20: Demographics

What is your gender? *(Gender questions in surveys can help with understanding the diverse perspectives and experiences of differing genders).*

1. Female
2. Male
3. Non-binary
4. Prefer not to disclose

Q21: Demographics

In what country do you currently reside?

Q22: Demographics

What sector do you work in?

The survey is completed, thank you for your participation.

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