Ai Based Techniques to Detect and Prevent Dark Personality Traits In Organizational Settings

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Abstract. This review paper analyses the role of HCI (Human Computer Interface) and AI (Artificial Intelligence) techniques in detecting dark personalities within organizational settings, focusing on personality screening and prediction. In this review, the effectiveness of AI, notably deep learning (DL) algorithms, in boosting the prediction diagnostic precision of personalities, minimizing false positives, and improving operational efficiency is showcased. Various DL and ML frameworks show great promise in supporting human resources personnel by enhancing both sensitivity and specificity in identifying personalities. Nevertheless, challenges such as algorithmic bias, implementation difficulties, need for training the data and the necessity for varied data sets impede widespread organizational implementation. Regardless, the results highlight that incorporating AI and HCI algorithms into organizational routines can transform dark triad of personality in workplace settings, facilitating earlier detection and optimizing resources. The analysis stresses the need for additional validation and training for human resource professionals to guarantee the smooth integration of AI technology into organizational practices.

Keywords: “AI in personality detection”, “dark triad traits detection using AI”, “Deep Learning (DL) in personality detection”, “Convolutional Neural Networks (CNN) in detecting personality”,” HCI and AI integration in the workplace”,” HCI in detecting personality” and “Ethics of AI in employee monitoring”

1 Introduction

Any organization’s success mainly depends on its employees’ teamwork and collaboration. When people from different departments work together for a common goal many complex problems get addressed and it fosters innovation. (Kozlowski & Ilgen, 2006). The Co-Spaces Collaborative Working Model (CCWM) identifies seven factors for successful collaboration in the workplace including Context, Support, Tasks, Interaction Processes, Team dynamics, Individual contribution, and Overarching Organizational factors. (Patel et al., 2012). Previous studies have proven the importance of successful collaboration in the workplace leads to positive results.(Kay & Skarlicki, 2020; Mickel, 2024) For effective collaboration, several factors play critical roles including positive communication, individual interpersonal skills such as empathy, reciprocity, trust, strategic leadership skills, and cultural and cognitive factors.(Mickel, 2024; O’Leary et al., 2012; Scott & Manning, 2022; Srivastava & Banaji, 2011).Personality traits of people play a major role in how they relate with each other, researches have proved that Many of the above factors intersect with personality traits of people, also researches indicate that work place collaboration positively correlate with some of the big 5 personality traits.(Marjanovi´c et al., 2023). This correlation may be true of the dark personalities as well, which can cause significant disagreements and disputes within the team in an organization. (Bai et al., 2024).

1.1 *Dark Personality and Workplace Collaboration*

Three Subclinical, non-pathological, offensive traits, including Psychopathy, Machiavellianism and Narcissism were grouped under an umbrella of “Dark Triad”. (Paulhus & Williams, 2002).

1.1.1 *Machiavellianism and workplace dynamics*

People with Machiavellian tendencies usually come across as individuals who like to use control and deceitful tactics on others to benefit self. (Dahling et al., 2009; Furnham et al., 2013). They perceive more opportunities to commit fraud. (Carr´e et al., 2020). They can use manipulative interpersonal strategies like lying and

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flattering (Jones & Paulhus, 2009). They are sensitive to social contexts and can switch between tactics of making others like them or emotionally manipulating others and making them feel guilty for their gain. (Lyons, 2019)

Anti-social workplace practices like social undermining usually occur because of individuals who score high in Machiavellianism. They tend to undermine the efforts of their colleagues for reasons of self-interest. They tend to value their gain over the collective effort. Additionally, with more of their efforts going to undermine their peers to navigate the competitive workplace dynamics, they tend to fall short of their core duties thus reducing productivity. (Castille et al., 2017; Thoroughgood et al., 2021). Due to their manipulative and un-ethical nature, they show a patten of Anti-organizational behaviors and show a disregard for ethical norms which can include lying for own benefit. (Castille et al., 2018)

1.1.2 *Narcissism and workplace dynamics*

Narcissists thrive on their need to dominate people for social status and their strong need for affiliation. (Zeigler-Hill & Dehaghi, 2023). They are also characterized by exploitation of others, lack of empathy, self-absorption, and grandiosity and entitlement. They may also exhibit unrealistic positive self-views and high conflict with others. (Brown et al., 2009; di Giacomo et al., 2023). Studies have proved that Narcissism can negatively impact workplace dynamics. Pathological narcissism has been positively associated with workplace bullying. (Jang & Lee, 2022). Narcissistic leaders tend to have unreasonably high self-perceptions of themselves and their abilities, which may contradict the perceptions of their subordinates, along with their high aggression levels leading to workplace deviance and low job satisfaction.(Judge et al., 2006; Michel & Bowling, 2013) .People who work under a narcissistic leader have usually reported disapproval for their leadership which leads them to act against their leader. (Braun et al., 2018)

1.1.3 *Psychopathy and workplace dynamics*

The psychopathy trait is linked with a range of deviant behaviors and emotional deficits. They are often characterized by lower cognitive reappraisal, less effective emotional regulation, and emotional intelligence, and high expressive suppression. (Miao et al., 2019; Walker et al., 2021). Anti-social behaviors are widely observed in Psychopaths. They are also less empathetic, most malevolent, and highly impulsive, which can lead to negative psycho-social outcomes. (Glenn & Sellbom, 2015; Muris et al., 2017)
When it comes to workplace dynamics, more than the other two traits' psychopaths are most likely involved in counterproductive workplace behaviors like intentionally holding knowledge (Knowledge sabotage) or information to gain personal advantage. This kind of intentional behavior is detrimental to team collaboration and is likely to spread because of workplace competitiveness, which can lead to a toxic work environment. (Serenko & Choo, 2020). Individuals high in psychopathic traits perceive the workplace as competitive and tend to use hard tactics like threats and punishment. (Jensen et al., 2022; Jonason et al., 2015)

1.2 *Management and Mitigation Strategies to promote work-place collaboration*

Organizations need to be aware of and take adequate measures to identify and filter the individuals because of their malicious nature, during the selection process to mitigate their negative impact. (Serenko & Choo, 2020) To identify the dark triad traits, we do have the traditional practices which include evaluating the simulated video recordings of the interviews by professional recruiters to identify the dark traits, (Nuzulia & Why, 2020), Scales like HEXACO/FFM/ZKA -PO (Naor-Ziv et al., 2022; O'Boyle et al., 2015)using observer reports (Rico-Bordera et al., 2024) and using personalized approach to reveal underlying personalities (McLarnon, 2022; McLarnon & Beck, 2025). While these models prove to be successful to some extent, they do have some limitations and challenges. The complexity of the traits could be a hindrance as it is not always possible to isolate and observe their effects, self-report bias, measurement challenges, and cultural variability. (Nuzulia & why, 2020; Rico-Bordera et al., 2024; Truhan et al., 2021)

1.2.1 *HCI in workplace collaboration*

Human-Computer Interaction (HCI) is swiftly growing multidisciplinary area of study. It simplifies human-machine interaction, making technology user friendly. It is usually backed by sophisticated AI and Machine Language tools along with insights from psychological theories and social sciences, considering cognitive, social, and organizational processes in real environments with the common goal of making computer systems usable and useful. (Olson & Olson, 2003; Zhang & Galletta, 2006). HCI has been used in various applications in the workspace, for example, HCI in Management Information Systems (MIS) is concerned with the various human interactions in workplace scenarios, like technologies, business, managerial, and organizational tasks, and analyzing the task effectiveness and outcomes. (Zhang & Galletta, 2006).

Artificial Intelligence (AI), these days, has been used widely along with Machine Learning (ML) in various day-to-day applications. More recently, physical operational elements including sensors and robotics use AI, revolutionizing the future for human-machine interactions. (Howard, 2019)
AI integration has been a crucial part of HCI, which has potential in various applications especially related to workplace scenarios. HCI along with ML algorithms plays a huge role in brain-computer interface, in recognizing human movements in motion-sensing games. The decision-making support systems help people make better choices combining innovative decision-making technologies along with information technology. Psychological issues which are usually handled using therapy techniques like CBT are being handled widely by Many AI chatbots and AI tools are revolutionizing mental health. (Balcombe & Leo, 2022; Yun et al., 2021)

The concept of personality detection using AI in workplace settings is relatively a new area of research involving HCI, personality computing, and psychological assessment. Novel AI and Deep Learning (DL) technologies have been trained to interpret non-verbal human cues and thus can predict personality traits based on a video recording. TensorFlow, an AI-based video interviewing system developed using AI recognizes “big five” personalities automatically (APR) with an a precision of 90-97 percent, thus replacing existing personality assessments, and eliminating the socially desirable results. (Suen et al., 2019) .AI chatbots and ML algorithms have also been used to infer personality from user’s text responses. The results show good convergent validity and acceptable reliability when compared to self-reported questionnaire-derived scores. (Fan et al., 2023)
Based on all these findings, there is a potential of integrating AI, with HCI to predict the dark triad traits. For example, in this study (Mereu, 2021), freely used AI has been successfully implemented to predict all the three dark triad traits. Various situations, including data gaps or decisions to formally examine a person, can make use of this. In another study, Employees’ Facebook status was evaluated for dark personalities using Linguistic Inquiry, Hogan Development Survey coupled with Word Count as well as several ML techniques. The results are based on the 11 scales of the HDS compared to the language used, proves that all dimensions of dark personalities are assessable through online language. (Akhtar et al., 2018).

The present study is designed to systematically review and investigate the efficacy of HCI-integrated AI technologies to effectively uncover malicious personalities in the workplace scenario. It also seeks to understand how AI can improve diagnostic accuracy, reduce bias, improve efficiency, reduce costs also enhance candidate matching to the job. Since this is a relatively new and growing field and not much literature is available for the same, this review paper also seeks to find the potential criticisms and limitations and comparison with traditional model of detecting personality of such implementations and the future direction of improvement regarding the same.

2. Purpose of Study

This review seeks to examine the AI-based personality identification, and organizational psychology to maximize team collaboration and organizational well-being. It will:

1. Review current research on how dark personality traits affect workplace dynamics.

2. Evaluate technical innovations in AI for identifying such traits, e.g., AI, NLP, sentiment analysis, Non-verbal cue analysis.

Explore intervention techniques, e.g., TensorFlow, CNN, Human robot Interaction (HRI), Non-verbal feature analysis, and LIWC (Linguistic Inquiry Word Count), to counteract detrimental behaviors. Aim at addressing ethical issues around AI-based employee surveillance, hiring and recommending guidelines for ethical adoption. By combining various disciplines in this review including studies from organizational behavior, AI and psychology, this paper highlights the ways in which AI based interventions can be very useful in preemptively identifying, rectifying and
forestall the repercussions of dark personality states in the organizations. The results have important implications for AI developers, managers, and HR professionals who are interested in designing more collaborative, inclusive, and psychologically safe workplaces.

3. Methodology

This study adopts a systematic literature evaluation (SLR) method to assess the available research on AI solutions to recognition and management of aversive personalities in collaborative work at the workplaces. The methodology uses a structured format to guarantee comprehensiveness, reliability, and applicability in synthesizing inter-disciplinary research in psychology, artificial intelligence, and organizational behavior.

3.1 Research Approach

This study utilizes a qualitative systematic analysis method, incorporating knowledge from different fields like psychology, computer science, human resource management, and ethics. The review critically analyzes the most recent empirical research, theoretical models, and AI-based technological interventions to evaluate their promise in detecting and preventing repercussions of toxic personality traits in the workplace context.

3.2 Data Collection and Search Procedure

This review paper was built on meticulous literature survey was carried out using peer-reviewed journals, conference proceedings, and reputable online databases, including:

- **PsycINFO** (for psychological studies on dark personality traits)
- **IEEE Xplore** (for AI-driven applications)
- **Scopus and Web of Science** (for multidisciplinary research)
- **Google Scholar** (for supplementary references)
- **ACM Digital Library** (for human-computer interaction studies)
- **PubMed** (for behavioral and neuroscientific aspects)

A **keyword-based search strategy** was employed using the following search terms:

- *"AI in personality detection"*

- *“*Dark triad traits detection using AI”
- *“*Deep Learning (DL) in personality detection*”*
- Convolutional Neural Networks (CNN) in detecting personality”
- ” HCI and AI integration in the workplace”
- ” HCI in detecting personality”
- “Ethics of AI in employee monitoring”

Boolean operators (NOT, OR, AND) were used for search optimization and retrieve relevant, high-quality publications.

3.3 Selection Criteria:

To maintain relevance and scientific precision, studies were screened in line with the following standards:

Criteria for Inclusion:

These inclusion criteria were used to ensure the systematic review focuses on the most relevant and recent developments in integrating AI for detecting dark traits of personality. Studies qualifying under the following criteria were selected:

1. Papers were published within the period of 2015 and 2025, to cover the most recent advancements.
2. Studies focusing on integrating AI technology for personality detection.
3. Studies utilizing advanced AI driven methodologies including DL and ML in Organizational personality profiling.
4. Papers discussing real-world or potential applications in improving diagnostic accuracy and reducing errors.
5. Studies analyzing dark personality traits and their impact on teamwork.
6. Papers discussing ethical and privacy concerns of AI based personality detection.

Criteria for Exclusion:

The criteria for exclusion were chosen for refining the parameters of the systematic review and confirming that only the most significant and impactful studies are selected. Studies with the following criteria were excluded:

1. Studies using solely traditional personality detection using scales without modern AI or DL advancements.
2. Papers which are not focused on personality detection or organizational improvements in work-place screening programs.
3. Exclusion of papers without practical or clinical validation of AI techniques.
4. Papers published before 2015.

3.4. Data Extraction and Analysis:

The selected studies were analyzed using a **thematic coding approach**, categorizing them into key themes:

Identification of Dark Personality Traits

- AI-based personality assessments (ML algorithms, NLP, behavioral tracking).
- Sentiment analysis, emotion detection, Language and deep learning models.
- Social network and communication pattern analysis.

Intervention Strategies in Workplace Collaboration

- AI-driven hiring process and collaboration.
- AI based screening and evaluation.
- AI-driven adaptive feedback mechanisms.

Ethical and Privacy Considerations

- Transparency, fairness and awareness in AI-driven employee monitoring.
- Bias and ethicality concerns related to organizational innovation and attractiveness.
- Psychological, legal implications and recommendations of using AI in HR.

3.5. Quality Assessment and Mitigation

To make sure the review is **valid** and **reliable**, measures as described below were taken:

- **PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses)** guidelines were complied with to maintain an organized literature review methodology (Moher et al., 2009).
- **Cohen's Kappa inter-rater reliability** was employed to evaluate agreement between researchers in study selection and thematic coding (McHugh, 2012).
- Studies were **cross verified with multiple sources** to minimize bias and ensure balanced representation of perspectives.
- Ethical concerns were **explicitly addressed** by incorporating research on **fair AI practices**.

3.6. Coding

In this review, thematic coding was used to systematically synthesize and analyze the chosen studies from various interdisciplinary domains, such as psychology, AI and ML driven technologies, organizational behavior and human-computer interaction (HCI). Following the initial screening with inclusion and exclusion criteria, pertinent articles were imported into qualitative data analysis software and manually screened.
Thematic coding consisted of several structured steps:

Open Coding: Every article was carefully read, and significant concepts or patterns concerning the research aim were noted. Initial codes like "NLP," "R," "Machiavellianism," "CNN," "HR analytics," and "ethical surveillance" were noted.

Axial Coding: The initial codes were subsequently aggregated into larger categories based on conceptual similarity. For example, codes for "text analysis," "voice recognition," and "facial detection" were combined under the theme AI-based Personality Assessment. Likewise, "HR restructuring," "real-time feedback," and "emotional tracking" were combined under Intervention Strategies.

Selective Coding: Final themes were created by combining the axial codes into three general categories consistent with the study's goals.

4 Results of Search Process

The initial systematic search process resulted in many records:

- Google Scholar: 8,650 records
- Science Direct: 447 records
- PubMed: 77 records

These records were screened based on pertinence to the field of study, peer-reviewed trials which adhere to the inclusion criteria. The following records were shortlisted for further analysis:

- Google Scholar: 250 records
- Science Direct: 130 records
- PubMed: 20 records

These evaluations led to the exclusion of irrelevant studies:

- Google Scholar: 4640 records
- Science Direct: 317 records
- PubMed: 57

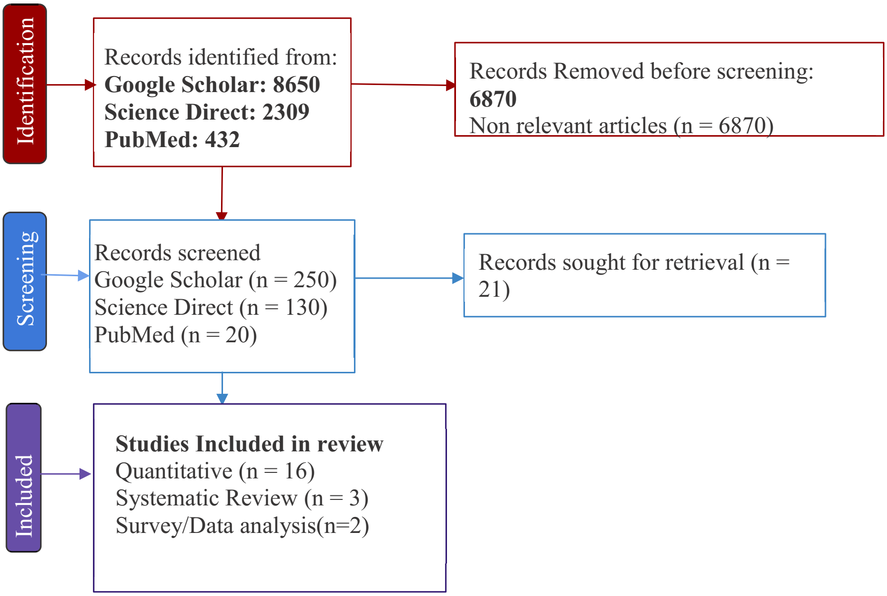
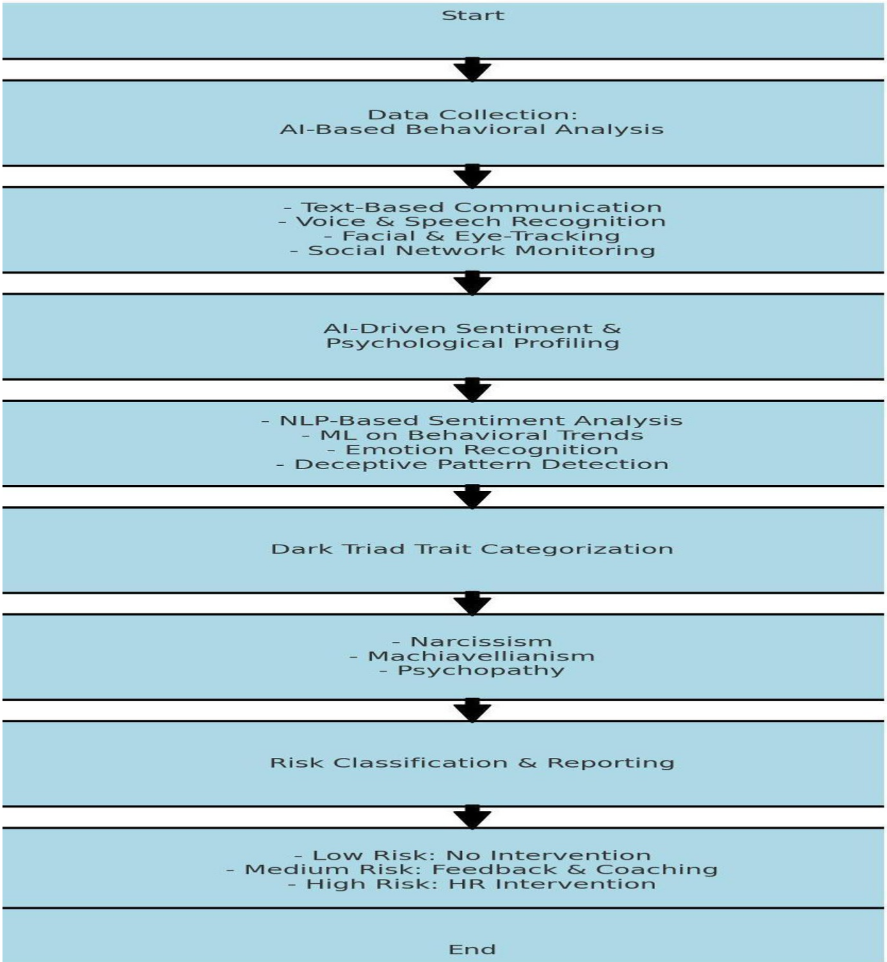


Figure 1: Flowchart of study selection according to PRISMA guidelines

4.1 Results

Figure 1: HCI-Driven Detection and Intervention Model for Dark Personality Traits in the Workplace


Start
Data Collection:
AI-Based Behavioral Analysis
- Text-Based Communication
- Voice & Speech Recognition
- Facial & Eye-Tracking
- Social Network Monitoring
AI-Driven Sentiment &
Psychological Profiling
- NLP-Based Sentiment Analysis
- ML on Behavioral Trends
- Emotion Recognition
- Deceptive Pattern Detection
Dark Triad Trait Categorization
- Narcissism
- Machiavellianism
- Psychopathy
Risk Classification & Reporting
- Low Risk: No Intervention
- Medium Risk: Feedback & Coaching
- High Risk: HR Intervention
End

4.2 Summary of each theme

Table 1: Advancing Workplace Dynamics: AI Approaches to Personality Profiling, Intervention, and Ethical Monitoring

Theme	Study	Objective	Findings	Technology Used
Detecting Dark Traits	Mereu, A. (2021)	AI predicts the third score, when two scores of dark traits are given.	Fair performance especially for Machiavellianism and psychopathy.	R
	Reece Akhtar et.al (2018)	Predicting the dark personality as given in the Hogen Development Survey (HDS)using social media updates.	Full spectrum of dysfunctional dispositions can be measured by using online language.	ML methods, Linguistic Inquiry and word count.
	J. Serrano-Guerrero et.al (2024)	Predict personality using social media texts.	The proposed model outperforms the classical ML models with an average accuracy of 72.69%	Multiple ML and DL models using various conceptual and language-based features.
	K. El-Demerdash et.al (2020)	Trait structure prediction and classification	In comparison to my Personality datasets and gold standard Essays ,there is a notable accuracy Amplification of about 1.25% and 3.12%	NLP in language models with prior training namely BERT Elmo and ULM Fit
	Pavan Kumar et.al (2022)	Examining the user activity in social network Twitter, to detect users' Latent personality	A Linguostylistic personality assessment (LPTA) system can reliably estimate the respondent's covert personality using 50 tweets or less.	
	Zhancheng Ren et.al (2021)	A Emotion aware DL technique for Personality detection usingtext	Accuracy improvement of 6.91% and 6.04% on MBTI and Big five data sets respectively.	BERT a Neural network- based model, emotional and semantic feature, is used
	T. Zlokazova et al. (2021)	Big five personality traits prediction with AI	Agreeableness and Extroversion traits can be predicted by AI	R

	Yash Mehta et al. (2019)	Personality Identification Using DL	DL methods along with multimodal data have revolutionized personality detection.	ML models focusing especially on DL based methods
	E. Ryumina et.al (2024)	Personality detection using Cross-hemiface strategy and OCEAN-AI	Non-neuroticism and Openness depend on the participant demographics. Agreeableness and conscientiousness are dominant for left hemiface, extroversion is dominant for right hemiface.	OCEAN-AI,an open-source AI framework, which can detect Big five personality type o a person using EmoFormer, using features of both sides of human face(hemifaces)
	Anam Naz et.al (2024)	Deep Learning Model for Prediction of Extroversion Personality Trait using MTBI data set with various feature engineering techniques	Bi-LSTM accomplishes the maximum accuracy of 92.52%	Shallow M, ensemble modelling and DL models
	Anum Jaffar et.al (2024)	Five factor framework using a multimodal humanoid system	100% accuracy in personality prediction via expert insights, and 75% using questionnaire-based approach.	Multi-modal analysis using facial expressior module, Face Emotion Recognition (FER+), the data set is trained with CNN
Intervention Strategies in Workplace Collaboration	Hung-Yue Suen et al. (2024)	To predict the communication style and personality in an interview set up	AI model was successfully able to predict the communication style as well as personalities such as openness, agreeableness, and neuroticism on par with the human counterpart, but could not predict personality factors such as conscientiousness and extraversion as much as a human.	Online interview platform with an AI agent based on TensorFlow Convolutional Neural Network (CNN) called AVI-AI
	Antonis Koutsoumpis et al. (2024)	To explain personality and performance in interviews	More variance in Assessor reports and interview competence than self-report. The system also found to have algorithmic bias favouring women.	AVI (Asynchronous video recording)
	Louis C. Hickman et al. (2021)	Deducing personality of applicant through video evaluations	The interviewer's rating of the employee was precisely predicted than self-reports.	Language-based ML algorithm
	Salam et al. (2017)	Completely Machine-Driven Analysis of Involvement and Its Association between Personality in Human- Robot engagement.	Extroverted humans and robots derived the optimum performance while worst performance when all are introverted.	Humanoid robot system trained to predict the Big-5 traits

	Jinyan Fan et al. (2023)	Indirectly evaluating personality scores through AI-Chat bot.	Acceptable reliability of personality scores when compared to a self-reported questionnaire, but inadequate discriminant validity and a diminished validity related to criterion.	AI-chatbot using ML algorithm
	Ivan Hernandez & Nie (2022)	Personality scale item development through AI	Scale generation using Transformer GPT-2 AI model.	Transformer model based on chat GPT 2
Ethical and Privacy Considerations	Diro et al. (2025)	Organizational protection and confidentiality impact in the GenAI age	GenAI in workplaces poses significant data security and privacy risks, requiring targeted countermeasures.	Comprehensive Review
	Pant, A et al. (2023)	The awareness of AI ethics and challenges in incorporating ethics, from the point of view of AI practitioners	Formal training is considered somewhat helpful for some AI practitioners.	Survey and data analysis
	Da Motta Veiga, S et al. (2023)	Perceived ethicality of using AI in the hiring process	Using AI in personnel-selection are positively associated with workplace innovativeness and attractiveness.	Survey and data analysis
	Ashok et.al (2022)	Digital ethics implications of AI use in digital technologies	Novel ontological framework detects fourteen digital implication of ethics	Systematic Review

5. Discussion

This systematic review indicates CNN, a DL technique, has shown enhanced identification of the identification of personality traits via video interviews, chat messages and social media texts. Research consistently underscores the enhanced diagnostic accuracy of DL, and AI algorithms showcasing advancements in reliability and validity when compared to traditional models.In comparison with traditional personality detection scales, DL models have demonstrated better performance, simultaneously decreasing the rates of false positives and negatives. However, despite the encouraging outcomes, obstacles such as model validation, interpretability, and the incorporation into organizational practices persist, needing additional research and development to facilitate broad organizational implementation.

Table 2: AI v/s Traditional Methods Key Metrics in Personality Detection

Metric	**AI, DL and HCI inferred Metrics**	**Traditional Methods (Psychometric Scales)**
Measurement Approach	AI can analyze video interviews, social media behaviors and chat/text messages to predict personality.	Self-reported questionnaires e.g.: Big Five Inventory (BFI)

Reliability & Validity	Some studies show the AI models have weaker discriminant validity, Robust convergent validity, and poor validity related to criterion.	High in validity and reliability as well, may be limited by self-perceptions and self-serving bias.
Sensitivity	AI predictive models are said to be highly sensitive that enhances identification of personality dimensions.	Highly sensitive, when validated appropriate scales are used.
User Perception	Users prefer AI-inferred results equally as traditional methods but prefer traditional methods because of ease of use.	Users prefer traditional methods as they find them quicker and easier to use.
Data Requirements	Uses large scale data sets from various chat repositories, text or video input, involving novel and advanced algorithms and resources.	Requires input from Individuals directly often through questionnaire surveys
Advantages	● Can provide input from non-verbal cues and language use ● can analyze large scale data and digital traces, ● Usually, there is a high accuracy in detecting personality traits.	● Fast, inexpensive ● Psychometric properties are well validated and established
Limitations	● May be prone to algorithmic bias, requires advanced ML algorithms, computational power and data. ● Some AI models need to be trained in the specific data set before they can be useful, however newer alternatives like Zero-shot Learning (ZSL) can adapt without any prior training.	● It can be prone to social desirability bias and limited to self-perceptions. ● Cannot infer items which are not there in the survey.

AI exhibits considerable benefits over conventional techniques in the identification of personality, especially regarding analyzing large data sets, using digital traces of social media data to detect personality and sensitive to non-verbal cues and languages. Furthermore, AI enhances workflow efficiency by alleviating the organizational workload of detecting the individual's personalities in a workplace scenario, thus shortening the cycles of interviews needed to hire the fittest talent for the job. Also to identify malicious personalities in the workplace, thus providing the management with an opportunity for further decisions. The advanced Personality prediction using AI video interview also facilitate an earlier and more precise risk stratification. These advantages position AI as a transformative instrument in enhancing personality screening and mitigating the drawbacks associated with traditional methodologies.

The emergence of AI, has made a huge improvement in the domain of personality detection for personnel selection. Organizations are increasingly relying on AI and HCI decision-making models for human resource sourcing. (Hickman et al., 2021). AI can analyze video interviews, social media behaviors and use online chat to predict personality. (Akhtar et al., 2018; Fan et al., 2023; Hickman et al., 2021; Suen et al., 2020). Identifying of Dark personality traits through AI models is still at the infancy stage, not much research is available, many studies have proved the efficiency of ML models using other personality scales like Big-5 (Zlokazova et al., 2021). It has also been observed that a text-based DL algorithm to measure personality improves personality prediction by 10-20 percent compared to traditional models. (K. Yang et al., 2022). Weaker discriminant and criterion validity is seen prevalent in AI models, while convergent validity has been seen to be favorable. (Fan et al., 2023). Many AI models have a unique advantage over traditional models as they can analyze large-scale and complex data sets for example in this study, (Ryumina et al., 2024), complex data sets such as features of both sides of the faces are used in detecting the big 5 personality traits, using DL models. OCEAN-AI, an open source network, can easily be incorporated for various application domains. One of the other features that AI excels in than traditional models is recognizing non-verbal cues, for example in this study, (Jaffar et al., 2024), non-verbal cues have been used to detect all the 5 traits of the Big-5 personality scale, during a human-humanoid interaction, the system has achieved 100 percent in predicting the traits that AI models can have improvements in many cases, as some AI models have mentioned having algorithmic bias, which is AI models can either reproduce existing real-life biases or form a new bias which does not exist in the dataset (Koutsoumpis, Ghassemi, Oostrom),studies have proved that when comparing the traditional models to ML models, the ML models have excelled in personality prediction using digital footprints compared to traditional models. (Wu et al., 2015).

5.1 Ethical considerations:

Like any new change which creates some initial chaos, implementing AI based behavioral interventions in organizations continues to have key challenges in ethical and privacy concerns.
Resistance to implementation and integration of AI based practices in organizations continues to be a key challenge. (Romeo, E. (2025)).
While AI and DL tools have excellent potential in mitigating various issues that arise in organizations, privacy and questions like, how far are we willing to take AI? cannot be ignored. For example, Diro et al. (2025) in his comprehensive review highlights various ways to counteract the vulnerabilities and threats within GenAI systems like the development of explainable AI (XAI) and establishing clear guidelines for ethical data usage along with policy changes to promote secure adaptation of GenAI in workplace. Though AI practitioners have good understanding of ethical practices while developing AI framework, some could benefit from formal training. (Pant, A et al. (2023)). When coming to implementing these AI based strategies, in organization there is always a perceived ethicality especially in hiring process. Da Motta Veiga, S et al. (2023) has studied this in his survey and data analysis and concludes that the organizations implementing AI based strategies have perceptions of organizational attractiveness and innovativeness.
Finally, Ashok et.al (2022)'s systematic review on implications of digital ethics in digital technologies has identified 14 such implications in 7 digital technology archetypes using a framework.

To understand the full potential of involving AI and HCI in the field of personality detection, the results of this study emphasize the importance of cross-disciplinary collaboration, well developed ethical processes accompanied by robust validation processes. These findings signify the importance of collaborative effort across disciplines with effective validation processes and focus on prediction accuracy-oriented innovations to fully leverage the potential of AI and HCI in detecting dark personalities. Future studies should investigate how multimodal AI systems incorporating behavioral, voice tone analysis, text analysis and non-verbal feature and gesture analysis for an integrated strategy for personality detection. Second, incorporating more Explainable AI (XAI) frameworks, in areas where decisions making is involved especially may lead to the improved acceptance of AI especially when it acts as an assistant to human judgement rather than replacing it. Finally, there is a need for a stronger ethical, legal framework to ensure privacy and guidelines have to be developed with the consent of employees and management for ensure more transparency and trustability also reducing the dangers of surveillance abuse.

6. Conclusion

The findings of this review highlight the novel and advanced capabilities of AI, DL models as well as HCI along with ML models. The DL frameworks, particularly those using multi modal data, have been shown to have high precision, sensitivity and specificity. These will help the human resource personnel of an organization with the ability to detect dark personalities thus minimizing multiple selection rounds. Ultimately, with advanced technologies like detecting personalities with facial features and non-verbal cues, social media texts, virtual interviews hold a significant potential as it can improve the diagnostic precision and accuracy of the prediction.

However, significant challenges remain such as tackling algorithmic biases, training the datasets and interpretability and ease of use of AI systems, ethical considerations when using various data needs a regulatory framework for organizational implementation. It is important to take these challenges through inter-disciplinary, collaborative research through thorough testing, considering the ethical implementation of the system and ongoing innovation to fully harness HCI's potential in detecting and preventing Dark triad of traits. Nonetheless, issues such as training the dataset, interpretability of data persist, and organizational implementation persist.

7.Future Scope

Further studies should focus on culture-specific data sets and seamless integration into the existing organizational model to fully capitalize and key advantage of AI models in the field of personality detection.

Adaptive and Personalized AI: Understanding and designing trustworthy AI systems which can be adapted to specific personality traits have to be still explored. (Riedl, R et.al ,2022).

Ethical and Legal Frameworks: Stricter ethical guidelines and framework should be implemented with the consent of the people involved working with technology day-to-day. This will improve acceptability, trustability, transparency and address privacy concerns. (Ashok, M et.al,2022). This is especially true as the future society will need to focus on managing new challenges dealing with different cultures, societies using AI frameworks and exploring different aspects of personalities that might become important in the future. (Matthews, G,2021)

Human-Centered and Interdisciplinary XAI: Explainable AI (XAI) is an emerging field which has practical, ethical benefits across all domains. More human centered interdisciplinary research based on open and ongoing challenges must be addressed with collaborative efforts across multidisciplinary domains and broader perspective. (Longo, L, et.al,2023)

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