

PREDICTIVE ANALYTICS FOR EMPLOYABILITY IN CREATIVE FIELDS

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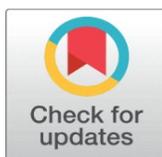
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ABSTRACT

The field of employability assessment is getting revolutionized by predictive analytics in creative industries because it can be used to assess skills, portfolios, and career paths based on data. The creative labor markets (design, visual arts, media, and digital content production) can be described by their heterogeneous skills, subjective quality standards, and quickly changing demand trends, which renders the conventional methods of employability assessment ineffective. This paper hypothesizes a predictive analytics system to be used in forecasting employability within the creative industry by incorporating portfolio artifacts, talent profiles, project assessments, and labor market indicators. The methodology is a mix of structured attributes based on education, experience, and performance metrics and unstructured textual and visual data taken out of portfolios and job adverts. Various predictive models are used such as Random Forest, XGBoost, Artificial neural networks, and BERT-based language models to align the nonlinear relationship and semantic alignment between creative work and market need. SHAP-based explainability helps to determine which drivers of employability, including skill diversity, project relevance, aesthetic coherence, and industry alignment are most important using model interpretability. The results of the experiments prove that ensemble and deep learning models are superior to traditional ones, they are more accurate and robust in employability prediction in creative sub-sectors. This can be used in practice to create AI-based portfolio analysis, a customized identification of skill-gaps, and integration with online talent markets to enhance workforce planning and development.

Keywords: Predictive Analytics, Creative Employability, Portfolio Assessment, Machine Learning, Skill-Gap Analysis



1. INTRODUCTION

The concept of employability within the creative sector has only become more and more complicated and dynamic due to the swift change in technology, the pressures on the labor market and the continuous increase and digitization of

creative work. Design, visual arts, media production, animation, photography, and digital content creation among others are no longer appraised based on formal qualification or number of years worked. Rather, employability depends on a mixture of the quality of portfolio, diversification of skills, flexibility, relevance to project, and compliance with the current market trends. With the expansion of creative labour market through freelance markets, digital studios and worldwide talent markets, systematic and data-driven methods of evaluating and forecasting outcomes of employability become increasingly important. The conventional ways of evaluating employability in the creative sector are heavily dependent on subjective analysis by professionals, recruiting officers, or even instructors. Portfolio reviews, interviews and peer judgments are valuable but tend to be time consuming, inconsistent and biased. In addition, the methods cannot be easily scalable in the context where thousands of portfolios and applications of creative individuals need to be filtered effectively [Chen et al. \(2022\)](#). The growing access to digital portfolios, online learning history, project archives, and job market information can be seen as a chance to stop making judgments based on intuition and implement predictive analytics, which could facilitate making evidence-based decisions. Predictive analytics is the practice of using statistical models, machine learning, and artificial intelligence tools to predict the future with the use of historical and real-time information. Within the domain of employability, predictive models have the potential to measure variants of skill, creative output, learning pathways and job market indicators in their relationship to employment success, job stability or career progression [Rios-Campos et al. \(2023\)](#). The skills, performance, and industry alignment of the employability of AI-based analytics are combined as demonstrated in [Figure 1](#). Although predictive analytics have been extensively used in other areas like finance, health, and workforce planning in the engineering field, its use in the creative areas is comparatively very low.

Figure 1



Figure 1 Predictive Analytics Framework for Employability Assessment in Creative Fields

This is in part because creative performance is inherently subjective and creative artifacts are multimodal, comprising visual, textual, and behavioral elements that are hard to measure using standard measures. The recent developments in machine learning, natural language processing, and representation learning have enabled people to model complex and unstructured data much better [Singh and Alhamad \(2022\)](#). Ensemble learning, deep neural networks, transformer-based language models are all techniques that allow identifying meaningful patterns on portfolios, statements by artists, descriptions of their projects, and [Gaikwad and Damodaran \(2024\)](#) job descriptions. In conjunction with systematic predictors like skills credentials, project appraisals, and work experience, these approaches

can provide an encouraging basis of predictive modeling of employability in creative fields. Notably, explainable AI methods have become a useful tool enabling the stakeholders to know what features contribute to the model predictions to ease the worries regarding transparency and reliance in the algorithmic decisions [Alhamad and Singh \(2024\)](#).

2. LITERATURE REVIEW

2.1. PREDICTIVE ANALYTICS AND EMPLOYABILITY MODELLING FRAMEWORKS

Predictive analytics have become dominant methodological tools of learning and predicting the outcomes of employability in education and labor development. The initial models on employability were based on econometric and statistical approaches, which centered on the demographic factor, educational attainment factor, and work experience as the predictor of employment. Although useful in the macro-analysis of labor, these models had weak predictive ability at the individual level in areas where skills are important, and non-linear. As digital learning platforms and data on the labor market grow, machine learning-based models have become more and more popular to predict employability as a multifactorial and dynamic construct [Hoca and Dimililer \(2025\)](#). The current frameworks of employability model combine academic performance, skills acquisition, behavioral and labor market signals through supervised learning models like logistic regression, decision trees, random forests, and gradient boosting. Such methods allow finding out the complicated relationships between skills, learning patterns, and labor market results. Even more recent models include temporal modelling to model career progression and skill development with time, and to treat the result of employability as a longitudinal process instead of a static one [Wziątek et al. \(2023\)](#). Explainability has become significant too, and such techniques as feature attribution and post-hoc interpretation have been employed to enhance transparency and stakeholder trust.

2.2. AI/ML ADOPTION IN CREATIVE LABOR MARKETS (DESIGN, ARTS, MEDIA)

The digitization of the creative production and distribution has resulted in the acceleration of the adoption of artificial intelligence and machine learning in the creative labor market. Design, visual arts, media, and content production are becoming more and more active in the data-rich environment of online portfolios, freelance platforms, social media, and online marketplaces. It is currently moving towards algorithmically mediated creative work ecosystems using AI-based tools to discover, recommend, and match talents with projects. Machine learning models are used in recruitment and talent platforms to compare creative profiles, project histories, and client feedback and rank applicants or forecast the chances of project success [Nosratabadi et al. \(2022\)](#). AI systems are also applied to assess audience engagement, content performance and trend alignment in design and media industries, indirectly affecting employability by determining the demand of particular skills and style. The presented developments imply that the employability in creative sectors is not defined by the mastery of artistic skills anymore but by the information-based measures of relevance and flexibility. Nevertheless, AI application in creative labor markets poses severe issues [Prasad and De \(2024\)](#). Creative work is situational and culturally rooted and its generalizability across style and sub-sector using generic models is hard. Issues associated with prejudice, standardization of creative work, and underappreciation of unorthodox talent are often raised in the literature.

2.3. PORTFOLIO EVALUATION AND SKILL ASSESSMENT TECHNIQUES

Portfolio review has always been the foundation of talents evaluation in creative fields as it has been one of the leading markers of skills, style and professionalism. The traditional portfolio assessment is based on the judgment of the experts, the review of peers, and the usage of qualitative rubrics, which takes into consideration the originality, technical work, clarity of ideas, and logicity. Although these techniques are sensitive to the finer details of creative quality, they are naturally subjective and they are challenging to rank with a large number of applicants. Most recent studies have examined computational methods of portfolio assessment by deriving quantifiable attributes of creative artworks and descriptions of those artworks [Joloudari et al. \(2023\)](#). Visual analysis methods measure elements like the color harmony, composition balance and structural complexity whereas textual analysis measures narratives, project descriptions and reflective statements. Skill evaluation systems are also integrating these outputs and metadata including tool usage, project diversity, pattern of collaboration, and timelines of completion [Raza et al. \(2022\)](#). [Table 1](#) indicates development of employability forecasting systems with creative skill analytics. Assessment models based on machine learning seek to

map these characteristics in an attempt to use them to apply to employment related results, like a possible hire or a successful project. The most notable is a blend of automated scoring with human involvement, which is fair as it is not so efficient yet sensitive to context.

Table 1

Table 1 Summary of Related Work on Employability Prediction and Creative Skill Analytics					
Domain Focus	Dataset Type	Key Features Used	AI Techniques	Evaluation Metrics	Limitations
Graduate Employability	Academic records	Grades, attendance	Logistic Regression	Accuracy, AUC	Ignores creative outputs
Digital Media Jobs Duan and Wu (2024)	Job postings	Skill keywords	NLP + SVM	Precision, Recall	No portfolio data
Design Education	Student portfolios	Project scores	Random Forest	Accuracy, F1	Subjective labels
Freelance Platforms	Platform logs	Ratings, reviews	Gradient Boosting	AUC	Platform-specific bias
Creative Arts	Mixed (text + scores)	Skill diversity	ANN	Accuracy	Limited explainability
Media Industry Ma et al. (2024)	Employment history	Experience duration	XGBoost	RMSE, AUC	Static modelling
Online Learning	Course data	Learning behavior	LSTM	Recall, F1	Not domain-specific
Graphic Design	Visual portfolios	Color, layout metrics	CNN	Accuracy	Small dataset
Cultural Industries Young et al. (2025)	Surveys	Soft skills	Regression	R ²	Self-reported bias
Creative Recruitment	CV + portfolios	Text semantics	BERT	AUC, Precision	High computation cost
Art and Design Schools	Academic + portfolio	Creativity index	RF + SHAP	Accuracy	Limited modalities
Talent Marketplaces	Platform analytics	Skill relevance	Hybrid ML	F1, AUC	Ethical concerns
Creative Fields Mullens and Shen (2025)	Multimodal (portfolio, jobs)	Skills, text, performance	RF, XGBoost, ANN, BERT	Accuracy, AUC, SHAP	Multimodal data scarcity

3. METHODOLOGY

3.1. DATASET DESCRIPTION (PORTFOLIOS, SKILLS, JOB POSTINGS, PROJECT EVALUATIONS)

The data set employed in this research is intended to reflect the multidimensional nature of employability in creatives area by combining heterogeneous source of data. The main unit is creative portfolios, which comprise visual objects, project texts, and reflective texts obtained via the platforms of digital portfolios, and institutional repositories. These portfolios are considered to be different creative fields, such as design, visual arts, media production, and creation of digital content. Each profile is correlated with structured expertise of technical skills, software expertise, creative methods, and soft skills, which are acquired through self-reports, certifications, and learning history [Antoniuk et al. \(2025\)](#). The labor market demand is included by obtaining job posts via online creative market places and recruitment sites. Such postings give details about the skills needed, level of experience, the style that is preferred, and scope of the project. Job descriptions contain natural language materials that are preserved to allow them to be analyzed semantically and attached to portfolio stories. Also, the project evaluation information is provided to represent the actual performance. This information includes expert ratings, client ratings, peer ratings and project completion ratings including promptness and number of revisions [Do et al. \(2025\)](#).

3.2. FEATURE ENGINEERING FOR CREATIVE PERFORMANCE AND EMPLOYABILITY INDICATORS

Extraction of meaning through feature engineering is very important in converting the complex creative data to meaningful employability indicators. The structured features are based on skill profiles and project metadata, such as skill diversity indices, experience depth, numbers of tool proficiency and project completion rates. The human behavioral

aspects of learning in terms of their temporal characteristics encompass learning tracks, the frequency of updating the portfolios, and the rate of skill acquisition, which depict flexibility and lifelong learning. Portfolio and job posting data, which are unstructured, is converted to numerical data by text and visual feature extraction. The textual characteristics incorporate semantic embeddings of project descriptions, artists statements and job requirements, which allow measuring the content relevance and market fit. The number of keywords used, the use of domain-specific terminology and the level of coherence of the narrative are also calculated. Computer vision-based descriptors are used to describe compositional balance, color variance and stylistic consistency using visual features where applicable. The composite indicators of employability are created through the use of multiple groups of features. There are portfolio coherence scores, market relevance index and the creativity-consistency trade-off measures. These pointers will be used to reconcile between originality and professional reliability that is key to employability in imaginative labor markets. The dimensionality reduction and feature normalization are implemented to overcome the differences in scale and redundancy. Notably, domain expertise is used to design features in order to maintain interpretability. This makes sure that features that have been engineered do not only enhance predictive performance, but also give actionable insights to scholars, teachers and employers.

3.3. PREDICTIVE MODELLING TECHNIQUES (RF, XGBOOST, ANN, BERT-BASED TEXT MODELS)

Several predictive modelling models are used to assess the effect of employability and obtain various data features. Random Forest (RF) models can be considered a strong baseline because they can be used to address nonlinear relations and mixed data types. RF models combine several decision trees, which reduce over fitting, but also produce feature importance measurements, which can be used to aid in the interpretation. XGBoost is an ensemble algorithm that is high performance and optimizes gradient boating by regularizing and optimizing tree building. The ability to capture complex interactions of features gives it great applicability to employability prediction, where there are complex interactions of skills, portfolio quality and market alignment affecting the outcome. ANN are proposed to learn more details about nonlinear patterns among engineered features. Multi-layer architectures support representation of latent relationships which might not be directly represented in the process of feature design. In the case of textual data, language model BERT is used to create contextual embeddings using portfolio stories and employment opportunities. Such embeddings include semantic similarity and intent alignment between creative products and the labor market demand. Embeddings are either trained with hybrid models as well with structured features or directly fine-tuned to use on employability classification. Cross-validation and standard performance metrics are used to model evaluation and the explainability techniques are used to assure transparency. A combination of these modelling methods would give a comparative analysis of predictive employability performance in creative professions.

4. PRACTICAL APPLICATIONS

4.1. AI-DRIVEN PORTFOLIO ASSESSMENT TOOLS

One of the most direct ways to use predictive analytics in regard to employability in creative disciplines is represented by AI-inspired portfolio assessment tools. They are aimed at assisting teachers, recruiters, and creative specialists in the process of evaluation of digital portfolios that is structured and uses data to draw informed conclusions. An AI system can produce reliable appraisals of large amounts of portfolios by analyzing visual artifacts, project descriptions, and reflective narratives to resolve issues of scalability and time limitations which are associated with manual reviews. These tools are usually a combination of machine learning models and domain-specific evaluation criteria and they can be used to translate qualitative creative qualities into a form of interpretation. Portfolio coherence metrics, skill diversity metrics, project relevance metrics and stylistic consistency metrics are calculated and displayed in dashboard interfaces. AI-driven evaluation systems are not substitutions of human judgment but rather as a decision-support system, which points to areas of strength, areas of weakness, and allows the comparison of candidates or cohorts. In the case of creative professionals, the tools provide formative feedback that facilitates self-reflection and self-improvement. Automated insights can be used to refine portfolio refinement to propose underutilized abilities, styles, or incompatibility with job targets. In the context of institutions and employers, AI-based portfolio evaluation contributes to the increased level of transparency and the minimization of bias through the implementation of standard criteria on a regular basis.

4.2. SKILL-GAP DETECTION AND PERSONALIZED LEARNING PATHWAYS

By employability analytics, predictive analytics, particularly skill-gap detection is a major practical consequence of enabling actions to be taken on creative learners and professionals. Through the comparison of the skill profile and characteristics of the portfolio of a given individual and the labor market demand indicators, AI systems can help detect the mismatch between the competency of the individual and the skill needed. These gaps can be associated with technical tools, new creative methods, conceptual capabilities, or other soft skills like collaboration and communication. Predictive models are a type of analysis that uses past employment results to figure out the strongest combinations of skills that are correlated with employability success in particular creative occupation. Figure 2 indicates that AI identifies skill gaps and individualizes learning processes. On the basis of this analysis, customized learning paths can be created, suggesting courses, projects or other types of experiential learning opportunities that are individualized.

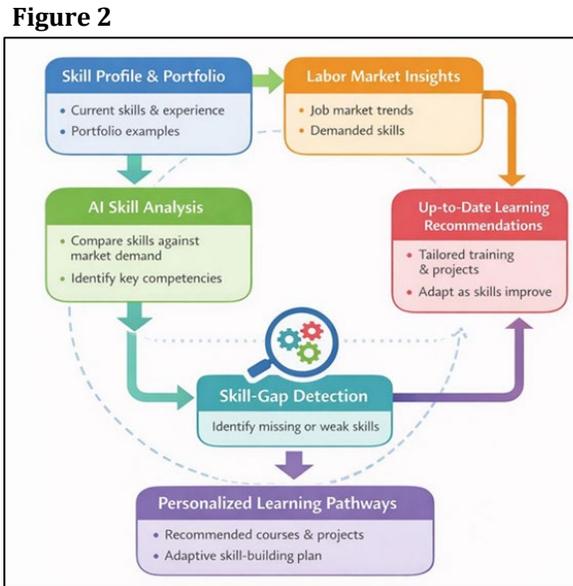


Figure 2 AI-Driven Skill-Gap Detection and Personalized Learning Pathway Framework

In contrast to generic training recommendations, these paths are dynamic and context sensitive and change with the acquisition of new abilities by the user or changes in market needs. In the case of educational institutions, the skill-gap analytics can be used to help in aligning the curriculum with industry demands by identifying systemic gaps among the learner groups. It allows to make prompt curriculum changes and to produce competency-based learning modules. Personalized career trajectories can promote lifelong learning and adaptability in unstable labour markets to creative professionals.

4.3. TALENT-MARKETPLACE INTEGRATIONS FOR CREATIVE PROFESSIONALS

Predictive analytics to digital talent marketplaces should be considered a valuable activity to both creative individuals and employers. The method of using algorithms to match talent and projects, clients, or full-time positions is becoming more common in creative labor platforms. With employability prediction models integrated into these platforms, the matching processes can shift their focus on the keyword-based filtering to holistic and performance-based recommendations. Predictive analytics helps a platform to determine the suitability of a candidate by evaluating the portfolio quality, relevance of their skills, previous output of the project, and alignment to the role. This not only increases the accuracy of matches, but also minimizes friction during search and also increases the success rate of projects. To creative professionals, these integrations can be more visible as their profiles are being suggested in positions that reflect their strengths and growth paths, and no longer based on their previous experience only. Further, predictions of employability can be incorporated into features of talent marketplaces to guide career development, including recommendation of readiness scores on a job or profile improvement. Employers can save themselves the effort of screening and they have confidence in recruiting. The culture of ethical concerns is of paramount importance in this

regard, and clear and explainable matching systems cannot be avoided to eliminate any form of exclusion or bias. Talent-marketplace integrations, when done in an environmentally friendly way, make predictive analytics an enabling infrastructure that allows equitable access, informed decision-making, and sustainable creative careers of digital workplaces.

5. RESULTS AND ANALYSIS

5.1. MODEL PERFORMANCE COMPARISON ACROSS ALGORITHMS

This experimental data shows that there are distinct differences in performance among the tested predictive models. Conventional ensemble procedures like Random Forest offer fixed point performance, which can cope with mixed types of features and overfitting is minimized. Nevertheless, the gradient-boosting algorithms, and especially the XGBoost, always demonstrate better prediction accuracy and AUC, which suggests higher performance in the modeling of intricate interactions between skills, portfolio characteristics, and labor market characteristics. Artificial Neural Networks are more effective in recalling employability-positive cases since it contains more nonlinear patterns which, however, should be carefully tuned to preserve generalization. BERT-based text models can be used to a significant benefit in terms of performance when the portfolio narratives and job descriptions are implemented, which will lead to better semantic correspondence and more contextual awareness.

Table 2

Table 2 Predictive Employability Model Performance Comparison				
Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score
Logistic Regression	74.6	71.2	69.4	0.7
Random Forest (RF)	82.8	80.5	78.9	0.8
XGBoost	86.9	84.7	83.1	0.84
ANN	85.4	82.9	84.6	0.84
BERT (Text Only)	83.7	81.6	82.4	0.82

A comparative analysis of predictive models used to use employability forecasting in the creative industry is provided in [Table 2](#), showing that there are evident differences in performance among the algorithms. The poor accuracy, 74.6, and F1-score, 0.70 of Logistic Regression, indicate its inability to predict the nonlinear relationships and highly interactive feature relationships in the data of creative employability. [Figure 3](#) indicates that proposed model has better accuracy, precision, recall, and F1-score. Although it can be interpreted, it is limited by linear assumptions to have efficiency in modeling subjective and multifactorial drivers of employability.

Figure 3

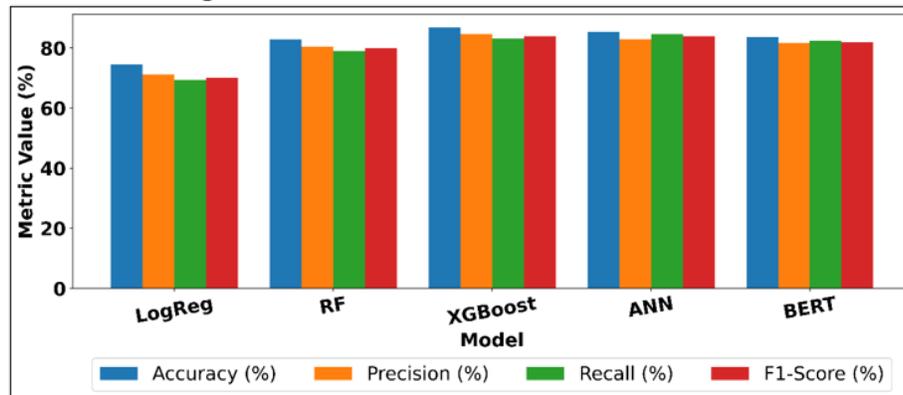


Figure 3 Comparison of Accuracy, Precision, Recall, and F1 Across ML Models

Random Forest has a tremendous improvement in performance with 82.8% accuracy and an F1-score of 0.80. This advantage shows that ensemble learning is useful when a heterogeneous set of features like skills, portfolio characteristics, and project ratings should be used. XGBoost also beats by a greater margin.

Figure 4

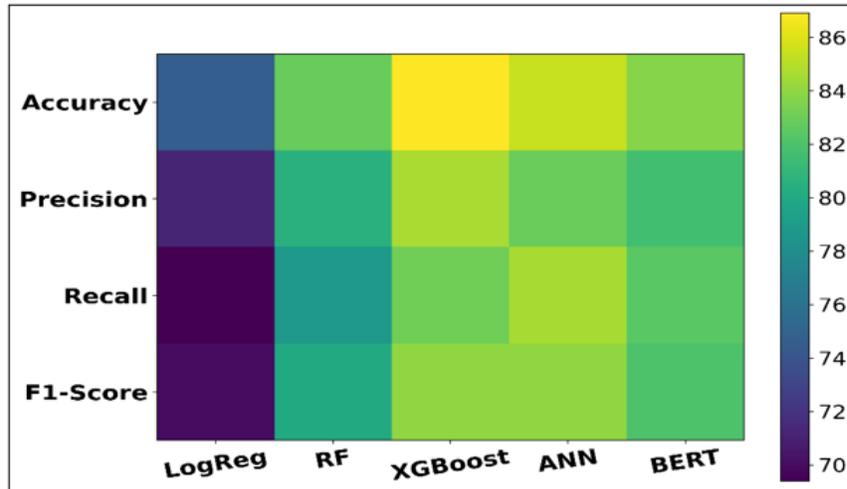


Figure 4 Visualization of Evaluation Metrics Across ML Models

Random Forest, which had the best accuracy (86.9%), high precision (84.7%) and recall (83.1%). Its gradient-boosting model is quite successful in the modeling of subtle interactions among indicators of creative performance and labor market fit. Figure 4 indicates that machine learning models have evident performance differences in metrics. The artificial neural networks (ANNs) have similar F1-scores (0.84) and recall (84.6 percent), indicating their capability to be more sensitive when detecting cases in employability-positive cases, which is also useful in talent discovery tasks. The use of semantic knowledge of portfolio narratives to compute competitively using BERT-based text models, but with a lower overall accuracy rating suggests that textual information is not enough, in the absence of more structured features.

6. LIMITATIONS AND FUTURE RESEARCH

6.1. DATA QUALITY, HETEROGENEITY, AND SUBJECTIVITY ISSUES

The quality and heterogeneity of data is one of the main restrictions of predictive employability analytics in creative industries. Creative portfolios, skill profiles, and project assessments are most frequently gathered across a variety of platforms with varying ad hoc standards, formats, and detail. Self-reported skills can be exaggerated or old-fashioned, whereas project reviews can be quite diverse based on the level of skills of the evaluator, his/her expectations, and culture. This unpredictability brings about noise and bias to predictive models and this is likely to cause their compromises on credibility and fairness. Creative assessment is a subjective phenomenon, and aspects like quality, originality, and relevance are issues that are subjective and hard to be evaluated in an objective way. Although machine learning models can discern patterns in a high volume of data, it can also unconsciously learn prevailing stylistic standards, excluding unorthodox or new creative manifestations. The next step of the research should be on better data curation, standardized metadata schemas and checking mechanisms to increase consistency. Subjectivity-related risks can be further reduced by means of the introduction of multiple evaluators, uncertainty modelling, and fairness-conscious learning methods. The solution of these problems is necessary so that the predictive employability systems will be reliable, inclusive, and ethical.

6.2. TRANSFERABILITY ACROSS CREATIVE SUB-SECTORS

The other major limitation is related to the transferability of the predictive models to other creative sub-sectors. The creative industry is a diverse practice that incorporates graphic design, fine art, animation, media production, and interactive content, which have different skills, assessment standards and dynamics in the labor market. The classification models which are trained using the data in one sub-sector might not generalize well to other sub-sectors, resulting in low prediction accuracy and mis-interpretation of the employability signals. This has been increased by the fact that creative technologies and trends are changing at a very rapid rate, making the learnt patterns outdated. As an

example, the skills that are appreciated in the field of traditional print design can be quite different in the field of immersive or AI-assisted creative activity. Future studies are needed to understand the domain-adaptive and transfer learning methods that enable the models to store fundamental employability features whilst adjusting to sub-sector-based settings. Dynamic updating can also be supported by modular modelling architectures and constant learning approaches as creative practices keep changing. It is important to ensure that the transferability is achieved in order to develop scalable employability analytics frameworks that will not lose their relevance within the diverse and changing environment of creative professions.

6.3. NEED FOR MULTIMODAL DATASETS (VISUAL, TEXTUAL, BEHAVIOURAL)

Existing methods of employability predictions usually have the drawback of being data-intensive, that is, based on structured skill data or textual descriptions. Nonetheless, creative work as a whole is multimodal and includes visual evidence, textual stories, and behavioral cues including patterns of collaboration, efficiency of workflow, and interaction of learning. The lack of combined datasets that include multimodal data makes the possibility of capturing the entire range of the creative competence and employability potential of the models limited. Research in the future is advised to focus on the creation of huge multimodal datasets that integrate the visual characteristics of portfolios, semantics of the textual material, and the behavioral signs based on project management tools or learning platforms. New improvements in multimodal representation learning and cross-modal alignment provide a way to look forward to the integration between these various sources of data. Data collection, consent, and privacy-saving methods will be required and necessary to facilitate responsible dataset creation. With the help of a rich multimodal data, the future employability models will be more accurate, inclusive and contextually sensitive and will eventually be able to offer more holistic and meaningful measurements of creative talent and career readiness.

7. CONCLUSION

The present paper has explored how predictive analytics can be used to improve employability in creative professions, where conventional assessment tools are prone to reducing the complexity and subjectivity of creative work. Using portfolio artifacts, skill profiles, project evaluations, and labor markets indicators, the suggested structure indicates that data-driven solutions can be useful in augmenting human judgment in determining career readiness and employment opportunities. The comparative evaluation of machine learning models demonstrates the efficiency of ensemble and deep learning as approaches to the modeling of nonlinear relationships between creative performance and market demand. In addition to predictive accuracy, the research states the need to have interpretability and practical relevance. SHAP-based explanations and analysis of feature importance give clear information on the main drivers of employability, including the skill diversity, portfolio coherence, market alignment, and adaptability. These insights turn the process of employability prediction into a more developmental approach to assessment rather than an evaluative approach to assessment, allowing learners, educators, and professionals to make suitable decisions about skills development and career planning. The practical examples given above such as AI-based portfolio evaluation, personalized skill-gap identification, as well as the integration of constituent elements of a talent-marketplace, demonstrate how predictive analytics can facilitate more efficient, inclusive, and responsive creative labor markets. Such systems, when designed in a responsible way, can enhance the access to opportunities, screening bias, and encourage lifelong learning in the fast moving creative industries.

CONFLICT OF INTERESTS

None.

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