HHAI 2024: Hybrid Human AI Systems for the Social Good
F. Lorig et al. (Eds.)

doi:10.3233/FAIA240178

Beyond Skills: The Role of Values in Job Seeking in the Era of Industry 5.0

Ajaya ADHIKARI [a,1], Quirine SMIT [a] Joost A.G.M. VAN GENABEEK [a]
Steven DHONDT [a,c] and Cor J. VEENMAN [a,b]
[a] *TNO, The Netherlands*
[b] *Leiden University, The Netherlands*
[c] *KU Leuven, Belgium*
ORCiD ID: Ajaya Adhikari https://orcid.org/0000-0003-2518-7740, Quirine Smit https://orcid.org/0009-0008-8890-4261, Joost A.G.M. van Genabeek https://orcid.org/0000-0002-3873-7951, Steven Dhondt https://orcid.org/0000-0002-8888-5231, Cor J. Veenman https://orcid.org/0000-0002-2645-1198

Abstract. Jobseekers typically not only seek job vacancies matching their skills but also a company aligning with their values. This relates to Industry 5.0, a European Commission initiative emphasizing a more fulfilling role for workers. This study explores the relationship between skills and values in job vacancy selection and suggests several ways in combining these aspects for decision making. The first baseline system only uses skills, the second assigns equal importance to both skills and values, and the third, a hybrid intelligence system, leverages Pareto Optimality, leaving the ultimate decision on the trade-off between skills match versus values match to the jobseeker. Additionally, a small scale user study explores the impact of values on vacancy selection and evaluates the proposed matching systems. The results show that, participants seek a balanced trade-off between both skills and values. Accordingly, systems considering both skills and values outperform the baseline system. The system with equal weights and the Pareto optimality-based system have similar performances, possibly due to the large overlap in their output. Future work with more participants in a real-world application is needed to further validate our first exploration of the relationship between skills and values.

Keywords. skills and values-based matching, Industry 5.0, labor-market, multi-criteria decision making, pareto optimality

1. Introduction

Industry 5.0 is an European Commission initiative aimed at reshaping EU industrial policy [1]. Addressing concerns about the prior focus on technology and profit in the Industry 4.0 policy [2] being insufficient [3], Industry 5.0 emphasizes that the industry should be more human-centric, sustainable, and resilient [1]. In the human-centric aspect of Industry 5.0, ensuring the well-being and meaningful engagement of workers is crucial. This is also seen in the labor market from the jobseekers perspective, particularly post-

[1] Corresponding Author: Ajaya Adhikari, ajaya.adhikari@tno.nl

COVID-19, where the significance of *passion for work* is growing [4]. Jobseekers are increasingly seeking roles that are meaningful and fulfilling. Moreover, jobseekers increasingly place importance on having their values match those of their potential employers [5,6].

Wanberg et al. [7] highlight seven key factors that impact jobseekers' decisions on which job vacancies to pursue. These factors include skills-related aspects, alongside one called "social capital," which reflects the values of the jobseeker. Social capital represents the social context in which the jobseeker operates and offers values that resonate with the jobseeker. However, determining how important skills-related aspects are in comparison to values for effectively matching jobseekers with job vacancies is difficult [7]. Are skills-related factors more crucial, or are value-related factors equally important?

This study explores the interplay between skills and values in job vacancy selection and suggests potential matching systems based on skills and values. Three matching systems are proposed to provide relevant job vacancies for jobseekers. The first baseline system only considers skills for matching, the second system assigns predefined equal importance to both skills and values, and the third system employs a hybrid intelligence approach, where the decision on the importance between skills and values is left to the jobseeker using Pareto optimization. At last, this work describes a small user study with 20 participants to explore the role of values on the selection of job vacancies, while also assessing the performance of the matching systems compared to the baseline system.

This paper is structured as follows. Section 2 describes the related work. In section 3, we elaborate on the different matching systems and the setup of the userstudy. Section 4 reports the results. At last, sections 5 and 6 contain the discussion and the conclusion of our work.

2. Related Work

In the domain of recruitment, skills-based matching emphasizes aligning jobseekers' skills with the skills requirements of available positions, diverging from traditional methods that predominantly consider academic qualifications and sector-specific experience. Various works has been conducted by labor market entities [8,9] and academic studies [10,11] to facilitate skills-focused matching. These works, however, largely overlook the incorporation of personal and organizational values in the matching process, highlighting an important area for improvement in recruitment approaches.

When matching on both skills and values the problem becomes a Multi Criterion Decision Making (MCDM) problem. Rather than optimizing for only one criterion (skills), the best solution (vacancy) is found by matching on two criteria (skills and values). We highlight three MCDM methods each with different advantages and disadvantages: self-learning, predefined weights and Pareto Optimization.

Self-learning AI methods are widely used in decision-making processes [12]. They can assist decision-makers or automate decisions entirely [13]. For our use case an AI model could be trained on past jobseeker-vacancy matches to identify characteristics that predict good matches. Its advantage lies in being able to automatically learn the relation between skills and values. It, however, assumes that future choices mirror past ones, which may not be applicable in our use case. If jobseekers' priorities shift, the model may not adapt, relying on outdated preferences. It also assumes similar decision-making among jobseekers with comparable profiles. At last, obtaining the necessary data, including vacancy details and jobseeker information such as application decisions and interview invitations, is difficult due to its sensitive nature and the volume needed.

The second method involves predefined weights, where users, in this case jobseekers, rate the relative importance of skills and values in advance. These ratings are then used to compute ideal matches [14]. This method is mathematically straightforward and can offer users insights into their priorities. However, obtaining accurate user weights can be challenging [14,15], as people may struggle to articulate their true preferences [7].

The third method, uses Pareto optimality [16] to select relevant job vacancies. Unlike other methods, Pareto optimality method does not assign weights to objectives. Instead, it offers users a variety of optimal solutions, enabling the users to choose without the need for predefined weights. While easily understandable in two dimensions, the method's explainability diminishes with increased complexity in higher dimensions.

In this study, we include the method solely based on skills as a baseline and compare it to other two methods based on predefined weights and Pareto optimality.

3. Methodology

This section describes the methodology, implementation choices and user study setup for the pipeline that matches jobseekers with job vacancies, as illustrated in in Figure 1. The subsections elaborate on the various components of the pipeline.

3.1. Template of skills and values

This section explains how we create a template for skills and values. This template is used to describe both a job vacancy from an employer's perspective and a jobseeker's resume, as illustrated on the left side of Figure 1. For jobseekers, the template lists their skills and values. For job vacancies, it outlines the company values and the required job skills.

We use the European skills standard ESCO v1.1.1[2] to define a template of skills. ESCO defines a hierarchy of skills which are connected to different occupations. From this hierarchy, we select a subset of 24 skills at level 2. These skills fall uniformly under level 1 skills such that we get a broad selection of skills. These skills are specific enough for jobseekers to assess their own ability, yet not too specific that they don't apply to many occupations. A jobseeker's or job vacancy's skills profile is represented by a vector of length 24 with possible numeric items of 0, 0.5, or 1, indicating the possessed or required skill level, respectively.

We define a template for values aligned with Industry 5.0, drawing from a recent report on the conceptual framework of Industry 5.0 [17]. Ten values are chosen and slightly adapted for our application such that jobseekers have a clear idea about the company values. To quantify the values profile for a jobseeker or job vacancy in a vector of size 10, we use a ranking ranging from 0.1 (least important) to 1 (most important), prompting individuals and companies to explicitly express the relative importance of their values. The list of the chosen skills and values are shown in the first column from the row 17 to

[2]https://esco.ec.europa.eu/en

40 and 5 to 14, respectively, in Figure 2. A vector with 34 (24 skills and the 10 values) numeric items is regarded as a profile of a jobseeker or a job vacancy.

3.2. Generation of synthetic vacancy data and gathering of participant data

On the top left-hand side of Figure 1 the vacancy data is portrayed. For this study synthetic vacancies were generated to be suggested to the jobseekers based on ESCO. For each occupation in ESCO a synthetic job vacancy is created. The 24 skills defined in section 3.1 are considered as the skills profile of these job vacancies. Each skill gets a value of 1, 0.5 or 0, if the skill is present in the essential list, optional list or not present in the skills profile of the corresponding ESCO occupation. The 10 values are randomly ranked for each vacancy. This results in 3007 synthetic vacancies, each comprised of an ESCO occupation skills profile and a randomized company values profile. Figure 2 show two examples of job vacancies with their sills and values profiles in the columns C and D.

The other half of the matching system's input, located on the lower left-hand side of Figure 1, comprises the jobseekers' data. As a first exploration to validate the pipeline of Figure 1, we collect skills and values profiles from our colleagues within our data science research group. In line with ethical user-study guidelines of our institution, participants were informed about the research goals, the intended use of their data, and were asked for their voluntarily consent to participate. Thirty participants completed a questionnaire outlining their skills and values using the template in Section 3.1. The participants in this user study are primarily Data Scientists with at least a bachelor's degree, all currently employed, and as far as we know, not actively seeking new employment. They were asked to imagine that they were looking for employment. For simplicity they are referred as "jobseekers" in this paper.

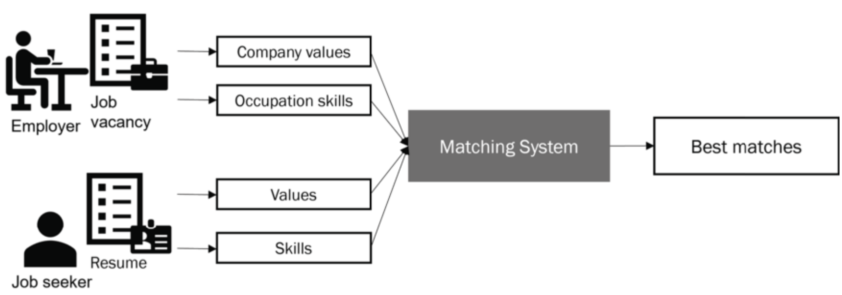


Figure 1. Visualization of the proposed pipeline of matching jobseekers with job vacancies.

3.3. Matching systems

Given the skills and values profiles of a jobseeker and a list of vacancies, a matching system can select a subset of vacancies which are relevant to the jobseeker as shown in Figure 1.

For each jobseeker, two scores per vacancy are calculated; the skills-matching score and values-matching score. The skills-matching score is calculated by taking the cosine similarity between the skills vector of the jobseeker and the skills vector of a vacancy.

	A	B	C	D
1	**Values and Skills**	**Job seeker**		
2			**Vacancy 1**	**Vacancy 2**
3	**Company name**		Company D_1025	Company E_1000
4	Values matching score		0,945454545	0,963636364
5	provides training and education opportunities	1	0,8	1
6	values workers participation in decision making processes	0,9	1	0,9
7	values workers interests	0,8	0,7	0,7
8	values creativeness	0,7	0,9	0,6
9	values innovation	0,6	0,1	0,5
10	includes human centric-values (such as diversity and inclusiveness) in business model and kpis	0,5	0,5	0,4
11	includes sustainability values in business models and kpis	0,4	0,6	0,8
12	ensures human oversight in automated processes	0,3	0,4	0,1
13	makes and promotes 'green choices'	0,2	0,3	0,2
14	designs and implements circular processes	0,1	0,2	0,3
15	**Occupation name**		component engineer	geographer
16	Skills matching score		0,770328887	0,804361815
17	conducting studies, investigations and examinations	1	1	0,5
18	using digital tools for collaboration, content creation and problem solving	1	0,5	0,5
19	writing and composing	1	0,5	0,5
20	advising and consulting	1	0,5	0,5
21	providing information and support to the public and clients	1	0	0
22	organising, planning and scheduling work and activities	1	0,5	1
23	developing objectives and strategies	1	0,5	1
24	programming computer systems	1	0	1
25	analysing and evaluating information and data	1	0,5	0,5
26	liaising and networking	0,5	0	1
27	moving and lifting	0,5	0	0
28	allocating and controlling resources	0,5	0,5	0
29	using digital tools to control machinery	0,5	0	0
30	using hand tools	0,5	0	0
31	documenting and recording information	0,5	0,5	0,5
32	using precision instrumentation and equipment	0	0,5	0,5
33	protecting and enforcing	0	0	0
34	providing health care or medical treatments	0	0	0
35	finishing interior or exterior of structures	0	0	0
36	installing interior or exterior infrastructure	0	0	0
37	transforming and blending materials	0	0	0
38	operating machinery for the extraction and processing of raw materials	0	0	0
39	installing, maintaining and repairing electrical, electronic and precision equipment	0	0	0
40	building and repairing structures	0	0	0
41				
42	**I like these companies' values the most (pick 3-5)**		1	1
43	**I like these roles/occupations the most (pick 3-5)**			1
44	**These vacancies suit me the most (pick 3-5)**			1

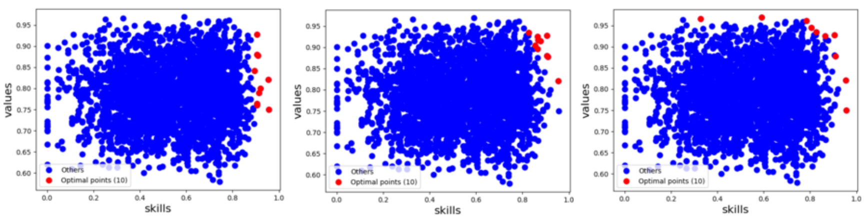
Figure 2. An example a skills and values profile of a jobseeker and two suggested vacancies in Excel format. The first column lists the different value names (row 5-14) and the different skills names (row 17-40). The second column shows self-reported skills and values profile of the jobseeker. The rest of the columns show the suggested vacancies by the different matching systems including their company name, values matching score, values profile, occupation name, skills profile and skills matching score (in the user-study the jobseekers could get up to 15 job vacancy suggestions). To evaluate the suggested job vacancies, the jobseekers filled in rows 42, 43 and 44 in which they had to pick 3-5 companies of which they liked the values, occupation and vacancy the most.

Previous research has shown the effectiveness of the cosine similarity in the context of calculating skills-matching scores [10]. The values-matching score is computed similarly by calculating the cosine similarity between the values vector of the jobseeker and the values vector of a vacancy. Given the two scores of each vacancy, we define three matching systems which select a sub-set of relevant vacancies of size n. Figure 3 visualizes an example of the three matching systems with $n = 10$.

The baseline, *skills-based* matching system only considers the skills-matching score and selects the top n vacancies with the highest skills-matching score. This method does not consider the values matching score. Looking at Figure 3 (a), we see that the vacancies which are highest on the x-axis are selected.

The second, *predefined weights-based* matching system considers both skills and values-matching scores by assigning them predefined equal weights. A matching score is computed by taking the average of the two scores. The top n vacancies with the highest matching scores are selected. Looking at Figure 3 (b), we see that the vacancies in the top right corner are selected.

Third, we consider the multi-criteria system based on Pareto optimality. In this case, no prior weights between skills match and values match scores are assumed. The *Pareto optimality-based* matching system provides a sub-set of vacancies for which one dimension (skills-matching or values-matching score) cannot improve without the other dimension worsening. In Figure 3 (c), we see a spread of selected vacancies in a curved shape along the highest points on the y-axis and x-axis. The p amount of Pareto optimal points, however, can be variable per jobseeker. To get a fixed amount of vacancies per jobseeker, we sample a random sub-set of size n from the Pareto optimal vacancies if p is greater than n. When p is smaller then n, the Pareto optimal points are complemented with $n - p$ other vacancies. These other vacancies are randomly sampled from the vacancies that are Pareto optimal after removing the initial optimal vacancies. This step is repeated if the amount of the new Pareto optimal points is less then $n - p$. The Oapackage 2.7.13 python library [18] was used to compute the Pareto optimal points.



(a) Skills-based (b) Predefined weights-based (c) Pareto optimality-based

Figure 3. An example of the three matching systems. It visualizes the 10 selected vacancies by each system from a large pool of synthetic vacancies for a jobseeker. The x-axis shows the skills-matching score and the y-axis the values-matching score. Note that the x-axis goes from 0 to 1, while the y-axis ranges from 0.55 to 1.

3.4. Evaluation of Best Matches

In order to evaluate which of the three systems works best, the top 5 vacancies for all three of the methods were collected and presented to the jobseekers. Due to overlap of the selected vacancies per system, jobseekers saw 5 to 15 vacancies. The vacancies were presented to the jobseekers in an Excel sheet as the example shown in Figure 2.

Note that only the skills-based and the predefined weights-based matching systems provide an ordering of the results while the third does not. We discard the ordering and present the 5 to 15 vacancies in a random order. Jobseekers then objectively evaluate the suggested vacancies without being able to trace them back to the various matching systems.

Jobseekers were shown their self-reported values and skills and the vacancies suggested by all three matching systems. Each vacancy is made up of a company with values and an occupation with skills. For the values part of the vacancy a synthetic and anonymous company name was presented, as well as a values matching score and the score for each value. For the skills part of the vacancy the ESCO occupation name was shown as well as a skills-matching score and and its corresponding ESCO skills profile.

In the evaluation, the jobseekers answered three separate questions regarding which companies, occupations and vacancies they liked the most. The statements are: (1) *I like these companies' values the most*, (2) *I like these roles/occupations the most*, and (3) *These vacancies suit me the most*. For each statement the jobseekers were asked to pick, respectively, 3 to 5 companies, occupations and vacancies which corresponded to the statement best. A total of 20 jobseekers completed this second part of the questionnaire.

4. Results

First, we examined the influence of values and skills on jobseekers' choices of suitable vacancies in the user study. By assessing the correlation between the chosen companies' values and the chosen vacancies, we gauged the impact of values on their choice of vacancies. Similarly, the correlation was determined for skills by comparing chosen occupations to vacancies. The Pearson correlation between chosen company values and vacancies was 0.2 ($P<0.001$), while the correlation between chosen occupations and vacancies was 0.44 ($P<0.001$). The chosen vacancies are twice as highly correlated with the chosen occupation skills than with the chosen company values. At the same time, we see that both chosen company values and chosen occupation have a low correlation with the chosen vacancies.

Second, we evaluated the performance of the three matching systems. Note that only the results from the three matching systems were shown to jobseekers, and they are required to choose a minimum of three vacancies per statement. This means that the evaluation reflects the relative performance of the systems in comparison to each other, rather than their general performance. Per jobseeker, we calculated the percentage of the suggested vacancies by each matching system that the jobseeker finally selected. On average, jobseekers chose 39.3% of the vacancies suggested by the skills-based system, 50.8% from the predefined weights-based system, and 49.2% from the Pareto optimality-based system. Note that the sum of the three percentages are higher than 100% due to the overlap between the suggested vacancies by the different systems. On average, there was a 0.75 out of 5 vacancies, or 15%, overlap in selected vacancies by the skills-based and predefined weights-based systems. There was a 1.45 out of 5 vacancies, or 29%, overlap between the skills-based and Pareto optimality-based systems. Lastly, there was a 1.95 out of 5 vacancies, or 39%, overlap between the predefined weights-based and Pareto optimality-based systems. The systems considering both skills and values outperform the skills-based system. The predefined weights-based system and the Pareto optimality-based system have similar performances. This might be due to the large overlap of 39% between the output of the both systems.

5. Discussion

This study shows that adding company values as additional selection criterion next to skills for job selection, in line with the Industry 5.0 initiative, fits the needs of jobseekers. Still, the current study has some limitations that need consideration.

First, the scale of the user study was limited, which impacts on the significance of the results. Second, our participants were employed data scientists, presumably not seeking new jobs, which may influence their vacancy evaluations differently than active job seekers. Third, the users could only select from the ranked and selected vacancies by the proposed methods. The sheer volume of vacancies made it infeasible for a comprehensive evaluation of all listings. Accordingly, we could not evaluate whether or not there were vacancies outside the selected sets that would have been preferred by the participants. Finally, our study used synthetic vacancies. Real companies already have an image possibly supported by marketing appearance. Such an image may support, conflict or at least differ from their real company values. In this experiment the users were not influenced by a company image. However, the skill sets were accompanied by an occupation name. The image of these occupations could influence the opinions of the participants of the study.

Future research could explore if these results apply in real-world settings, on a larger scale, and with a broader audience. Moreover, in a real-world setting, there is a need to develop methods for accurately assessing the values of both companies and job seekers. This is difficult because there is often a discrepancy between what people and companies say they value, what they really value and what others perceive them to value. Furthermore, while our study addresses a bi-criterion problem, subsequent research could delve into more detailed analyses by assessing matches based on specific skills and values, either individually or in groups. Another research path could involve the enhancement of matching methods through interactive visualizations, allowing users to customize weightings based on personal preferences. Other similarity measures besides cosine similarity, like metric learning, can also be explored. Finally, our research primarily viewed the job-seeking process from the candidates' perspective. Future studies could investigate the applicability of our methodology in aiding recruiters and companies in the selection process among numerous applicants.

6. Conclusion

This work investigates the relationship between skills and values in the process of selecting job vacancies and proposes possible systems for matching based on both skills and values. Three matching systems to match jobseekers with job vacancies are proposed: one considers only skills, another gives predefined equal weights to skills and values, and a third uses a hybrid intelligence approach based on Pareto Optimality, letting jobseekers decide the relative importance of skills and values. In addition a user-study was conducted to evaluate the relative performance between the matching systems and explore the relationship between values and skills when matching jobseekers with synthetic vacancies.

The results show that skills play a bigger role than values when choosing a vacancy. At the same time, it shows that the best job vacancies only based on skills is often not chosen. Participants seek a balanced compromise between matching both skills and values. Accordingly, systems that consider both skills and values outperform the baseline skills-only system. The system that assigns equal weights and the system based on Pareto optimality perform similarly, likely because there is a significant overlap in their output.

References

[1] Breque M, De Nul L, Petridis A. Industry 5.0. Towards a Sustainable, Human-Centric and Resilient European Industry. In: Policy Brief, DG Research and Innovation. European Commission, Brussels; 2021. .

[2] Hermann M, Pentek T, Otto B. Design principles for industrie 4.0 scenarios. In: 2016 49th Hawaii international conference on system sciences (HICSS). IEEE; 2016. p. 3928-37.

[3] Genz S. The nuanced relationship between cutting-edge technologies and jobs: Evidence from Germany. Policy Brief, Brookings Institution, Center on Regulation and Markets, Washington, DC. 2022.

[4] Cech EA, Hiltner S. Unsettled employment, reshuffled priorities? Career prioritization among college-educated workers facing employment instability during COVID-19. Socius. 2022;8:23780231211068660.

[5] Frambo MB, Kok H, Fon B. The Importance of Corporate Social Responsibility in Recruitment: Between Saying and Doing. Journal of Human Resource and Sustainability Studies. 2021;9(4):608-21.

[6] Jepsen DM, Grob S. Sustainability in recruitment and selection: building a framework of practices. Journal of Education for Sustainable Development. 2015;9(2):160-78.

[7] Wanberg CR, Hough LM, Song Z. Predictive validity of a multidisciplinary model of reemployment success. Journal of applied psychology. 2002;87(6):1100.

[8] Prevoo T, Heyma A, Künn-Nelen A, Montizaan R, Steens S, Goedhart R. Inzicht in skills: een verkenning van Nederlandse initiatieven. Tijdschrift voor Arbeidsvraagstukken. 2022;38(2):261-73.

[9] Rentzsch R, Staneva M. Skills-Matching and Skills Intelligence through curated and data-driven ontologies. In: Proceedings of the DELFI Workshops; 2020. .

[10] Adhikari A, Vethman S, Vos D, Lenz M, Cocu I, Tolios I, et al. Gender mobility in the labor market with skills-based matching models. AI and Ethics. 2024:1-5.

[11] Rácz G, Sali A, Schewe KD. Semantic matching strategies for job recruitment: A comparison of new and known approaches. In: International Symposium on Foundations of Information and Knowledge Systems. Springer; 2016. p. 149-68.

[12] Duan Y, Edwards JS, Dwivedi YK. Artificial intelligence for decision making in the era of Big Data–evolution, challenges and research agenda. International journal of information management. 2019;48:63-71.

[13] Edwards JS, Duan Y, Robins PC. An analysis of expert systems for business decision making at different levels and in different roles. European Journal of Information Systems. 2000;9(1):36-46.

[14] Singh M, Pant M. A review of selected weighing methods in MCDM with a case study. International Journal of System Assurance Engineering and Management. 2021;12:126-44.

[15] Odu G. Weighting methods for multi-criteria decision making technique. Journal of Applied Sciences and Environmental Management. 2019;23(8):1449-57.

[16] Grierson DE. Pareto multi-criteria decision making. Advanced Engineering Informatics. 2008;22(3):371-84.

[17] Peter, Oeij and et al . Conceptual framework of Industry 5.0 to study workforce skills; 2023. https://bridges5-0.eu/publications/.

[18] Eendebak PT, Vazquez AR. OApackage: A Python package for generation and analysis of orthogonal arrays, optimal designs and conference designs. Journal of Open Source Software. 2019;4(34):1097.