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THE DIGITAL TALENT TRAP IN THE SME SECTOR: MAKE OR BUY SOLUTION APPROACH

Lutz SOMMER
Department of Industrial Engineering
Albstadt-Sigmaringen University, Germany
sommer@hs-albsig.de

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Abstract: *The purpose of this study is to answer the question of what options companies have when competing for digital talent. SMEs in particular, with their limited resources and significant backlog in terms of the digitalisation of corporate processes, find themselves in a digital talent trap which threatens to grow ever larger as digitalisation progresses. In other words, the digital talent gap could become a digital talent trap for SMEs in terms of digitalisation. The aim of this work is to derive from this insight a pragmatic and cost-effective solution which, in addition to the highly competitive "buy" option – i.e., classic recruitment via the labour market – offers a "make" option for SMEs that focuses more on their own employee resources.*

The research approach was based on two steps. In the first step, various literature approaches for recording and measuring digital skills were analysed in order to summarise them and derive potential digital talent profiles. The second step was to search for suitable software packages that are able to detect these profiles or skills in company documents. With these data sets, an analysis was carried out in the third step using AI algorithms – created in Python – in order to identify potential digital talents. An anonymised personal data set was used to test the above decision-making process.

The findings show that SMEs could already access powerful, user-friendly and low-cost digital AI tools when searching for digital talent – especially in the search for digital talents within the company. The assumption that only larger companies with the corresponding financial resources can afford this option cannot be confirmed.

The originality of the work lies in the finding that suitable AI tools exist for SMEs to search for digital talent, but that these are not currently being used extensively. Barriers such as prohibitively high costs or the low user-friendliness of AI tools could not be confirmed within the scope of this study.

Keywords: *SME, Digital Talent, Artificial Intelligence, CV-Parsing, Digital Skills*

JEL Classification: *J40, J53, M15, Q34, C69*

1. Introduction

Digital transformation is becoming increasingly important in the global business environment. This results in high demand for employees who have the ability to work in digital teams, bring digital know-how into everyday work and develop digital skills (Deloitte, n.d.). This affects large companies, on the one hand, and smaller and medium-sized companies on the other (Statista, 2023). In SMEs in particular, the battle for digital talent is becoming a critical competitive factor (Redzepi et al., 2018) – especially as government institutions are now also making intensive efforts to recruit skilled workers in the field of digitalisation (Steinbrecher, 2021). The scale of these challenges in SMEs – compared to in large companies – is illustrated by the study of the Institut für Mittelstandsforschung Bonn (2022).

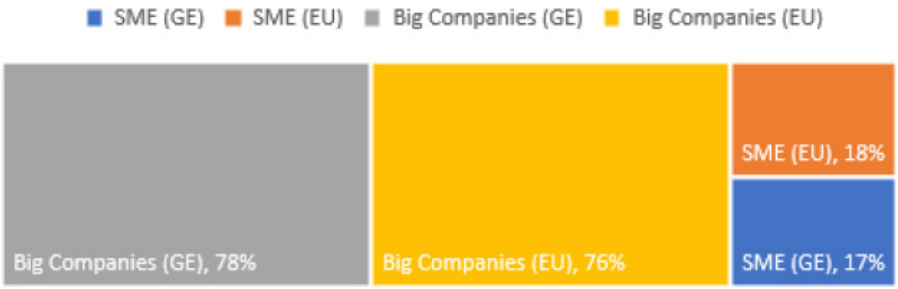


Figure 1. *Percentage of SMEs and big companies in Germany and EU with dedicated ICT experts*

Source: *Institut für Mittelstandsforschung Bonn (2022)*

Figure 1 shows that 78% of all German and 76% of all EU big companies' employees have a background in information and communication technology (ICT), whereas in SMEs only 17% of employees in Germany and 16% in the EU have a corresponding background (Institut für Mittelstandsforschung Bonn, 2022). This status is alarming if the aspect of digital intensity, understood as the degree of implementation of digital technologies and processes in companies (Deflorin et al., 2017), is also taken into account (Institut für Mittelstandsforschung Bonn, 2022).

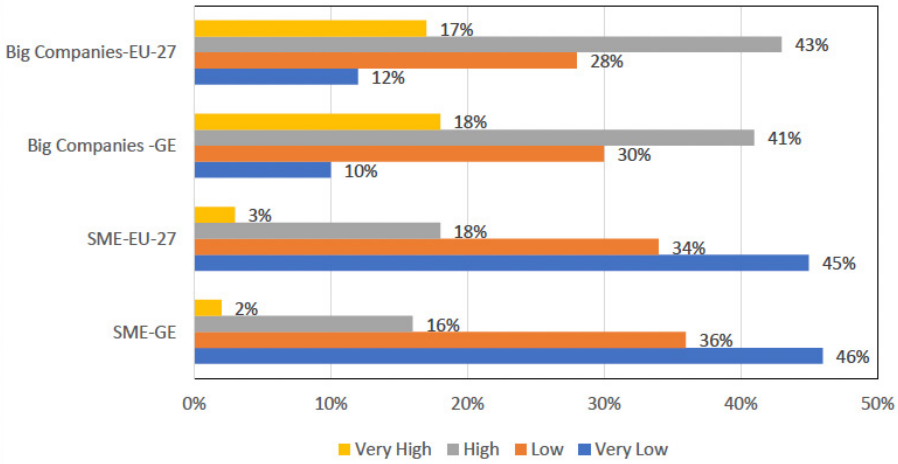


Figure 2. *Percentage of digital intensity in Germany and in the EU in SMEs and big companies*

Source: *Institut für Mittelstandsforschung Bonn (2022)*

Figure 2 documents the comparatively low digital intensity of SMEs compared to large companies (Institut für Mittelstandsforschung Bonn, 2022), which means that under the conditions of the existing competition for digital talent, SMEs will not be able to simply close this intensity gap via the labour market in the foreseeable future. In other words, there is a risk that the digital talent gap will become a trap for companies, as the necessary digitalization depends on the staff in these companies. This poses a recruitment challenge for companies in general and SMEs in particular, as their business models can only be adapted to digital requirements at the required speed with suitable staff. Therefore, the following objectives are pursued within this article:

1. capturing the current state of research in terms of understanding what digital talent is, its importance to the labour market and the different manifestations of digital skills and how they are measured;
2. analysing whether AI algorithms or corresponding AI software packages could make a contribution to closing the digital talent gap;
3. analysing whether the digital talent gap in SMEs should be closed via the labour market (the buy approach) or via internal training (the make approach);
4. analysing whether AI software packages available on the market are suitable for SMEs;
5. analysing the results that can be achieved with cost-effective solutions, illustrated by the example of a use case from a medium-sized company.

The aim is to enable SMEs to close the gap in digital talent largely on their own. In

order to achieve this objective, the first step is to conduct a detailed literature review to record the current state of research. In the second step, suitable AI software packages are identified and applied to a suitable data set. In the third step, a recommendation for action is derived.

2. Literature Review

In short, SMEs find themselves in a competitive situation with larger companies in the "war for digital talent" (Papadopoulos et al., 2022), which poses a challenge. SMEs are in a digital talent trap, so to speak – i.e., either they are prepared to pay higher wages in the competition for digital talent, they focus on training and developing their own employees, or they implement both measures. As mentioned, this creates a "make or buy" decision in the HR departments of these companies. In connection with this, human resources management in both large and medium-sized companies is faced with the question of the company-specific digital skills that will be in demand in the future and how to meet the company-specific need for suitable employees (Deloitte, n.d.). Answering the question of sourcing suitable staff can become a matter of survival for SMEs in the age of digitalisation. Finding suitable digital talents with the ability to implement the process of digital transformation (Arora et al., 2021) in the company (Capgemini, 2017) has gained significant importance in recent years. Companies unable to solve these tasks risk a loss of competitiveness.

2.1. Digital Talent – a Definition

Before the search for talent starts, however, it must be made clear what one is actually looking for. In other words, what makes a digital talent? Is there an accepted definition for the term digital talent? The Capgemini Digital Transformation Institute (2017) explored this question and chose the following definitional approach:

> In our survey, we analyzed Digital Talent in three ways: (a) Hard digital skills (such as data analytics); (b) Soft digital skills (such as comfort with ambiguity) that constitute a "digital-first mindset" and are necessary for a successful digital transformation; (c) Digital roles that have been created as a result of digital transformation activities within an organization or the emergence of disruptive technologies (Capgemini, 2017).

Put simply, they distinguished digital talents from the perspective of hard and soft digital skills and their role. In distinction to this, there are a variety of other terms as well as definitions for employees with digital know-how, such as "digital natives, digital immigrants and digital citizens" (Saleeb & Dafoulas, 2010). Prensky (2001) provided an important basis for this definition – put simply, digital natives and digital immigrants can be distinguished as follows: "Digital natives are the new generation of young people who were born into the digital age, whereas digital immigrants are those who learned to use computers in a phase of adulthood" (Prensky, 2001). Does this mean that every digital

native is also a digital talent? The answer is no, because, as already mentioned, a variety of digital skills are required, not all of which are necessarily acquired by growing up in the digital age. This is also confirmed by studies that define digital talent as follows: "While digital transformation of products, services and processes requires employees with IT-related knowledge, skills and abilities (KSAs) ..." (Gilch & Sieweke, 2021). Another, more general approach is provided by the DQ Global Standards Report (2019).

2.2. Digital Talent – the Gap

Based on the above definition and the corresponding research, a global digital talent gap can be identified, which continues to widen (Capgemini, 2017). A comparable result for Asia was provided by the 2022 Digital Talents Insight survey, commissioned by Huawei, which concluded that "...we are witnessing a rise in the demand of emerging technologies and Digital Talents" (Huawei, 2022). The Arthur D. Little consultancy even goes one step further, and speaks of a "war for digital talent" in its 2022 study (Papadopoulos et al., 2022). In summary, they perceived the lack of digital talent as a threat to the development of companies: "The digital skills shortage presents a tangible risk to every business and organisation – especially since 'software is eating the world' and every organisation is now practically a technology company" (Papadopoulos et al., 2022). The Boston Consulting Group even spoke of the "Year 2035: Talent War in the Digital Age" (Ruan et al., 2017). Experts at PwC also confirmed that there is extensive competition for talent (Papadopoulos et al., 2022).

In sum, it can be stated that a large number of well-known management consultancies assume that currently, and for the next few years, there is extensive competition among companies with regard to the recruitment of digital talents – i.e., that the topic of digital talents is on the agenda of companies. This inevitably raises the question of suitable approaches for the needs-oriented selection or identification of suitable candidates. With regard to SMEs, the make aspect – i.e., the further training of their own staff – plays a prominent role in the recruitment of digital talents, as the buy aspect – i.e., competition with larger companies for suitable staff – often cannot be successfully implemented (European Union, 2022). In other words, the make or buy decision tends to shift towards make for SMEs. This means – in addition to recruitment in the labour market – that the increased internal search for employees who are already digital talents or could become one through education and training is of vital importance. However, with often limited resources and underdeveloped IT competences in their human resources departments, it is challenging for SMEs to carry this out in a cost-efficient and effort-reducing way. This can be achieved, among other methods, by screening the company's own HR data using AI-based software tools (e.g., text mining tools), which are available as open source, freemium (Chełkowski et al., 2021), or fully functional commercial software.

2.3. Digital Talents – Skills

Digital skills are currently named and weighted differently in terms of their importance. This applies both to companies and to studies that deal with this topic. Four different studies that have examined the topic of digital skills will be included in this section. Study 1, from the Capgemini Digital Transformation Institute, divides the relevant skills as follows (Capgemini, 2017).

Table 1. *Digital skills according to the Capgemini Report – Study 1*

Study 1: Soft digital skills	**Study 1:** Hard digital skills	**Study 1:** Digital roles
Customer-centricity	Cybersecurity	Information security
Passion for learning	Cloud computing	Chief digital officer
Collaboration	Analytics	Data architect
Data-driven decision making	Web development	Digital project manager
Organizational dexterity	Mobile application design and development	Data engineer
Comfort with ambiguity	Data science	Chief customer officer
Entrepreneurial mindset	Big data	Personal web manager
Change management	Master data management	Chief Internet of Things officer
	Innovation strategy	Data scientist
	User interface design	Chief analytics officer

Source: *Capgemini (2017)*

The results of Study 2 – the 2022 Digital Talent Insight for hard digital skills (Huawei, 2022) – shown in Table 1 – provide a similar picture, but with key differences in parts. Study 3, the DQ Global Standards Report 2019, speaks of digital intelligence (DQ) as a manifestation of digital skills (DQ Institute, 2019). Finally, Study 4 presents a comparative literature review on 21st-century digital skills" (van Laar et al., 2020).

Table 2. *Digital skills according to Studies 2–4*

Study 2: Hard digital skills	**Study 3:** Digital intelligence (DQ)	**Study 4:** 21st-century digital skills
Artificial intelligence	Digital identity	Technical
Big data	Digital use	Information
Cloud	Digital safety	Communication
Internet of Things	Digital security	Collaboration
5G	Digital emotional intelligence	Critical thinking
	Digital communication	Creativity
	Digital literacy	Problem solving
	Digital rights	

Source: *Huawei (2022); DQ Institute (2019); van Laar et al. (2020)*

Table 2 summaries the main results of Studies 2–4. Further details on skills and roles can be found in the individual studies. Looking at Studies 2–4, it is noticeable that in some cases no distinction is made between hard and soft skills, hard skills are not considered at all, or, as in van Laar et al. (2020), an approach is taken that presents seven digital skills in summary form.

Study 3 is a mixture of different digital skills which can be partly assigned to the above manifestations of skills. In contrast, Studies 1 and 2 provide information on digital skills at the level of specific technical knowledge (Dworschak et al., 2020), e.g., cloud computing. Compared to the above methodological and social competences, evidence of this is easily ascertainable via screening, e.g., via a search for keywords in CVs, assessments or certificates. If redundant technical skills and skills that are more likely to be assigned to methodological and social skills (Dworschak et al., 2020) are removed (e.g., innovation strategy), this leaves 10 technical digital skills (Capgemini, 2017; Huawei, 2022). This results in the following overview of all digital skills.

Table 3. *Digital skills according to Studies 1–4*

Digital skills – main focus: **Methodological & social competence**	Digital skills – main focus: **Professional competence**
Technical	Cybersecurity
Information	Cloud computing
Communication	Artificial intelligence/analytics
Collaboration	Web development
Critical thinking	Mobile application design
Creativity	Data science
Problem solving	Big data
	Master data management
	User interface design
	Internet of Things

Source: *Capgemini (2017); Huawei (2022); DQ Institute (2019); van Laar et al. (2020)*

According to table 3, two groups of competences can be identified: (a) the group of methodological and social competences, consisting of 7 digital skills; (b) the group of professional competences, consisting of 10 digital skills.

2.4. Digital Talents – the Measurability of Skills

The measurability of digital skills is a major challenge (Winsborough & Chamorro-Premuzic, 2016). If we look at criteria such as the effort required to record these skills, tools for recording, and their data availability, it becomes clear that the group of subject-specific digital skills can be evaluated or analysed relatively easily:

Table 4. *The allocation of digital skills according to methodological, social, and professional competence*

Digital skills **Measurability**	Digital skills – main focus: **Methodological & social competence**	Digital skills – main focus: **Professional competence**
Capture of skills	Capture via generation of new data	Simple capture based on existing data
Tools for recording skills	E.g. survey tools, interview or observation tools	Evaluation of certificates, CVs, appraisals, education and training e.g. via data scan
Data availability of skills	Generally not available, as neither direct nor indirect recording is available.	Usually available in parts, as e.g. CVs, certificates are usually available

Table 4 allows for the conclusion that subject-specific digital skills can be collected with little effort via software tools. These tools are often available as free or low-cost software packages. In other words, the use of subject-specific digital skills in the sense of the pre-selection/screening of digital talents via software tools can be a low-effort, low-cost option for larger and smaller companies (Mittal et al., 2020; Affinda, 2023b), even if this is not yet recognised by SMEs in particular (Dahm & Dregger, 2019).

2.5. Digital Talents – Software Packages

If a gap in digital skills has been identified in an internal company analysis, the make or buy options must be examined. In addition to the buy option, the make option is particularly important for SMEs in terms of training and further education (Goulart et al., 2022). Software packages with artificial intelligence (AI) algorithms are suitable for both options (Strohmeier & Piazza, 2015; Tambe et al., 2019; Pan et al., 2022). The question of which software tools are specifically suitable for SMEs requires a detailed analysis. There is extensive discussion in the literature on the application of AI approaches in human resource management (Ćormarković & Dražeta, 2022; Qamar et al., 2021; Alghanemi & Al Mubarak, 2022). For example, the capterra.com (2023) internet platform lists various easy-to-use software providers – specifically for HR (Capterra, 2023) – that use AI algorithms (Riedel, 2020). However, information is necessary in order to carry out the analysis, which is sometimes the greater challenge. For example, the ItyX AG (2023) provider states that "traditional data extraction from documents has a low degree of efficiency: this is because only a fraction of the specialist data in transaction entry in companies can be automatically recognised and utilised via rules and items ...., which leads to high costs and delayed processing". In other words, there are at least two challenges for companies and their HR departments in terms of suitable software: costs and efficiency.

3. Research Question and Hypothesis

From the above, the following options were derived specifically for SMEs in terms of the war for digital talent (Papadopoulos et al., 2022):

- SMEs can recruit digital talents in competition with other companies on the labour market (the buy option), identify digital talents in their own companies and train them accordingly (the make option), or combine both options;
- SMEs can assess the need for digital skills in the company with suitable software packages in order to, among other things, start a needs-based search for digital talents;
- SMEs can use suitable software packages in human resources management for the implementation of the buy option as well as the make option, which are already widely used in SMEs in comparison to larger companies;
- SMEs can choose between different software solutions depending on the resources of the company, opting for open source, freemium or commercial software.

In summary, SMEs do not have a cognition or awareness problem when it comes to finding digital talent. Rather, the challenge lies in the practical implementation of solutions. How can SMEs, with their limited financial resources and knowledge of AI technologies, find a way to use these technologies as a tool for cost-effective solutions to the problem of recruitment? This question is not examined in the majority of publications on this topic. Instead, as illustrated in the literature review section, the focus is primarily on the recognition of the fact that this problem exists, the assessment of size of the gap, or the definition of skills – not on the question of cost-effective, efficient solutions for SMEs. Therefore, the following research question (RQ) can be defined:

> ***RQ:*** *Is it possible to develop an SME-oriented solution with which digital talents can be identified via specific software packages in the sense of a make or buy decision with high accuracy and low cost/effort?*

Based on the research question, two hypotheses can be defined. H1 considers whether there are already enough software packages on the market that meet the requirements of SMEs; H2 checks their accuracy based on a case study.

> ***H1:*** *Easy-to-use software packages with specific AI algorithms exist on the market that enable SMEs to collect data sets on potential digital talents at low cost based on internal company personnel data (the make option) or applicant data (the buy option).*
>
> ***H2:*** *Software packages for the analysis of personnel data with specific AI algorithms exist, which enable SMEs to identify potential digital talents at low cost on the basis of the determined data sets, with an accuracy of more than 80%.*

4. Method

In order to consider H1, the first step was to conduct a literature and internet search in which software packages on the market were examined and evaluated in terms of cost. H2 saw the application of the selected software packages to an anonymised company data set – 166 persons – in order to test their accuracy. In the context of this study, anonymisation meant that names, date of birth, marital status and place of birth, among other things, were removed from the data set. Furthermore, sorting by department was

removed. Missing values in the data set were replaced by integer mean values if only one value was missing. Data sets with implausible values or more than one missing value were removed. The number of records removed was less than 10% of the total. The investigation was carried out on the basis of selected software packages. The following approaches, algorithms and data were used to conduct the study:

- Approach – CRISP-DM for machine learning with Python (Machine Learning Mastery Pty. Ltd., 2023b; Scikit-Learn, 2023a; IBM, 2021): (1) Business & Data Understanding; (2) Data Preparation; (3) Modelling; (4) Evaluation; (5) Predictions.
- Algorithms – (Machine Learning Mastery Pty. Ltd., 2023b): (1) LR – Logistic Regression; (2) LDA – Linear Discriminant Analysis; (3) KNN – K-Nearest Neighbours; (4) CART – Classification and Regression Trees; (5) NB – Gaussian Naive Bayes; (6) SVM – Support Vector Machines.
- Data set – the anonymised data set of sample company A was created based on the assumption that, of the 10 subject-specific, detailed digital skills, 4 skills were relevant for the search for digital talents in relation to sample company A. These skills were selected as: (a) DS-1 cybersecurity; (b) DS-2 cloud computing; (c) DS-3 AI; (d) DS-4 data science. CVs and job descriptions including training and further education documents were used as databases. For each digital skill, the maximum value was 2 (i.e., found in both databases) and the minimum value was 0 (i.e., not mentioned at all). The detailed assessment of the extent of the individual's experience as well as its benefit for sample company A was not the subject of this screening approach, but would be the subject of a subsequent detailed personal interview. Employees with a high score in all four digital skills were classified as digital talents, employees with medium skills were considered potential digital talents, and those with low skills were considered non-digital talents. The scores for the above classification into the three groups were defined by sample company A itself. For this purpose, one can fall back on the experience of assigning values for one's own digital talents.

5. Results

5.1. Hypothesis 1

Based on H1, we sought to investigate whether there are software packages on the market that are able to identify specific data – including skills – from CVs at low cost. CV parsing software tools belong to this class (Buttiker et al., 2021). Indeed (2022), as one of the major platform providers in the HR sector and also a provider of CV parsing software, distinguishes between three main forms of parsing:

- *grammar-based parsing* – "Grammar-based parsing involves using grammatical rules to understand the context of each word in a sentence" (Indeed, 2022);
- *statistical parsing* – "Involves using numeric models to interpret the words in a CV" (Indeed, 2022);

- *keyword-based parsing* – "Works by detecting buzzwords in a CV. They use industry-specific terms to enable recruiters to select suitable candidates" (Indeed, 2022).

The following table provides an overview of 40 AI analytics tools from six 2022–2023 rankings that can extract data from CVs for recruitment purposes (Hemminga, 2021; TrustRadius, 2023; Wade, 2022; Edis, 2023; SourceForge, 2023; GetApp, 2023).

Table 5. *Overview of 40 CV parsing tools*

Software	Number of Rankings*	Homepage
1. Affinda	**4 of 6**	https://affinda.com/
2. Alex Resume	2 of 6	www.hireability.com
3. Bullhorn	1 of 6	https://www.bullhorn.com/de/
4. Burning Glass Lens	**4 of 6**	https://www.burningglassinstitute.org/
5. CleverConnect	1 of 6	https://www.cleverconnect.com/
6. CVViZ	1 of 6	https://cvviz.com/
7. DaXtra	**6 of 6**	https://www.daxtra.com
8. Ducknowl	3 of 6	https://ducknowl.com/
9. eGrabber Hiring	**4 of 6**	https://www.egrabber.com/hiringprospector/
10. Employa	3 of 6	https://employa.org/
11. Flocareer	1 of 6	www.flocareer.com
12. Freshteam	2 of 6	www.freshworks.com/hrms
13. Grove HR	1 of 6	https://www.grovehr.com/
14. HireAbility	**4 of 6**	https://www.hireability.com
15. hireEZ	3 of 6	https://hireez.com/
16. HireLakeAI	1 of 6	www.hirelake.ai/
17. HireXpert	3 of 6	www.talentxpert.com/hirexpert-product.html
18. HireZE	1 of 6	www.hirize.hr
19. Indeed.com	1 of 6	www.indeed.com/hire
20. Insperity Talent Connect	1 of 6	https://brightmove.com/
21. JobConvo	1 of 6	https://www.jobconvo.com/
22. Peoplehum	2 of 6	www.peoplehum.com
23. Rchilli	**5 of 6**	https://www.rchilli.com/
24. RESUMate	1 of 6	https://resumate.com/
25. ResumeMill	1 of 6	www.platinasoft.com/resumemill/
26. Scismic	1 of 6	https://scismic.com/
27. Seekout	1 of 6	https://www.seekout.com/
28. Skillskan	1 of 6	www.arca24.com
29. Smart Recruit Online	1 of 6	https://www.smartrecruiters.com/
30. Sovren	**6 of 6**	https://sovren.com/
31. Superparser	2 of 6	www.superparser.com
32. Tamago	2 of 6	www.tamago-db.com
33. Textkernel	3 of 6	https://www.textkernel.com

Software	Number of Rankings*	Homepage
34. Timetrex	1 of 6	www.timetrex.com
35. Tobu	2 of 6	www.tobu.ai/
36. Tracktalents	1 of 6	https://www.tracktalents.com/
37. Tribepad Applicant	1 of 6	https://tribepad.com/
38. Turbohire	2 of 6	www.turbohire.co/
39. Visiotalent	1 of 6	www.visiotalent.com/en
40. Zoho Recruit	**4 of 6**	https://www.zoho.com/de/recruit/

*Note: * = number of mentions in six examined rankings*

Source: *Hemminga (2021); TrustRadius (2023); Wade (2022); Edis (2023); SourceForge (2023); GetApp (2023)*

Table 5 shows that out of the 40 CV parsing tools examined, only 8 were mentioned in at least 4 of 6 the CV parsing rankings. In sum, the above table thus provides initial indications with regard to frequently mentioned software products without, however, claiming to be complete or objective. Taking into account the reservations mentioned, it was thus possible to derive a trend, at least with regard to 8 market-relevant CV parsing tools on three levels. According to H1, it was then necessary to examine the costs of the software packages available on the market.

Table 6. *Overview of costs per parsed document for different CV parsing tools*

Ranking	Software	Costs per parsed document
1. First Level	7. DaXtra	Upon request
	30. Sovren	10,000 parses/$1,450 per year = $0.145/parse (Sovren, 2023)
2. Second Level	23. Rchilli	6,000 parses/$825 per year = $0.138/parse (RChilli, 2023)
3. Third Level	1. Affinda	6,000 parses/$800 per year = $0.133/parse (Affinda, 2023a)
	4. Burning Glass Lens	Upon request
	9. eGrabber Hiring	5,000 parses/$695 per year = $0.139/parse (Bodapati, 2023)
	14. HireAbility	Upon request
	40. Zoho Recruit	250 active jobs/€50 per year = $0.200/parse (Zoho, 2023)

Source: *Sovren (2023); RChilli (2023); Affinda (2023a); Bodapati (2023); Zoho (2023)*

The results in Table 6 show that cost of the service per parsed document for a CV parsing tool ranges from $0.133 to $0.200. It should be noted here that, when comparing providers, it is important to consider not only the price but also the type of documents that can be processed by the software. As a rule, standard file formats (e.g., PDF, DOC,

DOCX) are processed. However, the ability to process other text formats as well as images (e.g., JPEG, JPG) and the correct processing of the captured data via AI algorithms (Inda, 2021) is also important.

5.2. Hypothesis 2

H1 identifies the various software packages that can be used to read data records regarding digital skills from documents. H2 examines how these data records can be evaluated in such a way that digital talents can be recognised at an early stage in the sense of a make or buy decision when screening. For this purpose, one could use paid, free or freemium solutions. In the context of this study, the free option was investigated, as this would be a suitable option considering the limited resources of SMEs. For this purpose, a free Python code that includes classical AI algorithms (Machine Learning Mastery Pty. Ltd., 2023a) was used to find digital talents inside or outside of the company according to a company-specific requirement profile. The Machine Learning Mastery Pty. Ltd. (2023b) approach was used for this purpose. The analysis of the data set provided the following results (see Appendix A).

	Cybersecurity	Cloud Computing	Artificial Intelligence	Data Science
count	166.000000	166.000000	166.000000	166.000000
mean	0.626506	0.337349	0.578313	0.530120
std	0.742001	0.534327	0.585077	0.684678
min	0.000000	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.000000	0.000000
50%	0.000000	0.000000	1.000000	0.000000
75%	1.000000	1.000000	1.000000	1.000000
max	2.000000	2.000000	2.000000	2.000000

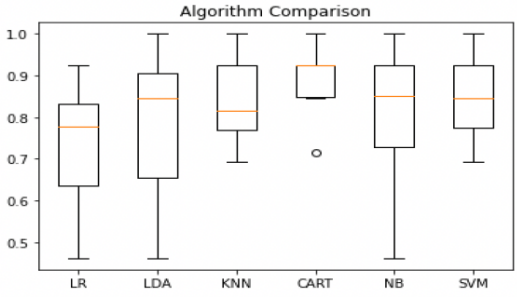
Typ

Digital Talent	12
Non-Digital Talent	99
Potenial Digital Talent	55

dtype: int64

Figure 3. *Descriptive statistics in relation to the data set of 166 persons (Appendix A)*
Source: *Implemented with Machine Learning Mastery Pty. Ltd. (2023a)*

Figure 3 shows that the competences were unequally distributed: competences in AI were present in more than 70 people, whereas competences in the other three areas were significantly less prevalent. When we then modified the freely available Python program from Machine Learning Mastery Pty. Ltd. (2023b) and applied it to the data set of 166 persons from sample company A (see Appendix A) with regard to the identification of digital talents, we received the following picture (Machine Learning Mastery Pty. Ltd., 2023a).



Estimated accuracies for each algorithm:

```
LR: 0.741758 (0.139348)
LDA: 0.780769 (0.160952)
KNN: 0.832967 (0.101677)
CART: 0.895604 (0.080039)
NB: 0.810989 (0.164747)
SVM: 0.840659 (0.099449)
```

Figure 4. *Selection of algorithms*

Source: *Implemented with Machine Learning Mastery Pty. Ltd. (2023b)*

Figure 4 shows that the accuracy achieved by the CART algorithm – Classification and Regression Trees – was 89.5%, while the lowest value of 74.2% was achieved by Linear Regression. In the next step, a validation dataset was used to check these results (Lim & Loh, 2000; Machine Learning Mastery Pty. Ltd., 2023a). This report provides an overview of the "precision, recall and f1-score" indicators (Machine Learning Mastery Pty. Ltd., 2023a).

Table 7. *Classification report, implemented with Machine Learning Mastery Pty. Ltd. (2023b)*

	precision	**recall**	**f1-score**	**support**
Digital Talent	0.67	1.00	0.80	2
Non-Digital Talent	0.93	1.00	0.96	25
Potenial Digital Talent	1.00	0.57	0.73	7
accuracy			0.91	34
macro avg	0.86	0.86	0.83	34
weighted avg	0.93	0.91	0.90	34

The interpretation of these results is also possible for those who are not AI experts, as shown in Table 7. For this purpose, it is recommended to use trustworthy internet platforms such as developer.google.com or Sklearn (2023), which provide simplified interpretations as follows: (a) Precision: "What proportion of positive identifications was actually correct?" (Google Developers, 2023); (b) Recall: "What proportion of actual positives was identified correctly?" (Google Developers, 2023); (c) F1-Score: "The F1 score can be interpreted as a harmonic mean of the precision and recall, where an F1 score reaches its best value at 1 and worst score at 0" (Scikit-Learn, 2023b). If the interpretations presented are applied to the results of sample company A, it becomes clear that the precision and recall values are above 90% in two out of three cases, and the F1 score in all cases is at least 70%. On the basis of these results, the corresponding HR department now has the task of conducting targeted interviews with potential or current digital talents in order to analyse the second group of digital skills. This second group – methodological and social competences – cannot be recorded by means of screening, or if it potentially could then it would involve great difficulty.

6. Discussion

6.1. Hypothesis Testing

The results of testing H1 confirm that there are at least 40 software packages on the market that are capable of extracting data from various documents and making it available for subsequent analysis within a limited time. In addition, it was shown that the costs per parsed document range from $0.13 to $0.20, which are affordable for SMEs. In this respect, the study confirms that a large number of suitable, cost-effective software packages exist that could be applied to both the make and buy options. H2 questioned whether software packages exist that can identify digital talents on the basis of the identified data sets, at low cost, with reduced effort, and with an accuracy of more than 80%. The results show that free software packages exist that are able to analyse data with limited time expenditure. Digital talents were identified based on the data set of sample company A using a CART – classification and regression trees – algorithm with 89.5% accuracy. The F1 score was at least 70%. Thus, in addition to the cost-efficiency and availability of suitable software packages, the suitability with regard to a data set from a medium-sized company was confirmed.

6.2. Limitations

The present study was based on a modified data set that was already available. In other words, the testing of the software packages regarding data extraction from HR documents was not the subject of this work. In this respect, to confirm the present results, it is recommended that the entire process – from the extraction of data from documents to the analysis of the collected data – be carried out with real data from an SME. Furthermore, only one software package was checked for accuracy. Further studies should review a sample dataset with different software packages, both in terms of results and usability.

7. Conclusion and Implications

In summary, it can be said that SMEs must accept the challenge of digitalisation when searching for digital talent. The main finding is that AI algorithms or suitable software packages are available for this purpose at low cost. However, the results of the present work show that the availability of inexpensive tools and SMEs' awareness of the problem of the lack of availability of digital talent does not mean that the problem is solved. The first additional finding is that more problems were discovered, including: (a) a lack of experience in dealing with corresponding software packages in SMEs; (b) the often insufficient digitisation of paper-based documents; and (c) the failure to process personal data records. The second additional finding is that the above software tools can be helpful in terms of analysing personnel data. However, this does not solve the problem of SMEs being exposed to massive competition from large companies when recruiting staff via the labour market – the buy option. Conversely, for the make option – i.e., the training of suitable personnel within the company – these software tools can make a significant contribution in relation to the identification of suitable employees. The third finding is based on the derivation of a guideline that can facilitate practical implementation for SMEs.

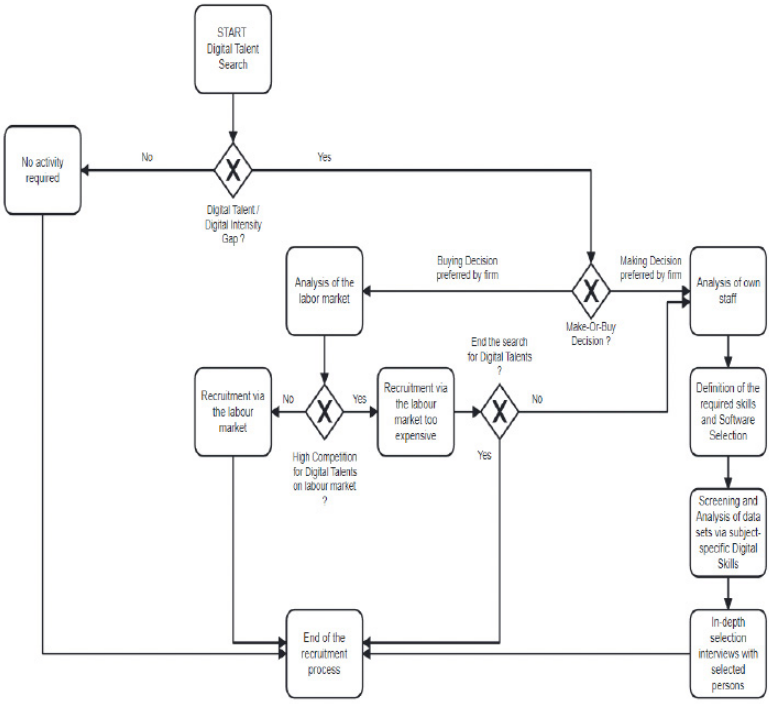


Figure 5. *A simple SME-oriented Business Process Model and Notation (BPMN) for searching for digital talent, implemented with bpmn.io*

The BPMN in figure 5 can be described as follows. (1) EU and German SMEs have a deficit in digital talents and digital intensity compared to large companies, and are thus effectively in a digital talent trap which is increasing with the digital transformation of companies. (2) SMEs can reduce the gap in digital talent through either a make or buy strategy in human resource management, whereby the buy strategy (recruitment via the labour market) represents a major challenge due to competition with large companies. (3) The make strategy (training the company's own staff) seems to be a more interesting option for SMEs, but this requires the search for potential and current digital talents on the basis of certain digital skills in SMEs. (4) Digital skills can be subdivided according to methodological and social competences as well as specialist competences, where the latter can ideally be used for screening available documents in the sense of the pre-selection of digital talent. (5) For the screening of documents (e.g., CV parsing), there is a need for a more comprehensive search for potential digital talents. (6) The data sets resulting from the screening can be analysed with a high degree of accuracy using free, paid or freemium analysis tools with regard to the identification of digital talents. (7) After the successful completion of pre-selection via subject-related digital skills, method- and social-specific digital skills can be used for the final selection of digital talents.

In summary, it can be stated that SMEs can identify and then train and develop potential digital talents within the framework of the digital talent trap primarily via the decision to "make", with limited effort and at low cost. The results also show that neither the costs nor the effort associated with the use of these software packages should represent an obstacle for SMEs. The decision to buy, on the other hand, remains a challenge for SMEs in the current labour market conditions.

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Appendix A.

DS-1	DS-2	DS-3	DS-4	Type
2	2	1	1	Digital Talent
2	1	1	2	Digital Talent
2	2	1	2	Digital Talent
2	1	1	2	Digital Talent
2	0	2	2	Digital Talent
2	2	2	2	Digital Talent
2	0	2	2	Digital Talent
2	2	2	1	Digital Talent
2	0	1	1	Digital Talent
2	2	2	2	Digital Talent
2	0	1	2	Digital Talent
2	0	1	2	Digital Talent
0	0	0	0	Non-Digital Talent
1	0	0	0	Non-Digital Talent
0	0	0	0	Non-Digital Talent
1	0	1	0	Non-Digital Talent
0	1	1	0	Non-Digital Talent
0	0	0	0	Non-Digital Talent
1	0	1	0	Non-Digital Talent
0	1	0	0	Non-Digital Talent
0	0	0	2	Non-Digital Talent
0	0	1	0	Non-Digital Talent
0	0	0	0	Non-Digital Talent
0	0	0	0	Non-Digital Talent
0	0	0	1	Non-Digital Talent
0	0	0	1	Non-Digital Talent
1	0	2	0	Non-Digital Talent
1	0	0	2	Non-Digital Talent
0	1	0	0	Non-Digital Talent
0	0	1	0	Non-Digital Talent
0	0	0	0	Non-Digital Talent
0	0	1	0	Non-Digital Talent
0	0	0	0	Non-Digital Talent
0	0	1	0	Non-Digital Talent
0	0	1	0	Non-Digital Talent
0	1	0	0	Non-Digital Talent
1	0	1	0	Non-Digital Talent
0	1	0	0	Non-Digital Talent
0	0	0	0	Non-Digital Talent
1	0	1	0	Non-Digital Talent
0	0	0	0	Non-Digital Talent
1	0	1	0	Non-Digital Talent
0	0	0	1	Non-Digital Talent

DS-1	DS-2	DS-3	DS-4	Type
0	0	0	0	Non-Digital Talent
0	0	0	0	Non-Digital Talent
0	0	0	0	Non-Digital Talent
1	0	0	0	Non-Digital Talent
0	0	0	0	Non-Digital Talent
1	0	1	0	Non-Digital Talent
0	1	1	0	Non-Digital Talent
0	0	0	0	Non-Digital Talent
1	0	1	0	Non-Digital Talent
0	1	0	0	Non-Digital Talent
0	0	0	2	Non-Digital Talent
0	0	1	0	Non-Digital Talent
0	0	0	0	Non-Digital Talent
0	0	0	0	Non-Digital Talent
0	0	0	1	Non-Digital Talent
0	0	0	1	Non-Digital Talent
1	0	2	0	Non-Digital Talent
1	0	0	2	Non-Digital Talent
0	1	0	0	Non-Digital Talent
0	0	1	0	Non-Digital Talent
0	0	0	0	Non-Digital Talent
0	0	1	0	Non-Digital Talent
0	0	0	0	Non-Digital Talent
0	0	1	0	Non-Digital Talent
0	0	1	0	Non-Digital Talent
0	1	0	0	Non-Digital Talent
1	0	1	0	Non-Digital Talent
0	1	0	0	Non-Digital Talent
0	0	0	0	Non-Digital Talent
1	0	1	0	Non-Digital Talent
0	0	0	1	Non-Digital Talent
0	0	0	0	Non-Digital Talent
0	0	0	0	Non-Digital Talent
0	0	0	0	Non-Digital Talent
1	0	0	0	Non-Digital Talent
0	0	0	0	Non-Digital Talent
1	0	1	0	Non-Digital Talent
0	1	1	0	Non-Digital Talent
0	0	0	0	Non-Digital Talent
1	0	1	0	Non-Digital Talent
0	1	0	0	Non-Digital Talent
0	0	0	2	Non-Digital Talent

DS-1	DS-2	DS-3	DS-4	Type
0	0	1	0	Non-Digital Talent
0	0	0	0	Non-Digital Talent
0	0	0	0	Non-Digital Talent
0	0	0	1	Non-Digital Talent
0	0	0	1	Non-Digital Talent
1	0	2	0	Non-Digital Talent
1	0	0	2	Non-Digital Talent
0	1	0	0	Non-Digital Talent
0	0	1	0	Non-Digital Talent
0	0	0	0	Non-Digital Talent
0	0	1	0	Non-Digital Talent
0	0	0	0	Non-Digital Talent
0	0	1	0	Non-Digital Talent
0	0	1	0	Non-Digital Talent
0	1	0	0	Non-Digital Talent
1	0	1	0	Non-Digital Talent
0	1	0	0	Non-Digital Talent
0	0	0	0	Non-Digital Talent
1	0	1	0	Non-Digital Talent
0	0	0	0	Non-Digital Talent
1	0	1	0	Non-Digital Talent
0	0	0	1	Non-Digital Talent
0	0	0	0	Non-Digital Talent
0	0	0	0	Non-Digital Talent
2	1	1	1	Potenial Digital Talent
2	1	1	1	Potenial Digital Talent
2	1	1	0	Potenial Digital Talent
2	1	1	1	Potenial Digital Talent
2	0	1	0	Potenial Digital Talent
2	0	1	0	Potenial Digital Talent
2	0	1	1	Potenial Digital Talent
2	1	0	1	Potenial Digital Talent
2	0	0	1	Potenial Digital Talent
2	0	1	1	Potenial Digital Talent
2	1	1	2	Potenial Digital Talent
2	0	1	1	Potenial Digital Talent
2	0	1	2	Potenial Digital Talent
1	1	1	1	Potenial Digital Talent
1	1	1	1	Potenial Digital Talent
0	0	1	1	Potenial Digital Talent
2	1	1	1	Potenial Digital Talent
1	1	2	1	Potenial Digital Talent
1	1	0	1	Potenial Digital Talent
1	2	0	1	Potenial Digital Talent

DS-1	DS-2	DS-3	DS-4	Type
1	1	1	1	Potenial Digital Talent
0	0	1	1	Potenial Digital Talent
0	0	1	1	Potenial Digital Talent
1	1	1	1	Potenial Digital Talent
1	1	1	2	Potenial Digital Talent
0	1	1	1	Potenial Digital Talent
1	0	1	2	Potenial Digital Talent
1	1	1	0	Potenial Digital Talent
0	1	0	1	Potenial Digital Talent
1	0	1	1	Potenial Digital Talent
1	1	1	1	Potenial Digital Talent
1	1	0	1	Potenial Digital Talent
1	1	1	1	Potenial Digital Talent
1	0	1	1	Potenial Digital Talent
1	1	1	1	Potenial Digital Talent
1	1	0	0	Potenial Digital Talent
1	0	1	0	Potenial Digital Talent
1	0	0	1	Potenial Digital Talent
1	1	1	1	Potenial Digital Talent
1	1	1	1	Potenial Digital Talent
1	1	1	1	Potenial Digital Talent
1	1	1	1	Potenial Digital Talent
1	1	1	1	Potenial Digital Talent
1	1	1	0	Potenial Digital Talent
1	1	0	0	Potenial Digital Talent
1	0	0	1	Potenial Digital Talent
1	1	1	1	Potenial Digital Talent
2	0	1	1	Potenial Digital Talent
0	1	1	1	Potenial Digital Talent
1	1	2	1	Potenial Digital Talent
1	1	1	0	Potenial Digital Talent
1	1	1	0	Potenial Digital Talent
1	1	2	1	Potenial Digital Talent
1	0	1	1	Potenial Digital Talent
1	0	1	1	Potenial Digital Talent