The Impact of Basic Data Literacy Skills on Work-Related Empowerment: The Alumni Perspective

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The purpose of this research is to measure the impact of data literacy on psychological empowerment in workplace for newly employed graduates. Since data play an increasingly important role in our lives, including the work environment, it incites research on whether data literacy skills, those related to collecting, processing, analyzing, and effectively communicating information retrieved from data models have a significant role in the psychological empowerment of alumni in the labor market. Statistical analysis methods were used to measure the correlation between indicators of data literacy and the psychological empowerment of alumni in their work. Competencies in using data models affect the self-efficacy of newly employed alumni at the workplace, mostly in terms of data-driven communication. The findings were discussed in the context of the increasing significance of the data librarian role as a possible method of supporting students and alumni via librarians who are now more involved in creating the educational outcomes of a given college or university.

Introduction

For years, data have been a driving force in science,[1] and now it is the same in business,[2] where the ability to interpret facts is often the basis for success. In the era of big data, fake news, and misinformation, the sheer quantity of digital resources has become so overwhelming that data are interpreted as elementary components of facts. Therefore, the extraction, gathering, processing, and use of data for analysis and decision making form the basis of self-efficacy that empowers people in everyday life and work.[3] This phenomenon is referred to as datafication.[4] Data—as the smallest numeric unit of information—are now the basis for understanding reality in an objective way. We can observe the effect of datafication in business and social life.[5] Data literacy, considered in this paper as a component of information literacy, stems from mistrust of virtual information, and from users' propensity to gather raw facts (data), rather than accept someone else's interpretation of those raw facts (information). Apart from their specialist knowledge, people might need such competencies as data literacy to function comfortably and confidently in the world of

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virtual information. This may also apply to students during their study programs as well as to a postgraduate workplace where data literacy skills might prove useful in career development.

This research study explores the link between data literacy and work-related empowerment in the case of alumni at the beginning of their professional careers. Data literacy (DL) can be understood as the ability to create and use data models in the workplace. The term should be interpreted as belonging to the broader field of information literacy (IL): that is, critical and analytical thinking about information and its various cultural forms.[6] We consider data literacy to be a research subject located at the intersection of three sets of competences of formula based on the information literacy concept: quantitative reasoning, authentic context, and data/computer science.[7]

Kjelvik and Schulthei[8] have assumed that a person who is data-literate (that is to say, able to understand and evaluate information acquired from authentic data, or facts), should have the ability to combine mathematical concepts with the context of an authentic problem that falls within his/her area of expertise and needs. IT skills, as a third component of data literacy, are intended to facilitate the process of analysis and synthesis of data by representing facts in a virtual form. The virtuality of data, or its coding in a digital form, facilitates communication and the reception of information. Therefore, a person with basic skills of data literacy should, first and foremost, be able to find and effectively manipulate IT tools suitable for his/her needs. However, teaching IT skills is difficult, insofar as users tend to explore database tools only when feeling a genuine need to collect and use data.[9] Therefore, it is problematic to insist that people acquire such skills *in abstracto*, in a purely simulated educational setting.

Psychological empowerment is the process of acquiring and possessing self-confidence in the workplace.[10] Surprisingly, the relationship between the alumni's information literacy and workplace empowerment is rarely studied—both in library science literature and business literature.[11] There is abundant literature reporting on the relationship between the graduates' IL level and employability[12] especially on IL skills at the workplace[13] with a strong emphasis on the requirements and satisfaction of employers rather than on the well-being of the employee in general, which should include empowerment. There is also no shortage of research using diverse methods of assessing the compliance of employers' expectations regarding newly hired employees' IL level with the actual IL and DL level of graduates in various fields of activity.[14] In this case, the interest of researchers has tended to focus on recognizing the needs and expectations of employers, while the state of mental readiness of graduates to take up employment is treated as a side problem.

One of the few, and thus far scarcely quoted, studies devoted to IL-DL-workplace empowerment relations was performed by Debra J. Borkovich and Robert Skovira. Using a complex of qualitative methods, the authors studied the impact of agile technologies deployed in an organization on the employees' ability to cope with information overload. The feeling of being drowned in information was considered by the authors as the main yardstick by which to measure employee comfort and empowerment in the workplace. The study reached the following conclusions:

- data literacy favors employee empowerment, but only if appropriate organizational solutions effectively protect them from information overload;
- an individually high level of DL, defined as an isolated personal feature of the employees (candidates for employees), as in our study, is not enough to give them a sense of control over their professional duties;

- incorrectly prepared implementation of technical solutions for the scope of organizational agility not only blocks the possibility for an employee to use their own DL-IL competence to improve self-efficacy, but also causes harmful distress related to information glut, context collapse, culture shock, and workplace injustices;
- employers ignore the potential of the DL-IL-knowledge-wisdom combination by organizing the information ecosystem in the workplace in such a way that, despite high individual skills and a good level of information awareness, they are nonetheless unable to cope with the flood of information that is being multiplied by agile technologies.[15]

An important finding of the study by Borkovich and Skovira is that DL can by no means be considered an intrinsic variable whose impact does not depend on the context. High DL performance, both subjectively assessed by the employee in the course of self-assessment (as in our study) and verified in practice, stimulated by the real needs that occur in the workplace, is subject to the mitigating, sometimes hampering influence of objective factors, such as irrational management of data and information flows in the organization.

Data literacy is a concept interrelated to information literacy, especially when the area of education and practice is academic.[16] In the DL-IL relationship, the quality of information is crucial. The measure of information quality is the degree of trust in the source (that is to say, ensuring transparency, based on easy identification of the authenticity of facts, speed of understanding the logic of facts, the usefulness of data, and consistency with the requirements).[17] In data literacy, the ability to evaluate source material is the knowledge of mainly (though not exclusively) quantitative techniques of data model development, as a structure describing a set of systematically collected facts.[18] Information literacy is a broader concept in this respect, in which the quality of information is verified much more often by qualitative analytical techniques.[19] Si et al.[20] stressed that data literacy in practice should be supported by critical thinking about information resources, as in information literacy.

"Data literacy today is a competency as essential as information literacy. The two are complementary and clearly form part of libraries' educational role in the furtherance of the significant use of information resources to generate knowledge and innovate. Its inclusion in libraries' instructional programs is therefore wholly justified."[21] Data librarians and embedded librarians might use data literacy skills to build learning programs to integrate with the faculty and demonstrate the fruit of their work, to prevent a situation where the outcomes of their work in academia might be imperceptible.[22]

We have assumed that, since information literacy is one of the conditions for self-efficacy in the workplace,[23] then it is also data literacy—as a set of specific competencies that determine an employee's level of information and communication literacy—that can increase their agency and self-efficacy, which empowers alumni in the workplace. We have limited our study to the basic level of education of quantitative techniques and data modeling, which also draws on information literacy to better understand the context of data.[24] In our study, we omitted the alumni's knowledge of qualitative and sociosemantic text analysis techniques (such as using CAQDAS software) to maintain clarity in the selection of measurement indicators and avoid including information literacy indicators while analyzing the correlation of data literacy and empowerment.

While we may expect data literacy to form a vital component of work-related empowerment, the relationship between data-related skills and employees' psychological empowerment has not been examined. As an initial step to fill this gap, we pose the following two research questions:

RQ 1: How can one identify the relationship between data-related skills of alumni and their psychological empowerment while entering the labor market?

RQ 2: What is the relationship between data literacy skills and factors of psychological empowerment in the work-related empowerment of alumni on the labor market?

Data Literacy (DL)

The differences between data literacy and other forms of literacy and communication skills—such as communication literacy, information literacy, visual literacy, digital literacy, statistical literacy—are difficult to define. The subject matter is as versatile as the terminology used by researchers concerning data, information, and knowledge. Terminology in data literacy is closely related to the context of research in different disciplines.[25] Data literacy does not have a single universal concept that clearly defines its subject or level.

Tibor Koltay[26] suggested differentiating the concept of data literacy in the context of (1) data-related skills education from the context of (2) gaining data-related skills in work practice by information professionals. The former aspect is the ability to match hard digital skills (such as appropriate data processing techniques) with specific information needs. The latter is based on the assumption that a person who is an expert in a given profession, when using data models or other appropriate forms of data processing for a certain time, will at some stage have a high level of data literacy in a familiar range of tasks.

Koltay[27] also suggested that data literacy can be understood analogously to the concept of metaliteracy, which is a range of soft skills and standardized human behavior that increases the effectiveness of acquiring and communicating knowledge.[28] Whether data literacy is an independent competence for an employee or is tantamount to a whole package of metaliteracy skills depends on the adopted educational perspective or practical diagnosis of metaliteracy.

Metaliteracy is a level of conscious communication that supports the understanding of needs in the environment. It is described as "meta" because it tends to be based on informational behaviors and good practices in which the participant feels at ease and is considered effective in his/her environment. Their training is always embedded in a specific professional or social context (for example, academics and students in scientific communication).[29] Data-related skills are hard IT skills for professionals/practitioners, which they adapt to their communication styles. On the other hand, in the educational context adopted by us, data-related skills are an important part of metaliteracy, right next to information literacy, in which data carriers are consciously selected and created, then tailored to different communication needs.[30]

In the case of alumni in the labor market studied by us, data models that universally affect psychological empowerment in the workplace are important. Our research problem is on the educational side of this educational-practical distinction. Educational data literacy in the literature has been linked to problems of research data management,[31] research data services,[32] data curation,[33] bibliography,[34] and data behavior.[35] A significant quantity of data literacy publications concern the educational activities of academic libraries. Data literacy is intended to improve research and learning.[36] There is no lack of guidance in the literature on how to educate and develop knowledge about existing data resources among students and researchers.[37]

In this respect, an important role is played by librarians who implement information literacy principles for data management in higher education.[38] However, this article does not address the issue of data informed learning,[39] which includes the above publications through its academic-oriented context. Our goal is to examine how data literacy education at a late stage of higher education affects work-related empowerment further on in the careers of alumni. In this regard, academic librarians can conduct their educational activities both in the field of supporting data-informed learning during studies and also contribute to increasing the work-related empowerment as an educational outcome of interest supporting alumni who are entering the labor market—thus affecting university success or increasing educational outreach.[40]

There is a paucity of literature referring to the integration of different needs and knowledge of employees in the workplace with data models. In this respect, literature describing engineering features of data models dominates (for instance, in the development and implementation of a model for human behavior related to information security).[41] Data models are a very versatile tool supporting tasks, decisions, and processes in various industries. Choosing the adequate count data model to evaluate management policy translates into the effectiveness of decision-making and communication processes in organizations.[42] Data literacy education is based on the transfer of knowledge between workers about the selection and conscious interpretation of data models, mostly to prevent critical situations and alleviate decision-making anxiety. It has not been possible to find examples of literature describing data literacy models that would be directly suitable for verifying data literacy competencies to identify the level of education in this area in the labor market.

We would like to propose a research model in which data literacy competencies are first taught and graded during the final stage of studies among students of many disciplines, with the impact of these skills on psychological empowerment then being verified when they graduate. In our framework, data-related skills and the psychological empowerment of alumni result in work-related empowerment, which potentially influences self-efficacy in their career development. This might be especially important for academic librarians—data librarians and embedded librarians—as they are involved in generating educational and research outcomes in higher education. We have created an analogy to the data literacy model of Gibson and Mourad,[43] in which the authors describe the levels of student education in the field of life sciences. The authors have developed a multilevel competency model that focuses on quantitative data mining while being so universal that it can be used by students in a multidisciplinary environment. According to the educational concept adopted in this study, data literacy can be taught at three levels: basic, intermediate, and advanced.[44]

Basic data literacy skills include data/computer science, including data collection, calculation, analysis and interpretation, and communication. We measured these competencies with a test at the end of the course for students entering the labor market. Intermediate and advanced data literacy are relevant skills related to authentic context and quantitative reasoning,[45] which are difficult to assess in a multidisciplinary environment. They go beyond the scope of our observations. They were an important part of teaching critical analysis of the usefulness of the data model as part of the process of teaching basic data literacy skills to students. The goal is to verify the usefulness of a basic DL model in measuring DL skills and then to measure its influence on psychological empowerment of alumni in a coherent work-related empowerment framework.

Work-related Empowerment (WRE)

Empowerment is a fundamental concept for employees' efficiency at the workplace.[46] Like data literacy, empowerment is considered from both practical and educational points of view.

The practice of empowerment is a way of motivating employees to demonstrate proactive attitudes so they might initiate action themselves. This understanding of empowerment is important for management. Empowerment can also be based on the ability of employees to use their experiences and competencies creatively to overcome difficulties at work.[47] In our study, we try to measure the impact of the data literacy competence on empowerment based on the measurements of the employee's data literacy knowledge gained during the course that prepares students to effectively enter the labor market.

There are several leading models of workplace empowerment. Laschinger et al.[48] measured the relationship between structural empowerment based on the classical Kanter concept,[49] psychological empowerment according to Spreitzers' most-used empowerment scale[50] and global job satisfaction (global empowerment). In our study, we can only use the scale of psychological empowerment, because it is an indicator that only describes cognitive reactions to the professional environment. Using this scale, we can verify what the employees' job satisfaction means for them and whether the course has an impact on this. Structural empowerment describes the employees' professional environment as sociocultural working conditions that motivate them to perform tasks and be independent. The essence of this empowerment is what kinds of working conditions induce employees to perform their work in meaningful ways.[51]

Psychological empowerment (as opposed to structural empowerment) does not require a high degree of acculturation in the workplace, because it is a description of the mental state, sense of competence and awareness of one's own knowledge, in a context of dealing with professional and decision-making uncertainty.[52] It is a scale dependent on the professional status (structural empowerment) and work satisfaction (global empowerment), but it can be possessed by everyone who enters the labor market.

Spreitzer[53] developed a scale of psychological empowerment, which we used in our study. We want to measure the degree of correlation between the data literacy level and the four indicators of psychological empowerment: meaning, competence, self-determination, and impact.[54] Meaning determines the importance of professional goals for the employee, which are evaluated according to their own standards of needs and behavior. Competence measures the sense of effectiveness within the professional role. It is a set of beliefs about achieving a high level of capability in a given profession. Self-determination describes the degree of self-control over one's own behavior, as well as the employees' sense of influence on their actions, such as the choice of the methods of work and autonomy regarding communication with team members. The impact is the degree to which employees control their environment, and also to what extent they can influence the course of events and decisions.

Spreitzer's article has recently been a source of inspiration in research on employee performance,[55] multiple team membership,[56] trust in the workplace,[57] being educated beyond what is necessary or requested,[58] work engagement, and service performance.[59] The only type of literacy that has been correlated with psychological empowerment is health literacy.[60] We want to broaden our knowledge of the relationship between empowerment and the different competencies required in the workplace by examining its dependence on basic data literacy skills.

Background of the Data Literacy Course

The primary method of data collection was a questionnaire survey (see appendix A). However, before our survey on psychological empowerment, we conducted a data literacy course at-tended by final-year students at Jagiellonian University in Poland entering the labor market. Their backgrounds were varied, including management and communication, political studies, law, philology, philosophy, history, and biology (see table 3). During the course, participants did an individual project based on datasets given to them. At the end of the course, the students completed a data literacy competency test. Their projects and final tests were checked by the instructor, and students received grades used in this study as measures of their data literacy competency (see appendix B). Within six months after completing the course, we emailed each participant to obtain information from them about their situation on the labor market. Second, we sent them psychological empowerment questionnaires, in which working alumni and active jobseekers referred to their professional experience in connection with the acquisition of data literacy.

The competency tests included four main sections taken from the Gibson and Mourad data literacy model[61] (see table 1). All criteria for assessing the data literacy skills of alumni are listed in appendix B. In Collection and Recording, the students were examined in terms of their ability to use instruments and technology to collect and store data and also to select appropriate tools to build a data model. In Calculation, the students' capability of using statistical and logical formulas by using spreadsheets and Data Analysis Expressions (DAX) was tested. In Analysis and Interpretation, the students were checked in terms of extracting statistical information about data by creating calculation fields and measures and conducting statistical tests. In Communication, the students' knowledge was verified regarding their capability of presenting data extracted from the data model in pivot tables, business intelligence dashboards, graphs and datasheets. The students were rated on a scale from 1 to 5. Where 1 means a fail with less than 50% (unsatisfactory), 2 a pass at 51%–60% (satisfactory), 3 a pass at 61%–70%, 4 a pass at 71%–80% (good), and 5 a pass at above 80% (very good).

During the course, 99 students from 9 departments at the Jagiellonian University in Poland formed 9 groups. Each group averaging 11 students had to complete a 12-hour data literacy course. It was necessary to conduct such a course so that their competency could be checked at the end of the course and then to measure its impact on their psychological empowerment via a survey after they graduate. The course was conducted in the Polish language. The sample size was limited by internal regulations regarding didactic projects at the Jagiellonian University. Application to the course was voluntary. The number of students in this project was

TABLE 1
Summary of Data Literacy Variables

Code	Variables	Example items
		Data literacy skills—Rating scale: 1–5
Collection 1 **Collection 2**	Collection	Know how to use instrumentation and technology to collect and store data. Be able to collect and record data accurately using technology.
Calculation 1 **Calculation 2**	Calculation	Know how to conduct mathematical calculations. Be able to use spreadsheets and software to conduct calculations.
Analysis 1 **Analysis 2**	Analysis and interpretation	Know how to describe data with statistics. Be able to describe patterns in data.
Communication 1 **Communication 2**	Communication	Know how to use technology to construct tables and figures. Be able to describe graphical and tabular presentations of data.

limited to 15 people per group. However, even by using all means to promote this course, it was unlikely to achieve this limit with students willing to commit to such an additional activity after classes. Our study is therefore preliminary and represents the quasi-experimental approach with unrelated design.[62] It is assumed that external influences of the labor market are affecting the groups to the same extent during the study.[63] The sample size of 99 is low when it comes to determining strongly significant correlations. Therefore, it is necessary to carry out statistical procedures, in particular the Kaiser-Meyer-Olkin (KMO) test, to confirm the merit of the results.

TABLE 2
Summary of Study Participants

	Number
Gender	N = 99
Female	82
Male	17
Domain	
biology	17
history	7
law	8
management and communication	34
philology	9
philosophy	7
political studies	17
Degree (100% full-time program in Poland)	
Bachelor's (3 yr.)	44
Master's (2 yr.)	49
Master's (5 yr.)	6

Method

In this paper, the survey items were all adapted from previously validated study, but they were adjusted context of the completed course and the use of new competencies in the workplace. The psychological empowerment questionnaire contains four main sections on Meaning, Competence, Self-Determination, and Impact, with three items for each section from Spreitzer's psychological model (see table 3). All items are presented as statements with which respondents indicate their level of agreement on a scale of 1 (strongly disagree) to 5 (strongly agree).The psychological empowerment questionnaire survey (see appendix A) was conducted online and hosted on

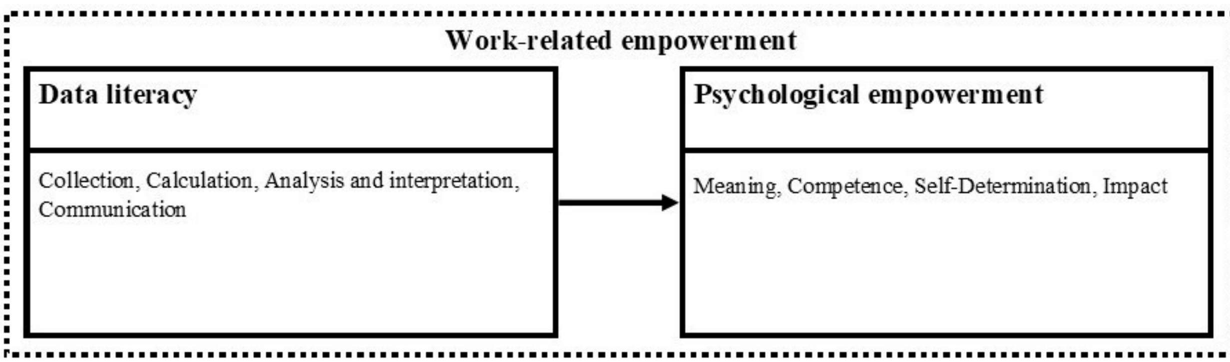
TABLE 3
Summary of Data Literacy Variables

Work-related Empowerment—Likert Scale: 1–5		
Meaning 1 **Meaning 2** **Meaning 3**	Meaning	The work I do is very important to me. My job activities are personally meaningful to me. The work I do is meaningful to me.
Competency 1 **Competency 2** **Competency 3**	Competency	I am confident about my ability to do my job. I am self-assured about my capabilities to perform my work activities. I have mastered the skills necessary for my job.
Self-Determination 1 **Self-Determination 2** **Self-Determination 3**	Self-determination	I have significant autonomy in determining how I do my job. I can decide on my own how to go about doing my work. I have considerable opportunity for independence and freedom in how I do my job.
Impact 1 **Impact 2** **Impact 3**	Impact	My impact on what happens in my department is large. I have a great deal of control over what happens in my department. I have significant influence over what happens in my department.

a server at the Jagiellonian University. Participants accessed the survey remotely via a webpage link. They could only answer in Polish language versions of the survey. Ninety-nine valid responses were collected and entered automatically into a database. The database of DL scores and WRE responses were subsequently organized in spreadsheets and imported into *IBM SPSS Statistics 25* for statistical analyses.

We present a factor analysis of the questionnaire items, and we highlighted the significant dimensions (see tables 4 and 5). Exploratory factor analysis was conducted to check whether all items of the Gibson and Mourad data literacy model (see table 1) and Spreitzer's psychological empowerment model (see table 3) match the work-related empowerment concept (see figure 1). We analyzed the relationships between rotated factors of WRE in the two domains (DL and PE) by using correlation analysis and multilinear regression analysis to explore the nature of the correlations observed based on the level of statistical dependence between them. We have thus confirmed that data literacy and psychological empowerment are interrelated concepts that can be studied together and demonstrate the level of work-related empowerment of alumni (see figure 1).

FIGURE 1
Data Literacy in Work-related Empowerment



This research aims to explore four dimensions of data literacy skills based on the Gibson and Mourad data literacy model (see appendix B) and the relation of these skills with the psychological empowerment factors in the work-related empowerment framework of newly graduated alumni (see appendix A).

Results

We used exploratory factor analysis to check the consistency of the data literacy model and psychological empowerment survey in a work-related empowerment framework. Answering RQ1— How can one identify the relationship between data-related skills of alumni and their psychological empowerment while entering the labor market?—we have to check to see if the variables used to describe the alumni's skills measure their DL competencies within a framework of four factors and eight items (see table 4). It was also necessary to check how the 12 items of work-related empowerment characterize the four factors in the Spreitzer model (see table 5). To answer RQ2 in our study—What is the relationship between the factors of psychological empowerment in the workplace and data literacy skills of alumni at the labor market?—we used normal correlation and multiple regression to measure the effect of data literacy skills on work-related empowerment (see table 7).

In tables 4 and 5 we described the results of exploratory factor analysis separately for describing factors of data literacy and psychological empowerment. The number of variables that should be used in the analysis remained unchanged. We made this decision based on the Jolliffe criterion, according to which the selection of factors describing a given variable should include those with an eigenvalue of >~ .70.[64] For each of the two domains of WRE—the level of DL and PE—factor analysis showed four main components. We used the IBM SPSS program to carry out a scree plot test that selected factors on the steep part of the eigenvalue plot. The factors were extracted using a principal components analysis (PCA) with Varimax rotation. We used PCA Varimax rotation to see if the two adopted conceptual models accurately reflect the two main domains of this study—DL and PE—and to extract the factors that describe them. Through Varimax rotation, we maximize the variance of loads between factors describing two domains and minimize their variance within a concept of rotated factors in WRE.[65] We confirmed that the factors describing DL and PE are not strictly interrelated and that their mutual external relationship can be measured.

TABLE 4
Data Literacy—Factor Analysis (α = .779)

	Rotated Component Matrix[a]				
		Component			
		1	**2**	**3**	**4**
Calculation (α = .977)	Calculation 2	**.966**	.061	.048	.187
	Calculation 1	**.964**	.092	.089	.199
Collection (α = .967)	Collection 2	.036	**.973**	.157	.029
	Collection 1	.123	**.942**	.249	.108
Analysis (α = .959)	Analysis 2	.000	.157	**.970**	–.060
	Analysis 1	.141	.244	**.943**	.013
Communication (α =. 957)	Communication 2	.125	.027	-.043	**.974**
	Communication 1	.272	.108	-.004	**.939**
	Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.[a]				
	[a]Rotation converged in 6 iterations.				

The DL skills analysis (see table 4) extracted four factors that accounted for 81 percent of the total variance in data literacy dimension of WRE. The Cronbach alpha reliability ratio for the DL competence test was more than .70 and, for all selected variables, more than .90. The remaining factors are Calculation, Collection, Analysis, and Communication. The sample adequacy based on the KMO's test should be considered meritorious at 0.718, which means a representative dataset describing the data literacy of alumni.

In the case of the work-related empowerment questionnaire, we extracted four factors that accounted for 84 percent of the total variance in results. For the items loaded onto the factors—Impact, Competence, Self-Determination, and Meaning—the Cronbach's alpha ratio for each is more than .80 and in general is equal to .931, which falls within the scope of very high reliability.[66] The sample adequacy based on the KMO's test should be considered meritorious at 0.863, which indicates that, despite the small sample size, sufficiently representative and descriptive data on the psychological empowerment of alumni have been obtained.

TABLE 5
Work-related Empowerment—Factor Analysis (α = .931)

	Rotated Component Matrix[a]				
		Component			
		1	2	3	4
Impact (α = .891)	Impact 1	**.831**	.298	.160	.157
	Impact 2	**.829**	.098	.264	.241
	Impact 3	**.784**	.252	.338	.191
Competence (α = .842)	Competence 3	.106	**.810**	.315	.114
	Competence 2	.286	**.790**	.309	.234
	Competence 1	.384	**.636**	.149	.255
Self-Determination (α = .902)	Self-Determination 2	.231	.280	**.856**	.163
	Self-Determination 1	.349	.402	**.682**	.206
	Self-Determination 3	.523	.291	**.668**	.161
Meaning (α = .841)	Meaning 3	.211	.463	.030	**.782**
	Meaning 1	.195	–.086	.434	**.764**
	Meaning 2	.252	.491	.109	**.751**
	Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.[a]				
	[a]Rotation converged in 6 iterations.				

Table 6 shows the mean scores of DL skills related to the respondents' degree of agreement with given statements about work-related empowerment. The scores indicate strong agreement (> 3.7) with items related to Competence and Meaning, which are significantly correlated at .625. Respondents mostly agree that after the course the work they want to do gained more importance to them, and it became more meaningful to their professional careers (3.78). Alumni also agreed that after the course they became more confident about their ability to be specialists in their profession and became self-assured about their capabilities and skills related to job activities (3.72). There was slightly less, but still strong agreement with statements relating to Impact and Self-Determination (> 3.5), meaning that they rather agree that after the course they achieved some sense of autonomy and independence in dealing with job activities, which also had a significant influence on their sense of self-efficacy regarding having an impact on what happens in the work environment (see table 7, .698).

In general, the mean scores on data literacy skills are significantly greater than the empowerment variable, because student assessment is a process that is dependent on the teacher's opinion. However, as the result of variance and the Cronbach's alpha (.779) shows, while the average indicator of alumni competencies was very high, they generally also agreed that they felt these competencies can play an important role in their professional lives. All variables describing psychological empowerment can be considered interrelated at high correlation measures .560–.698. This means that all PE indicators developed in a very similar way in alumni after the course.

The practical skills results in Calculation 1 were the most difficult for students (~4.2), but, according to the factor loading analysis, they were the most representative to the theoretical knowledge about calculation functions—(Calculation 2) (see table 4). Difficulties of acquiring

TABLE 6
Descriptive Statistics

	N	Mean	SD	Variation
Collection	99	4.561	.7080	.5013
Calculation	99	4.202	1.0049	1.0098
Analysis	99	4.414	.8331	.6941
Communication	99	4.667	.6813	.4643
Meaning	99	3.778	.8598	.7392
Competence	99	3.721	.9144	.8361
Self-determination	99	3.505	.9372	.8784
Impact	99	3.657	.9588	.9194
Valid N (listwise)	99			

the theoretical knowledge about calculation functions was most representative of the learning outcomes associated with data literacy regarding the count data models.

Differences in the degree of skills are noticeable between the DL variables taken into account (4.2–4.7). Students are best at communicating information based on data used in business intelligence (BI) dashboards (~4.7). This was the skill with which they most easily identified and combined their needs. They demonstrated a very high level of both theoretical knowledge and practical skills in creating BI reports and pivot tables based on data from the count data model. The effectiveness of data-driven communication is dependent on the selection of appropriate logical and statistical functions. Therefore, the Calculation and Communication (see table 7) variables are characterized by the highest correlation in the WRE model (.464).

Table 7 shows correlation coefficients between the variables of the DL and PE models. The least correlative variable is Analysis, which was generally considered unrelated to the variables in both models, except for data collection skills. The correlation between Analysis and Collection is the second-highest internal correlation in the DL model (.454). The importance of this correlation results from the fact that conducting statistical analyses describing

TABLE 7
Correlations between Data Literacy Skills and Work-related Empowerment Measures

	Mean	SD	Collection	Calculation	Analysis	Communication	Meaning	Competence	Self-determination	Impact
Collection	4.5606	.7081	1	.287**	.454**	.264**	.162	.097	**.210***	.144
Calculation	4.2020	1.005	.287**	1	.231*	**.464****	**.263****	**.395****	**.320****	**.297****
Analysis	4.4141	.8331	.454**	.231*	1	.097	–.010	.044	.041	–.003
Communication	4.6667	.6814	.264**	**.464****	.097	1	**.212***	**.359****	**.362****	**.258***
Meaning	3.7778	.8598	.162	**.263****	–.010	**.212***	1	.625**	.566**	.560**
Competence	3.7205	.9144	.097	**.395****	.044	**.359****	.625**	1	.678**	.607**
Self–determination	3.5051	.9372	.210*	**.320****	.041	**.362****	.566**	.678**	1	.698**
Impact	3.6566	.9589	.144	**.297****	–.003	**.258***	.560**	.607**	.698**	1

*Correlation is significant at the 0.05 level (2-tailed).
**Correlation is significant at the 0.01 level (2-tailed).

facts requires excellent knowledge of the source and type of data that the developed model integrates. Unfortunately, both of these skills have a very small average impact on the work-related empowerment of alumni—well below the average correlation level in this framework (see table 7). The Pearson correlation between the sum of the DL test results and the overall WRE level, calculated as the sum of the values of the four variables, was significant at $p < .01$ and amounted to .372. This is an average overall correlation between the DL skills level and the empowerment of alumni in the labor market.

The DL model variables most correlated with the WRE variables are Calculation and Communication (~.30). Their strong interdependence (.464), as well as the fact that they are respectively the most difficult and easiest competences for students (see table 6), can influence the subjective feelings of satisfaction with gaining such skills. The students had difficulty in understanding and using calculation formulas. After overcoming this difficulty, they were able to translate the calculation results into a relatively easy to construct and interactive BI product. In this way, they transformed the collected facts into a virtual form accessible to many professional users. This impact seems to be confirmed by the average level of correlation between the Calculation and Communication variables with the Convertible Competency (.395/.359), Self-Determination (.320/.362), and Impact (.297/.258). These are significant correlations at the $p < .01$ level. The three WRE variables correlate with each other at a high level of .60–.70. Their average dependence on the level of Calculation and Communication (>.30) indicates that they may give students entering the labor market a sense of the importance of their competencies, as well as greater determination to pursue their profession.

The second noticeable dependence in the model, albeit not so important, combines the competencies of DL—Calculation and Communication—with the Meaning variable in the WRE model (.268/.212). The standardized regression coefficients of WRE are significant at $p < .05$. These are important relationships, but they should be considered as weaker. It can be inferred from this result that these skills have little effect on the interpersonal meaning of the profession. According to our results, the diagnosed DL competencies have very little influence on the awareness of the profession's mission.

To examine the effect of Calculation and Communication variables while controlling the effect of the WRE dimension, multiple regression of two DL skills on the PE was performed. In our study, both the Calculation and Communication variables explain the variations in the WRE results. The models' adjusted R^2 is .216, and the F values are significant at $p < .01$. We then can assume that only in the case of data-related calculation and communication skills can we predict that the level of DL skills will influence the psychological empowerment of alumni at the workplace. In our case, it is ~22 percent of the variance in work-related empowerment (WRE). This is especially important for data librarians, who will have to justify to the faculty the potential outcome of creating data literacy courses.

It should be remembered that the data literacy test and empowerment surveys took place at very remote time intervals, which minimizes, at least partially, any potential response bias. If the regression values we demonstrated were based on one DL-WRE survey, it would most likely be much higher. The resulting impact value is not high enough to conclude that DL and WRE are closely related. However, this is a background correlation that is important enough to confirm at least the partial impact of two types of data literacy skills (Calculation and Communication) on the three areas of work-related empowerment (Competency, Self-determination and Impact) of alumni.

Discussion and Conclusion

This exploratory research examined the relationship between data literacy skills and work-related empowerment. We also explored the relative impact of two data literacy skills with the highest correlations in our framework (Calculation and Communication) on the work-related empowerment indicators. Referring to RQ1, the analysis extracted four sets of data literacy skills that in general might be used not only to improve data literacy among alumni but also to empower them at the beginning of their professional careers. This model is useful to measure the basic level of skills in data literacy, even in such a multidisciplinary group as alumni. It is worth mentioning that an experimental approach to measuring data literacy skills was taken. Further studies involving the proposed framework of work-related empowerment should be conducted on a much larger group to measure the impact of data literacy in different domains of alumni specialization.

Knowing that the technique presented by us yields reliable information, the implication for us is to reuse this framework for further research in different domains. The data literacy of alumni on the labor market can be characterized by the ability to create a data model to collect data (Collection), to select and use logical and statistical functions adequately to work-related needs (Calculation), to use statistical analysis to describe and verify data outputs (Analysis), and to conduct data-driven communication based on dashboards, pivot tables, and visualizations (Communication). Each skill should be also graded by taking into account the student's theoretical knowledge necessary to develop a data-based project. This causes difficulty in reproducing the procedure in the workplace. The value of the presented educational-research model is important for fulfilling the role of data librarians as educators who can use it to monitor their educational outcome contributing to the success of universities through the preparation of alumni for the needs of the labor market.

We recognize that work-related empowerment is a measurable outcome that can be determined by four variables such as Meaning, Competence, Self-determination, and Impact, but not all of them are correlated with DL skills. However, a hypothesis can be suggested that, along with a more profound acculturation of the employee in the organization, the significance of data literacy competencies for the level of empowerment will increase, because the recognition of the employee in communication with colleagues and the informal learning of the employee will also grow. Data literacy competencies, especially in the field of data-based communication, require involvement in organizational problems.[67] The correlation between data literacy and work-related empowerment skills may increase with the duration of employment and the conditions for demonstrating one's competencies. Therefore, the second implication of our study is to measure the level of data literacy in the workplace, as a factor that depends on sociocultural organizational circumstances characterized by structural empowerment. To reproduce a procedure for diagnosing the work-related empowerment level, it is necessary to choose one of the two ways described in the previous paragraph and include structural empowerment variables in the analysis.

Referring to RQ2, this study shows a positive and significant relationship between the data literacy level and degree of psychological empowerment in the framework of work-related empowerment. It should be noted that the results of the statistical analysis are based on a small sample for determining significant correlations. Further research must be conducted to confirm that the ability to create calculation formulas and data-driven communication are competencies that affect all four work-related empowerment indicators used in the study.

The selection of logical formulas (that is, combining the data structure with a specific need) has a theoretical impact on the sense of ability to perform the job.

The second key aspect of the data literacy, data-driven communication was particularly interesting for all studied groups of students. The calculations were better handled by science students, who showed more commitment during the course. Data-driven communication techniques were an important subject for all students, including humanities; they showed a high level of skill in creating business intelligence dashboards and other reports. Technology for using data models and communication based on data or BI products is becoming increasingly popular.[68] However, their use is very limited without the knowledge of calculation formulas and the knowledge of data model capabilities in this area.[69] Therefore, it should be remembered that the data literacy model used is a set of internally integrated competences. Even if one or two competencies will have a greater impact on work-related empowerment, the effectiveness of their learning depends on knowledge in the whole data literacy model.

Implications and hypothesis: a study of the wider information literacy and data literacy competencies in the workplace, combined with a study of structural and psychological empowerment, should be carried out to check what proportion of the factors influencing the work-related empowerment are data literacy skills. Data literacy has a cross-disciplinary impact on work-related empowerment, but business intelligence technologies like interactive dashboards are most often useful in analyzing data-driven communication. Good orientation in business intelligence systems and the ability to extract information in the data model affects the analysis.[70] Extending data literacy and work-related empowerment research to further business areas, different market sectors, and academia has the potential to increase our awareness of the impact of datafication on employees, business, and society.

Data librarians as active or embedded members of a faculty can now use the proposed work-related empowerment framework to check and compare data literacy competence of students, alumni, and academic staff and measure its impact on their work-related empowerment or academic empowerment, as this model can be also useful within the academic environment. Through data literacy outcomes, librarians can get more involved in increasing the general efficacy of higher education institution by demonstrating measurable outcomes in work-related empowerment to the faculty. Having such a framework might be helpful given that "the higher the level (or degree) of librarian integration, the more likely librarians can contribute to the growth and success of their library and ultimately the mission and goals of their home institution."[71] This framework can be useful in the three areas of embedded librarianship body of work proposed by Wu and Mi. We propose three hypotheses for further research in librarianship practice. Faculty members or the department might be unaware of the true value or merit of embedded librarians,[72] so the following hypotheses may be worth checking:

- *Involvement hypothesis*: The development of a data literacy course and presentation of its potential impact on educational or research outcomes will be a way to connect the librarians' work to their important "customer" outcomes. Will our work-related empowerment framework be helpful for librarians to fully integrate into a specific academic unit and understand their needs?
- *Support hypothesis*: Measuring data literacy skills of academics and students will be the right strategy to build close relationships with faculty members from multiple disciplines to improve the quality of teaching, learning, and research.

- *Collaborative hypothesis*: The promotion of embedded/data librarian services based on potential learning outcomes in data literacy can be useful to maintain the professional image of librarians and increase the frequency of collaborative work with faculty and students.[73]

Students and academic staff prefer to gain knowledge in data literacy from colleagues. Often one of the least preferred options for consulting their data-related skills is to contact a librarian or information specialist.[74] Given that 50 percent of faculty members are either not sure or not confident in their data management skills or they need more guidance and education on best practices in data literacy,[75] our work-related empowerment framework could be considerate as a "passkey" to the faculty. Embedded librarians need to make a specific data literacy offer and convince the university authorities about the importance and outcomes of data literacy education. These outcomes are tacit as its concept is based on psychological factors and self-efficacy measures, so academic librarians might face a challenge in explaining its value in the indirect economical context of institutional effectiveness.

The digital revolution, referred to as the fourth industrial revolution 4.0, consists in implementing cyberphysical systems and the rapid processing of huge datasets.[76] The gradual implementation of solutions of economy 4.0 causes a significant increase in the demand for employees with very high competencies classified as information literacy, especially data literacy. As far as our research indicates the existence of a positive correlation between the level of data literacy skills and psychological empowerment in the workplace, its practical implication is to demonstrate the necessity to assess the alumni's level of data literacy competence because this parameter is a relevant gauge of university education success that determines the graduate's efficiency in the workplace. Any academic community (students, teachers, librarians), and its large pallet of formal and informal methods of teaching data literacy, is possibly able to determine the status (position) and achieved results of graduates on the labor market. The review of the literature on the subject shows that academic librarians are becoming increasingly involved in data literacy education processes. The data librarians may contribute to the data literacy affects teaching outcomes of the university.[77]

APPENDIX A
Psychological Empowerment Measures (Likert Scale 1–5)

Based on my experience in using the skills and knowledge gained during the course, I can say that:

Meaning

The work I do gains more importance to me.
My job activities are personally more meaningful to me.
The work I do is more meaningful to me.

Competence

I am more confident about my ability to do my job.
I am self-assured about my capabilities to perform my work activities.
I have mastered the skills necessary for my job.

Self-Determination

I have easily gained significant autonomy in determining how I do my job.
I can be more decisive on how to go about doing my work.
I have considerable opportunity for independence and freedom in how I do my job.

Impact

My impact on what happens in my department is large.
I have a great deal of control over what happens in my department.
I have significant influence over what happens in my department.

APPENDIX B

Code	Factor	Example Items	Open Test Questions	Task in Project
Data Literacy Skills—Evaluation Points: 1–5				
Collection1	Collection	Know how to use instrumentation and technology to collect and store data.	Describe the commercial and open tools that can be used to create data models and in what situations they are useful.	—
			Point usability features of Power Pivot add-on in creating and combining data models in MS Excel environment.	
Collection2		Able to collect and record data accurately using technology.	—	Connect the data model to the source on the SQL server.
				Prepare the data for analysis and clean up from errors.
Calculation1	Calculation	Know how to conduct mathematical calculations.	Explain the calculations of basic statistical measures like mean, standard deviation, coefficient of variation.	—
			Match DAX and Excel functions to mathematical formulas.	
Calculation2		Able to use spreadsheets and software to conduct calculations.		Use the spreadsheet formulas to transform the data according to the needs of the data model.
				Use Excel's mathematical, textual, and logical functions to calculate statistical values.

Analysis1	Analysis and interpretation	Know how to describe data with statistics.	Explain basic reliability tests and what statistical formulas are needed to perform it in spreadsheets.	
			Describe the differences in creating descriptive statistics in statistical packages and in Excel.	
Analysis2		Able to describe patterns in data.		Perform data correlation and reliability analysis using Excel formulas.
				Create a relational database model that allows you to gather data to automatically perform statistical analysis.
Communication1	Communication	Know how to use technology to construct tables and figures.	Describe the usefulness of pivot tables and charts depending on the data source.	
Communication2		Able to describe graphical and tabular presentations of data.		Create a BI dashboard describing the collected data and create an explanatory operational information resource as a help for the dashboard user.

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