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Empowering Nonprofit Managers: The Impact of Technical Training on Big Data Integration in Business Operations

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Abstract

This nonexperimental survey-based online quantitative study measures how technical training for nonprofit managers affects their use of big data technology. The research employs the Unified Theory of Acceptance and Use of Technology as a theoretical framework to evaluate whether nonprofit managers receive adequate training on big data technology. By adopting a quantitative approach, this study aims to address the knowledge gap regarding the technical training that nonprofit managers receive in utilizing big data technology. Data is one of the most valuable resources available today, and nonprofits need to keep pace with advancements in big data technology. To make informed decisions that maximize their societal impact, nonprofits must leverage big data technology to monitor and evaluate their program activities. Nonprofit managers can enhance their effectiveness by using big data technology to gain insights into solving issues related to education, unemployment, poverty, and social exclusion. The study seeks to determine how technical training (facilitating conditions) for nonprofit managers who utilize big data technology differs from that of managers who do not. This research may help close existing gaps in knowledge regarding the use of big data technology and the technical training necessary for managers. The study is centered exclusively on nonprofits in the United States, which would restrict the generalizability of the findings in other organizational settings by potentially limiting its broader applicability.

Keywords

UTAUT, Facilitating Conditions, Technical Training, Big Data Technology, Skills, Learning

1. Introduction

Nonprofit professionals use the available time and resources to support their programs by completing essential business operation goals that require technical training (Santos et al., 2021) that enhance decision-making and maximize their impact on society by leveraging big data technology to monitor and evaluate program activities. These initiatives aim to address community issues such as social exclusion, poverty, unemployment, and low educational attainment. Additionally, supporting to obtaining the technical training necessary to achieve competence, confidence, and technological capability (Indrawati & Khalik, 2020) where training interventions are designed to encourage the adoption of technology, which can help develop informed business leaders who embody and fulfill the organization's mission (Duan & Deng, 2021).

It is imperative to comprehend the effects of training in the rapidly evolving big data technology era on the labor market (Fritsch et al., 2021) and the current technological developments throw professionals' knowledge off balance, increasing the risk of unemployment and rendering professionals obsolete in the labor market. Acquire new skills and knowledge to stay current with emerging technologies and obtain insights that quantify and measure the programs (Kar et al., 2021), giving professionals the tools they need to understand and apply these methods to gather data and make choices that enable program results to be accurately tracked (Mayer, 2019). It is important to get timely, relevant, and up-to-date training in big data technology to acquire flexible and developable skills (Papa et al., 2021) to assist in finding helpful information through big data technologies, thereby reducing the possibility of program errors.

2. Literature

To support technological advancement, it needs opportunities for education, training materials, and technical support (Chin et al., 2020) with a clear goal and advantages to raise awareness of big data technology so they can participate in initiatives that support their company's social objective. Finding the correct program information quickly by devoting a substantial amount of time to searching, filtering, and probing is an example of how using data without big data technology usually necessitates more training and education (Chin et al. 2020). Hands-on training is crucial in the workplace to become competent and develop resourcefulness with access to sufficient training and equal opportunities for professional growth. The professional's knowledge and skills must be updated through hands-on training whenever a need for knowledge requests emerges (Bammidi & Hyndhavi, 2019). Nelson (2020) asserts that meeting social missions in business management will be the future requirement and using information technology training is essential to meeting program objectives and facilitating quick learning of the requirements of big data technology.

According to Peñarroja et al. (2019), the literature search was prompted by whether sufficient technical training supports the adoption of big data technologies with a lack of capacity restricting the ability to track results, manage data, and evaluate the effectiveness of their programs. Research indicates that few assess the programs, and even fewer professionals are trained in evaluation methods (Shapiro & Oystrick, 2018). The inadequacy can lead to failures and the inability to sustain community-focused programs due to insufficient training (De Rezende Francisco et al., 2019; Gong & Janssen, 2021).

The study identifies three key pillars for nonprofits to adopt big data technology successfully: 1) digital education, skills, and culture; 2) training infrastructure and technology interaction; and 3) long-term partnerships and ecosystems (Brunetti et al., 2020). It emphasizes that digital transformation requires more than standalone interventions, as nonprofits must first focus on training and adapting organizational vision before investing in technology. The study also highlights the need for technical and soft skills to support data-driven decision-making. Key tools for big data include data analysis software and visualization tools, and a learning, collaboration, and agile culture must be developed to leverage big data technology fully integrated. Challenges include a lack of management awareness, underfunded talent initiatives, and a disconnect between senior leadership and middle management (Kavanaugh, 2020).

Fostering a culture of lifelong learning and adaptiveness is essential for navigating the evolving digital landscape. The fast-paced changes in today's business environment highlight the growing demand for skilled professionals, especially as big data technology emerges (Lee & Kim, 2020). Successful adoption requires a collaborative approach between public institutions, educational entities, industry, and community organizations (Persaud, 2021), which needs hard and soft big data skills to drive data-informed decisions. However, qualified professionals are scarce (Anderson & Williams, 2019), and many lack competency evaluations to help assess and address skill gaps, which hinders progress. Prioritize talent development and training programs supporting technical and interpersonal competencies (Nair, 2019) to fill the generational differences also affect learning preferences, with Gen X favoring flexibility and self-direction and Gen Y being highly motivated when given engaging, purposeful instruction (Lowell & Morris, 2019).

3. Method

The Senior executives, IT managers, or business managers employed by nonprofit organizations across the US make up the target population (see **Table 1**). The data was gathered from the target population using a random sampling technique (see Demirel 2022), and survey tool was asked to recruit study participants. As stated by the U. S., 1,369,470 nonprofit managers, or 8 percent of the total, are listed by the U.S. Bureau of Labor Statistics (2022) (see **Table 2**). Sixteen million people are working for nonprofit organizations in the US, according to Ariella (2022). Inviting participants to collect data to create a sample population comes next after determining the target population.

Table 1. Nonprofit target population.

Managers	Population	Nonprofit target population
Computer and information research scientists	126,700	12,670
Computer and information systems managers	509,100	50,910
Financial managers	730,800	73,080
Top executives	98,100	9810
Total jobs	1,464,700	146,470

Note: Nonprofits account for roughly 10% of jobs in the United States (U.S. Bureau of Labor Statistics, 2022).

Table 2. Nonprofit managers.

Nonprofit managers	**Target population**
Financial managers	73,080
Fundraisers	105,800
Health education specialists and community	126,700
Public relations and fundraising managers	98,100
Social and community service managers	173,700
Social workers	708,100
Business managers	**1,285,480**
Computer and information systems managers	50,910
Computer and information research scientists	12,670
Information technology manager	**63,580**
Top executives	9810
Emergency management directors	10,600
Senior executives	**20,410**
Total nonprofit managers jobs	**1,369,470**

Note: Data retrieved from the U.S. Bureau of Labor Statistics (2022).

Using power calculation with an integrated statistical calculator displayed in a graphical user interface (GUI), Utilized an online analysis tool to determine the random sampling population from the target population. The value used in the calculation is a confidence level of 95%, and the error margin corresponds to a value of $\alpha = 1 - 0.95 = 0.05$. According to the information obtained from the U.S. Bureau of Labor Statistics (2022), there are about 1,369,470 nonprofit managers worldwide, and the survey of 385 people comprises the entire sample population administered using a survey tool and contained survey questions to gather information on technical training and the use of big data technologies.

The UTAUT model constructs serve as the theoretical basis for this investigation (Venkatesh et al., 2003). Eight different models have been empirically compared to the UTAUT model to develop a cohesive approach. Included in these eight models are the following: the Theory of Reasoned Action, the Technology Acceptance Model, the Motivational Model, the Theory of Planned Behavior, a model that combines the Theory of Planned Behavior and the Technology Acceptance Model, the Model of PC Utilization the Innovation Diffusion Theory and the Social Cognitive Theory (Wedlock & Trahan, 2019). According to original data tests, the UTAUT model performed better than these eight separate models (Lawson-Body et al., 2020).

The UTAUT model is not just used to study information technology adoption, it has been extensively validated in various fields. It has also been tested in management, social psychology, and marketing because it shares similarities with numerous other theories and frameworks. The UTAUT model is very flexible, and its development has been followed by a sizable number of studies conducted in various contexts and integrating various disciplines. Its ability to work with other models and theories makes it a strong foundational theory for nonprofit organizations (Fadzil et al., 2019). Harris et al. (2018) note that although this topic has been studied, it has not been thoroughly examined and as a result, there is limited information in the past three to five years of peer-reviewed research regarding whether nonprofit managers receive the training necessary to utilize big data technology for overseeing business operations. Due to the legacy practices followed by big data technology, its adoption often requires more profound understanding and acceptance (Chauhan & Sood, 2021). While the topic has been explored, more research is needed to assess the correlation between the independent variable of technical training and the dependent variable of big data technology use, thereby addressing the research gap. Furthermore, there is a shortfall in the current peer-reviewed literature regarding empirical findings on business managers' perspectives on the adoption and training of big data technology (Harris et al., 2018).

How do nonprofit managers differ in technical training (facilitating conditions) using big data technology compared to managers who have not used big data technology to manage business operations?

H0: Nonprofit managers differ in technical training (facilitating conditions) and do not use big data technology to manage business operations.

Ha: Nonprofit managers differ in technical training (facilitating conditions) do-use big data technology to manage business operations.

Participants were given access to a structured survey instrument based on UTAUT to gather data. I have been granted written permission to use this published instrument (Queiroz & Pereira, 2019), using survey questionnaire data in the collection process to determine whether technical training, an independent variable, predicts the dependent variables' use of big data technology that was determined by conducting correlation and linear regression using measure and comprehend the statistical analysis because the participants in this nonexperimental design are chosen at random, and the independent variable is not altered.

In order to test the hypothesis, a statistical calculation was performed on the data collected from the survey participants that allowed for observing whether the p-value was below the chosen alpha level, which signifies that the test failed to reject the null hypothesis (Maennig et al., 2022). According to Cabrera-Sánchez and Villarejo-Ramos (2019), two big data researchers, the UTAUT model needs to keep improving to offer more compelling justifications for why new technologies are adopted. The quantitative data was collected using closed-end survey questionnaires, limiting respondents to what they were expected to answer. The respondents specified their level of agreement by selecting the most appropriate option on the 7-point Likert scale that allows measuring the result in numerical values. The scale of measurement used in the Likert scale is continuous and interval scale. A survey on big data technology was gathered from nonprofit managers across the United States as part of the planned research design. A 7-point Likert scale rating was used to interpret the survey questions, which aligned with the research question with responses recorded on a 7-point Likert scale (1 being strongly disagreed and 7 being strongly agreed.

4. Results

The final sample population resulted in 385, which met the minimum required for this study, and the data were exported into SPSS (Version 28). The study assessed the relationship between technical training (independent variable) and big data technology use (dependent variable) using correlation and linear regression (Frankfort-Nachmias et al., 2020). Both variables were measured on an interval scale, and univariate analysis showed that the data was clustered around the Mean with a low standard deviation. The sample consisted of 385 nonprofit managers, primarily female (73%) and aged 41 - 50 years (22.1%). The sample size of females with less than one year of big data experience has an impact. Therefore, this raises concerns about how well these results represent the broader population of nonprofit managers, which could limit the ability to generalize the findings to all nonprofit managers (**Table 3** and **Table 4**).

Table 3. Gender distribution.

Gender of participants	*n*	%
Male	102	26.5
Female	283	73.5
Total	385	100.0

Table 4. Years of experience using big data technology.

Years of experience	*n*	%
Less than 1 year	163	42.3
1 - 3 years	61	15.8

Continued

4 - 6 years	38	9.9
7 - 9 years	28	7.3
10 - 12 years	28	7.3
13 - 15 years	10	2.6
15+ years	57	14.8

Many respondents had less than a year of experience with big data technology. In Figure 1, the histogram shows the plotted point distribution close to a straight line at a 45-degree angle, bell-shaped and symmetric around the mean. It indicates the independent variable technical training and shows that the distribution is approximately normal, indicating normality. The geographical distribution throughout the United States allows focusing on regions where participants are located (see Figure 2). The East North Central region has a significant percentage (20.26%) of participants, followed by Mid Atlantic (17.92%). New England has the fewest participants (5.19%). The geographical distribution shows the involvement of the nonprofit by region.

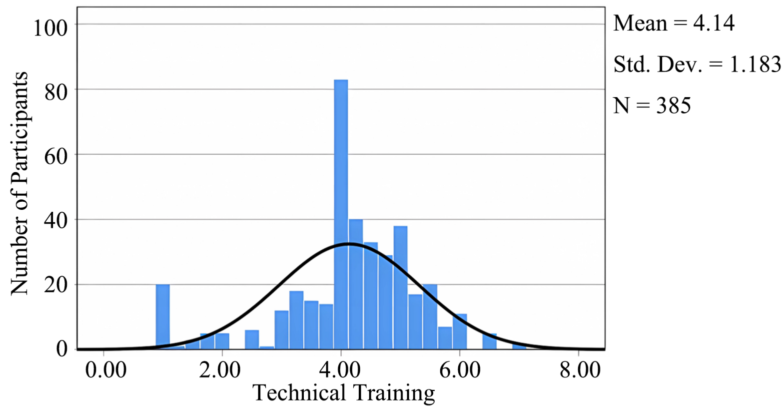

Figure 1. Histogram for technical training.

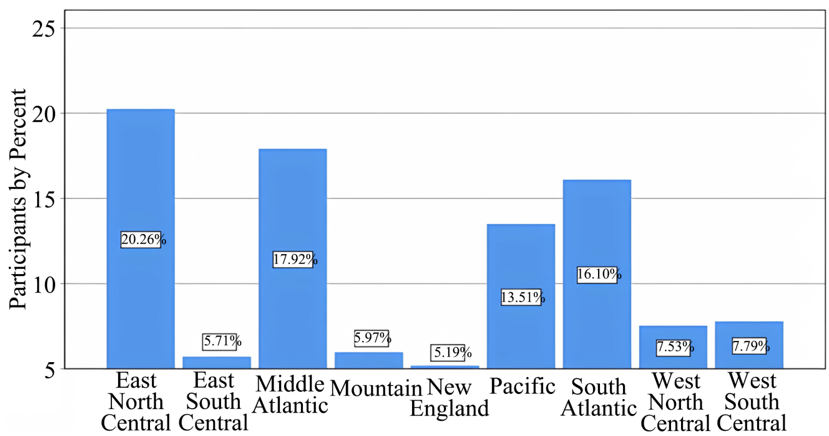

Figure 2. Bar chart by participants in U.S. regions.

The data distribution was normal, and hypothesis testing showed a significant relationship between technical training and big data use. The Pearson correlation coefficient ($r = 0.580$) indicated a moderate positive correlation, with a p-value less than 0.05, supporting rejecting the null hypothesis (Laureate Education, 2016).

$$r = \frac{\sum_{i=1}^{n}\left(X_i - X^{-}\right)\left(Y_i - Y^{-}\right)}{\sqrt{\sum_{i=1}^{n}\left(X_i - X^{-}\right)^2 \sum_{i=1}^{n}\left(Y_i - Y^{-}\right)^2}}$$

r is the Pearson correlation coefficient. X_i and Y_i are the individual data points for variables X (use of big data technology) and Y (technical training). X^{-} is the Mean of X (use of big data technology). Y^{-} is the Mean of Y (technical training). In **Table 5**, $N = 385$ is the number of observations. Pearson Correlation Coefficient $r = 0.580$. Significance (p-value) < 0.001, indicating the Correlation is statistically significant at the 0.01 level. Sample Size $N = 385$. This means that for the given dataset of 385 observations, the linear relationship between the use of big data technology and technical training is moderately positive ($r = 0.580$) and is statistically significant at the 0.01 level.

Table 5. Correlations.

		Use of big data technology	Technical training
Use of big data technology	Pearson correlation	1	0.580**
	Sig. (2-tailed)		<0.001
	N	385	385
Technical training	Pearson correlation	0.580**	1
	Sig. (2-tailed)	<0.001	
	N	385	385

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

In **Table 6**, a large F-statistics is the variation among group Mean has a higher value indicating evidence against the null hypothesis indicating that result is statistically significant and p-value less alpha (α) having statistical significance regression model, F (1, 383) = 193.726, $p < 0.001$.

Table 6. Analysis of variance (ANOVA)[a].

Model		*SS*	*df*	*MS*	*F*	Sig.
1	Regression	91.582	1	91.582	193.726	<0.001[b]
	Residual	181.060	383	0.473		
	Total	272.642	384			

[a]Dependent variable: Use of big data technology. [b]Predictors: (Constant), Technical training.

The regression equation $y = a + b \times x$, where y is the dependent variable use of big data technology on the y-axis, x is the independent variable technical training plotted on the x-axis, "b" in **Figure 3** has a value of =0.58 which is the slope of the line and "a" has a value of =2.229 of is the y-intercept, therefore $y = a + b \times x = 2.229 + 0.58 \times x$. The regression indicates a positive correlation of an upward slope on a scatterplot between the use of big data technology and technical training.

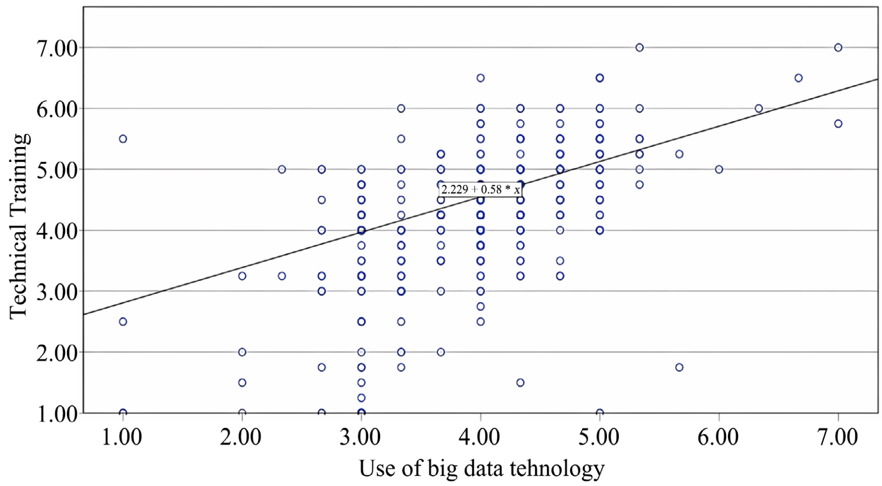

Figure 3. Plot chart.

The findings show a favorable correlation between big data technology use and technical training, and the model predicts an increase of 0 - 413 units for every unit increase in technical training (one-tenth of a standard deviation). Although many studies have clarified the adoption of 4.0 technology in the industry, more research is still required on UTAUT theoretical framework training (facilitating conditions) (Khin & Kee, 2022). Thus, the results of this study demonstrate that training (facilitating conditions) positively impacts decisions to use industrial 4.0 big data technology and requires operational resources such as qualified personnel with technical expertise. Technical training is necessary for qualified professionals to possess the knowledge of business operations and experience of overseeing the current operations.

5. Limitations

Although the study acknowledges certain limitations, the discussion fails to provide a thorough analysis of these issues, leaving the potential implications for the study's validity and generalizability insufficiently explored and largely unexplained. The constraints noted in this study are that it is necessary to measure the size of nonprofit organizations by looking at small nonprofits with fewer managers managing various tasks to achieve organizational objectives. On the other hand, large organizations employ a high level of work specialization to function more effectively. Respondents are less tech-savvy and require more technical expertise to understand technology, as evidenced by the majority of participants having less than a year of experience with big data technology. There is a closed-ended question in the survey tool. A previously validated instrument is used for data collection to get around the limitations. Nonprofit managers operating abroad who do not share U. S. characteristics might not find the research findings applicable to US nonprofit entities. The study does not provide a detailed examination of the specific types of technical training participants received or assess how effectively these training programs developed the big data skills necessary for nonprofit management. Therefore, the study does not delve into the specific types of technical training and effectiveness in developing relevant big data skills.

6. Future Research

Exploring the effectiveness of technical training on factors like learning time, teaching format, and quiz evaluation for mobile or web interfaces. Investigating the relationship between technical training and big data technology across different levels of nonprofit organizations and examining the need for new technical skills in response to technological advancements, ensuring efficient access to current learning materials, identifying training needs, and assessing their competencies to align with emerging big data technology. Assess whether technical training programs meet objectives, align with general skill sets, and evaluate their impact on decision-making. Investigating the cost-effectiveness of technical training on productivity and manager development. Further exploring big data technology and AI for cognitive decision-making algorithms in nonprofit systems, enabling improved decision-making and societal impact. Using diverse nonprofits across regions to validate the study's findings. Although UTAUT offers a helpful framework, the study could gain a more nuanced understanding of the phenomenon by integrating additional pertinent theories related to organizational learning, technology adoption, or nonprofit management to provide a more nuanced understanding of the phenomenon.

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Conflicts of Interest

The authors declare that they have no conflicts of interest in relation to the publication of this paper.

References

Anderson, J. S., & Williams, S. K. (2019). Turning Data into Better Decision Making: Asking Questions, Collecting and Analyzing Data in a Personal Analytics Project. *Decision Sciences Journal of Innovative Education, 17,* 126-145. https://doi.org/10.1111/dsji.12173

Ariella, S. (2022). *25 Incredible Nonprofit Statistics [2022]: How Many Nonprofits Are in* *the U.S.?* Zippia. https://www.zippia.com/advice/nonprofit-statistics/

Bammidi, M., & Hyndhavi, P. (2019). Training Effectiveness on Job Performance—An Analytical Study with Reference to Dairy Industry. *Sumedha Journal of Management, 8,* 134-147.

Brunetti, F., Matt, D. T., Bonfanti, A., De Longhi, A., Pedrini, G., & Orzes, G. (2020). Digital Transformation Challenges: Strategies Emerging from a Multi-Stakeholder Approach. *The TQM Journal, 32,* 697-724. https://doi.org/10.1108/tqm-12-2019-0309

Cabrera-Sánchez, J., & Villarejo-Ramos, Á. F. (2019). Factors Affecting the Adoption of Big Data Analytics in Companies. *Revista de Administração de Empresas, 59,* 415-429. https://doi.org/10.1590/s0034-759020190607

Chauhan, P., & Sood, M. (2021). Big Data: Present and Future. *Computer, 54,* 59-65. https://doi.org/10.1109/mc.2021.3057442

Chin, P. Y., Evans, N., Liu, C. Z., & Choo, K. R. (2020). Understanding Factors Influencing Employees' Consumptive and Contributive Use of Enterprise Social Networks. *Information Systems Frontiers, 22,* 1357-1376. https://doi.org/10.1007/s10796-019-09939-5

De Rezende Francisco, E., Kugler, J. L., Kang, S. M., Silva, R., & Whigham, P. A. (2019). Beyond Technology: Management Challenges in the Big Data Era. *Revista de Administração de Empresas, 59,* 375-378. https://doi.org/10.1590/s0034-759020190603

Demirel, D. (2022). The Effect of Service Quality on Customer Satisfaction in Digital Age: Customer Satisfaction Based Examination of Digital CRM. *Journal of Business Economics and Management, 23,* 507-531. https://doi.org/10.3846/jbem.2022.15328

Duan, S. X., & Deng, H. (2021). Hybrid Analysis for Understanding Contact Tracing Apps Adoption. *Industrial Management & Data Systems, 121,* 1599-1616. https://doi.org/10.1108/imds-12-2020-0697

Fadzil, A. S. A., Nasir Syed Mohamad, S. J. A., Hassan, R., Hamid, N. A., & Zainudin, M. I. (2019). Change Management Designed for Schools: Expanding the Continuum of UTAUT on Education Reform. *Global Business & Management Research, 11,* 340-350.

Frankfort-Nachmias, C., Leon-Guerrero, A., & Davis, G. (2020). *Social Statistics for a Diverse Society* (9th ed.). Sage Publications.

Fritsch, M., Sorgner, A., & Wyrwich, M. (2021). Types of Institutions and Well-Being of Self-Employed and Paid Employees in Europe. *Small Business Economics, 56,* 877-901. https://doi.org/10.1007/s11187-019-00274-2

Gong, Y., & Janssen, M. (2021). Roles and Capabilities of Enterprise Architecture in Big Data Analytics Technology Adoption and Implementation. *Journal of Theoretical and Applied Electronic Commerce Research, 16,* 37-51. https://doi.org/10.4067/s0718-18762021000100104

Harris, M. E., Mills, R. J., Fawson, C., & Johnson, J. J. (2018). Examining the Impact of Training in the Unified Theory of Acceptance and Use of Technology. *Journal of Computer Information Systems, 58,* 221-233. https://doi.org/10.1080/08874417.2016.1230725

Indrawati, & Khalik, S. (2020). End-User Acceptance Analysis in the Implementation of Enterprise Resource Planning in ABC Company Using Modified UTAUT. *Advances in Natural and Applied Sciences, 14,* 72-81.

Kar, S., Kar, A. K., & Gupta, M. P. (2021). Industrial Internet of Things and Emerging Digital Technologies-Modeling Professionals' Learning Behavior. *IEEE Access, 9,* 30017-30034. https://doi.org/10.1109/access.2021.3059407

Kavanaugh, J. (2020). Cultivating Digital Cultures. *Strategic HR Review, 19,* 2-6. https://doi.org/10.1108/shr-11-2019-0083

Khin, S., & Kee, D. M. H. (2022). Factors Influencing Industry 4.0 Adoption. *Journal of Manufacturing Technology Management, 33,* 448-467. https://doi.org/10.1108/jmtm-03-2021-0111

Laureate Education (2016). *Correlation and Linear Regression* [Video File].

Lawson-Body, A., Willoughby, L., Lawson-Body, L., & Tamandja, E. M. (2020). Students' Acceptance of E-Books: An Application of Utaut. *Journal of Computer Information Systems, 60,* 256-267. https://doi.org/10.1080/08874417.2018.1463577

Lee, C. W., & Kim, H. K. (2020). Technology Capability and Technology Level Analysis. *Management Review: An International Journal, 15,* 93-106.

Lowell, V. L., & Morris, J. (2019). Leading Changes to Professional Training in the Multigenerational Office: Generational Attitudes and Preferences toward Learning and Technology. *Performance Improvement Quarterly, 32,* 111-135. https://doi.org/10.1002/piq.21290

Maennig, W., Sattarhoff, C., & Stahlecker, P. (2022). Retire Statistical Significance? Reevaluation of the Employment Effects of the 2006 World Cup. *International Journal of Sport Finance, 17,* 73-88. https://doi.org/10.32731/ijsf/172.052022.02

Mayer, L. H. (2019). The Promises and Perils of Using Big Data to Regulate Nonprofits. *Washington Law Review, 94,* 1281-1336.

Nair, K. (2019). Overcoming Today's Digital Talent Gap in Organizations Worldwide. *Development and Learning in Organizations: An International Journal, 33,* 16-18. https://doi.org/10.1108/dlo-02-2019-0044

Nelson, E. (2020). Stakeholder Engagement in Curricular Design: Addressing Current and Emergent Community Needs. *Journal of Nonprofit Education and Leadership, 10,* 25-48. https://doi.org/10.18666/jnel-2020-v10-i1-8954

Papa, A., Chierici, R., Ballestra, L. V., Meissner, D., & Orhan, M. A. (2021). Harvesting Reflective Knowledge Exchange for Inbound Open Innovation in Complex Collaborative Networks: An Empirical Verification in Europe. *Journal of Knowledge Management, 25,* 669-692. https://doi.org/10.1108/jkm-04-2020-0300

Peñarroja, V., Sánchez, J., Gamero, N., Orengo, V., & Zornoza, A. M. (2019). The Influence of Organisational Facilitating Conditions and Technology Acceptance Factors on the Effectiveness of Virtual Communities of Practice. *Behaviour & Information Technology, 38,* 845-857. https://doi.org/10.1080/0144929x.2018.1564070

Persaud, A. (2021). Key Competencies for Big Data Analytics Professions: A Multimethod Study. *Information Technology & People, 34,* 178-203. https://doi.org/10.1108/itp-06-2019-0290

Queiroz, M. M., & Pereira, S. C. F. (2019). Intention to Adopt Big Data in Supply Chain Management: A Brazilian Perspective. *Revista de Administração de Empresas, 59,* 389-401. https://doi.org/10.1590/s0034-759020190605

Santos, T., Oliveira, M., Gomes, S., Sousa, M., & Lopes, J. M. (2021). Strategic Management and Value Creation in Non-Profit Organizations. *Journal of Management Information and Decision Sciences, 24,* 1-9.

Shapiro, S. J., & Oystrick, V. (2018). Three Steps toward Sustainability: Spreadsheets as a Data-Analysis System for Non-Profit Organizations. *Canadian Journal of Program Evaluation, 33,* 247-257. https://doi.org/10.3138/cjpe.31157

U.S. Bureau of Labor Statistics (2022). *Home: Occupational Outlook Handbook.* http://www.bls.gov/ooh/

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User Acceptance of Information Technology: Toward a Unified View. *MIS Quarterly, 27,* 425-478. https://doi.org/10.2307/30036540

Wedlock, B. C., & Trahan, M. P. (2019). Revisiting the Unified Theory of Acceptance and the Use of Technology (UTAUT) Model and Scale: An Empirical Evolution of Educational Technology. *Research Issues in Contemporary Education, 4,* 6-20.